"MODELLING, FORECASTING, AND RIDING CREDIT RISK IN THE STERLING EUROBOND MARKET"

by

Katiuscia Manzoni

Research Thesis in Fulfilment of the Requirements for the Degree of

Doctor of Philosophy

Department of Banking and Finance
City University Business School
London, UK

CITY City University Business School London

March 20, 2002

Table of Contents

List of Tables vi
List of Figures vii
Acknowledgements viii
Abstract ix

INTRODUCTION **1**

PART ONE

Chapter I: **THE EUROBOND MARKET**

1.1. Main features of the Eurobond market **10**
1.2. Research studies on Eurobonds **12**
1.3. Development and future of the Eurobond market **14**

Chapter II: **THE NATURE OF CREDIT RISK**

2.1. Credit risk definition and dimensions **29**
2.2. Credit risk versus Market risk **31**
2.3. Credit risk and diversification **38**
2.4. An increasing role for credit risk analysis **41**

Chapter III: **MEASURING CREDIT RISK**

3.1. Background and recent developments in credit risk modelling **46**
3.2. Approaches to risk measurement **48**
3.2.1. The portfolio approach 48
3.2.2. The default model and the mark-to-market models 49
3.2.3. Aggregative versus Structural Models 50
3.2.4. Advantages of Portfolio Credit Risk Modelling 52
3.3. Assessing the probability of default **54**
3.3.1. The traditional approach: Expert Systems 54
3.3.2. Loan and bond rating systems 55
3.3.3. Accounting-based Credit Scoring Systems 56
3.3.4. Bond prices approach 58

3.3.5. The structural approach and the KMV Credit Monitor Model 62
3.3.6. The VaR approach and the J.P. Morgan's CreditMetrics Model 65
3.3.7. The Macro Simulation Approach and the McKinsey Model 69
3.3.8. The Actuarial Approach: the Credit Risk+ Model 70
3.4. Model Validation 74
3.4.1. Backtesting 74
3.4.2. Stress Testing 76
3.4.3. Monte Carlo Simulations 77
3.4.4. Sensitivity Analysis 79
3.4.5. Benchmarking 80
3.4.6. External assessment 81
3.5. Capital-based pricing 81
3.6. Credit risk and regulatory capital 83
3.6.1. The 1988 Basle Accord 84
3.6.2. The European Directives 87
3.6.3. The 1995 BIS market risk proposal: the 1996 amendment 88
3.6.4. The proposed New Capital Adequacy Framework – BIS, 1999 92

Chapter IV: **LITERATURE REVIEW ON CREDIT RISK**

4.1. Introduction 95
4.2. Determinants of the credit risk premium 96
4.2.1. Risk of default and marketability 97
4.2.2. Demand and supply factors 98
4.2.3. Business cycle and confidence variables 99
4.2.4. Discounted certainty equivalent flows 102
4.2.5. Coupon, sinking fund, security status, and price volatility 103
4.2.6. Actual default rates and macroeconomic variables 104
4.2.7. The term structure of interest rates 106
4.2.8. Marketability 112
4.2.9. Other factors 114
4.2.10. Do credit spreads differ by type of obligor? 116
4.2.11. Bond spreads versus loan spreads 119
4.2.12. Limitations of credit spreads as indicators of credit risk 121
4.3. The specification of the term structure of credit spreads 122
4.3.1. Term structure of interest rates for default-free bonds 123
4.3.2. The term structure of interest rates for risky bonds 124
4.3.3. Estimation and measurement of the term structure of credit spreads 124
4.3.4. Evidence of independence between default risk differential and bond's maturity 126
4.3.5. Financial risks and the shape of the term structure 128
4.3.6. The credit yield curve and the leverage factor 129
4.3.7. Interaction between interest rate risk and default risk 134
4.3.8. The recovery rate and the term structure of credit spreads 135
4.3.9. The impact of different parameterisations of the event of default 137
4.3.10. Alternative models for the term structure of default risk 138
4.3.11. Implications of imperfect accounting data 139
4.3.12. An upward-sloping credit yield curve for speculative-grade firms 140
4.4. Valuation of risky debt 142
4.4.1. The proprietary models 142
4.4.2. The structural approach 144
4.4.3. The reduced form approach 145
4.4.4. The middle-way approach 148
4.4.5. Credit spreads based models 148

4.4.6. Credit-Rating Models ... 150
4.5. The CAPM and credit selection decisions ... 151
4.6. The empirical distribution of credit spread changes ... 152
4.7. Credit spreads and the extreme value theory ... 153
4.8. Conclusions ... 153

PART TWO

Chapter V: MODELLING CREDIT SPREADS

5.1. Introduction ... 157
5.2. Literature review ... 159
5.3. Time series properties of credit spreads ... 163
5.3.1. The data ... 163
5.3.2. Credit spreads stylised facts ... 166
5.3.3. The variables ... 167
5.3.4. Autocorrelation structure ... 173
5.3.5. Credit spreads stationarity ... 177
5.3.6. Cointegration analysis ... 179
5.4. Modelling credit spreads ... 182
5.4.1. The OLS model ... 183
5.4.2. GARCH models ... 186
5.4.2.1. ARCH(4) ... 187
5.4.2.2. GARCH (1,1) ... 187
5.4.2.3. GARCH (1,1)-Component ... 188
5.4.2.4. Additional tests ... 191
5.4.3. Asymmetric analysis ... 192
5.4.4. Summary results ... 194
5.5. Conclusions ... 195

Chapter VI: THE DYNAMICS OF BOND SPREADS AROUND RATING REVISION DATES

6.1. Introduction ... 198
6.2. Literature review ... 200
6.2.1. Stock Market Reaction ... 201
6.2.2. Bond Market Reaction ... 201
6.2.3. Event studies and Event-Induced Variance ... 205
6.3. Data and methodology ... 206
6.3.1. Rating Transition Matrix ... 207
6.3.2. Standard Event Study ... 209
6.3.3. Asymmetric Responses ... 210
6.3.4. OLS Panel Estimation ... 212
6.3.5. Event-Related GARCH ... 216
6.4. Empirical Results ... 218
6.5. Conclusions ... 226

Chapter VII: **MODELLING EUROBOND CREDIT RATINGS AND FORECASTING THE DOWNGRADE PROBABILITY**

7.1. Introduction...... 237
7.2. Review of the bond rating related literature...... 240
7.2.1. Linear regression analysis...... 240
7.2.2. Multiple discriminant analysis (MDA)...... 241
7.2.3. Probit Models...... 243
7.2.4. Neural Networks...... 244
7.3. Data and Methodology...... 245
7.3.1. Sample selection...... 245
7.3.2. Variables...... 246
7.3.3. Preliminary statistics...... 251
7.4. Empirical Results...... 257
7.4.1. Ordered Probit Results...... 257
7.4.2. Binary two-step Probit Model Results...... 260
7.4.2.1. Measuring Goodness of Fit...... 265
7.4.2.2. In-Sample Fit...... 267
7.4.2.3. Out-of-Sample Forecasts...... 268
7.4.2.4. Forecasting with Neural Networks...... 270
7.4.2.5. Combining Forecasts...... 272
7.4.2.6. Forecast stability...... 273
7.4.2.7. Small and Large Firms...... 273
7.5. Conclusions...... 278

CONCLUSIONS...... 282

REFERENCES...... 286

List of Tables

Table 3.1 Comparative analysis of credit models.......... 72
Table 3.2 Risk-capital weights by on-balance sheet asset category (WA).......... 86
Table 3.3 Risk-capital weights for off-balance sheet credit equivalent by type of counterparty.......... 86
Table 3.4 Add-on factors by type of underlying and maturity.......... 86
Table 3.5 The 1996 Amendment.......... 88

Table 5.1 ISMA Eurobond Index composition over time, 1992-1999.......... 164
Table 5.2 Unconditional Daily Distributions.......... 169
Table 5.3 Bivariate Unconditional Daily Correlations.......... 172
Table 5.4 Autocorrelation structure.......... 174
Table 5.5 The Chow's breakpoint test.......... 184
Table 5.6 Linear and nonlinear estimates for daily credit spread changes.......... 189
Table 5.7 Residuals Diagnostic Checking.......... 190

Table 6.1 Rating Transition Matrix, 1992-1999.......... 208
Table 6.2 Descriptive Statistics for Abnormal Yields (AY).......... 214
Table 6.3 Mean and Median CAR tests.......... 221
Table 6.4 OLS Pooled Estimation for Abnormal Yields (AY) around event dates, 1992-1999.......... 223
Table 6.5 GARCH Pooled Estimation for Abnormal Yields (AY) around event dates, 1992-1999.......... 224
Table 6.A1 GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Industry Sector.......... 229
Table 6.A2 GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Maturity.......... 230
Table 6.A3 GARCH(1, 2) Pooled Estimation for Abnormal Yields (AY) broken down by Coupon Rate.......... 231
Table 6.A4 GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Negative Pledge Guarantee.......... 232
Table 6.A5 GARCH(1, 2) Pooled Estimation for Abnormal Yields (AY) broken down by Amount of Bonds Outstanding.......... 233
Table 6.A6 GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Rating History.......... 234
Table 6.A7 GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Country of the Issuer.......... 235
Table 6.A8 GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Rating.......... 236

Table 7.1 Description of Variables.......... 248
Table 7.2 Descriptive statistics for the estimation sample.......... 252
Table 7.3 Mean, Median and Variance Differences Tests for downgraded and stable firms.......... 253
Table 7.4 Ordered Probit Model Estimates for Eurobond Ratings, 1992-1999.......... 258
Table 7.5 Two Step Probit Model Estimates for Eurobond Downgrades, 1992-1999.......... 263
Table 7.6 Hosmer-Lemeshow Goodness-of-Fit Test.......... 266
Table 7.7 The Expectation-Prediction Table.......... 269
Table 7.8 Type I and Type II Forecast Error and Hit Rates for 5 Sets of Forecasts.......... 275
Table 7.9 Comparison of the Prediction Accuracy of the two-step Probit Model and a Neural Networks Model.......... 276
Table 7.10 Downgrade Model for Small and Large Firms.......... 277

List of Figures

Figure	1.1	Volume of Bond Issuance in EMU	20
Figure	1.2	Euroland Bond Market (end H1, 1997)	20
Figure	1.3	Eurobonds by currencies	21
Figure	1.4	Euroland Eurobonds by currencies	21
Figure	1.5	Maturity of Euroland Eurobonds	22
Figure	1.6	Euroland Eurobond by issuer	22
Figure	1.7	Average Issue Volume	24
Figure	1.8	EUR Eurobonds by issuer's nationality	24
Figure	1.9	EUR Eurobonds of Sovereigns	26
Figure	1.10	Euroland Eurobonds by Rating	26
Figure	1.11	USD Eurobonds by Rating	27
Figure	2.1	Distribution of credit returns versus market returns	32
Figure	2.1	Integrated Market and Credit Risk Distributions	34
Figure	2.3	Required target return on credit-risk exposure in a portfolio context	41
Figure	3.1	Loss distribution	49
Figure	3.2	KMV Distribution of the firm assets value at maturity of the debt obligation	63
Figure	3.3	CreditMetrics framework	67
Figure	3.4	Statistical features of credit models	73
Figure	3.5	The Relationship between PDF and Allocated Economic Capital Losses	83
Figure	4.1	Valuing Risky Debt	116
Figure	4.2	Merton (1974)'s implications	130
Figure	5.1	Time Series of Daily Credit Spread Levels, Changes and Absolute Changes	168
Figure	5.2	Sample Autocorrelation Function for daily CS, $\lvert CS \rvert$ and $(CS)^2$ $(dCS)^2$	175
Figure	5.3	Sample Partial Autocorrelation Function (PAF) for CS and ΔCS	176
Figure	5.4	The variance ratio test for stationarity	181
Figure	5.5	Cointegration between credit spreads and the FTSE All Share Price Index	182
Figure	5.6	The CUSUM test for OLS residuals and squared residuals	185
Figure	5.7	Asymmetric Responses and News Impact Curves	197
Figure	6.1	Abnormal Yields for Downgrades and Upgrades	213
Figure	6.2	The impact of rating revision announcement on Eurobond mean and volatility spreads	225
Figure	7.1	Number of Eurobond Downgrades by Year, 1992-1999	246
Figure	7.2	Eurobond Volume Distribution over time	247
Figure	7.3	The marginal effects of the explanatory variables	259
Figure	7.4	Probability Response Functions	264

Acknowledgements

I wish to express my appreciation to Professor Roy Batchelor. I am grateful to him for his guidance and support throughout my research. I will always be indebted to him for fostering and developing my modelling abilities without ever turning aside from reality. Special thanks to Professor Michele Salvati for showing me the way to this greatest achievement of mine. His encouragement and confidence in my strengths lead me to make choices I would have never made and that, above all, I would have never thought I could carry on. I want also to express my infinite gratitude to my parents and my ever "little" brother for their love and continuous encouragement throughout my long educational journey. I dedicate this thesis to them. I must also thank Margaret Busgith for her extraordinary efficiency and Erik Larsen for his dedication to improve the PhD programme at City University Business School. Last but not least, I am especially grateful to Stefano Mengoli. His talent and sharpness inspired me and constantly stirred my mind and work. I could not have attained what I have without all of them.

All the mistakes in this thesis are my own.

Abstract

This thesis aims to make a contribution to the understanding of credit risk dynamics in the Sterling Eurobond market. The background to the thesis is the increasing size, complexity and volatility of all debt markets, where the tasks of measuring, understanding and forecasting credit risk are of central importance to investing institutions and to corporate and sovereign borrowers.

We investigate the changes in the perceived credit quality of bond issuers through three different approaches.

First, we describe the evolution of credit spreads over time, exploring whether they reflect economic fundamentals, or whether they represent a self-generated force. This question is central to the fixed income literature in general, and to the pricing of risky debt and credit derivatives in particular. The time-series properties of our credit spreads provide strong evidence of mean-reversion, non-linearities, and directional and persistent volatility. All these stylised facts are captured by time-varying volatility models.

Second, we assess the information value of bond ratings, by examining the dynamics of bond spreads around rating revision dates. In contrast to standard event studies we apply a novel GARCH model to the panel data. This lets us examine the effects of the re-grading event on the volatility of bond yields as well as the yields themselves. We find that downgrades are viewed as informational events, but upgrades are not. An asymmetric pattern is also observed in the dynamics of volatility.

Third, we build a predictive structural model for the downgrade probability using a two-step estimation procedure. This allows us to disentangle the effects of credit rating and various financial and accounting ratios. We find evidence of non-linear effects from both company indebtedness and credit risk. The forecasting model is benchmarked against both a naïve model, and a more sophisticated neural network model. Unlike the field of default prediction, little research has been done on forecasting the downgrade event. Filling this gap is of interest to banks and investors in periods of relative economic stability, in the context of value-at-risk models, and for the pricing of credit risky instruments.

INTRODUCTION

Possible contributions and structure of the thesis

The overall objective of the thesis is to contribute to the understanding of credit risk dynamics in the Sterling Eurobond market. My interest in this topic arose from two facts. First, this market is little researched. Second, the interest by academics and practitioners alike to learn more about credit risk is growing remarkably over the recent years.

This work comprises two parts. The first part discusses credit risk along its main dimensions and statistical properties and critically reviews various quantitative models for assessing a company's default probability. It also introduces regulatory issues, crucial in the context of credit risk and its impact on financial market stability. An extensive overview of the studies conducted in the credit risk area is offered as well. The aim of this first part is twofold. First we would like to provide the reader with the main theoretical concepts and general issues regarding credit risk. Second, this allows us to correctly pose and outline the problems originating the empirical investigations performed in the second part of the thesis.

The second part is structured as follows. Firstly, we describe empirically the dynamic evolution of credit spread changes, exploring whether they reflect economic fundamentals, or whether they represent a self-generated force. Secondly, we assess the information value of bond ratings by examining the dynamics of bond spreads around rating changes announcements. To this aim we carry out a novel event-related GARCH methodology that allows the rating change to impact volatility as well as market yields. Finally, we develop a predictive model for the downgrade probability introducing a two-step estimation procedure to disentangle the effects of default risk and financial/accounting variables. In summary, changes in the perceived credit quality of bond issuers are captured and investigated through different approaches: a time series approach to credit spread changes, an event-related GARCH-type approach to a rating revision, and finally a two-step probit regression approach to forecast the downgrade probability.

While credit risk is important to all fixed income markets (including the sovereign risk of government bond markets), this study is primarily concerned with credit risk in the Eurobond market. Although there is some sparse published evidence on the behaviour of the prices of US-dollar denominated bonds in the euro-market, no empirical work has employed UK-sterling denominated issues to test the theory about the determinants of bond yields in general and credit spreads in particular. A potential of our research is to fill this void in the literature. A brief outline of the empirical studies on the Eurobond market along with its historical developments, current features and structure is presented in Chapter I.

Credit risk is often compared with its counterpart, market risk, and many of the techniques developed to measure and control market risk have been applied to credit risk. In chapter II we review the factors that tend to differentiate credit risk from market risk, and that dominate the assessment, evaluation, management and pricing of credit risk in general and credit derivatives in particular. While we highlight fundamental differences between the two risks we also acknowledge the relevance of their interactions. The difficulty of modelling these interactions, in addition to the scarcity of readily available input data, the subjective nature of the estimation of default probabilities, correlations, and recovery rates, the typical illiquidity, and the dynamic nature of credit risk are all barriers to the design and implementation of credit risk models.

Once the main features and properties of credit risk are established, the next step is the measurement of default timing, default events, and recoveries. A long debate among practitioners, academics, and regulators has been taking place about these fundamental measurements. Various statistical and probabilistic credit risk models have been introduced to estimate the probability density function on a portfolio basis. These models are responses to the increasing role of credit risk and the growth of credit derivatives, on one side, and to regulators' pressures to define correct economic capital requirements, on the other side. Credit risk models and internal capital allocations play increasingly important roles in banks' risk management and performance measurement processes, including performance-based compensation, customer profitability analysis, risk-based pricing, active portfolio management and capital structure decisions. Chapter III offers a comprehensive overview of the better-known credit risk models and of related regulatory issues.

The first part of this work concludes with Chapter IV where a synthesis of the literature related to credit risk is presented. The literature has focused on three main aspects: explanation of credit risk premia, specification of the risk structure of credit risk premia, and valuation of risky debt. The first works in this field study the determinants of bond yields or yield premia using cross-sectional regression analysis. A second stream of the literature concentrates on the term structure of credit spreads according to the idea that spreads on corporate bonds vary with maturity holding all other bond characteristics constant. Third, we consider a variety of default-risk pricing models. The basic idea is that the inherent risk of any credit transaction should be compensated by way of return (calculated as the spread received) commensurate with the risk of default (both on expected and unexpected losses), the credit exposure, and the recovery rate in the event of default.

The second part of the thesis is largely empirical and looks at changes in perceived credit risk from three different perspectives. Changes in the credit quality of bond issuers are captured first by movements in credit spreads, second by rating revisions (downgrades and upgrades), and third by modelling and forecasting the downgrade probability. We outline below the aim of our investigations, their possible contributions, and the main results we achieved.

In Chapter V we investigate the forces driving credit spread changes (and their volatility) as a proxy for a mark-to-market change in the credit quality of bond issuers. Credit spreads, computed as the difference between corporate and government yields of similar maturity, are a fundamental tool in fixed income analysis. Being theoretically attributable entirely to the corporation's default option, they are used as measures of relative value in the pricing models of corporate debt.

Unlike most of the credit spreads literature, we follow a time series approach. The identification of a process that describes the dynamic evolution of credit spreads is of interest both to practitioners and academicians. This type of analysis is in line with the current need for a continuously updated information and for the understanding of the dynamic process of credit risk. This has implications for term structure models of corporate yields, the pricing of credit derivatives, and methods for measuring credit risk.

Banks have been devoting resources to the development of a benchmark model enabling them to set the credit spread on a loan sufficiently high to earn the bank target return on the economic capital that has to be set aside for the loan. Bond investors are also interested in understanding how credit spreads are determined in the market as essential element in their risk-reward analysis. A better comprehension of credit spreads will be beneficial for issuers too, by helping them to manage investor perception of their credit risk and ultimately improving their access to the capital markets.

Modelling and predicting credit spreads volatility might have also risk management implications. If volatility increases so will Value at Risk (VaR). Investors may want to adjust their portfolios to reduce their exposure to those assets whose volatility is predicted to increase in order to achieve an optimal proportion of assets in the portfolio. Predictable volatility means also that assets directly depending on volatility, such as options, will change in value in a predictable fashion. Moreover, the returns investors earn on risky debt must not only compensate them for an higher average of default risk, but also for the risk that the credit spread could differ substantially from its historical average. Concluding, in a rational market, equilibrium asset prices will be affected by changes in volatility and investors who can reliably predict changes in credit spread volatility should be able to better control the risk associated to credit positions.

Knowledge of the time series dynamics of credit spreads, and their basic relationships with variables of interest, is also useful when bonds of different credit ratings are actively traded and/or hedged. If the interest rate risk of a risky bond or debt portfolio has to be hedged using government bond based derivatives, traders have to know how the credit spread behaves with respect to interest rate changes to minimise basis risk. For example, hedge funds often take highly levered positions in corporate bonds while hedging away interest rate risk by shorting treasuries. As a consequence, their portfolios become extremely sensitive to changes in credit spreads rather than changes in bond yields. Finally, new hedging tools, the so-called credit derivatives, are priced on the basis of the credit spread (e.g. credit spread options). Evidently, the stochastic process followed by the credit spread has to be determined.

The main results of our first empirical investigation can be summarised as follows. First, we find that credit spreads are characterised by a cyclical behaviour and by a clustering of outliers across time, which is symptomatic of a persistent volatility process. Second, the unconditional distribution of both credit spread levels and changes is found to be more peaked and fatter tailed than a normal distribution. Third, credit spreads result to be integrated of order 1, and weak long-run co-movements (cointegration) are observed with the FTSE All Share return index. Fourth, credit spread levels and changes are not an *i.i.d.* process and they are characterised by mean reversion, nonlinearities and persistence in the conditional variance. Nonlinear dynamics and time-varying volatility structure are captured by a GARCH model able to explain 30 percent of the variation in credit spreads using factors suggested by traditional models of default risk -return on the stock market, exchange rate, and the term premium. Finally credit spread volatility is found to be directional, rising with higher spreads.

After studying the time series pattern of credit spreads, we narrow our analysis to look at spreads over a shorter time period around the announcement of rating revisions. In this case adjustments in the credit quality are captured by rating changes, and are measured by the spread between the re-graded bond and a stable bond with similar characteristics. Our aim is twofold. On one side, we want to assess the information value of bond ratings, on the other side, we want to look at the impact of the event on the spread volatility. This exercise is done in Chapter VI.

Research on whether bond-rating information is valuable has produced mixed results so far. The reason for this might be the lack of an established theoretical framework or the use of an incorrect methodology. We propose a new approach, an event-related GARCH methodology, to directly address both spreads (i.e., the differences between downgraded corporate bond yields and the yields of equal-maturity non downgraded bonds) mean and volatility dynamics surrounding rating change announcements.

This work provides insight on the relative importance of downgrades and upgrades as conditioning factors and on their asymmetric behaviour. Moreover, testing yield reactions to rating changes may provide evidence of the joint hypothesis of market inefficiency and of non-publicly available information incorporated into the assigned ratings. This paper also offers preliminary evidence of the magnitude of the profitability of trading strategies following the announcement considered.

Our main results are as follows. While downgrades are accompanied by a significant increase in the bond spreads during the announcement and post-announcement periods, the incremental information content of upward revisions is not statistically significant. An asymmetric effect is also observed on volatility. Upgrades are associated with significant increases in volatility during and around the event period. The results are reversed in the case of downgraded bonds where volatility is significantly depressed during and around the time the information is released. The persistence of volatility is also evaluated. Announcement shocks do not persist and rating information takes 1-2 days to be incorporated into yields. This implies that bond yields quickly incorporate public information and that the trading process does not generate persistent volatility in response to news.

The behaviour detected in the mean and volatility dynamics for downgrades and upgrades might be exploited accordingly to execute appropriate trading strategies. If it is known *in advance* that a rating revision is taking place in the near future, one might anticipate changes in the mean (or variance) during the period preceding or following the disclosure and act consequently. According to our results there is evidence of significant cumulative abnormal returns for downgrades and various sub-samples of downgraded bonds even *after* the release of the new information.

Finally we move away from a daily marked-to-market picture, to approach a longer-term (1-year) perspective. Also in line with the results from the event-related GARCH study, Chapter VII proceeds in building a predictive model for the downgrade probability. While a large number of theoretical and empirical studies have provided evidence about the variables helpful in predicting bond ratings and defaults, no empirical work has been done to model directly the probability for a bond rating to be downgraded. We attempt to fill this gap identifying the bond and firm specific factors beneficial to predict a rating downgrade.

Modelling transitions has started recently and only within the framework of rating transition matrices. Reasons for the early stage of these studies might be three. First, it was only recently that the rating agencies began releasing their data about rating actions. Second, most banks still think in "default mode". Because loan trading has developed only recently, they have just started to care about transitions short of default. Third, transitions are not really a fundamental economic event, whereas default is. Transitions might be seen just as changes in the rating agencies' opinions, so modelling transitions means modelling the agencies opinions. Thus, the first question might be why caring about those opinions.

However, it is increasingly common for banks to sell loans, to securitise loans, or to enter into credit swaps, all of which are means of transferring credit risk. This has lead banks to shift from a "default mode" way of thinking to a transition short of default perspective. Moreover, despite default is considered the ultimate outcome, it is clearly not the only credit event. Events such as rating migration may have significant impact on the pricing of credit risk as documented in Chapter VI. For an investor holding a bond, a downgrade in the bond's rating can result in a financial loss even if the bond's issuer has continued to make all scheduled payments. Furthermore, we may detect whether the causes of downgrade are different from the causes of outright failure. Finally, while a default model might be a fundamental tool during periods of exceptionally high failure rate, a downgrade model might serve more during periods of relative stability in the economy.

Having outlined the theoretical and practical justifications for a downgrade model, we want in particular to assess the role of company financial information and of credit quality in determining the downgrade probability of firms issuing sterling-denominated Eurobonds. To this scope we develop a two-step estimation procedure. In the first step the conditional expectation of default risk is estimated as a function of bond specific and firm specific characteristics by an ordered probit model. In the second step, we disentangle the impact of default risk –as obtained from the conditional mean estimate in step 1- from that of accounting ratios on the downgrade probability using a binary probit model.

The model developed in the first step might be useful for updating ratings ahead of ratings agency announcements, monitoring short-term changes in the credit quality of corporate obligors, and identifying profitable bond strategies. This last contribution is of special interest in light of the evidence of significant cumulative abnormal returns and bond spreads reaction presented in Chapter VI.

We find that the probability of being assigned a higher rating class is inversely related to leverage, firm growth rate, and increases in tangible fixed assets. On the other hand, it is directly related to size, profitability, earnings coverage, and earnings' instability. Moreover, a downgrade is less likely to happen in the presence of a negative pledge guarantee and when growth opportunities are higher. In contrast it is triggered by positive changes in tangible assets. There is also evidence of a non-linear relationship between leverage and downgrade probability on one side and risk of default and downgrade probability on the other side. Finally, accounting ratios and market-based risk measures result to be more informative for larger firms than for smaller firms.

Further studies in this field may provide several practical benefits for risk measurement and management practices. A deep understanding of credit risk requires further contributions to keep the pace with the overall increase of risk in debt markets and with creation of innovative and complex types of securities. In an environment of increasing complexity and volatility of debt markets, the task of correctly measuring and forecasting credit risk becomes essential to investment decisions. Investors will require access to timely and adequate information regarding the true nature of their credit risk exposures. Equally there is an essential need for a framework of credit risk evaluation that enables comparisons across the new diversity of issues and issuers and that helps investors to price debt securities properly. Finally, market regulators stimulate further the development of new (internal) credit risk models and innovative ways to manage credit risk in the ultimate attempt to improve the capital standards of financial institutions. Future research topics in these areas are proposed in the conclusions alongside with a brief *ex post* critical discussion of the thesis.

PART ONE

Chapter I

THE EUROBOND MARKET

This study is primarily concerned with credit risk in the sterling Eurobond market, generally neglected by the financial-academic literature despite its size and relevance. Therefore, we start off by introducing the reader to the basic conceptual issues and the existing literature related to this market. We also present an historical background of the developments of the whole Eurobond market from its birth to its current structure and composition. Finally, we narrow our attention to the sterling "portion" of the market to provide a brief description of the specific features of the bond issues constituting our database. In fact, some of the special characteristics we are going to discuss below are relevant for our successive empirical analysis – i.e., rating quality, tax treatment.

1.1. Main features of the Eurobond market

Domestic bonds are bonds issued by a domestic issuer in the domestic currency. They are subject to domestic law and are usually traded via a national clearing system. Unlike domestic bonds, Eurobonds are bonds underwritten by an international syndicate and sold in more than one country – in most cases mainly outside the issuer's country. The issuing currency is in most cases not the issuer's own currency. They are traded via the international clearing-houses Euroclear or Cedel. Eurobonds differ also from foreign bonds, which are bonds issued by a foreign issuer but denominated in the domestic currency, subject to domestic law, and placed on the domestic market mainly through a domestic syndicate.

The Eurobond market is virtually unregulated. Although most issues are made in the London market and subject to UK law, it is a market in which self-regulation has worked remarkably well. The result has been a market distinguished by its variety of participants and its products. In fact, the US bond market has been influenced by many of the innovations coming from the Eurobond market, including floating-rate notes, zero-coupon bonds and convertible put bonds.

Many Eurobond issues are placed privately. This avoids virtually all attempts at regulating this market. The presence of huge underwriting syndicates helps to form the networks required to assure placement of large issues. Bond issues are typically underwritten by a syndicate of banks and financial institutions. To help place such issues, many work to give such bond issues a liquid secondary market. Banks can do this by acting as market makers and by actively trading their own portfolios of Eurobonds. Many issues are accompanied by sinking funds or purchase funds. In both cases the company commits to a gradual bond buy-back, increasing the market liquidity. Call provisions sometimes are also included to allow the issuer to benefit (partially) from the falling interest rates.

Activity levels in the Eurobond market has fluctuated over time, as these bonds are sometimes close substitutes for other financial instruments. Like other Euro-markets, they are rapidly evolving financial products that change in response to changing regulations, market conditions and opportunities.

Why does the Eurobond Market exist?

Like most of the rest of the euromarkets, Eurobonds exist because innovative competitive firms found a market niche for them. The waxing and waning of their popularity reflect their competitiveness with other financial products both as other products evolve, and as regulations vary. To understand their niche and competitors, we should understand their link to the domestic bond market, the Eurocredit markets, and the swap market.

Firms will issue Eurobonds just as long as such bonds are competitive with domestic bonds, one key factor being the cost, both in money and time, to issue the bond. From this perspective, Eurobonds can look attractive as long as they can avoid delaying regulations and sharp competition keeping underwriting costs low. Tax implications are also relevant. Unlike the U.S. (and some other nations) where publicly issued bonds must be registered Eurobonds are usually bearer bonds. This helps to streamline bond issues and lower administration costs. Since there is no central record of ownership, declaring the coupon payments received on personal income taxes is left for the honour of the individual. Just as importantly, this means there is no *withholding tax* on interest payments. Finally, the presence of any arbitrage opportunity that lowers the cost of financing should be taken into account. Note that some investors may have only limited access to the Eurobond markets, while risk perceptions may differ between the Euro and the domestic markets.

As far as the relationship of Eurobonds *versus* Eurocurrency loans is concerned, evolution has brought the Eurobanking market much closer to the Eurobond market in terms of the services they provide. Both offer fast cash in large quantities in a choice of currencies. Both offer syndication of risk and underwrite the sale of the firm's paper. As a result, the line between the two has blurred somewhat. However, Eurobonds have typically longer maturities and provide only annual coupons payments. Moreover, note issuance facilities (NIF) - i.e. a facility that guarantees the company the right to borrow from a group of banks up to some agreed maximum - and loans put more conditions on how the business must be run, while Eurobonds do not. This means that a good reputation (and therefore a good bond rating) does matter more for Eurobonds.

Finally the growth of the Eurobond market should be related to the introduction of swap contracts. Swaps are designed to cover the foreign-exchange risk associated with servicing outstanding bonds. Therefore, borrowing via Eurobonds and swapping the risks gives the equivalent of a domestic bond. Moreover, since domestic and foreign lenders may have different opinions of the borrowers, the rates offered might be different.

1.2. Research studies on Eurobonds

Mendelson (1972) is the first paper addressing specifically to the Eurobond market (EM) and its relation to the Eurodollar market. The paper inquires into the Eurobond market potency and limitations as an integrative force within the capital markets. The limitations of integration are explained in terms of legal impediments and of the structural character of the securities industry.

Mahajan and Fraser (1986) conduct a study to test the null hypothesis that no yield differentials exist between similar securities in the Eurobond and US bond markets. A sample of dollar Eurobond and domestic bond issues is carefully matched on five criteria: the same parent company, the same ratings, comparable coupon rates, comparable time to maturity, and yield observations belonging to the same month. Results support the null hypothesis. Market participants on the supply and demand side in the dollar Eurobond market and the US bond markets are able to arbitrage away yield differences. Finally, the issue size, the issuer's rating, and the market's familiarity with the issuer do not influence Eurobond pricing differently than domestic US bond pricing.

Kim and Stulz (1989) using a sample of 183 Eurobonds issued by US corporations during the period 1975-1985, present evidence of a significant positive stock-price reaction to the announcement of Eurobond issues. The pattern of abnormal returns over time is explained by the clientele hypothesis, which states that firms can increase shareholders' wealth by exploiting their comparative advantage in providing securities that are high in demand by a financial clientele. The hypothesis implies that, for periods of time, some firms can borrow at lower costs in the Eurobond market than in the domestic bond market. An estimate of the gains that accrue from issuing debt in the Eurobond market can be obtained. This estimate is helpful in explaining the cross-sectional variation in the stock-price responses to announcements of Eurobond offerings.

Beer (1995) provides a broad outline of the origin of the US dollar segment of the Eurobond market, its functioning, its legal aspects, and its future prospects. In addition, the actual characteristics of the market are studied using a sample of US denominated Eurobonds issued by European, Japanese, and US companies. The evidence indicates that the US dollar Eurobond market shares have dropped. The evidence also shows that issues by US companies have the longer life and the highest coupons. Four features have been shown to differentiate Eurobonds from domestic bonds: i) Eurobonds are of shorter maturity with a greater degree of sinking fund provisions; ii) Eurobonds are virtually free of regulation by monetary authorities; iii) in the EM, annual payments are typical; and iv) Eurobonds attract different investors than other bonds.

Batten, Ellis and Hogan (1999) investigate the scaling relationships for daily credit spreads, from January 1986 to May 1998, between AAA, AA and A rated Australian dollar denominated Eurobonds for various maturities. They find clear evidence of a credit term structure and co-movement in credit spreads by maturity. The credit spread return series is found to be time variant, leptokurtic, autocorrelated and exhibited different degrees of negative long-term dependence.

Clare et al. (2000) present evidence of the systematic relationship between macroeconomic and financial sources of risk and the U.S. dollar Eurobond market between 1992 and 1997. A small set of macroeconomic and financial variables, more frequently used to model the equity risk premium, can help explain the Eurobond risk premium. They are the default premium, the term premium, the exchange rate, a measure of unexpected inflation, and the return on the S&P. This multifactor model is applied to the problem of tilting portfolios to insulate returns against the individual sources of systematic risk.

Abou-Zeid and Savvides (1995) investigate the determinants of the yield on Eurobonds denominated in the European Currency Unit (ECU). Results show that the yield on ECU Eurobonds depends significantly on investors' perception of the attractiveness of such bonds, and that such attractiveness is negatively related to the real return on DM-denominated Eurobonds, while the ECU/dollar exchange rate and the yield on Eurodollar bonds do not significantly influence attractiveness.

Batten, Hogan and Pynnonen (2000) investigate the long-term equilibrium relationship between Australian dollar bonds of different credit quality. The results suggest that yields of different risk classes of Eurobonds are cointegrated with one another, with the higher-rated bond yields tending to lead the lower-rated yields. The paper also demonstrates that the cointegration relationship can be utilised in modelling the dynamics of the spread changes between Eurobonds and Government bonds.

Nickell, Perraudin and Varotto (2001) use price data on large dollar-denominated Eurobond portfolios to backtest systematically rating-based and equity-based credit risk models. Korean convertible Eurobonds are valued by Bailey, Chung and Kang (1996). Athanassacos and Schnabel (1997) empirically assess stockholder wealth gains from the issuance of Canadian dollar denominated Eurobonds, in lieu of domestic bonds, for a sample of Canadian firms which employed both types of bond financing during the period 1983-1990. Esho, Lam and Sharpe (1999) examine the determinants of incremental debt financing decisions made by large Asian firms from ten countries over the period 1989-1998. Their results suggest that floatation costs, agency costs and renegotiation and liquidation risk affect the choice between obtaining a syndicated bank loan or making a public issue in either Eurobond of foreign bond markets. Merrik (1999) uses Republic of Argentina US dollar-denominated Eurobonds to estimate the impact of the Russian default crisis on the expected recovery ratio and the default probability term structure on Argentine credit-sensitive sovereign bond prices. De Almeida, Duarte, and Augusto (1998) identify and simulate the most important factors driving the movements of a term structure of interest rates in the Brasilian Eurobond market. Scholtens (1999) focuses on the relationship between Eurobond yield differentials and country risk in the 1990s by calculating rank correlations for more than a dozen countries - both developing countries and industrialised ones.

1.3. Development and future of the Eurobond market

The impetus leading to the emergence of the Eurobond market and the influences that led to it being based in London arose principally as a result of the political and economic environment in the international capital markets after the Second World War, and the economic, monetary and fiscal measures undertaken by the US monethary authorities between the late 1950s and the early

1970s to redress the substantial US balance of payment deficits. Equally important was the regulatory environment in the major European and Japanese financial markets, which contributed directly and indirectly to the development of the Euromarkets.

Origin and growth of the Eurobond market

In the early days of the Eurobond market, before institutional investors came to play a significant role in the market, most issues were sold to groups of private investors, or to banks that dealt on their behalf. These retail investors, who still pay an important role in the market are attracted to these instruments because they are free from withholding tax, and the bearer nature of the bond in that it is a security for which the main determinant of ownership is the possession of the certificate and the attached coupons, as opposed to a registered security where ownership is recorded by the issuer, offers them anonymity.

Political and economic factors played a major role in the development of the Euromarkets. Possibly the earliest political factor of significance to contribute to the emergence of the Euromarkets was the Soviet and the Eastern block fear of their US dollar deposits by the US government as a result of some unforeseen development in the cold war. The Soviet bloc authorities transferred their US dollar balances to Western European banks outside the control of the US government and courts. These funds were then invested profitably as US dollar denominated currency loans via the European banks, giving birth to the Euromarket.

When banks found that these deposits could be used profitably they started to actively trade them. London banks began to use dollars to finance trade and make loans outside the restrictions of the Bank of England. The demand for these deposits was boosted by the restrictions imposed in 1957 on the use of sterling by third parties to finance trade credit in order to reduce the country's vulnerability to the threat of a politically induced currency crisis. In their attempt to overcome this restriction and maintain what was a highly profitable business UK banks used US dollars to finance the foreign trade activities previously financed in sterling.

This embryonic market was given a boost by regulations introduced by the US monetary authorities on domestic interest rates. Regulation Q imposed a relatively low deposit ceiling, and a relatively high lending floor. This ceiling encouraged the diversion of funds from the US to the Euromarkets. In contrast to the low deposit rate, a relatively high lending rate drove US high-grade or credit-rated borrowers to resort to the Euromarkets.

The outflow of US dollars in the early 1960s had created balance of payment problems for the United States. To redress the persistent US balance of payment deficit, the US government enacted the Interest Equalisation Tax (IET) in July 1963. This was the imposition of a levy of up to 15% on all purchases by US citizens of foreign debt and equity from Western Europe, Canada and Japan. The IET was followed in 1965 by a voluntary programme (later turned in a legal constraint) intended to stop the flow of funds from the US domestic economy in view of the escalating cost of the Vietnam war. These measures were responsible for the flow of net investment in favour of the US, but they also created a unified European capital market. They were also partly responsible for the creation and development of the Eurobond market and the internationalisation of investment banking.

The restricted amount of domestic funds that US firms could use to finance their overseas activities forced them to rely further on the Eurocurrency market. Moreover, European investors had a huge appetite for bonds issued by well-known US firms. These factors created opportunities for the European financial centres to compete with the United States to provide capital for foreign borrowers. As most of the European markets were diverse and highly regulated, London, being in an advantageous position, adopted the role of an entrepot for foreign capital, by lending and borrowing foreign capital. Several specific measures were undertaken by the UK monetary authorities to make London market more attractive to non-residents. The issue of bearer securities was again permitted and the tax on security transfers or sale was also reduced. Investment bankers for their part developed the technique of floating these issues of bonds denominated in US dollars or any alternative currency in ways which avoided both restrictions on borrowing in local currency, by placing the issue outside the country of currency denomination. This became known as the Eurobond market.

The stimulus to Eurodollar borrowing by US banks was the 1966 US monetary restraint programme, under which the discount and the prime rates were raised with the effect to cause interest rates on secondary market commercial deposit to rise to levels above the regulation Q ceiling. This created an interest rate differential in favour of the Eurodollar market and ultimately induced banks to withdraw from CD instruments, leading to huge reserve losses. In an attempt to finance these reserve losses, US banks turned to borrowing in the Euromarkets, increasing their liabilities to their overseas branches. The large volume of US borrowing exerted a strong impact and had a few long-term repercussions on the Eurodollar market.

In the 1970s the currency market opened up to the Eurobond market, when the first Australia dollar issue was launched in 1972. This was a dual currency A$ issue, where interest and principal were to be repaid at the investors' option either in Australian dollars or in Deutschmarks. A dual currency Eurobond is generally a bond issued in one currency bearing a coupon in that or another currency; upon redemption the principal can be paid in a different, usually a major, currency. Dual currency Eurobond issues involve investors in a forward foreign exchange transaction, but they are compensated in two ways for assuming the currency risk. Firstly, the coupon rate on the bond is usually higher than that available to holders of a comparable straight Eurobond issue. Secondly, the redemption amount usually includes a premium above the prevailing spot rate. The borrower, on the other hand, obtains relatively low cost finance without exchange rate risk. The proceeds of the issue are converted to a preferred currency at the spot rate. The issuer also chooses the currency to which interest payments are to be converted, at a forward rate fixed at the time of issue for the life of the bond.

In 1975 the first pre-priced deal took place. In a pre-priced deal the lead manager and its syndicate price and underwrite the whole of the issue, thereby substantially reducing the number of participants in the managing and selling group. In this kind of deal the competition in underwriting is much fiercer than in a traditional deal, where a syndicate is formed and terms agreed between its members after a period of open pricing to determine the final price that will ensure the success of the issue. With the introduction of pre-priced deals the syndicate members had to anticipate market conditions before the issue was placed, which would consequently increase the members' risk exposure.

The advent of right-wing governments in the major industrialised countries in the 1980s, with market-oriented policies, introduced a constant deregulation and elimination of barriers in their financial markets. This, coupled with the steady decline of interest rates between 1982 and 1986, led to a spectacular growth in the volume of new issues. This growth made possible the introduction of swaps, exchange rate options, futures, and commodity linked products. These, in turn, enabled both borrowers and investors to hedge their positions and to reduce most of the traditional risk associated with international investment.

The 1980s also saw the emergence of the institutional investor as a major player in the Eurobond market, resulting in larger issues and bigger average sizes. Japanese investors and borrowers also became major players in the market in the 1980s, partly as a result of Japan's substantial trade surplus between 1981 and 1987, and partly due to the rise in value of the Tokyo stock market. The latter made possible for Japanese issuers to place substantial equity-linked and convertible Eurobond products at a cheaper all-in-cost than was possible in their domestic markets.

The 1980s experienced also the introduction of the bought deal, where the investment bank gives a firm commitment to buy the entire issue outright from the issuing firm, and then undertakes to arrange the syndicate, participating and underwriting. This differs from a stand by commitment, where the syndicate agrees to buy the unsold part of an issue, and from a best effort commitment, where the syndicate agrees to use its best effort to sell the issue. Bought deals mean that the investment banks involved have to allocate more capital to each issue as they may find themselves with large quantities of unsold paper if the market moves against them or if syndication is not successful. On the other hand this form of issue favours the borrower, who can time the acceptance of the deal to the most opportune moment in terms of interest rates.

In July 1984 the US authorities lifted the 30% withholding tax on interest paid by US issuers to non-resident investors. The outcome of this was that the traditional relationship between US dollar Eurobonds and foreign bonds, where the yield on foreign bonds was higher because of the withholding tax, started to fade. This liberalisation spread to other markets in 1985, particularly to the yen and the Deutschmark sectors. The cautious decline in US interest rate levels in 1985, which was accompanied by an approximately 16% depreciation in the value of the US dollar on a trade weighted basis, enhanced liberalisation efforts in the non-US dollar sector of the Eurobond market. Non US dollar denominated Eurobond issues grew in popularity, while the growth of the dollar sector declined. The Euroyen market continued to expand as a consequence of continued relaxation in the Japanese financial markets as well as swap-driven Euroyen issues. Asset swaps also came into prominence with over US$10 billion of existing fixed rate Eurobonds being re-packaged and re-issued as high yielding FRNs by the use of interest rate swaps. The FRN market became the fastest growing sector of the Eurobond market from 1984 to 1986. This enabled issuers to successfully place novel and innovative instruments such as the reverse FRN, high margin FRNs and collateralised mortgage obligations, as well as introducing new currencies of denomination.

The inverting of the yield curve as a result of the rise in short-term interest rates between 1987 and 1990 created problems for the bond market, bringing the long bull market to an end as investors switched their holdings to cash or near cash instruments. Liquidity vanished and many traders stopped quoting prices. Intense competition and narrowing margins, on one side, and falling interest rates, on the other side, induced most issuers to go into fixed rate funding or the more flexible Eurocommercial paper market. The problems in the FRN market were the first sign that the growth of the Eurobond was coming to an end. In 1987 new issue activity dropped for the first time since 1980. The drop in public debt issued by sovereign borrowers reduced the liquidity of the market because of the small size of most corporate bonds.

The stock market crash in October 1987 made matters worse. The effect was to add to the weakness of the Eurobond market, in spite of the accepted conventional wisdom that in periods of falling equity values investors will switch to fixed income securities. Any switch to bonds was confined to government issues as investors looked for protection in high quality paper. Falling equity prices affected the credit standing of corporate Eurobond issuers and this helped depress prices further, while government bonds behaved as expected and increased in value. Since most bond traders had gone short of the market, this created a general problem of finding paper to cover their exposed positions. Liquidity in government bonds started to dry up and the spread between government bonds and Eurobonds widened, turning hedged positions in Eurobonds into losses.

The advent of event risk from 1988 onwards caused by the use of junk bonds for leverage buyouts and other unforeseen special events meant that corporate debt was avoided by investors, who took flight into quality names, namely issues by sovereign states and supranationals. Borrowers and investors began to rely on currency diversification as means of increasing their portfolio returns and reducing their exchange rate risk, prompting increased holdings in issues denominated in currencies such as the ECU, sterling, the Canadian dollar as high yielding alternatives to the US dollar.

Amid all this gloom, however, issues in US dollar values in the Eurobond market continued to increase. In the sterling sector, Eurosterling issues for the first time outstripped UK gilt volumes, especially during 1988. The effect of this capital inflow was a fall in sterling interest rates, which in turn affected the attraction of the currency, as well as narrowing spreads. The steady decline in short-term rate in 1991, as a result of attempts by the US authorities and the governments of most other English-speaking countries to reduce recessionary pressures in their economies, resulted in record issuing activity in the Eurobond market in 1991.

Current state

Over the last few years the significance of the Eurobond market has assumed an increasingly important role as a conduit for the financing of public and private-sector issuers. Figure 1.1 shows the annual Eurobond issue volume in Euroland currencies. It has tripled since the beginning of the 1990s thus impressively underlining the enormous dynamics and growing significance of this market segment. Within the overall Euroland bond market Eurobonds play an important role with a volume outstanding of ECU 628 bn (as of end of the first quarter of 1997) with government bonds and bank bonds predominating (Figure 1.2).

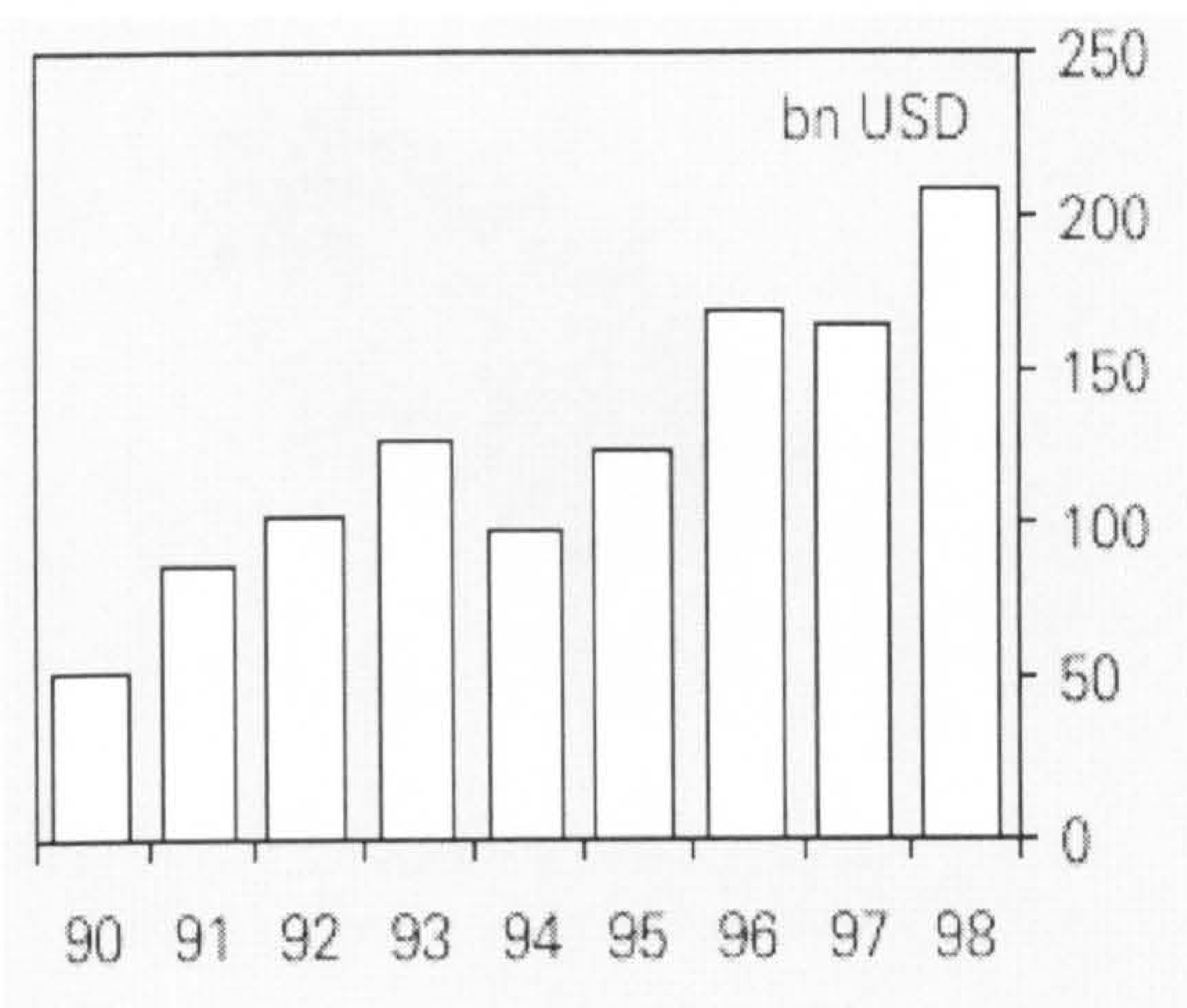


Figure 1.1 *Volume of Bond Issuance in EMU*

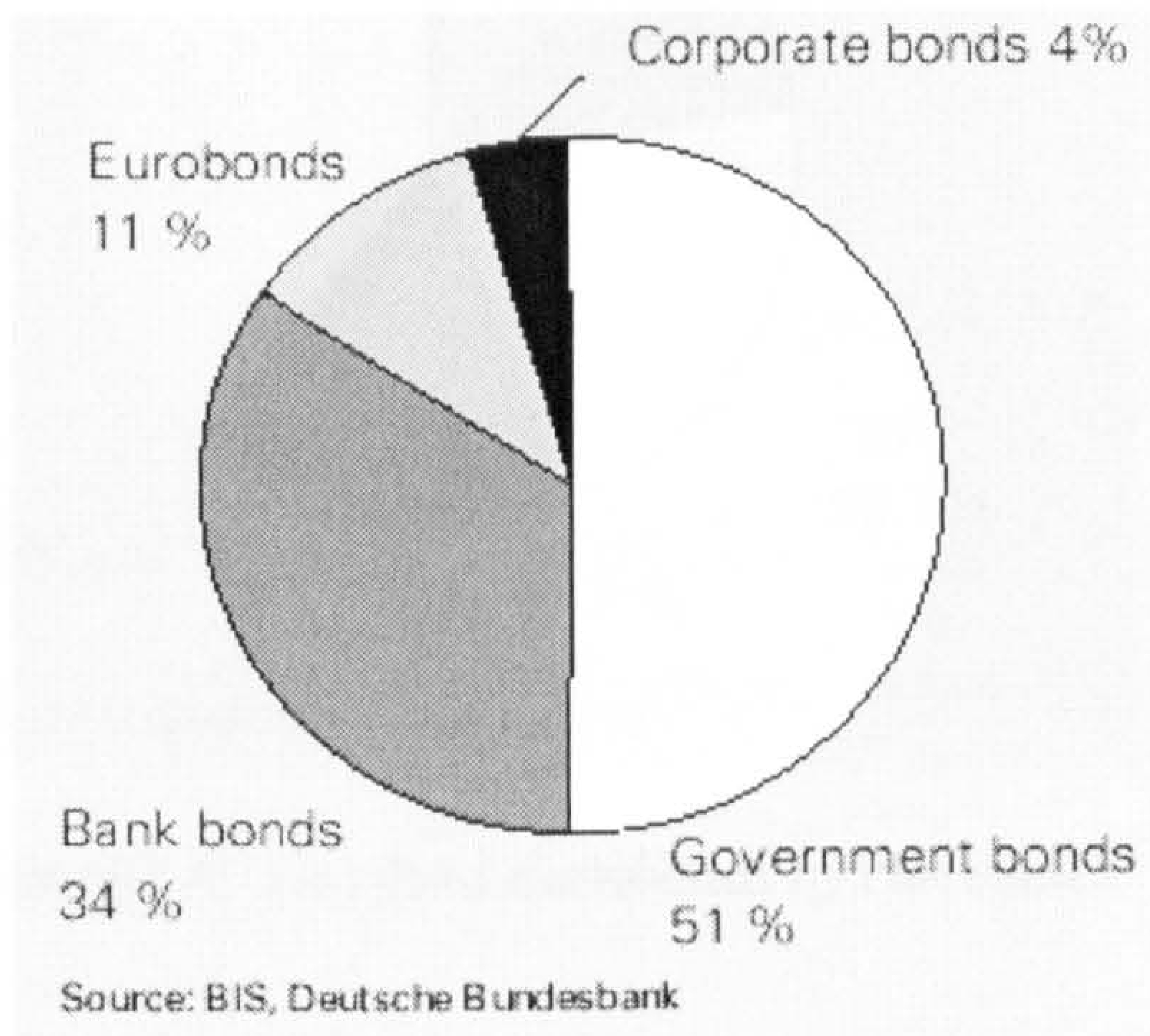


Figure 1.2 *Euroland Bond Market (end H1, 1997)*

The clearly dominating issuing currency on the Eurobond market (Figure 1.3) is the US dollar (USD). In mid-1998, the USD accounted for roughly USD 1 tr or 38% of the total volume. This is due to the history of the Eurobond market (regulation Q, collapse of the Bretton Woods system) and the position of the USD as the most important trade and reserve currency. The most recent developments, however, show that Eurobonds in Deutschmarks (DEM), lira (ITL) and French franc (FRF) are catching up. Before the start of EMU the outstanding volume of all Euroland Eurobonds (approximately USD 900 bn) accounted for 35% – almost the share of USD Eurobonds (Figure 1. 3).

Leaving these two large blocks aside, the EU-4 block (i. e. the pound Sterling (GBP), the Danish krone (DKK), the Swedish krone (SEK), and the Greek drachma (GRD)) account for USD 335 bn or 13% of market capitalisation, with the GBP alone accounting for USD 315 bn or 12% of market capitalisation. Apart from the traditional importance of the GBP as issuing currency, the revaluation of the British currency after the currency crises in Europe in 1992 has contributed to this increased weight measured in USD. Furthermore, investors who used to be or still are wary of the EUR regard the GBP as a diversification alternative to Euroland currencies. The fourth largest block are Eurobonds denominated in yen (JPY) with USD 262 bn or 10% of the total. The Canadian, Australian and New Zealand dollars (CAD/AUD/NZD) only play a subordinate role on the Eurobond market with 4% or USD 92 bn.

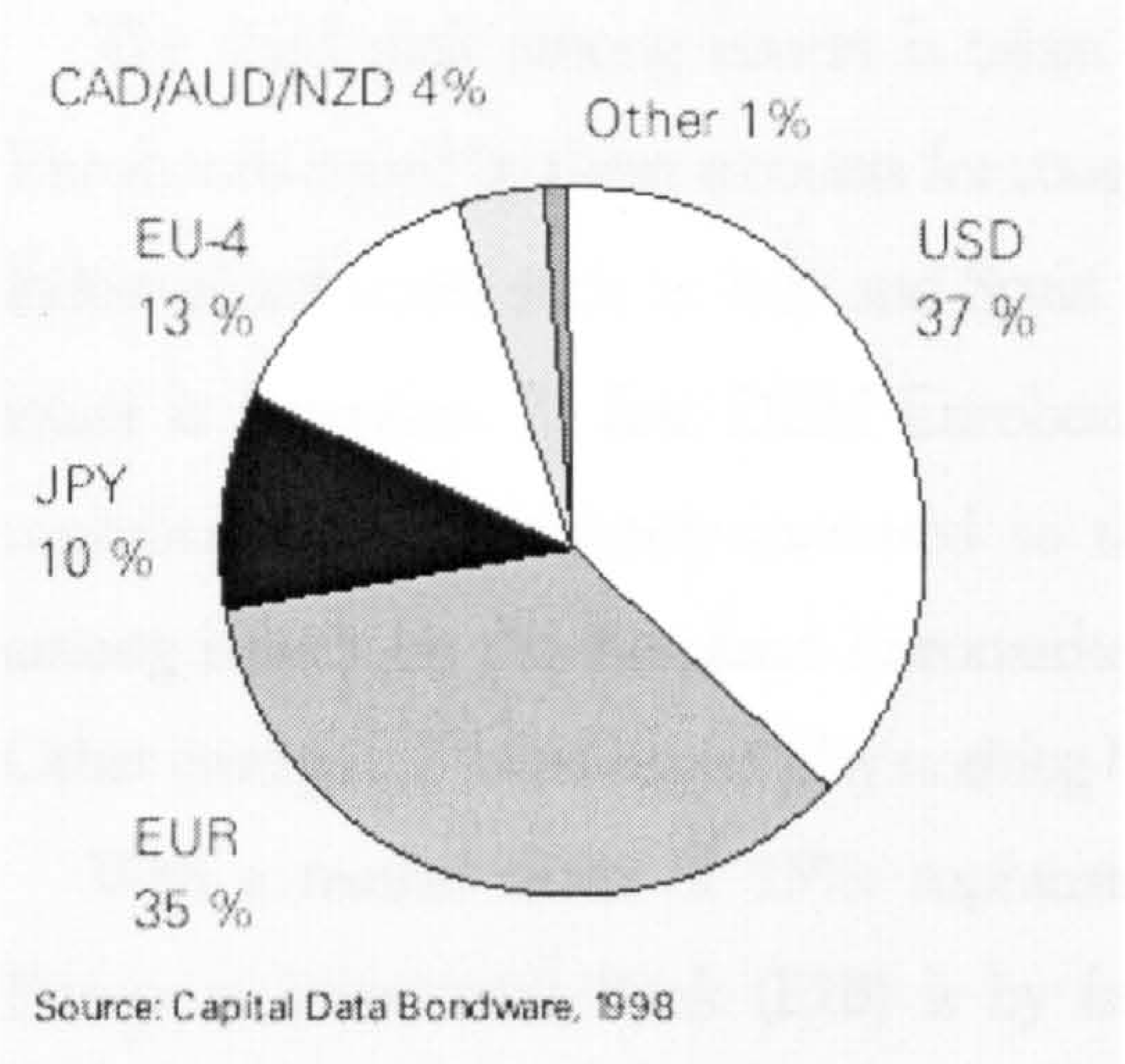


Figure 1.3 *Eurobonds by currencies (end H1, 1998, total volume USD 2584 bn)*

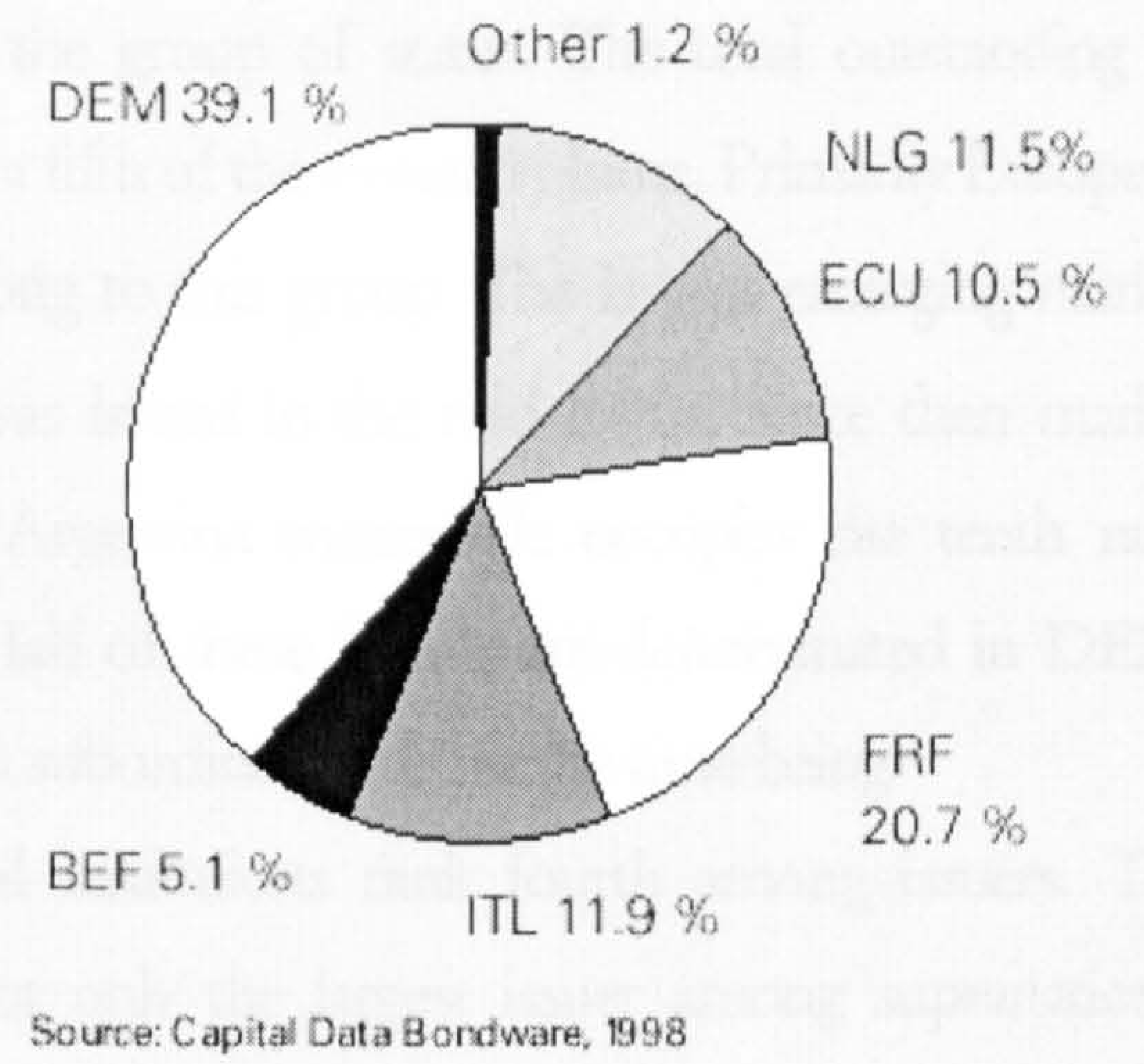


Figure 1.4. *Euroland Eurobonds by currencies*

The analysis of the structure of the Eurobond market cannot neglect issues like maturity and type of issuer. Figure 1.5 shows the maturity structure of Eurobonds as of end of 1998. It is based on the original maturities at issuance. The chart reveals that Eurobonds with an original maturity of four to seven years prevail. In the last few years, issuance of bonds with a maturity from eight to ten years has increased to cover the growing demand by institutional investors who wanted to profit from the steep yield curve and the ongoing rally on the international bond markets. The share of bonds with a short maturity (one to three years) and maturities over 10 years is rather small. As far as the sterling Eurobonds' maturity structure is concerned, a detailed presentation of the dynamics of the maturity composition from 1992 to 1999 is offered in Appendix [A]. From this analysis it emerges the decreasing portion of 7-10 years maturity bonds (from 40% in 1992 to 20% in 1999) and the increasing importance of 3-7 years maturity bonds (from only 3% in 1993 to 30% in 1999).

The composition of issuers on the Eurobond market is very heterogeneous. We can distinguish the following main groups: private and public financial institutions, states, supra-nationals, corporations and local or regional entities. Financial institutions comprise banks and insurers, with banks surpassing insurance companies in issuance volume. Private and public financial institutions used to be the most active issuers in the past. The volume of Eurobonds issued by them accounts for USD 295 bn or USD 202 bn respectively, i.e. 34% or 22% of all bonds issued in Euroland currencies. The most important borrowers are German and French institutions. Among public financial institutions the volume of German borrowers is by far the largest.

The third rank among issuers is taken by the group of states. The total outstanding of Eurobonds issued by them accounts for roughly a fifth of the overall volume. Primarily European industrialised states such as Italy and Spain belong to this group. The largest emerging market issuer is Argentina. Its first DEM Eurobond was issued in the mid-1990s. Since then market capitalisation has constantly increased so that Argentina meanwhile occupies the tenth rank among issuers on the Euroland Euromarket. Half of these bonds are denominated in DEM. Other emerging market issuers play nothing but a subordinate role for the time being.

With a market share of 13%, supranational institutions rank fourth among issuers. The European Investment Bank (EIB) is by far not only the largest issuer among supranational institutions but even among all issuers on the Eurobond market. The outstanding volume of its bonds accounts for 7% of all Eurobonds. As the financing institute of the European Union its tasks comprise the support of projects furthering the integration of member states.

Corporate bonds have played a minor role on the Eurobond market in the past. Their share covers only 10%. Also the bond volume of regional and local entities, i. e. provinces and municipalities, is still negligible. However, they – as well as corporate bonds – show a significant growth potential.

In the UK Eurobond market, the composition by issuer has been rather stable in time with financial, industrial, and government issuers covering 45%, 30%, and 20% of the market, respectively.

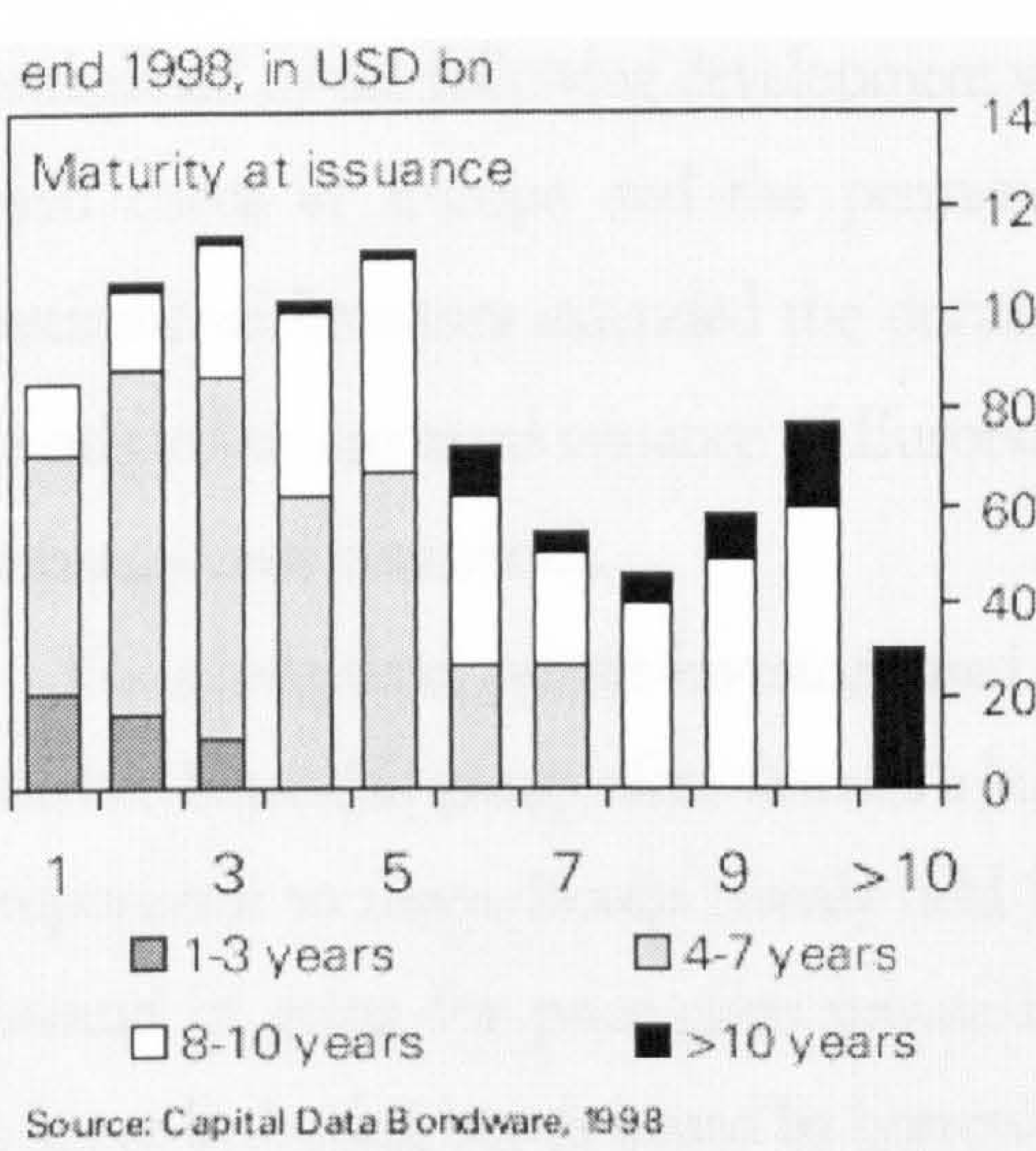


Figure 1.5 *Maturity of Euroland Eurobonds*

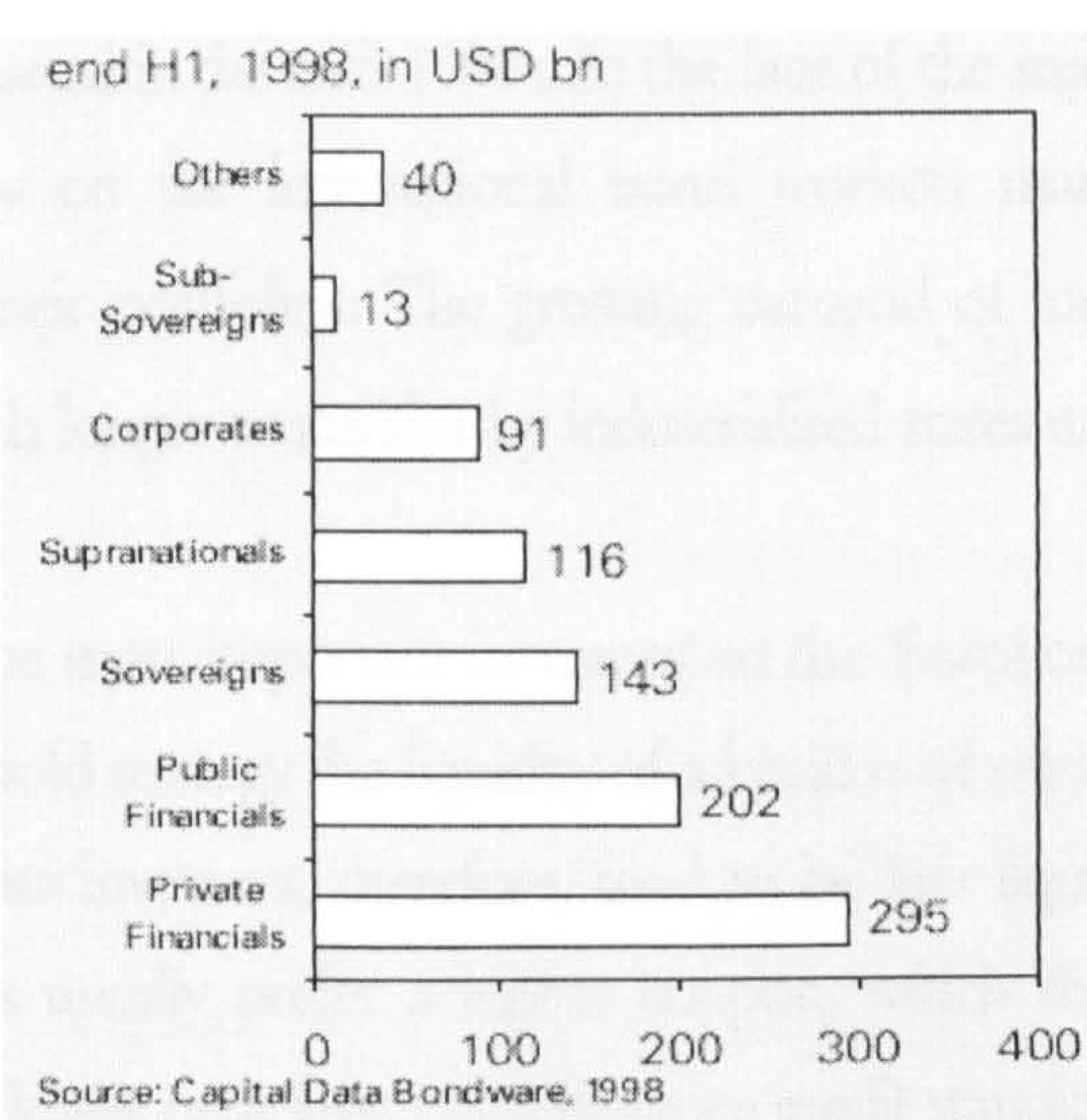


Figure 1.6 *Euroland Eurobond by issuer*

Another important characteristic for selection and pricing of a bond is its liquidity. Liquidity is mainly determined by the outstanding volume and investor structure. The bonds issued by different issuer groups differ largely in their average loan principal. This is, on the one hand, caused by the size of the individual issuer, and on the other hand, by its capital needs. For example, an industrialised state such as Italy can act differently as an issuer on the capital market than a corporation. Since there are also differences between issuers of one group, the volumes of the bonds issued by them partly differ largely, too.

Eurobonds issued by states have the largest average volume. By mid 1998 its value ran at USD 455 m (Figure 1.7). Italy and Spain have the largest issuance volumes with an average of over USD 1 billion. Although the outstanding total of Eurobonds issued by the Republic of Argentina surpasses Spain and Italy, the average loan principal is only one third. Further liquid bonds are issued mainly by supranational institutions. The most frequent issuer showing at the same time the largest average issuance volume is the EIB. Bonds issued by private financial institutions and corporations tend to have the lowest average loan principal.

The liquidity of a bond is closely tied to the structure of its investors. Issuers try to tailor their Eurobonds to the needs of their investors so that they can be well placed. Basically, investors can be split up in two groups: institutional and private investors. Institutional investors usually focus on liquidity and credit standing. Therefore, they are an important target group for liquid Eurobonds issued by industrialised states, supranational institutions and partly by large public financial institutions. The influence of investor needs on the structure of outstanding bonds was underlined by the following development which started in the mid-1990s. In the face of the steep yield curve in Europe and the permanent rally on the international bond markets many institutional investors extended the duration of their portfolios. The growing demand of long bonds led to increased issuance of Eurobonds with longer maturities by industrialised states and supranational institutions.

For a long time, private investors used to be the most important investors on the Eurobond market. Since this group often favours a buy-and-hold strategy the liquidity of a bond is of minor importance to them. Bonds mainly held by private investors, therefore, tend to be less liquid. Instead of going for price gains private investors usually prefer a higher coupon, which they achieve by buying bonds issued by borrowers of a lower or at least not a first-rate credit standing. These are primarily emerging markets and corporations.

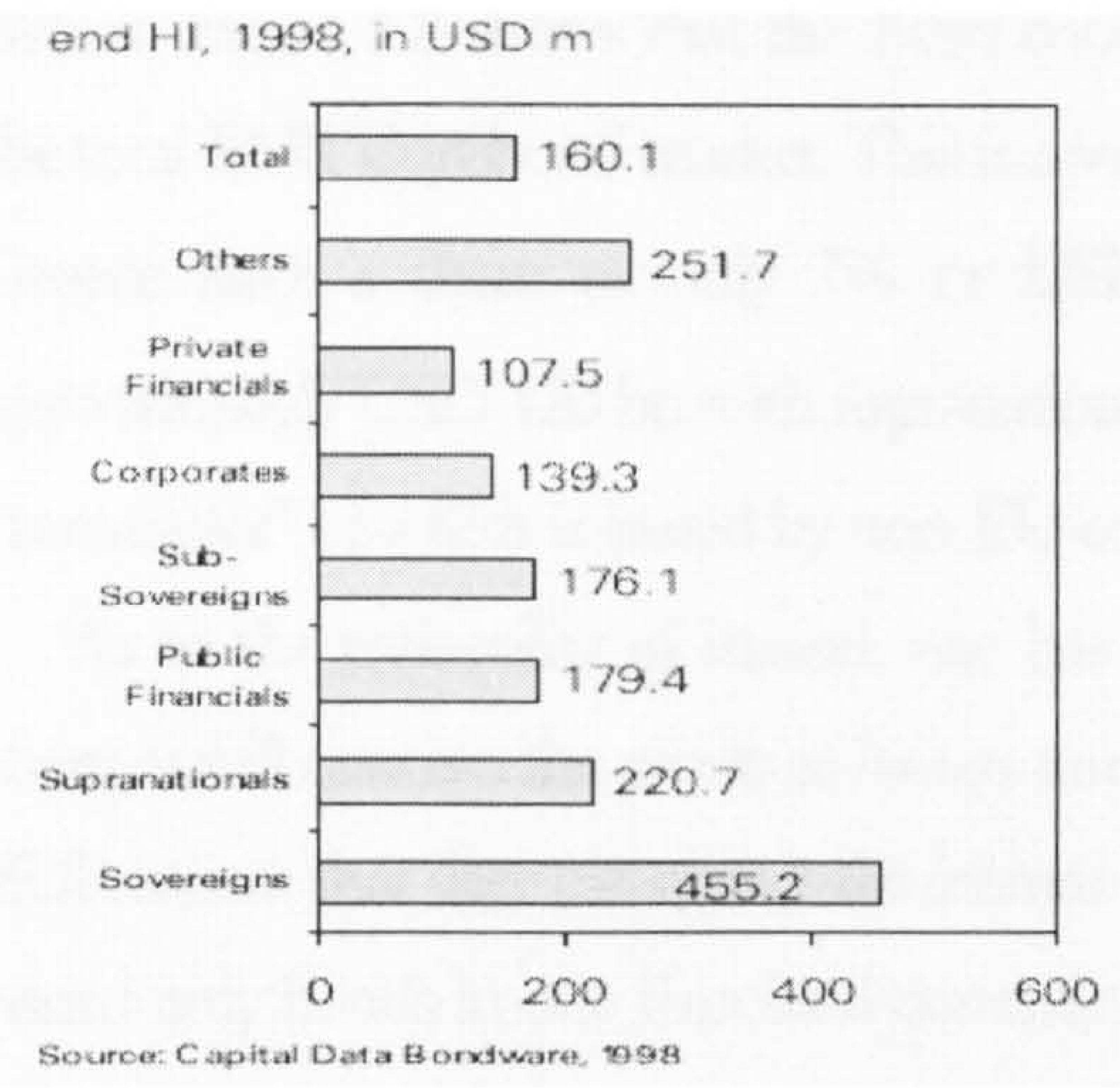


Figure 1.7 *Average Issue Volume*

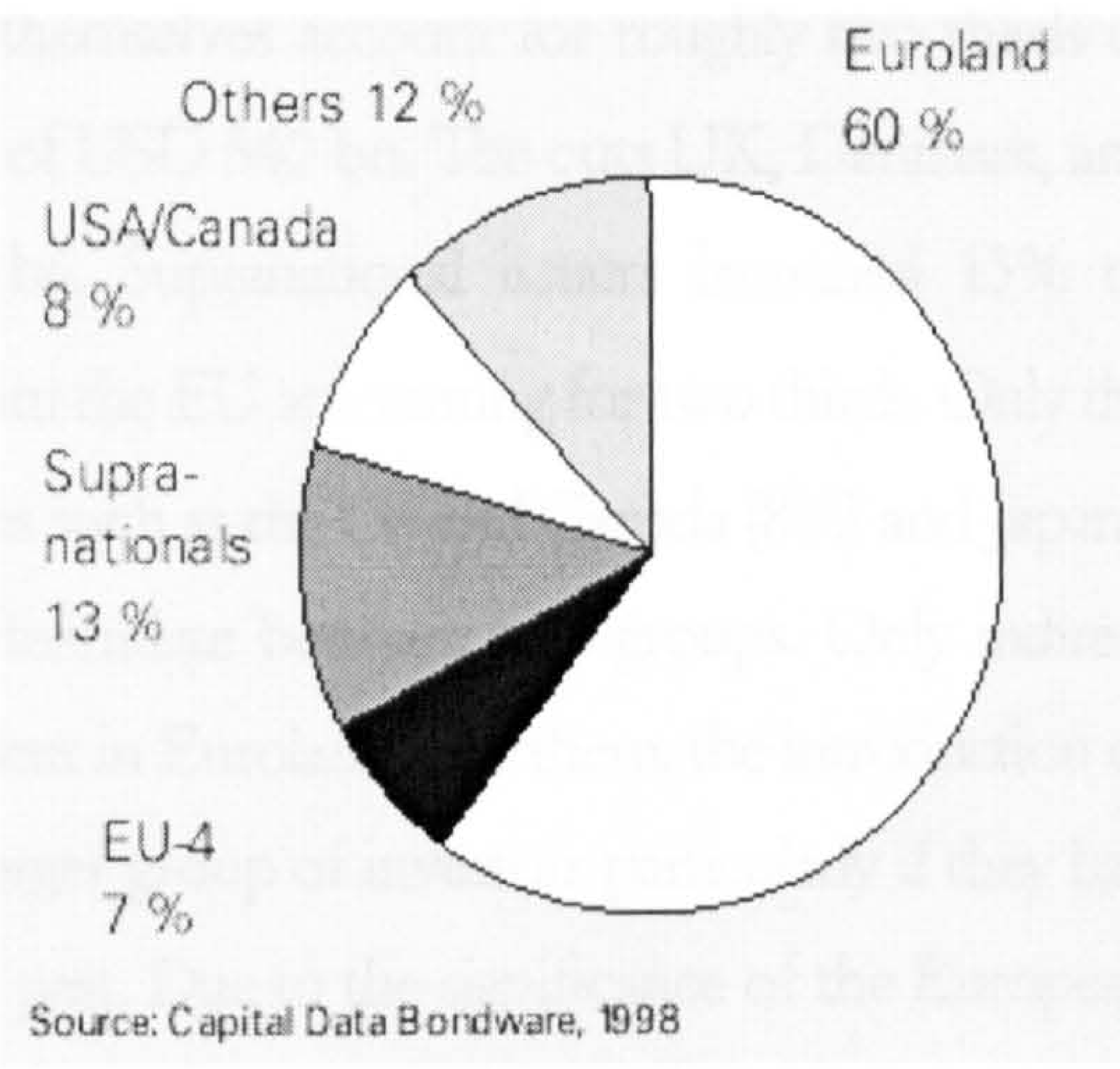


Figure 1.8 *EUR Eurobonds by issuer's nationality*

The future of the Eurobond market

In the short-term the leading players in the Eurobond market will continue to be the supranational organizations (EIB will be one of the leading issuers, since around the 85% of its outstanding debt is in Emu currencies) and government agencies (CADES in France and KFW in Germany) rather than sovereign borrowers themselves. Though sovereign borrowers will no doubt continue to have a presence in the Eurobond market, the severe budget constraints imposed by the Maastricht Treaty and the stronger captive domestic market of retail investors should influence them to opt to issue more domestically.

As the EMU gets under way, there is also significant growth potential with regard to the market for corporate and municipal bonds. However, we believe that several are the obstacles that will prevent an immediate development: the fairly limited propensity of European companies to fund themselves through the debt markets, the strong competition of structured banking products such as revolving credit facilities which often allow greater financing flexibility to corporate bonds, the presence of bureaucratic constraints in the case of municipalities wishing to tap the market for their funding, the decentralisation of taxation powers that will occur only gradually for many countries.

The start of EMU has not immediately influenced the legal framework of the Eurobond market. In spite of this, issuer behaviour is reckoned to change fundamentally. This is directly caused by the fact that from the viewpoint of currencies, monetary union leads to an amalgamation of the majority of what used to be foreign markets into one common Euroland bond market. This will drastically reduce the future foreign market and the share of foreign issuers. Figure 1.8 shows that the Euro countries themselves account for roughly two thirds of the total EUR Eurobond market. This is a volume of USD 540 bn. The outs UK, Denmark, and Greece have a share of only 7% or USD 63 bn. Supranational issuers launched 13% or approximately USD 120 bn with supranationals from the EU accounting for two thirds. Only the "remainder" of a fifth is issued by non-EU countries such as the US and Canada (8%) and Japan.

As to the nationality of issuers, one has to differentiate between two groups. Only indirect changes will concern the group of issuers non-resident in Euroland. For them, the introduction of EUR means that they can attract the interest of a larger group of investors particularly if they had issued only bonds in one Euroland currency in the past. Due to the significance of the European bond market which becomes the second largest bond market in the world more and more foreign borrowers are likely to use this market. States as well as private issuers should increasingly issue Eurobonds denominated in EUR.

The group of issuers resident in Euroland will face partly fundamental changes. In particular states such as Italy and Finland used to issue Eurobonds denominated in ECU or another Euroland foreign currency in the past to diversify their investor base. For a long time, arbitrage trades between the individual markets were another reason. With the introduction of EUR issuers can address all investors resident in Euroland with domestic bonds per se. The transparency of markets will further increase and arbitrage possibilities will vanish. Important reasons for a Eurobond issue will thus be eliminated. However, particularly for smaller states such as Finland and Portugal marketing their bonds via an international syndicate, i.e. via the euro-market, will remain attractive especially when investors outside Euroland are to be attracted. Since the share of Eurobonds issued by these small states is relatively small this market segment will probably decline.

The situation is somewhat different for the issuer groups of financial institutions and corporations. The amalgamation of the bond markets will certainly also affect their investor base. But there were other reasons apart from investor base why corporations and financial institutions decided to issue Eurobonds. These were primarily taxes and law. For example, due to the limited duty to publish an issuing prospectus issuing a Eurobond is often easier than issuing a domestic bond. Since the legal framework will not be changed in the short run these advantages will continue to exist.

The different behaviour of issuer groups will influence the structure of the Eurobond market. Approximately a fifth of the outstanding volume of all EUR Eurobonds was issued by states. Eurobonds by the 11 member states (as at 1998) account for almost half (Figure 1.9). These

Eurobonds will gradually disappear. The share of issuers such as corporations, emerging markets, and supranational institutions will, however, grow. The last two years have already seen more Eurobonds denominated in Euroland currencies by foreign corporations for example from the UK and US.

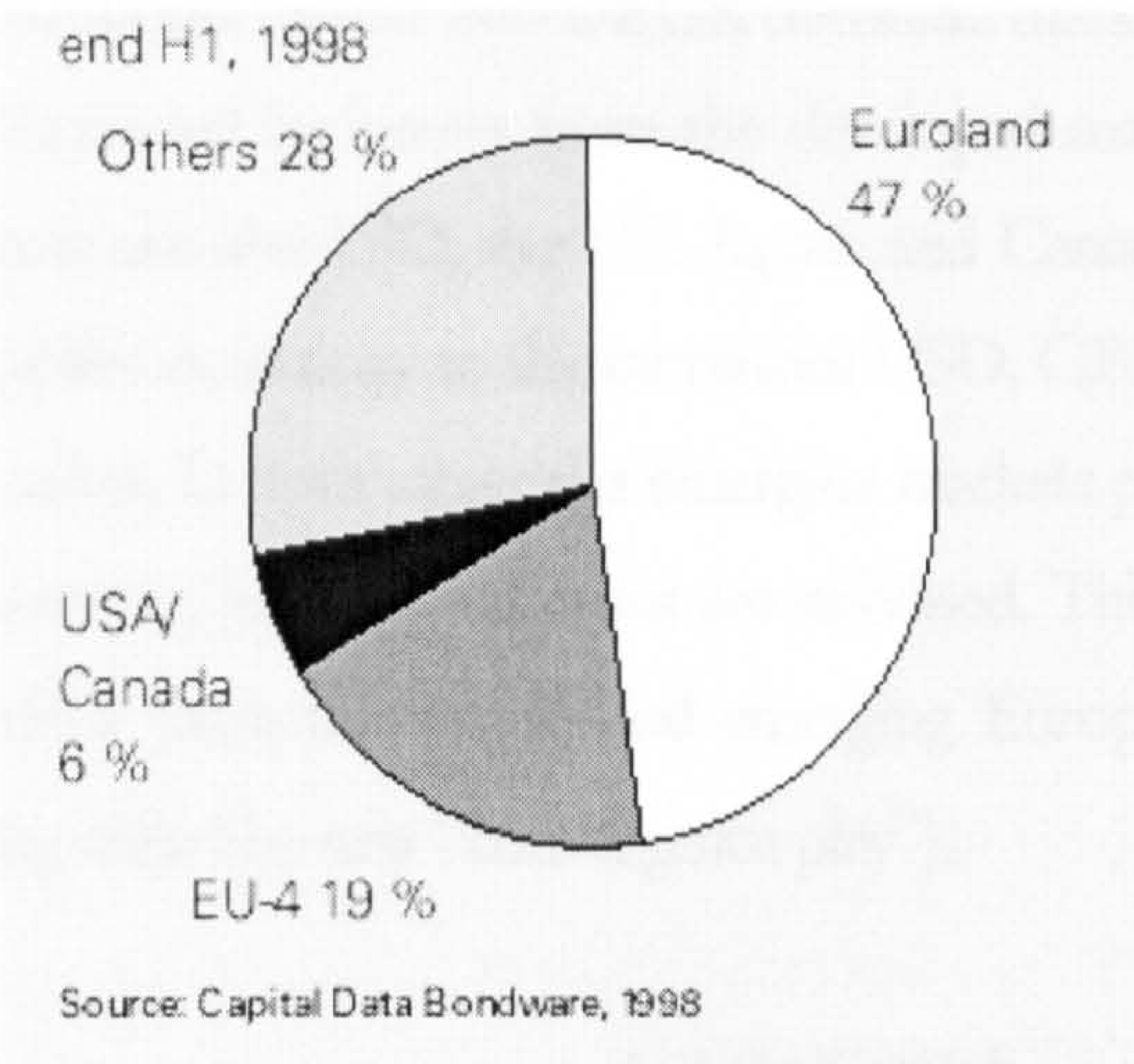


Figure 1.9 *EUR Eurobonds of Sovereigns*

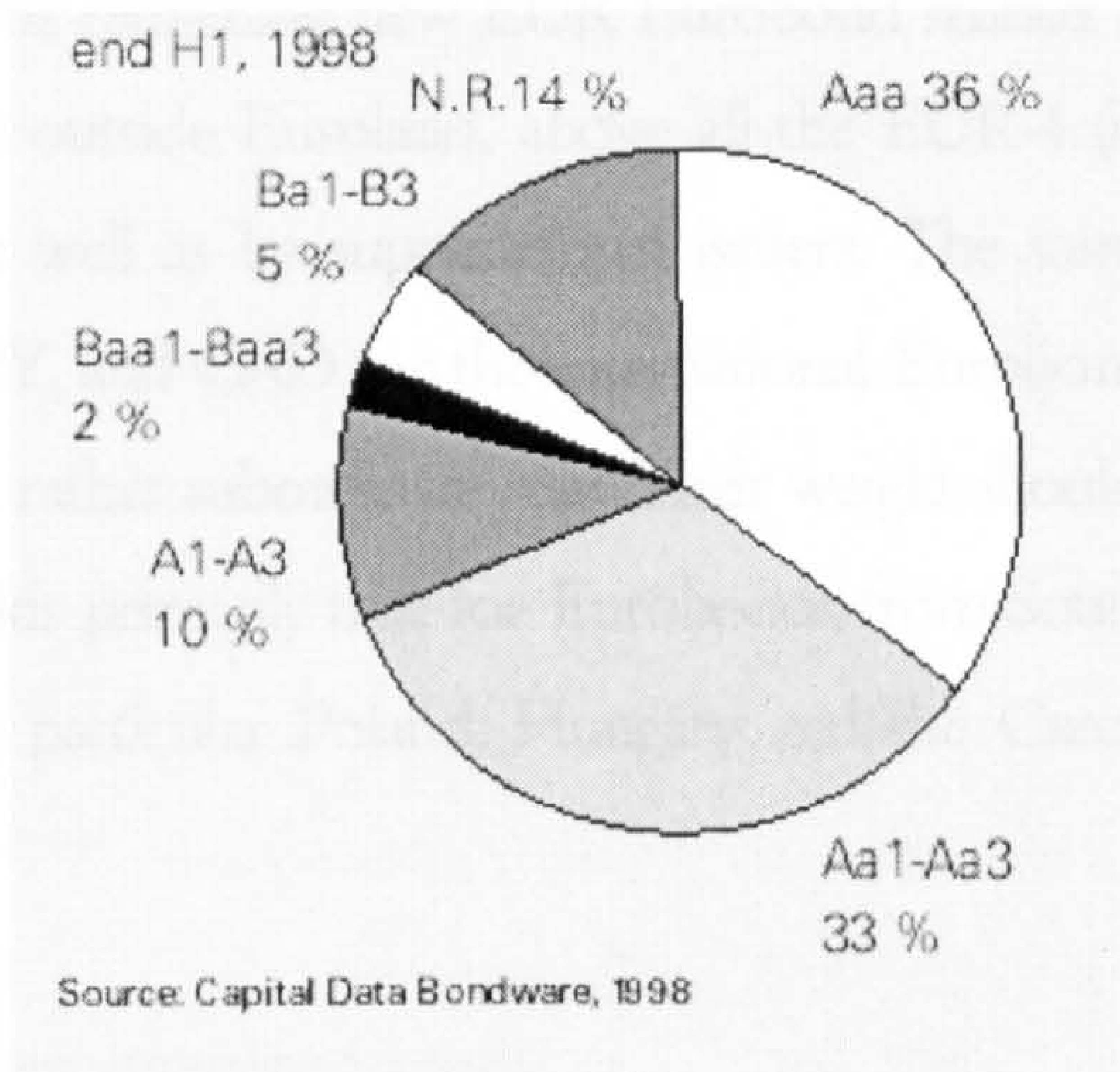


Figure 1.10 *Euroland Eurobonds by Rating*

Furthermore, issuers from emerging markets will have a stronger bearing. The box miscellaneous in Figure 1.8 comprises mainly these issuers (of course with the exception of Japan and Switzerland whose volume is, however, negligible). Among the emerging markets, Argentina, Mexico, Hungary, Brazil, Turkey, Russia, the Czech Republic, and Poland are worth to be mentioned.

This development also shifts the rating structure of the Eurobond market. Since states with a top-class rating will withdraw and, at the same time, issuer groups with a regularly lower rating will increasingly use the euro market the total rating level on the Eurobond market will decrease. This pattern has already been recognised in the sterling market, where AA-rated issuers have been replaced by A- and BBB- rated issuers (see Appendix [A]). At the same time, rating should become more and more common despite the high costs since it is increasingly demanded by international investors and is likely to become a *conditio-sine-qua-non* for a successful, tightly priced and broadly based issuance on the Eurobond market. On the whole, the Euroland market should get closer to the USD Eurobond market (Figures 1.10 and 1.11).

The monetary union will, furthermore, entail growing competition among investment banks. Particularly European investment banks will compete stronger with one another because the common currency abolishes the advantage for individual banks of playing at home. On the whole, the variety of currencies and issuers will stay around also in the "new" EUR Eurobond market. Due to the high share of EUR countries on the international bond markets in EMU currencies, the traditional division between domestic and foreign markets will hardly survive the next few years. The introduction of EUR in fact turns roughly two thirds of today's EUR Eurobond market into a EUR domestic market. The remaining new EUR Eurobond market is dominated by issuers from the developed markets outside Euroland, above all the EUR-4 (in particular the UK), the US, Japan, and Canada as well as by supranational issuers. The same applies in analogy to the currencies USD, GBP, JPY, and CAD for the international Eurobond market. In both categories emerging markets play a rather subordinate role. Their weight should, however, increase – if crises are stabilised. This holds primarily true for Eurobonds from South Africa (attractive yields) and emerging Europe, in particular Poland, Hungary and the Czech Republic (the new "convergence play").

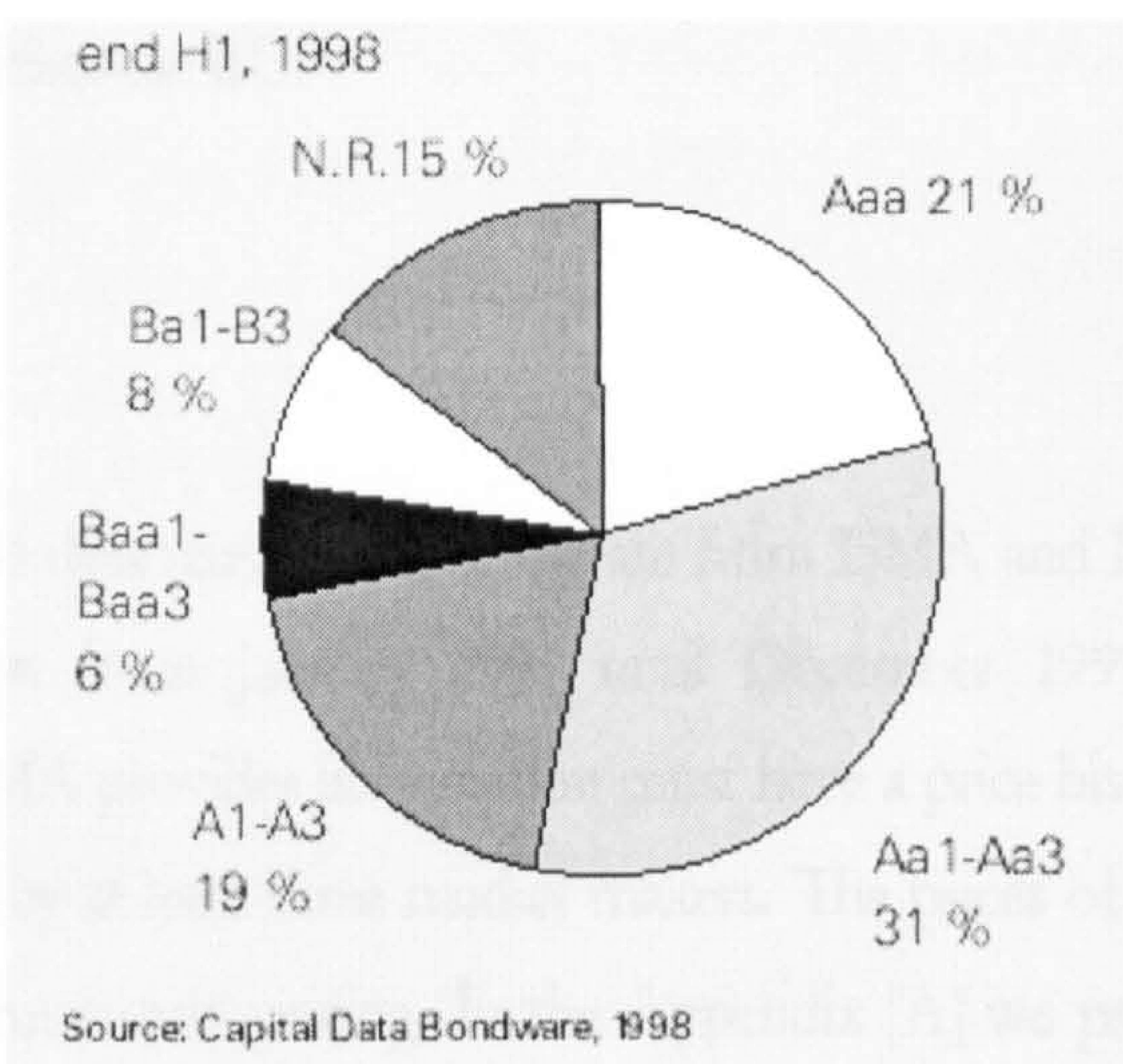


Figure 1.11 *USD Eurobonds by Rating*

The 20% withholding tax proposal

The pending proposal of a 20% withholding tax application to be deducted by agent banks on all interest earned by private investors residents in the EU has been strongly contested by all Eurobond market participants. The withholding tax would only apply to individual investors "avoiding domestic tax" and not to pension funds or institutional investors. By charging the tax at source, the proposed 20% savings tax is intended to stop individuals in high-tax countries such as

Germany from moving investments to countries with low or no tax on the interest on them or on non-residents' savings. Because of its attractiveness to non-residents, the UK has cornered the Eurobond market. By issuing Eurobonds, companies can borrow money over a longer period than they could at the bank without renewing the loan, and investors get an attractive rate of interest. But if the legislation is passed, banks in which the interest from investing in Eurobonds is deposited will have to notify non-residents' tax authorities or withhold 20%.

If this proposal were to be passed into law, it would be a downfall for the Eurobond market, as it would affect between 5% and 7% of the outstanding bonds. The *gross-up clause* application (according to which the investor's income loss due to changes in taxation would be compensated directly by the issuer) would involve an outright loss for investors since the issuer may reimburse bond at par. Moreover, were such a tax to be implemented, it would prompt a Euro Eurobond market's flight of funds toward Eurodollars and EuroYen. Despite it will be probably very difficult to get this proposal enacted into law, were it to be approved, it would pave the way for the disappearance of the Euromarket in the Emu area, and it would anticipate the fiscal harmonization process within the EU.

Sterling Eurobond data

The sterling Eurobond data used in this study are from ISMA and Datastream International. We collected information from January 1991 until December 1999. We remind that the Eurobonds for which ISMA provides information must have a price history since their issue date and must also be quoted by at least three market makers. The prices of the bonds in the sample are therefore not based on matrix pricing. In the Appendix [A] we present information about issuing volume, rating, sector, maturity for the sterling Eurobonds issued over the sample period 1992-1999.

Chapter II

THE NATURE OF CREDIT RISK

The aim of this chapter is to provide the reader with the main theoretical concepts and general issues relevant to the study and modelling of credit risk. The reader is first introduced to the discussion of credit risk along its main dimensions and statistical properties. We highlight that credit risk is a continuum with multiple states with each state representing an associated probability of default. This represents the first step towards the quantification and identification of credit risk. The focus is then posed on the conceptual differences between credit risk and market risk. While it is important that they are separately identified, the recognition of their interactions is essential in the correct modelling of credit risk. We conclude discussing the rapid expansion of credit markets and the factors that will stimulate the analysis of credit risk beyond the present role.

2.1. Credit risk definition and dimensions

Credit risk is defined as the loss in the event of default of the borrower, or in the event of a deterioration of the borrower's credit quality. In the case of traded instruments credit risk is the potential decrease in value generated by a change in credit standing during the holding period, while the risk in a bank loan lies primarily in the possibility that the borrower may not be able to make scheduled payments. Credit risk can arise also from other sources such as cash payments, long-term supply contracts, derivatives and other off-balance sheet contracts. The definition of credit risk and the risk premium investors require to assume the risk of higher losses can be developed further along its four major dimensions: default risk, credit migration risk, exposure risk, and recovery risk.

A default event can take the shape of a missed payment –when a scheduled payment has not been made for a minimum period after the due date-, a broken covenant or technical default –

when a financial ratio hits and breaks an upper or lower bound-, or an economic default -when the economic value of assets goes below the value of outstanding debts. Rating agencies consider that default occurs when a contractual payment has been missed for at least three months. Note that the various events of default do not necessarily generate immediate losses, but they certainly increase the likelihood of ultimate default, which is bankruptcy.

Credit migration risk captures less extreme changes in credit quality. In the case of a corporate bond, credit risk takes the format not just of default or insolvency risk -in which case the credit exposure is simply the face value of the bond-, but also of credit spread changes and thereby market values, changes in credit ratings, and generic changes in credit quality -in which case the credit exposure is given by the decrease in the price of the bond. Although it is usually the first stage of the financial distress of a firm, is the most important stage for the bondholders. In general, except for the lowest credit securities, the investor is concerned more with changes in the "perceived credit risk", than the actual event of default, since they can have an immediate impact on the value of a security. Due to the relative liquidity of bonds, bondholders are always in a position to sell them before the issuer's financial state deteriorates too far. Nonetheless, they will incur any fall in price resulting from the deterioration of the credit quality of the issuer.

Exposure risk is the outstanding balance lent to the borrower and generated by the uncertainty prevailing with future amounts at risk. In some cases, generally for all credit lines for which there is a repayment schedule, this risk can be considered as small or negligible. In other cases, committed lines of credit allow the borrower to draw on those lines whenever she wants to, so that the exposure is contingent upon her needs, some specific event, and subject to a limit fixed by the bank.

The amount at risk differs from the loss in case of default because of potential recoveries. Those depend upon any credit mitigators, such as guarantees, either collateral or third-party guarantees, the capability of negotiating with the borrower, and the funds available, if any, to repay the debt after repayment of other lenders. The recovery rate depends also on the industry type -the recovery rates are generally higher in the industries that generate tangible/tradable assets-, economic conditions – the recovery rates rise and fall depending on the market for corporate assets-, and seniority of the debt – senior loans enjoy a higher recovery. Estimates of recovery rates are available from several sources such as Moody's. Industry data shows that the recovery rates vary between 70% for secured bank loans to 30% for unsecured subordinate debt. Thus trade creditors who rank with other unsecured lenders can expect 30-50% recovery rates.

2.2. Credit risk *versus* Market risk

Credit risk encompasses both default risk and market risk. Default risk is the objective assessment of the likelihood that a counterparty will default, while market risk refers to the possibility of losses due to changes in the prices of financial assets. Shares of stocks are subject only to market risk because they do not carry a promise of payment. A US Treasury bond is the quintessential example of a security that has interest rate risk, but no credit risk. On the other hand, a bank loan carries only the risk that the borrower may default on its promised payments. However, the distinction between market and credit risk is not always so precise. A corporate bond, for example, carries both types of risk because its value is sensitive both to interest rates and to the creditworthiness of the issuer. Although both risks result from variations in value, they are generated by different sources. While market risk is the potential loss resulting from adverse market movements during a liquidation period, credit risk results from interactions between market risk and liquidity risk.

The first practical problem when dealing with credit risk is that input data is much harder to obtain than market risk input data. While market risk data (mainly market factor returns, and their variance/covariance matrix) is largely available on the market, most credit risk data is not readily available. Most companies do not have official ratings, so that default probability must be subjectively estimated. This is true for recovery rates and default correlations as well. The real reason for this difference is that the object of credit risk modelling is a (relatively) rare event like default, so that only little and often outdated historical data can be found.

Credit risk has many properties that make it different from market risk in other respects – especially for modelling purposes. Markets for credit risky debt are illiquid. The illiquidity is due in part to the size of the credit market, in part to the fact that the market for risky debt is segmented – each corporation issues its own debt that trades at prices representing the investors' perceptions for that particular corporation. As a result, instruments that would allow one to assume the credit risk of a particular corporation at a particular tenor may simply not exist; sometimes those that do exist either do not trade or trade for large transaction costs.

Moreover, changes in credit risk often cause the price of the associated debt instrument to "jump" and that jump can be very large, particularly when it is caused by default. An additional difference lies in the liquidation time horizon, which is very short (10 days) in the case of market risk, but are typically much longer (years) in case of credit risk, implying that the pricing approximations used for market risk management are inadequate. Finally, legal issues are very important for evaluating credit risk, while they are not applicable for market risk.

As a results of all these factors credit risk is more difficult to model than market risk. As we have seen the lack of a liquid market makes it difficult – or impossible – to price credit risk for a specific obligor. Moreover, true default probabilities and recovery rates in the market cannot be observed. Users must determine these probabilities by either inferring default rates based on observed historical experience of the public credit ratings, or determining the default rate through a subjective credit approval process. Default correlations are also difficult to observe or measure, making it hard to aggregate credit risk. For equities, the correlation can be directly estimated by observing high-frequency liquid market prices. For credit quality, the lack of data makes it difficult to estimate credit correlations from history. Finally, as Figure 2.1 shows, credit returns are highly skewed and fat-tailed while equity returns are relatively symmetric and are well approximated by normal distributions. The long downside tail of the distribution of credit returns is caused by defaults and is explained in terms of a large likelihood of earning a small profit and a small chance of losing large amount of investment. This implies that a credit portfolio's distribution cannot be simply represented by its mean and standard deviation and, ultimately, the computation of the appropriate capital/equity cushion will be more complex because of the estimation of tail risk probabilities of typical asymmetric, fat-tailed loss (credit) distributions.

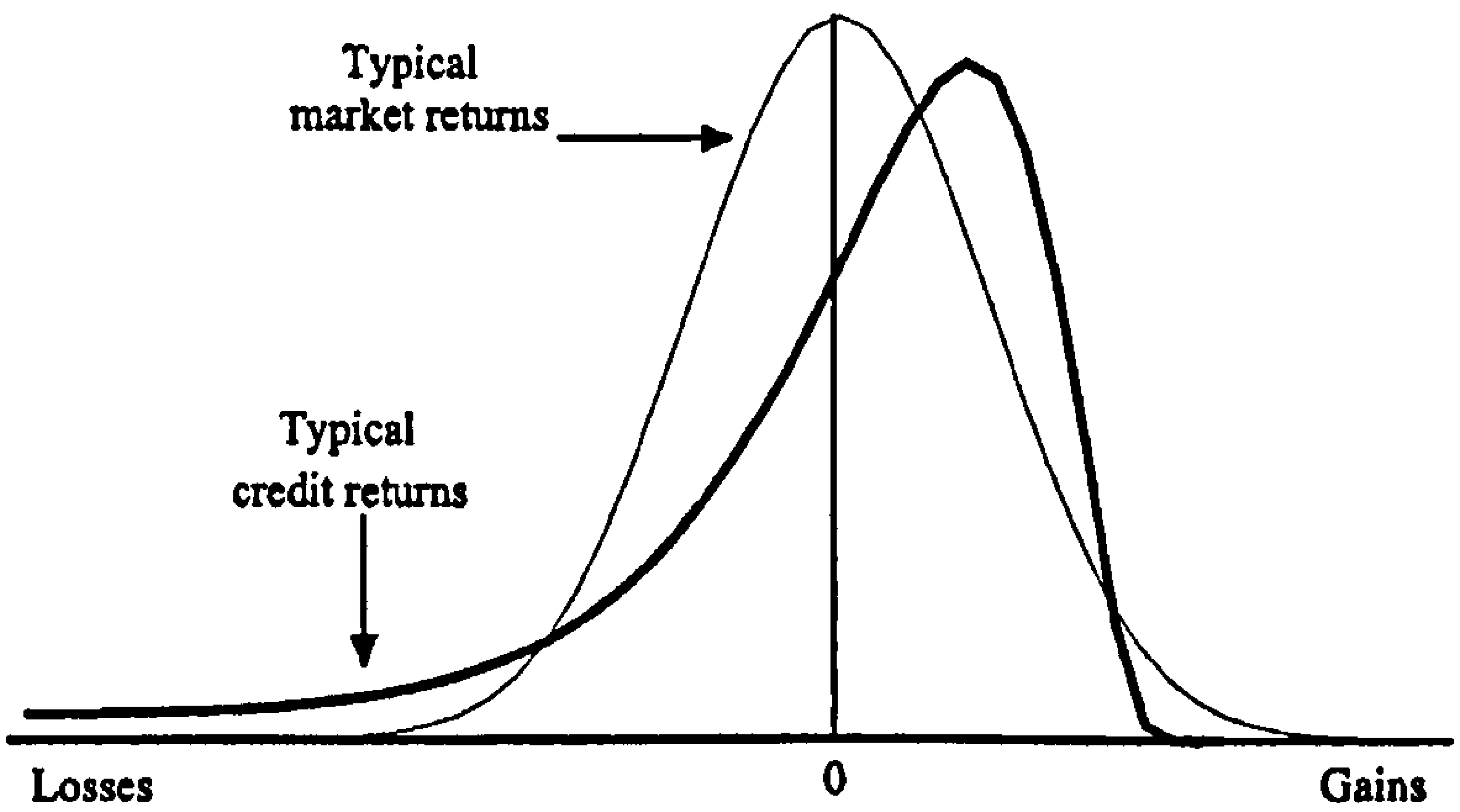


Figure 2.1 *Distribution of credit returns versus market returns*

The growing complexity of credit risk has fuelled the development of sophisticated methods for measuring credit risk at a portfolio level, rather than just at the level of an individual bond or loan. These methods are largely statistical and build on probabilistic models of creditworthiness and asset values. The variety of credit risk models available is even wider than for market risk models. While market risk models differ mainly in the way they try to obtain the same result (i.e.

the VaR of the trading portfolio), credit risk models often diverge even on the result they try to achieve. As for market risk, today some ready-to-use credit risk methodologies have become available (See Chapter III), however, most large banks rely on models developed or assembled internally and based on an internal credit rating systems. Despite the huge modelling effort, credit risk action following model results (for example the reduction in loan exposure to an individual counterparty or to a specific industry) can be hard to put in practice in some cases, due to commercial and customer relationship links. Lending is still a very personalised activity, where the weight of individual loan officers and commercial staff is still very relevant. This is in sharp contrast to trading activity, largely impersonal, where prices and execution quality are the main drivers.

Despite the differences outlined above, economic theory tells us that market risk and credit risk are intrinsically related to each other and, more importantly, that they are not separable. If the market value of the firm's assets unexpectedly changes -generating market risk- this will affect the probability of default -generating credit risk. If interest rates increase to a critical extent, borrowers may be default on their (floating) interest payments. Conversely, if the probability of default unexpectedly changes -generating credit risk- this may affect the market value of the firm -turning credit risk into market risk.

Some institutions have found it necessary to combine the oversight of credit and market risk. As Allen (1996) points out, integration of the two functions is desirable for at least three reasons. 1) There is a lot of transactional interaction between credit and market risk; 2) there is a need for comparability between returns on credit and market risk; 3) the emergence of hybrid credit and market risk product structures makes this necessary. We also remind that the integration between market and credit risk affects also the determination of economic capital, which is of central importance to regulators. It also affects the risk-adjusted return on capital used in measuring the performance of different groups within a bank (Crouhy, et al. 2000). This integrated approach, however, is far from being straightforward and requires a deep understanding of the correlation between credit and interest rate risk. A few papers have examined the degree of the correlation (Longstaff and Schwartz, 1995; Duffee, 1999; Morris, 1999).

Simulations to obtain an integrated market and credit risk distributions were run by Stein (1998). The distributions are shown in Figure 2.2. The lower credit-quality bond has an integrated distribution very different from the stand-alone market distribution of the same bond. On the other hand, the high-grade bond distribution highlights the marginal effect of the credit risk component. Although the credit quality of the bond has a clear impact on the risk measure, it affects the overall risk of higher-grade bonds by a significantly lesser amount. Results such as these may be relevant to recognise and promote an integrated view of market and credit risks, which in turn would allow for a more complete picture of the risk underlying trading activities. In fact, market and credit risk measures are very seldom successfully integrated in a single firm-wide risk measure. The reasons that hamper a successful integration of the measures are the followings.

SOURCE: STEIN, 1998

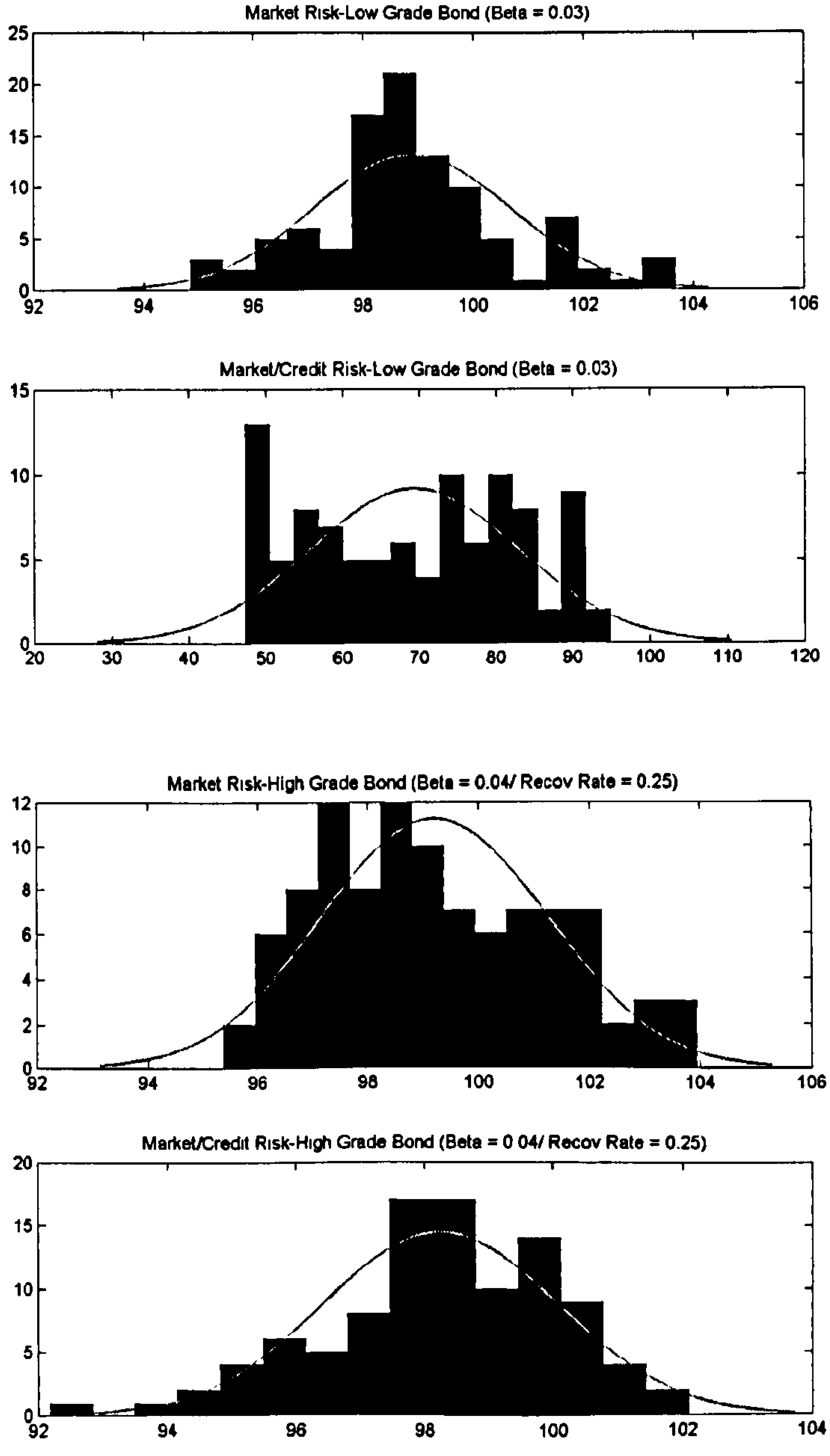


Figure 2.2 *Integrated Market and Credit Risk Distributions*

a) Choice of relevant time horizons

The daily horizon is an accepted industry standard for internal market risk management analyses. The choice of the daily horizon is based on the conviction that the unwinding of trading positions should be possible in 24 hours. This hypothesis is not always realistic, especially during sharp market movements when liquidity on some instruments tends to dry up considerably. Regulators, as an example, do not share such an optimistic view on the unwinding of trading positions and require that the market risk measure be calculated on a 10-day period.

Understanding which correct time horizon for a credit risk measure should be is unfortunately much more difficult. The first logical step should be establishing a criterion for the choice. In the market risk measure the criterion was given by the time needed to unwind the position. The unwinding criterion is more difficult to accept for credit risk measures, and even if accepted would lead to a very wide variety of different time horizons. The time needed to liquidate a position with a defaulting counterparty depends for example on the severity of the credit crisis, on the regulatory constraints, on the quality of the relationship with the counterparty.

An alternative criterion might be to use as a measurement horizon the time needed to appreciate a change in the counterparty credit quality. As credit quality changes are very slow to show up, we understand that also under this alternative criterion the time horizon should be much longer than one day, although it is not known how longer exactly this horizon should be. Assuming longer time evaluations inevitably widens the range of potentially acceptable horizons, so that achieving an industry standard in this field is much harder. The current practice of large international banks - when this figure is disclosed - is to use horizons included between two weeks (10 working days) and 1 year.

b) Scaling between time horizons

Assuming the achievement of a satisfactory solution to problem a), i.e. two time horizons have been chosen respectively for market and credit risk measurement with which the bank feels comfortable. The next step is to make the two measures comparable. In other words we must be able to understand if a 10 mn credit risk figure calculated on a 1-month basis is higher or lower than a 1 mn market risk figure estimated on the traditional 1-day horizon. One way to tackle the issue is to scale the two figures to a common time horizon. Given that the market risk horizon is usually shorter than the corresponding credit risk measure, there are just two alternatives: either scaling up the market risk figure to the longer credit risk time horizon or scaling down the credit risk figure to the corresponding market risk value.

Following the considerations expressed under point a), the first alternative (scaling up the market risk figure) seems more reasonable. While the choice of a long-term horizon for credit risk measures reflects the impossibility of obtaining a meaningful measure under a short-term horizon, the short-term choice in market risk is mainly dictated by technical reasons, i.e. the availability of more data under a daily horizon. A long-term horizon measure in market risk is perfectly meaningful, representing the risk related to holding the position for a longer period. However, if a rule existed that allowed us to stretch the market risk measure up to the longer credit risk horizon, then the two measures could be compared with a higher significance.

Such a rule exists, and it is known as the "square root of time" rule. The rule tries to model the behaviour of volatility in dependence of the time horizon on which it is measured. If we compare a return volatility measured on daily and on monthly data, we would expect 1-month volatility to be higher than 1-day volatility. This reflects the fact that longer time horizons are associated to a greater dispersion of potential returns. If we assume that daily returns are not serially correlated, then it is easy to show that

$$\sigma_{nt} = \sqrt{n}\ \sigma_t \tag{2.1}$$

where n is the number of short-term periods that build up the long period. Some care should be taken in using relationship (2.1) (Diebold, 1997). Whether rule (2.1) is a good approximation of reality depends on the level of serial correlation among returns, which is an empirical question. This rule might work for some time series and not for others; it might work better during some time periods than in others. Furthermore, it is evident that extreme time stretching is more dangerous, under a model risk point of view, than limited time stretching. Scaling 1-day volatility into 1-year volatility produces more dubious results than scaling 1-week volatility into 1-month volatility. Moreover, some of the hypotheses that allow the construction of the 1-day measure are hard to retain in longer horizons. For example the zero-mean hypothesis, which is plausible in the 1-day environment, can be questioned on sensibly longer time horizons, and especially on markets characterised by definite trends.

c) Correlation between market and credit risk measures

Assuming we have successfully gone through steps a) and b), by building relevant market risk and credit risk measures and by expressing both of them on a common time horizon. The next issue would be combining the two measures, i.e. formulating some hypothesis on the correlation between the two measures. The simplest possibility would be to compute the global exposure as the sum of the two individual (credit and market risk) exposures. This could be motivated only by extremely conservative assumptions, i.e. implicitly assuming that extreme market events, mainly related to the trading environment, will be coupled to extreme credit risk events.

A second, much more frequent approach is to assume that the market risk measure and the credit risk measure are not linearly correlated. This assumption can be justified whenever we expect factors affecting market and credit risk to be independent. A third alternative is to try to model explicitly the relationship between market and credit risk measures, determining in this way a correlation coefficient as a result either of a formal model, or simply estimated by qualitative assessment.

It is therefore necessary for the bank to evaluate which economic linkages might exist between market and credit risk. Possibly the most immediate link between market and credit risk measures is related to extreme market movements affecting both the profitability of the bank's business and the creditworthiness of some of the bank's counterparties. In the trading book, this could happen because market movements producing losses in the bank's own trading book undermine the financial solidity of other banks with higher trading exposure to the same factors. In the banking book, sharp foreign exchange and interest rate market movements could lead to a simultaneous reduction in the market value of loans and to a worsening of the creditworthiness of interest-rate sensitive and foreign exchange sensitive companies. However, in principle, the relationships described should not lead to a concentration of risk thanks to some form of internal hedging occurring in these two examples. In the trading example, at least the positions with the defaulting bank should be profitable, so that there should be little market risk associated to them; in the banking book example, the reduction in the market value of loans should tend to mitigate the counterparty's financial crisis.

d) Overcoming cultural differences in the achievement of a firm-wide measure

When trying to achieve a firm-wide risk measure, one major difficulty can derive from the cultural differences between credit and market risk management staff. This potential cultural clash stems from the contrast between the mainly quantitative trading environment where market (e.g. Value at Risk) measures were developed and the mainly qualitative credit department activity. While market risk VaR, no matter how it is calculated, has a strong dependence on quantitative assumptions, credit risk measurement is still largely the result of subjective human judgment. Introducing consistent firm-wide credit risk measurement procedures involves switching part of this subjective evaluation to objective quantitative models. This passage is often very hard to achieve because of natural resistance within the credit department. Credit staff can resist because they fear the model can be wrong, or because this will reduce their power within the institution (Carey and Hrycay, 2001). Furthermore, loan commercial staff will oppose the introduction of quantitative models, because high loan volumes are easier to achieve if risk is poorly or not controlled.

2.3. Credit risk and diversification

Financial companies can be considered as levered portfolios with long positions in assets of varying liquidity, and short positions in diverse debt obligations. Daily movements in interest rates, equity prices, and exchange rates affects the overall value of the portfolio/firm. In response to market conditions or customer demand portfolio's composition can be adjusted by managers. An ideal risk measurement system would produce a probability distribution of returns conditional on the firm's current portfolio composition. If such a distribution were available in real time, Value at Risk regulatory constructs could be easily calculated.

Measuring the diversification of a portfolio means specifying the range and likelihood of possible losses associated with the portfolio. All else equal, a well-diversified portfolio is one that has a small likelihood of generating large losses. The expected loss (EL) of a credit portfolio is not considered risk but is what we expect to loose. EL - defined as the probability of default times the loss we expect should default occurs - is not, therefore, subject to diversification: a portfolio's expected loss is simply the average of the expected losses of the assets in the portfolio. By contrast, risk is the deviation of the actual loss from what we expected, that is the unexpected loss, UL. If banks were able to diversify its credit risk so that unexpected losses were negligible in comparison to the expected losses, then the cost of capital would approximate to the bank's expected losses. It would follow that the price for the trade would be equal to the expected losses. If the degree of relatedness of the risks of the assets in the portfolio is high there will be little space for diversification. On the other hand, if the default risks are relatively unrelated, then considerable risk reduction via diversification is viable.

In practice, credit risk cannot be diversified away – and unexpected losses are not zero because of the illiquidity of the assets and liabilities hold, or because of the lack of *ad hoc* derivatives related to them. For example, long-term government securities can be hedged with futures to lessen or eliminate the risk of adverse movements in interest rates. In the case of corporate bonds, interest rates futures can hedge only a portion of the price volatility. Alternatively, for corporate bonds that are relatively liquid, the firm can alter its credit exposure simply by liquidating the position. However, with an illiquid portfolio, prices are not usually available, so that even for the part that is theoretically hedgeable with a derivative, the appropriate hedge ratio is hard to estimate. Often the firm cannot even terminate the position. As an ultimate consequence, risk managers often ignored illiquid positions and leave the job to diversification. Unfortunately concentration risk in credit portfolios of financial institutions is very high. This is the result of a number of factors.

Specialisation of banks/financial institutions. Limited resources and competitive forces, such as the knowledge and competence of the institution, relative competitive position and return requirements have inevitably forced banks into specialisation. This specialisation may take the form of industry specialisation, geographic specialisation (country or region) or type of client as classified by credit ratings.

Mismatch between origination capacity and diversification objectives. There is a parallel limitation in the scope of a financial institution being able to directly originate credit assets outside its natural markets. This is due to the focus of its client relationship, the presence and knowledge requirements of penetrating new markets, as well as the competitive behaviour of institutions with established market positions in the relevant market segment.

Incompleteness of credit markets. The lack of available credit assets with the required term structure and industry characteristics may itself increase specialisation.

High positive correlation. Many individual bonds share a common systematic component of credit risk. If we take into consideration a portfolio of many individual bonds, the net interest rate sensitivity can be hedged in large part with interest rate derivatives; changes in credit quality of individual companies do not result in significant volatility either, provided that the position is well-diversified. However, the interest rate position will still be risky because yield spreads move together. As a consequence, investors must reassess the probability of default for all bonds as the general outlook of the economy changes.

Changing structure of credit markets. Several trends in the pattern of capital market activity also create concentration risk. The trend to direct issuance of securities to investors by higher quality issuers as an alternative to bank financing has resulted in a change in the composition of credit-risk structure of bank-loan portfolios. These portfolios tend to have higher proportionate exposure to lower rated borrowers who do not enjoy the same access to capital markets. Moreover, the trend to corporations reducing the size of their core banking groups has increased the relative size and scale of bank exposure to individual clients.

Client relationship pressures. Banks have increased individual loan exposures to clients as a primary resource in establishing and maintaining major relationships. This has been done in the expectation that the dominant position as a major lender will allow the bank to gain access to other non-credit businesses from the clients. The inability to reduce this direct credit risk exposure often creates substantial concentration risks within credit portfolios.

From the viewpoint of portfolio theory the impact of concentration risk within credit-risk portfolios leads to the impossibility of the direct applicability of the traditional mean-variance theory. This reflects the typical features of credit portfolios we have discussed so far and that we summarise in the box below.

- returns appear to be skewed in well-diversified portfolios
- credit risk appears to be non-linear in nature
- the correlation between credit risks is generally highly positive
- the credit risk itself is dynamic and subject to large fluctuations
- credit risk appears to be exacerbated by the traditional illiquidity of credit risk
- credit risk can be reduced by increasing the size of the portfolio and increasing diversification, but the size of portfolio required to reach full diversification is large.

These factors which tend to differentiate credit risk from types of risks such as market risk dominate both the quantification and pricing of credit risk in general and credit derivatives specifically. It has also a significant impact on credit risk management. The portfolio manager that wants to cover the increased risk of concentration adequately will require returns that increase in a non-linear fashion (at an increasing rate), reflecting the fact that portfolio risk is a function of the individual exposures squared (see Figure 2.3).[1] This, in turn, dictates that the institution which has high levels of exposure to a particular credit should be prepared to pay a premium to market returns to reduce the risk of concentration. Similarly, the institution may require a lower than market return in increasing its exposure to credits to which is underexposed. This is predicated on the fact that while the returns on individual credits are determined by market prices, the return required to compensate for risk for a particular investor is related to the portfolio structure. Additionally, this view of diversification has an immediate concrete implication for capital adequacy. Given the frequency distribution of loss, we could determine the likelihood of losses which exceed the amount of capital held against the portfolio. This probability could then be set to the desired level by varying the amount of capital.

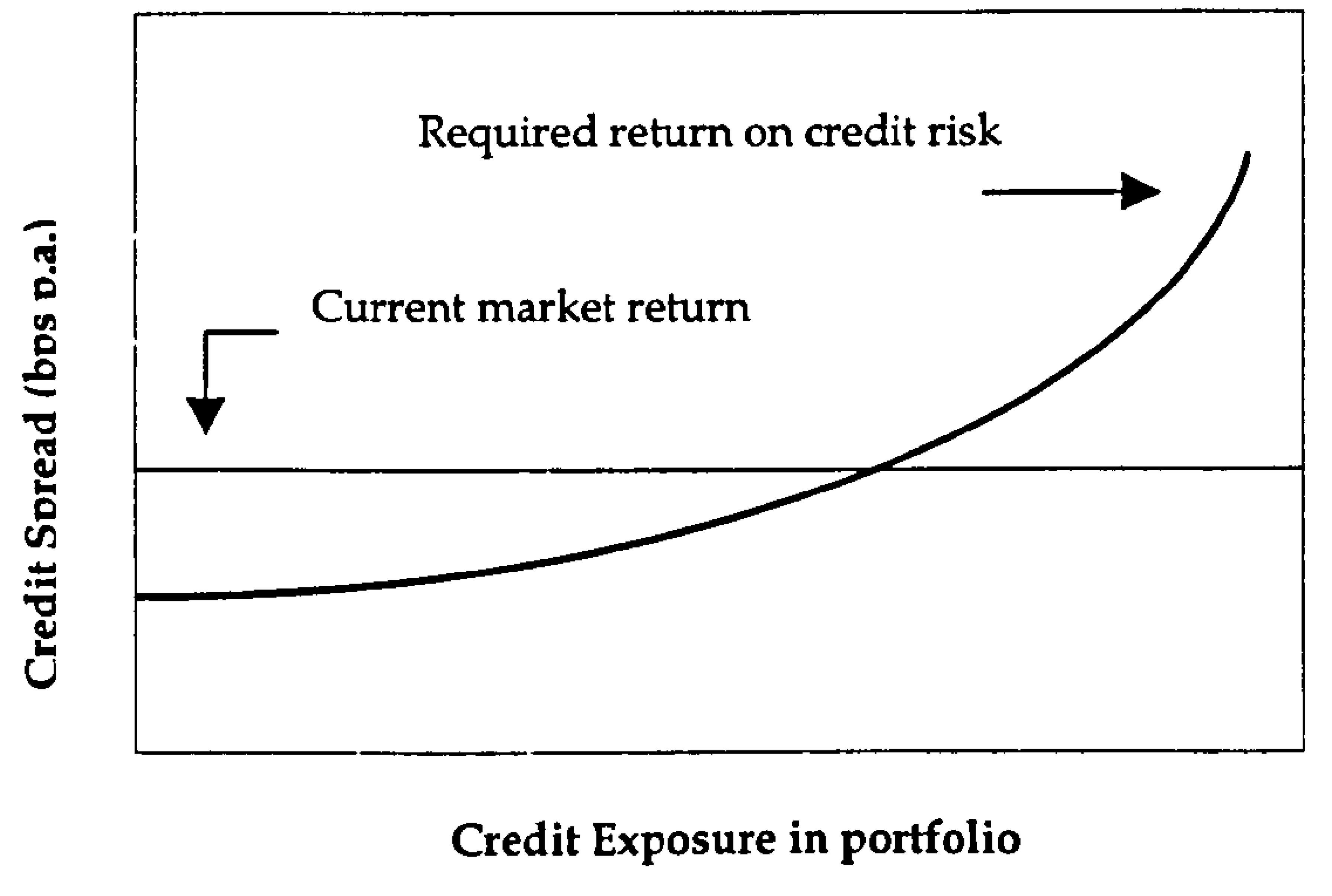


Figure 2.3 *Required target return on credit-risk exposure in a portfolio context*

2.4. An increasing role for credit risk analysis

The credit markets have been developing very quickly. Their rapid expansion is mainly due to the trend of the disintermediation, securitization, and globalisation of the credit markets. Along with the development of financial markets, a deep understanding of credit risk dynamics is increasingly guided by a growing recognition of the need for a mechanism that assesses credit risk and helps investors to price debt securities properly.

[1] Levin (1997) finds that the degree of diversification achievable in an equity portfolio with 30 names would require 350 names in a comparable debt portfolio to achieve an equivalent degree of diversification.

A more cost-efficient process in the public securities markets has progressively replaced the traditional role of banks as intermediaries between savers and users of capital. Recently in Europe, users of capital in the industrial, public utility, and financial sectors have chosen to finance their short-term capital needs through commercial paper, having realised that short-term funding costs are generally lower in this market. Capital markets therefore have become accessible to small and middle market firms producing a "winner's curse" effect on the credit portfolios of traditional financial institutions. The growth of large, financially sophisticated institutional investors, such as pension funds and mutual funds, has also spurred this trend. From the borrower's point of view, the advantages offered by this process of disintermediation are mainly in terms of a substantial cost savings. Lending rates in the public markets are often very competitive, because credit-worthy borrowers can choose the most economical source of funds from a wide range of domestic and international alternatives, rather than from a few banks.

A result of the disintermediation process is securitisation. The borrowers issue securities directly to investors in the public debt markets. The money they once would have borrowed from banks is now being borrowed by means of securities, that is, being securitised. The disintermediation and securitisation are fast becoming global phenomena. Many corporations, financial instituions, and sovereign nations have recognised the efficiencies of scale and the competitiveness inherent in the public securities market. The result has been a globalization of credit markets.

There are several additional trends that will further stimulate credit risk analysis and expand its applications beyond their present role. We discuss them below.

Financial market integration. Removing barriers to capital movements and harmonising standards should stimulate greater cross-border financial activity and the number of potential debt issuers will expand dramatically.

The trend towards privatisation. Around the world, governments are realising that the task of national resource allocation is extremely difficult and that highly centralised authorities simply cannot process information fast enough to manage vast economies and their financial systems efficiently. From a public point of view, the open-market discipline inherent in a broad and competitive public marketplace offers a more efficient means of channelling savings to national and local development. Continuing privatisation of formerly state-owned entities coupled with their subsequent need to fund their capital requirements in the public markets instead of the national budget will add to the ranks of potential issuers. With greater capital market integration, issuers will be able to diversify their funding sources well beyond their own domestic markets with relative ease. This trend is creating long-term risks for investors.

Expanding funds for investment. The pool of investment funds is likely to expand because, as the European population ages, there should be a greater propensity to save rather than consume. The individual may be reluctant to be an active and direct participant in the market and may prefer to invest through a pension fund or a life insurance company. Since, in an integrated market, the investor will have a wider selection of investment opportunities from which to choose, there is reason to believe that over time more of the investment decision making process will pass to the professional institutional investor.

The growing complexity of credit analysis. The growth of information technology continues at an exponential rate making the creation of global communications networks and the completion of complex transactions easier and cheaper. There is also a growing list of investment options available across thousands of possible issuers who operate in many different countries, with differing cultures, languages, and business practices. At the same time, financial engineering continues to create new types of securities with complex and often risky features. Investors will be forced to commit more resources to credit analysis because appropriate, reliable means must be found to compare relative risks across the new range of debt instruments and cross-border debt issuers. Increasingly, portfolio managers are concerned with optimising the value of their portfolios on a total return basis, taking into account income from interest payments and reinvestments as well as the current market value of each bond in the portfolio. The value of each debt security must be continuously evaluated according to current market value and quickly adjusted for any changes in credit quality that may have a direct and immediate impact on secondary market prices. The role of the credit analyst is thus becoming increasingly time sensitive –the objective being not only to weight the relative risk of default over the life of each debt instrument, but also to monitor and to forecast changes in credit risk over time.

Rise in credit risk. There is an overall trend towards increased credit risk. Most bankruptcy statistics show a significant increase in bankruptcies to the extent that they speak about a permanent or structural increase in bankruptcies world-wide possibly due to the increase in global competition. The same forces that are driving market growth are having a fundamental effect on the underlying credit quality of issuers. Improvements in information technology and the worldwide trend towards open-market economies are having serious consequences for the competitive business prospects and risks of a broad range of issuers. Technology is also driving competition by shortening the traditional product development cycle.

In addition to added risks for well-established issuers, the trend towards privatisation of government-owned enterprises throws up new challenges for the credit analyst. Following privatisation there is a major shift from government funding to investor funding. One aspect of privatisation is that the credit risks of an enterprise inevitably rise when it moves from government control to private ownership and management.

In a globalising and increasingly competitive free-market-oriented economy, the credit strenght of issuers is becoming less certain and more volatile. The most profound implication of the shift in financial intermediation from governments and the banking system to the individual debt investor is that it is the investor, not the banking system, who is absorbing all of the credit risk.

Technological developments. It has been also a steady increase in the willingness of corporations, financial institutions, and sovereign issuers to go beyond the confines of their own domestic markets and to seek out the efficiencies and competitive benefits that are available in other larger financial markets. The most conspicuous example of this is the Eurobond market. Advances in information technology have improved the efficiencies in the security markets by lowering the expense of communication and calculation. More importantly, information technology has enabled financial intermediaries to remove the barriers of geography, thus gaining opportunities in new markets.

The changing nature of credit decisions. Market liberalisation and technological innovation have created an explosion of opportunities in terms of broad-based debt markets for both investors and issuers. Investors are offered a vast range of debt instruments from which to choose. They can optimise yields on the securities they buy picking securities with the currency, maturity structure, and other features to match particular portfolio requirements. Borrowers, on the other hand, are offered a wide range of potential funding options, which may translate into an increased ability to finance in markets where interest rates are low or where particular funding needs in terms of currency or maturity can be more easily met.

From the perspective of asset managers in Europe, a greater capacity to analyse credit risk and a greater tolerance for credit risk could be expected to result from the euro's elimination of currency risk. Greater attention will be given to the duration and credit portfolio's choices and, in the search for higher yields, a greater tolerance of risk in both dimensions. With the euro, the capacity to perform from country allocation will be reduced, especially for European investors, who traditionally had a liking for diversification. Credit risk will become an important factor for helping fund managers in the selection of stocks, in particular non-government bonds, and will also allow them to enhance the performance of their portfolio.

More competitive margins. Despite the decline in the average quality of loans, interest margins or spreads, especially in the wholesale loan market, have become very thin. Among the possible reasons, an important factor has been the enhanced competition for lower-quality borrowers, much of whose lending activity has been concentrated at the higher risk-lower quality end of the market.

Declining and volatile values of collaterals. Concurrent with the recent Asian crisis, banking crises in well-developed countries such as Switzerland and Japan have shown that property values and real asset values are very hard to predict and to realise through liquidation. The weaker and more volatile collateral values are, the more risky lending is likely to be.

The growth of off-balance-sheet derivatives. The growth of derivative markets has extended the need for credit analysis beyond the loan book. The growth in credit risk off the balance sheet was one of the main reasons for the introduction by the Bank for International Settlement (BIS) of risk-based capital (RBC) requirements in 1993. Under the BIS system, banks have to hold a capital requirement based on the marked-to-market current value of each OTC derivative contract plus an add-on factor or potential future exposure.

The BIS risk-based capital requirements. Despite the importance of all the reasons discussed above, probably the greatest incentive for banks to develop new credit risk models has been dissatisfaction with the BIS and central banks' imposition of capital requirements on loans. Until 1992 all loans to private-sector counterparties had been subject to the same 8 percent capital ratio, irrespective of the size of the loan, its maturity, and the credit quality of the borrowing counterparty. Since 1997 in Europe and 1998 in US regulators have allowed certain large banks to calculate at their discretion capital requirements for their trading books using "internal models" rather than the "standardised" regulatory model. Despite much work needs to be done to replace the 8 percent rule with internal models, these models may still have a significant value to bankers, risk managers, and corporate treasurers. These issues are more extensively discussed in the next chapter.

Chapter III

MEASURING CREDIT RISK

As outlined in the previous chapter, credit risk carries specific features and properties that need to be incorporated into credit models. Obtaining adequate data and devising a satisfactory way of handling the covariability of credit exposures are only two of the various barriers to the design of these models. In this chapter we critically review a variety of statistical and probabilistic models introduced by the academic and professional world in the recent years. We will see how the radical changes undergoing the traditional commercial lending (i.e., securitization and credit derivatives), have lead to the abandonment of the expert systems traditional approach, where credit risk was managed at an individual level. Newer methodologies have been introduced that analyse credit risk in a portfolio context. Among these, econometric techniques, neural networks, optimization models, along with option theoretic formulations have all contributed to the progress in credit risk measurement. Practitioners and regulators have recommended the implementation of these "internal" models accompanied by rigorous validation methods. We therefore dedicate the last section of this chapter to present a review of the regulation and internal capital allocation issues that play increasingly important roles in credit risk investment and management decisions.

3.1. Background and recent developments in credit risk modelling

It is important to understand the background to the current interest in credit risk modelling. Recent developments should be seen as the consequence of three factors. First, banks are becoming increasingly quantitative in their treatment of credit risk. Second, new markets are emerging in credit derivatives and the marketability of existing loans is increasing through growth in securitizations and the loan sales market. Third, regulators are concerned to improve the current system of bank capital requirements especially as it relates to credit risk.

These three factors are strongly self-reinforcing. The more quantitative approach taken by banks could be seen as the application of risk management and financial engineering techniques initially developed in the fixed income trading area of banks' operations. However, they raise the possibility of pricing and hedging credit risk more generally and encourage the emergence of new instruments such as credit derivatives. Furthermore, if banks are adopting a more quantitative approach, regulators may be able to develop more sophisticated and potentially less distortionary capital requirements for banking book exposures. On the other hand, if regulators do permit the use of models in capital requirement calculations, banks will have a substantial incentive to invest further in the development of credit risk models.

Methods and models for evaluating and pricing credit risk have been around for as long as individuals and institutions have extended credit. The measurement of credit risk has grown substantially more complicated in recent years. In the past, banks made loans and generally held the loans on their books. Their success relied on their ability to gauge the credit-worthiness of clients. But it is increasingly common for banks to sell loans, to securitize loans, or to enter into credit swaps, all of which are mean of transferring credit risk. Fund managers are also taking advantage of new ways of transacting in credit risk through, for example, a burgeoning market for credit derivatives.

The basic problems in developing models of credit risk are (a) obtaining adequate data and (b) devising a satisfactory way of handling the covariability of credit exposures. On data, banks face the difficulty that they have only recently begun to collect relevant information in a systematic manner. Although serious, this difficulty is transitional and will be mitigated as time goes by and perhaps also as banks make arrangements to share data. The more serious data problem is that bank loans and even many corporate bonds are either partly or totally illiquid and mark-to-market values are therefore not available. This means that one must rely on some other measure of value in order to establish and track the riskiness of credit-sensitive exposures. Two approaches have been followed by credit risk modellers. JP Morgan and CSFP in their respective modelling methodologies, CreditMetrics and Credit Risk+, employ ratings and probabilities of ratings transitions as basis for measuring value and risk. The consulting firm KMV uses equity price information to infer a borrower's underlying asset value and the probability that it will fall below some default trigger level.

The second major problem faced by credit risk analysts is that of modelling the covariation in credit risks across different exposures. It is particularly difficult to do this in a tractable way while respecting the basic nature of credit risk, i.e., return distributions which are fat-tailed and highly skewed to the left. Two approaches have been taken. The CreditMetrics approach to covariation consists of supposing that ratings transitions are driven by changes in underlying continuous stochastic processes. Correlations between these processes (and hence in ratings transitions) are inferred from correlations in equity returns (to some degree therefore relying on the KMV methodology). Credit Risk+, on the other hand, allows parameters of the univariate distributions of individual exposures to depend on common conditioning variables (for example the stage of the economic cycle).

3.2. Approaches to risk measurement

3.2.1. The portfolio approach

Despite their different methodologies, all credit risk models create a distribution of possible credit portfolio values at some point in the future. Correlated changes in the credit quality of obligors result in changes in the value of exposures. These exposures are then aggregated to produce the portfolio loss distribution, which indicates the probability of achieving a certain portfolio value at the horizon date. The resulting loss distribution in Figure 3.1 is similar to those produced by VaR models for market risk.

Theoretically, the annual expected loss represents the amount that should be charged against the profit and loss account and added to the institution's loss reserve account. Referring to one standard deviation, the "unexpected loss" measures risk in the portfolio. Combining the expected loss and economic capital – the extra capital, in addition to the expected loss, needed to sustain possible losses within a defined confidence level – results in a VaR number indicating the maximum likely loss in a particular portfolio over a specified holding period and within a given confidence level. The confidence level indicates the probability of portfolio losses exceeding economic capital: a triple A institution may require a very high confidence level such as 99.98%, while a triple B institution may only require 99.85%.

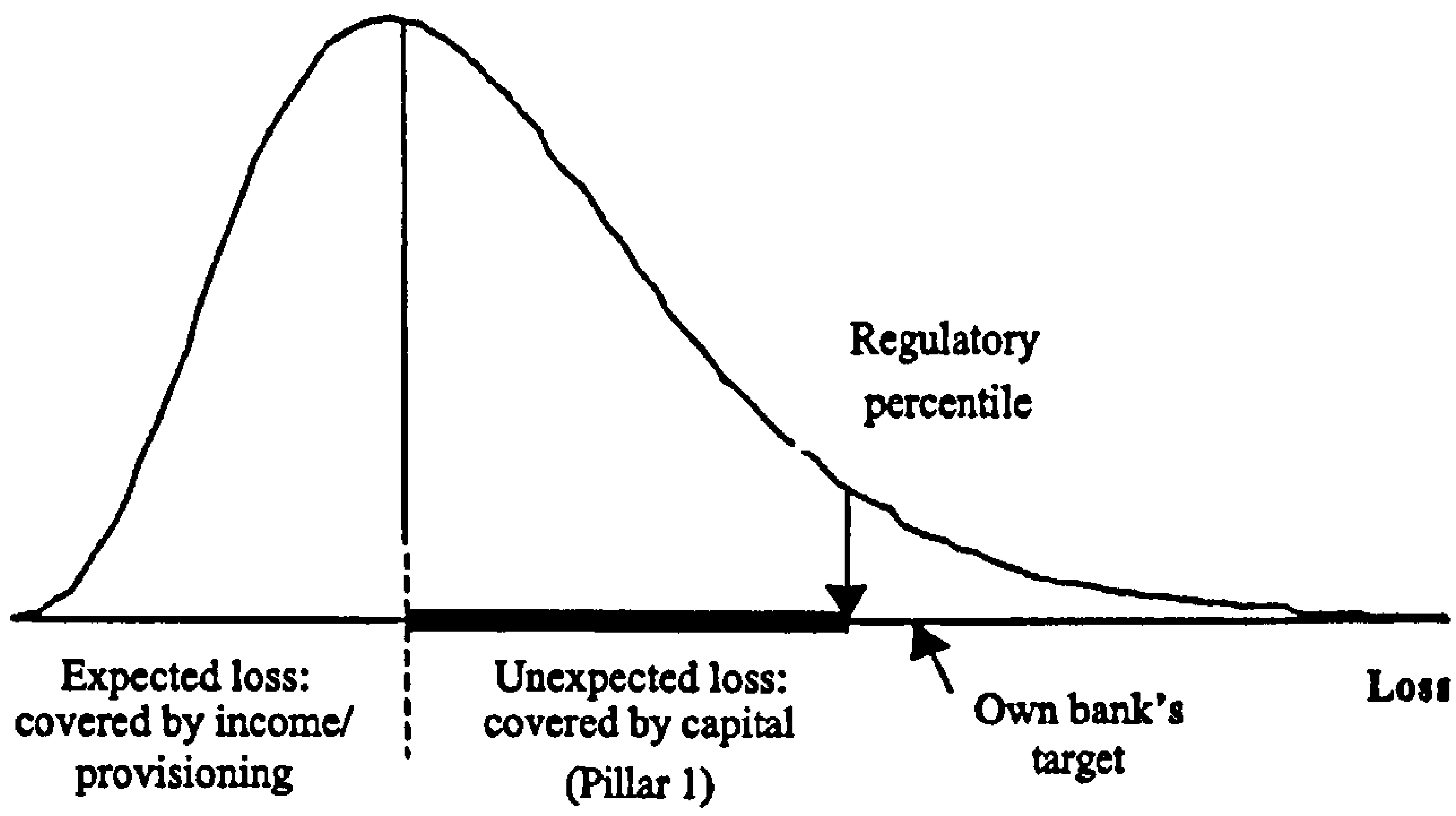


Figure 3.1 *Loss distribution*

Before discussing how the models predict loss, the meaning of loss must be defined. There are two fundamental methods of evaluating loss in a credit portfolio. The first, the default mode paradigm, only recognises a loss in the portfolio if the obligor has defaulted on its legal obligations within the modelled time horizon. The second method, the mark-to-market paradigm, recognises any gains or losses in the value of a debt security caused by changes in the credit quality of the obligor over the measured time horizon.

3.2.2. The default model and the mark-to-market models

The default mode (DM) is sometimes called a "two-state" model because only two outcomes are relevant: non-default and default. If the loan does not default, there is no credit loss. If the loan defaults there generally is a credit loss equal to the present value of the difference between the customer's contractual obligations and the loan's actual net cash flows over the workout period (e.g., recoveries less workout costs). The debt of a company that is near bankruptcy will thus be valued fully at par, although it will be trading on the market well below this price. The DM paradigm can be thought of as a representation of the traditional "buy and hold" lending business of commercial banks. Under this view, secondary loan markets are not sufficiently developed to support a full mark-to-market or trading approach to risk measurement. The default mode paradigm is therefore useful when market prices are not available or maturities are short. At present it is the most common approach used by banks for defining credit losses.

The MTM paradigm generalizes the DM approach by recognizing that the economic value of a credit instrument may decline even if the counterparty does not formally default within the planning horizon. The MTM model is "multi-state" in that default is only one of several possible credit rating grades to which the instrument could migrate over the planning horizon. In other words, MTM adopts the broader economic perspective that credit events short of default may generate falls, or increases, in the value of a debt security caused by changes in the credit quality of the obligor or by a widening of credit risk spreads in financial markets over the measured time horizon. If the credit of the obligors in a portfolio deteriorates as a result of recession, for example, the portfolio value will be lower, even without any defaults.

A market price for each debt security is obtained by discounting cash-flows on the obligor's credit curve. Two methods are generally used to value cash-flows which correspond to the way credit quality is measured. The first method uses discrete measures of credit quality such as ratings from Standard & Poor's or Moody's Investors Service. The second uses an obligor's probability of default as a continuous measure of credit quality. Instead of jumping from rating to rating, the obligor's credit quality smoothly adjusts between rating categories. The debt security at the end of the time horizon is then calculated using the default probability, remaining time to maturity and estimated recovery value in the event of default, as inputs into a valuation model.

While few banks currently use the MTM framework outside their trading accounts, many practitioners believe the industry is likely to evolve from largely DM-based risk models for the banking book to the more general MTM-based models over the coming years.

The two methods are identical if the debt instruments mature before the end of the time horizon. However, for portfolios with maturities much longer than the time horizon, the two loss paradigms can produce divergent values. A portfolio with a long average life and deteriorating credit quality will suffer a significant mark-to-market loss despite being valued at par by the default mode paradigm. Each of the credit models we present below assumes a different loss paradigm. CreditRisk+ assumes a default mode paradigm, while CreditMetrics uses a discrete mark-to-market loss paradigm. Portfolio Manager assumes a continuous mark-to-market paradigm. Either of the loss paradigms can be used in CreditPortfolioView.

3.2.3. *Aggregative versus Structural Models*

Measurement approaches can also be classified as "aggregative" and "structural" models. Aggregative approaches to risk measurement attempt to infer *total risk* (i.e. the sum of credit, market, and operating risks) directly from the capital ratios of competitors or from the historical volatility of the cash flows associated with an activity. Structural approaches, on the other hand, estimate total risk through a multi-step process encompassing separate models for credit, market, and operating risk. This section presents an overview of these alternative methodologies.

Aggregative models typically are "top-down" approaches that attempt to infer the total risk of a broadly defined business or product line using peer analysis or historical cash flow analysis. Peer group or "market comparables" analysis attempts to estimate the capital that would be needed to achieve a hypothetical "target" credit rating for a given activity (as if operated on a stand-alone basis) from the capitalization rates of competitors engaged in that activity. Typically, this approach is applied only to complete lines of business or broad product groupings (e.g. credit cards), for which data on publicly traded competitors are readily available. The other major aggregative technique, historical cash-flow analysis, attempts to estimate an activity's total risk from the volatility of its historical cash-flows. Implicitly, historical cash flow volatility (per dollar of notional size) is assumed to equal future volatility.

While aggregative models for allocating economic capital are quite common among nonfinancial firms for which operating risks predominate, they are less prevalent among banks, which are affected more significantly by credit and market risks. Among banks, aggregative models tend to be used mainly for assessing the performance of broad business or product lines, for making large-scale strategic business decisions (such as acquisitions or divestitures), or for validating structural risk models, rather than for day-to-day investment and risk management purposes.

This pattern of usage reflects two perceived limitations of aggregative models. First, as noted above, data availability often makes it difficult to apply these models at the level of individual transactions or customer relationships (e.g. in product pricing decisions). A second drawback is these models' relative insensitivity to variations in portfolio composition within the business lines that are separately analyzed. Peer analysis, for example, may be misleading if the credit quality of a bank's portfolio differs significantly from that of its competitors. Similarly, the historical cash-flow approach may be inappropriate if the current composition of the bank's portfolio (e.g., its sectoral make-up or the credit quality of the underlying customers) is substantially different from that historically observed.

In contrast to aggregative models, structural modelling approaches estimate total risk through the separate modelling of credit, market, and operating risks. With respect to the modelling of credit risk, most banks use multiple modelling approaches within the organization. Where changes in portfolio composition are a significant concern, banks appear to be evolving toward "bottom-up" approaches to credit risk modelling. This is already the predominant method for measuring the credit risks of large and middle-market customers. Unlike top-down methods, bottom-up models explicitly consider variations in credit quality and other compositional effects. A bottom-up modelling process attempts to quantify credit risk at the level of each individual credit facility (e.g., a loan or a line of credit) based on an explicit evaluation of the financial condition of the underlying customer and the structure of the credit facility. To measure credit risk for the portfolio as a whole, the risks of individual loans are aggregated, taking into account diversification/correlation effects.

3.2.4. Advantages of Portfolio Credit Risk Modelling

A portfolio approach to credit risk management is the most important alternative to the current standardised capital rules that should be made available to financial institutions. Portfolio credit risk modelling shares the same advantages of portfolio market risk modelling that have already been recognised by the international supervisory community. These include:

i) *The ability to take an integrated view of credit risk across a financial institution*. A modelling approach provides a comprehensive measure of risk across a firm, measuring credit risk regardless of where it arises – traditional lending activity, bond and equity trading or explicit credit trading through credit derivatives. By providing a common measure of credit risk, management is able to make judgements about the relative risk and return of different types of activity. Also, a common yardstick is provided to allow trade-offs between risk tenor, exposure size and collateral protection. Thus the relative risk of a 1-year $10 million loan, a 10-year $1 million bond and a 10-year partly collateralised swap with $10 million positive mark-to-market can be determined. This is a significant improvement over the current standardised rules for credit risk, which treat each form of risk in a separate category, subject to disparate rules.

ii) *Rational investment decisions and risk-mitigating actions*. Another important reason to take a portfolio view of credit risk is to more rationally and accountably address credit extension decisions and risk-mitigating actions. The bank lending marketplace has become increasingly competitive. As a result, good customer relationships have often become synonymous with heavily concentrated exposures as corporate borrowers command smaller bank groups and larger commitments from relationship banks. Yet, banks are often caught in a paradoxical trap whereby those customers with whom they have developed the most valued relationships are precisely the customers to whom they have the least capacity to take incremental risk. Bank portfolio managers have begun to harbor suspicions that they may be vulnerable to a possible turn for the worse in global credit cycles, and that current levels of spread income may not justify the concentration of risks being accumulated. Such concerns cannot easily be evaluated nor systematically reflected in pricing and credit extension decisions in the absence of a portfolio model.

iii) *The ability to assess concentration and diversification*. By taking a portfolio approach, a credit risk model recognises the risks of concentrated exposures to a single name or names that are highly correlated and – conversely – the benefits of diversification. In a portfolio context, the decision to take on ever higher exposure to an obligor will meet with ever higher risk. If relationship demands the extension of credit to a customer to whom the portfolio is overexposed, a portfolio model allows the portfolio manager to quantify (in units of under-compensated risk) exactly the extent of envisaged investment in relationship development. Consequently the risk-return trade-off of concentrated lending activity can be better managed. Conversely, the portfolio manager can rationally take increased exposure to under-concentrated names. Indeed, such names may be *individually* risky yet offer a relatively small marginal contribution to over-all *portfolio* risk due to diversification benefits. By incorporating this feature into the regulatory capital regime, firms would be rewarded for diversifying their credit positions and avoiding undue concentrations to single names. The current regulatory capital requirements for individual names provide no incentive for prudent portfolio risk management. For example, a single \$100 million loan and one hundred \$1 million loans to names of equal credit worthiness presently attract the same capital, even though the risk of the latter portfolio is demonstrably lower than that of the former.

iv) *Responding to market innovation*. There are also other, more practical, reasons why a quantitative approach to credit risk is important in response to continuing innovations in financial markets. Financial products have become more complex. The growth of derivatives activity has created uncertain and dynamic counterparty exposures that are significantly more challenging to manage than the static exposures of traditional instruments such as bonds or loans. End users and providers of these instruments need to understand such credit risk and its interaction with market risk. There has also been a proliferation of credit enhancement mechanisms that make it increasingly necessary to assess credit risk at the portfolio as well as the individual asset level. These include: third-party guarantees, credit derivatives, posted collateral, margin arrangements, and netting. Moreover, improved liquidity in secondary cash markets and the emergence of credit derivatives have made possible more active trading of credit risk based on rational pricing. Prudence requires that institutions thoroughly review existing risks before hedging or trading them. Finally, innovative credit instruments explicitly derive value from correlation risk or credit events such as upgrade, downgrade or default. Such risks are best understood in the context of a portfolio model that also explicitly accounts for credit quality migrations.

3.3. Assessing the probability of default

Credit risk models provide the decision-maker with objective insight or knowledge that would not otherwise be readily apparent or that would be available at prohibitive costs. A variety of tools are used in building financial models, including econometric techniques, simulation, optimization, neural networks, rule-based and expert systems, or hybrid systems.

The traditional credit risk analysis is mainly a "straight ratios-based" analysis. Changes in the credit quality of a firm could be estimated from inspection of the counter-party's financial statements. This type of approach was appropriate when interest rates were stable and investors bought bonds to hold them to maturity. Bonds are nowadays bought and traded with the purpose of making a profit on changes in interest rates or in absolute or relative credit quality. In this new environment a new modern analysis is taking place, focusing on changes in the perceived credit risk. We now present and discuss the main credit risk modelling approaches developed over the years.

3.3.1. The traditional approach: Expert Systems

Classic credit analysis is an expert system that relies mostly on the subjective judgement of trained professionals. The credit decision is left to the local or branch lending officer who decides on the basis of both its expertise and subjective judgement, and the weighting of key factors such as the reputation of the firm, the firm leverage, the volatility of the borrower's earnings, the provision of collaterals, the state of the business cycle, and the level of interest rates. The main problems that this system faces are consistency and subjectivity, which make comparability of rankings and decisions very difficult for an individual monitoring.

Historically, the primary mission of a bank was to finance working capital and trade, and bankers generally made loans that were secured by assets or other forms of collateral. As a consequence, deciding whether or not to make a loan was largely a matter of deciding whether the proposed collateral was sufficiently valuable. Additionally, banks used to make loans with a term of one year or less and while they were carefully reviewing balance sheets, they essentially ignored income statements. Classic credit analysis evolved in response to fundamental changes in the banking business and in the last 50 years banks moved from financing working capital to financing their customers' fixed assets. As a result, collateralization became irrelevant in the credit process and banks began to meet the demand for longer-term loans. Cash-flow lending replaced secured lending in the way that the value of a firm and its creditworthiness were estimated from the amount of cash-flow generated by its business. Still today many banks rely on annual review of their credits, basing their analysis upon the company's published financial reports. These reports are often obsolete by the time they arrive at the bank and they may not provide insight into the true risk that the company faces. Banks should therefore adapt the intensity and the frequency of their credit monitoring process to the size of the exposure and its riskiness in order to make their expert system work.

3.3.2. Loan and bond rating systems

Rating systems have been used for long time by regulators and bankers and originally were used to place an existing loan portfolio into five categories (OCC system) from four low-quality ratings to one high-quality rating. Different percentages of loan loss reserves were attributed to each category. Over the years the OCC system has developed to more finely subdivide the rating categories. It has been estimated that currently about 60 percent of US bank holding companies have developed internal rating systems for loans on a 1-10 scale (Fadil, 1997). Note that these loan-rating systems do not necessarily and exactly map into bond rating systems, especially at the lower-quality end.

Rating schemes, both internal and external, are also used for grading bond credit risk. Such ratings characterise debt issues rather than issuers. The reason is that some debt issues, from the same borrower, are less risky than others and because investors are more interested in the risk of the single issue, given its specific protection. External rating systems are provided by official rating agencies capturing and qualifying the risk of loss in the event of default through the combination of default probabilities and recoveries. As a result, ratings are rankings, not quantitative measures of risk quality. Common rating systems include from six to ten different ranks, which is sufficient to discriminate among risk classes. For bonds, future migrations across ratings, and down to default, can be projected from transition matrices across ratings. Any downgrading results in an additional market spread discounted in the bond value. The distribution of values, over a given horizon, is the image of all possible credit quality changes and measures directly the credit risk. This rating process has been frequently criticised of being a lagging rather than a leading indicator as it does not provide any new information that the market has not already absorbed.

Internal credit rating systems are designed to differentiate the credit quality of borrowers much more finely than under the five-point grading scale used by bank examiners (i.e., pass, special mention, substandard, doubtful, and loss). For risk measurement purposes, the importance of the credit rating process derives from the fact that, within most credit risk models, the internal credit risk grade is treated as a "sufficient statistic" for summarizing a facility's probability of defaulting within the relevant planning horizon. In general, the process of arriving at a credit rating for a customer or facility is accomplished through a three-step process involving first the traditional "spreading of numbers" in which financial and other characteristics of the customer (e.g., country and SIC code) and specific features of the facility (e.g., maturity) are incorporated into a relatively subjective approach to determining grades. Second, the construction of a concordance table relating the bank's internal credit grades to some external rating standard, usually S&P's or Moody's ratings for corporate bonds. For example a grade-1 loan may be deemed roughly equivalent to a S&P's bond rating from AA to AAA, a grade-2 loan equivalent to a bond rating of single-A, and so on. Finally, given this concordance, the probability of a customer defaulting on its obligations (or migrating to another credit risk grade) is usually inferred from (a) published tables of the historical default frequencies of similarly-rated corporate bonds, (b) any available internal data on the historical default rates of loans originated by the bank itself, and/or (c) consultants' knowledge of the default rates experienced by other banks. As a matter of fact, no bank relies solely on formal credit scoring models, whether developed internally or externally.

3.3.3. Accounting-based Credit Scoring Systems

Credit scoring models identify the key factors that determine the probability of default (bankruptcy) and combine them into a quantitative score. In some cases the score can be interpreted as a probability of default, in others the score is used as a classification system. Accounting-based credit scoring systems involve the comparison of various key accounting ratios of potential borrowers with industry or group mean and trend for these variables. In the univariate approach the credit analyst bases its decision on a particular ratio for a potential borrower and assesses whether it is significantly different from the norm of its industry. Generally, the most significant indicators used in univariate studies are profitability, liquidity, and solvency ratios (Beaver, 1966; Deakin, 1972). However, empirical studies disagree on which is the most effective predictor of bankruptcy potential. Moreover, it may be difficult to make credit-type judgements when individual ratios leads to different conclusions and when comparison measures are categorical rather than quantitative. These limitations lead to the extension of univariate studies to combine several measures into a meaningful predictive model (multivariate approach).

The most well known score model is the Altman (1968) Z-score model where both quantitative and categorical variables are combined and weighted to produce a measure (credit risk score) that discriminates between failing and non failing firms. Loan applicants would either be rejected or accepted according to whether their score falls below or above a critical benchmark. The model is constructed using multiple discriminant analysis, a multivariate technique that selects a set of variables to maximise the between-group variance while minimising the within-group variance. After assessing the contribution of each independent variable and evaluating the intercorrelations among the relevant variables, the predictive accuracy of the alternative sets of variables is assessed and the analyst expresses her judgement on the final profile of variables. Specifically, Altman Z-score model classifies corporate borrowers on the basis of the working capital ratio, retained earnings ratio, earnings before interest and taxes and sales to total assets ratios, and market value to book vale ratio. Revisions and extensions to the original Z-score model were introduced in order to score privately held companies (Altman, 1993) and to minimise the potential industry effect (Z'-score model), which is more likely to occur when an industry-sensitive variable is included in the model.

The basic Z-score model and credit scoring models in general have endured to this day and have been applied to emerging market companies and used to assign a bond rating equivalent to each score. They generally enable the analyst to assess the default probability of an applicant by observing the historical experience of each bond rating. From this point of view they can be viewed as an alternative to internal risk-rating system where this is lacking. They can also be used to review and update the credit quality of borrowers providing an early warning system to the lender. These models provide a low-cost and quick assessment of risk in terms of credit spreads or unexpected losses to include in pricing equations. Finally, they can facilitate the stratification and structuring of commercial loans for securitization. In order for these models to be effective over time, their coefficients need to be periodically re-estimated. The fact that, since after the scoring were first developed, a lot of attention has been given to choosing the right ratios to be used, may account for the continued stability of their predictive power and robustness.

Artificial neural network analysis (ANN) has recently been applied to credit scoring models (Altman, Marco and Varetto, 1994; Jensen, 1992 and 1996). ANN can be viewed as a development of discriminant analysis towards a nonlinear framework to solve the problem of risk classification. ANN drop the assumption that variables entering into the distress prediction function are linearly and independently related while introducing the potential explanatory and predictive power of "hidden" correlations, which are consequently included among the independent variables in the nonlinear distress prediction function. Despite ANN allow going beyond the linearity limitation of linear probability models and linear discriminant analysis, they have been criticised for their *ad hoc* theoretical foundation and their use of data mining to identify the hidden correlations.

All multivariate models are criticised for being "fitted" and "associative" since they are empirical models lacking a theory. However, the strongest criticism focuses on the book-value accounting data that these models use. Since accounting data is measured at discrete time intervals, it provides an incomplete and not contemporaneous picture of a firm's true condition and prospects. As a result, models based on this data fail to identify subtle and fast changes in borrower conditions. Moreover, for resource valuation, balance sheet structure, and regulation reasons, these models result to be unable to measure risk for utilities, financial companies, new companies, and companies in extraction industries such as oil and mining.

3.3.4. Bond prices approach

The bond prices approach estimates the probability of default of a counterparty on the basis of the credit rating assigned by rating agencies. Bond traders have developed procedures for taking credit risk into account when pricing corporate bonds. They collect market data on actively traded bonds to calculate a generic zero-coupon yield curve for each credit rating category. The probability of default of a company in a given year is therefore estimated from the yield curves for bonds of the same credit quality as those of the company. The idea is that the probability of default (PD) of a company in sector X and rated BB can be estimated using the aggregate fair market yield curve for BB-rated bonds in sector X.

To understand how this method works, let r and r^* be the current one-year risk-free rate and risky rate, respectively. For a \$1 principal, the repayment on the risk-free and risky borrowings are

\$(1 + r) and \$(1 + r*), respectively. Given that repayment under the risky borrowing is uncertain, the payoff of \$(1 + r) occurs with a probability of (1 – p), where *p* is the probability of default on the risky loan over the course of one year. Assuming that investors are risk-neutral, the expected repayment under the risky loan should equal the repayment from the risk-free loan. If we assume a fraction *f* of the loan is recovered in case of default, then

$$(1+r) = (1+r^*)(1-p) + fp \tag{3.1}$$

which gives us the probability of default *p* for a period of 1 year from now:

$$p = \frac{(r^* - r)}{(1 + r^* - f)} \tag{3.2}$$

In the case of a corporate bond, credit risk evolves from i) default, in which case the credit exposure is simply the face value of the bond, as well as from ii) credit migrations (up/down-grades), in which case the credit exposure is given by the decrease in the price of the bond. Assuming then that the higher yields on the corporate bonds are entirely compensation for possible losses from default, in both cases we can derive the present value of cost of defaults as difference between the value of a Treasury bond and the value of a corporate bond.

$$EXPECTED\ CREDIT\ LOSS = P_t\,(risk\text{-}free) - P_t^*\,(risky) \tag{3.3}$$

In order to measure the value of the risky bond between the current time t and maturity T, the horizon $\tau = T - t$ is chopped into *n* increments $\Delta t = \tau/n$. We define λ as the instantaneous rate of default, over a time interval Δt, default occurs with a probability of $\lambda\Delta t$. The probability of no default will be equal to $(1 - \lambda\Delta t)$. We also define *f* as a fraction representing the recovery rate, that is the residual payment to investors (after legal expenses) if default occurs and that can be modelled from historical experience.

Given all these factors, the price of the corporate bond at each point in time can be derived from the probability of default, the probability of no default, and the recovery rate as follows:

$$P_t^* = (1 - \lambda\Delta t)\,P_t + \lambda\Delta t\, f P \tag{3.4}$$

If λ is constant, the cumulative probability of no default is given by $(1 - \lambda\Delta t)^n$ which tends to $e^{-\lambda\tau}$ as n increases. The price of the risky bond at time t is given by two terms:

$$P_t^* = e^{-\lambda\tau} P_t + (1 - e^{-\lambda\tau}) f P_t \tag{3.5}$$

The first component of the right-hand side involves a fractional default-free bond and the second component is the default probability times the loss. Assuming no recovery, we have:

$$P_t^* = e^{-\lambda\tau} P_t \tag{3.6}$$

The rationale underlying eq. (3.6) is that for the same expected return to prevail from holding either the corporate bond or the government bond, it must be that the price of the corporate bond equals the price of the government bond times the probability of survival. To make this argument rigorous, we would have to make additional assumptions, e.g., that the corporate defaults are uncorrelated with changes in interest rates. Also the probabilities we obtain in fact reflect both the actual default probability and investors' risk aversion.

If y is the default free yield, the current price of the risk-free bond is given by:

$$P_t = e^{-y\tau} \tag{3.7}$$

Substituting eq.(3.7) into eq.(3.6) we obtain:

$$P_t^* = e^{-\lambda\tau} e^{-y\tau} = e^{-(y+\lambda)\tau} \tag{3.8}$$

In this way we can deduce the probability of default from the yield on the risky bond, y^*:

$$P_t^* = e^{-y^*\tau} \tag{3.9}$$

From eqs (3.8-3.9) we find:

$$y^* = y + \lambda \tag{3.10}$$

where the credit spread $(y^* - y) = \lambda$ represents an annualised default rate more generally accounting also for partial recovery. Credit spread can be transformed to a default probability by the logit function:

$$p_t = 1/(1 + e^{\alpha_t}) \qquad (3.11)$$

The pattern of dynamic credit exposure can be combined with future default probabilities to create a credit risk profile. At each point in time, the expected credit loss can be derived as:

$$ECL = P_t - P_t^* = e^{-\lambda\tau} \cdot e^{-y^*\tau} = e^{-y\tau}(1 - e^{-\lambda\tau}) \qquad (3.12)$$

In general the rate of default λ can vary over time, being correlated with the economic cycle, the age of the bond, corporate profitability indicators, geographical and industry considerations, and the state of the economy. The most general formulation for modelling the default probability allows there to be numerous macro and microeconomics variables that influence its level. For example, we could include the level of interest rates, the GDP, a market stock index, and the foreign exchange rate. Hence, the rate of default, given by the credit spread, can be modelled as a stochastic process of various forms.

The shortcomings of this approach are the following. In reality, investors are risk-averse, implying that probabilities of default are overestimated by a risk-neutral bond prices approach. Another disadvantage of the bond spreads approach concerns the nature of the input data available for the model. Corporate bonds typically have options embedded in them and it is difficult, if not impossible, to extract prices of pure bonds from the data. Also, factors other than credit quality can affect bond prices in the short run. For example, the spread over the treasury rates for corporate bonds of a given rating can be affected by the available supply of bonds in that rating relative to the treasury bonds. Also, the liquidity of the US Treasury market far exceeds that of any other bond market, and so corporate bonds require a premium to compensate for their liquidity risk. Finally, the probabilities of default are sensitive to the recovery rates. Recovery rates depend upon many factors including bond seniority and in practice they are difficult to measure due to the complexities involved in the bankruptcy process and its prolonged nature. Also, the recovery rates are usually not constant over time.

3.3.5. The structural approach and the KMV Credit Monitor Model

To the extent that stock price changes reflect and provide reliable evidence of a firm's creditworthiness, they constitute a powerful tool of credit risk management. The leading example of stock market-based credit measures is the expected default frequency (EDF) model of KMV. The model is a default prediction model for all major firms and banks whose equity is publicly traded. The KMV model extends the idea of applying option-pricing theory (Merton, 1974) to the valuation of risky loans and bonds. Thus credit risk is essentially driven by the dynamics of the asset value of the issuer. Given the current capital structure of the firm, i.e. the composition of its liabilities, once the stochastic process for the asset value has been specified, then the actual probability of default for any time horizon can be derived.

This approach, pioneered by Black, Scholes and Merton, views the equity of a firm as a call option on the assets of the firm, where the exercise price and maturity correspond to the face value and maturity of the outstanding debt. Equivalently, using put-call parity, the debt-holders of the firm can be considered to have sold a put option based on the firm's assets to the equity holders. The put option will be exercised whenever the asset value of the firm falls below the debt level. The probability of default of the firm then equals the probability that the put option is exercised, that is the probability that the value of the firm is less than the value of the debt.

The loan repayment incentive problem for the borrower (the equity owner of the firm) is then presented as a standard call option payoff. The value of the default option on a risky loan depends on the amount borrowed (B), the market value of the borrower firm's assets (A) at the end of the period, the short-term interest rate (r), the maturity of the bond or the time horizon for the loan (τ), the volatility of the firm's equity value (σ_s), and the volatility of the market value of the firm's assets (σ_A).

There are essentially three steps in the KMV methodology to determine the default probability of a firm. The first step is to estimate the market value and volatility of the firm's assets. As variables A and σ_A are not directly observable KMV have solved this problem introducing a theoretical relationship between σ_S and σ_A. Specifying explicit functional forms for the option pricing model of equity (OPM) and for the stock-price-asset volatility linkage, the A and σ_A values are estimated from the market value and volatility of equity and the book value of liabilities. This process is similar in spirit to the procedure used by option traders in the determination of the implied volatility of an option from the observed option price. These estimates are used together with the values assigned to B and τ to produce a theoretically based expected default frequency (EDF) score for any given borrower.

The second step consists in the calculation of the distance-to-default (DD), which is an index or measure of default. The objective is to provide an empirical EDF to overcome the strong assumption of normality of asset values and the simplifying assumptions about the capital structure of the firm necessary to produce theoretical EDFs. There are six variables that determine the default probability of a firm over some horizon *H* (see Figure 3.2): 1) the current asset value; 2) the distribution of the asset value at time *H;* 3) the volatility of the future assets value at time *H;* 4) the level of the default point, the book value of the liabilities; 5) the expected rate of growth in the asset value over the horizon; 6) the length of the horizon, *H.*

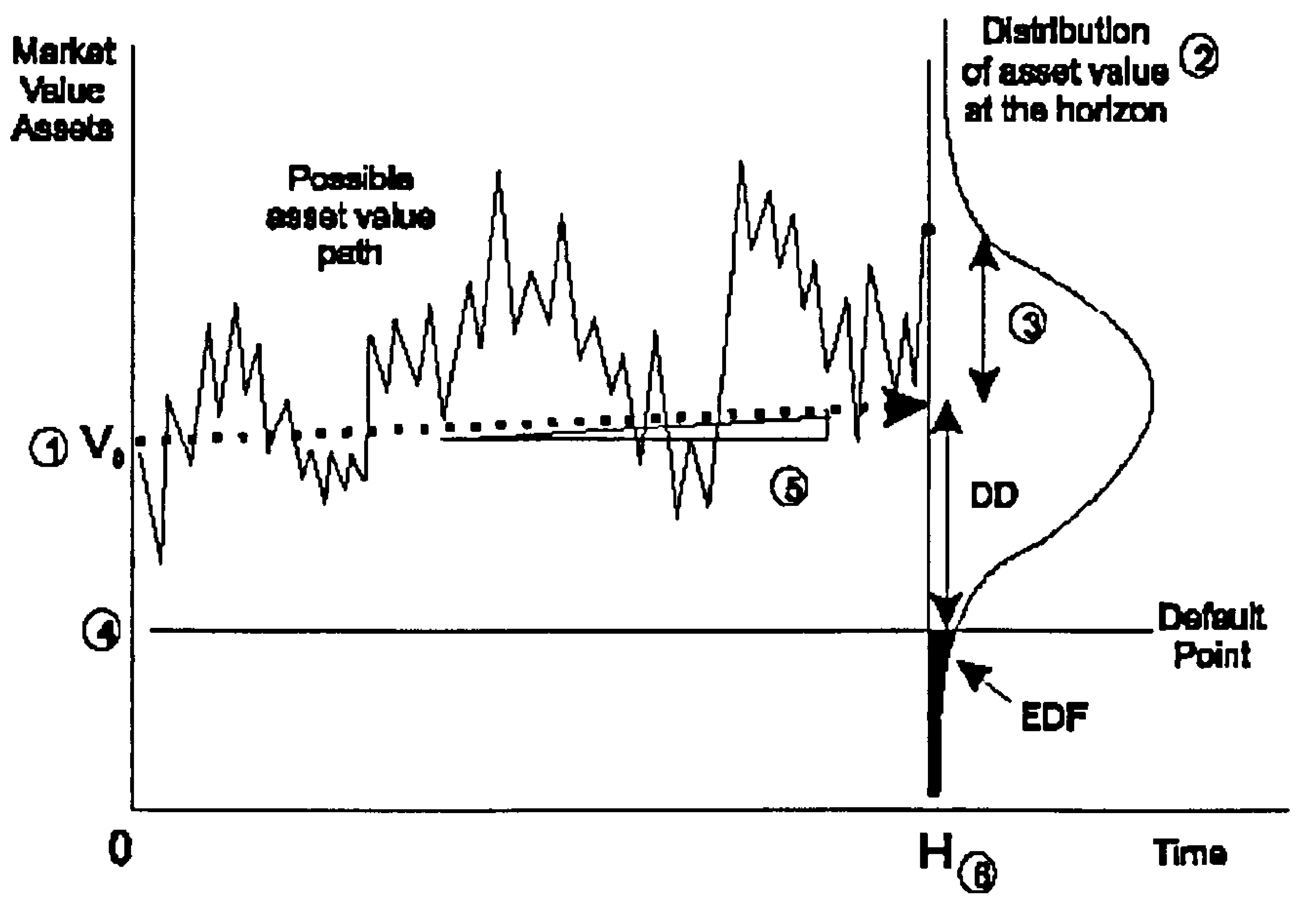


Figure 3.2 *KMV Distribution of the firm assets value at maturity of the debt obligation.*

If the value of the assets falls below the default point, then the firm defaults. Therefore, the probability of default is the probability that the asset value will fall below the default point. This is the shaded area (EDF) below the default point in Figure 3.2. If the future distribution of asset values were known, the default probability would simply be the likelihood that the final asset value was below the default point. However, in practice, the distribution of the asset values is difficult to measure. Moreover, the usual assumptions of normal or lognormal distributions cannot be used. Consequently, the distance-to-default is measured as the number of standard deviations the asset value is away from default and uses empirical data to determine the corresponding default probability. The distance-to-default is calculated as

$$\left[DD\right] = \frac{Mkt\ Value of\ Assets - Default Point}{Market Value of\ Assets - Asset\ Volatility}, \tag{3.13}$$

and represents the number of standard deviations between the mean of the distribution of the asset value, and a critical threshold, set at par value of current liabilities (including short-term debt).

In the last step the relationship between distance-to-default and default probability is obtained from data on historical default and bankruptcy frequencies. This is done building up a large worldwide database of firms and firms defaults and from these data a frequency table can be generated which relates the likelihood of default to various levels of distance-to-default. In other words, the percentage of firms that defaulted within a period $t_0+\tau$ and with asset values of x standard deviations from B at t_0 over the total population of firms that were x standard deviations away from default at t_0 is derived.

The probability of default therefore results to be a function of the firm's capital structure, the volatility of the asset returns and the current asset value. The EDF incorporates through the DD and via the asset value and volatility, the effects of industry, geography and firm size. Although EDF is firm-specific, it can be mapped into any rating system to derive the equivalent rating of the obligor. EDFs can be viewed as a "cardinal" ranking of obligors relative to default risk, instead of the more conventional "ordinal" ranking proposed by rating agencies.

To derive the loss distribution for a portfolio, KMV use the "risk neutral" or martingale approach to the pricing of securities, which derives prices as the discounted expected value of future cash flows. The valuation of risky cash-flows involves first the valuation of the default-free component and, in the second place, the valuation of the component exposed to credit risk. The full loss distribution of the portfolio at a given credit horizon is derived analytically, not simulated.

The EDF model differentiates from other approaches in a few major aspects. First, it relies on the information in equity prices. Historically, banks have ignored stock market prices in their lending decisions. By contrast, the KMV model stresses the need to monitor equity market valuations constantly and interpret the implications for credit risk. Second, it does not try explicitly to be predictive. It simply relates the current value of the firm to its default point and historical volatility. Thus, if it has predictive power, it is because the current value of the firm is a good predictor of future values. Finally, it is a conceptual rather than empirical or statistical approach, in the way that it is the option theory and the relation between debt and equity prices that drive the choice of the variables to be included in the model.

The strenghts of the KMV approach are the following. First, it can be applied to any public company. Second, by being based on stock market data rather than historic book value accounting data, it has a greater sensitivity and it is forward-looking. Third, being a structural model based on the modern theory of corporate finance and options, it has strong theoretical foundation. However, the model presents also some weaknesses. Theoretical EDFs can be constructed only under the strong assumption of normality of asset returns; EDFs for private firms cannot be calculated directly; bonds and loans are not distinguished by seniority, collaterals, covenants, and other features; finally the model is static in the sense it assumes the firm's debt structures is kept unchanged even for different levels of firm's assets. Since the probability that a firm's asset value will fall below a boundary B declines remarkably as the default horizon approaches to zero, the KMV model implies that credit spreads at the short end of the time horizon also tend to zero. Since there is no empirical evidence for this implication, KMV type of models seem to underestimate the probability of default over short horizons. Finally, the assumption of deterministic interest rates limits the usefulness of the KMV methodology when applied to loans and other interest rate sensitive instruments.

3.3.6. The VaR approach and the J.P. Morgan's CreditMetrics Model

JP Morgan and its co-sponsors introduced CreditMetrics in April 1997. This represents one of the first publicly available attempts using probability transition matrices to develop a portfolio credit risk management framework that measures the marginal impact of individual bonds on the risk and return of a portfolio. The objective is to provide a process for estimating the value distribution of any portfolio of assets subject to changes in credit quality (including default).

The CreditMetrics model of default is familiar to econometricians as an ordered probit model. Credit events are driven by movements in underlying unobserved latent variables. The latent variables are assumed to depend on external "risk factors". Common dependence on the same risk factors gives rise to correlations in credit events across obligors.

Like KMV, CreditMetrics is a Merton-based model, relying on Merton's model of a firm's capital structure: a firm defaults when its asset value falls below its liabilities. A borrower's default probability then depends on both the amount by which assets exceed liabilities, and the volatility of those assets. If changes in asset value are normally distributed, the default probability is expressed as the probability of a standard normal variable falling below some critical value. In other words, CreditMetrics is a value at risk (VaR) framework applied to the valuation and risk of tradable and nontradable assets bonds.

In addition to the credit-portfolio related difficulties generated by a non normal distribution and by the complex effect of credit diversification, applying VaR to nontradable loans, such as loans and privately placed, involves further problems such as the non observability of the current market value of the loan (P) and consequently the impossibility of calculating the volatility (σ) of P. The problems related to P and σ are solved in CreditMetrics using i) data on borrowers' credit rating, ii) probabilities from the rating transition matrix; iii) data on recovery rates on defaulted loans; and iv) credit spread and yield data. To overcome the problem of asymmetry of the credit return distribution, CreditMetrics produces two VaR measures based on both a theoretical normal distribution and the actual distribution of loan values.

CreditMetrics risk measurement framework is well summarised by Figure 3.3 that shows the two main building blocks, i.e. value-at-risk due to credit for a single financial instrument, and value-at-risk at the portfolio level. The first step in this model is the specification of the transition matrix and the calculation of critical values corresponding to each borrower's default probability (mapped from the borrower's credit rating). The mean of the bond/loan's value after 1-year horizon is derived as the sum of each possible bond/loan value at the end of year 1 times its probability to "transit" to any other rating class. Unlike in KMV's framework, CreditMetrics assumes that all issuers are credit-homogeneous within the same rating class, with the same transition/default probability.

In the second step the credit risk horizon is specified. By convention, much of the academic and credit agency data states the risk horizon on an annual basis. In a sense, the use of a one-year horizon is merely a convenient convention as is the use of annualized interest rates. Also in this respect, CreditMetrics differentiates from KMV model that uses market data, easily updated daily.

In the third step, the forward pricing model is specified. For each possible credit quality, a spread curve is required to price the bond in all possible states, with all obligors within the same rating class being marked-to-market with the same curve. The spot zero curve and the forward zero-curve are used to determine the current spot value and the forward price of the bond in 1 year, respectively. The sum of the discounted - at the appropriate rate - cash flows will provide the value of the bond in 1 year. In case the issuer defaults at the end of the year a recovery rate factor is estimated from rating agencies' historical information.

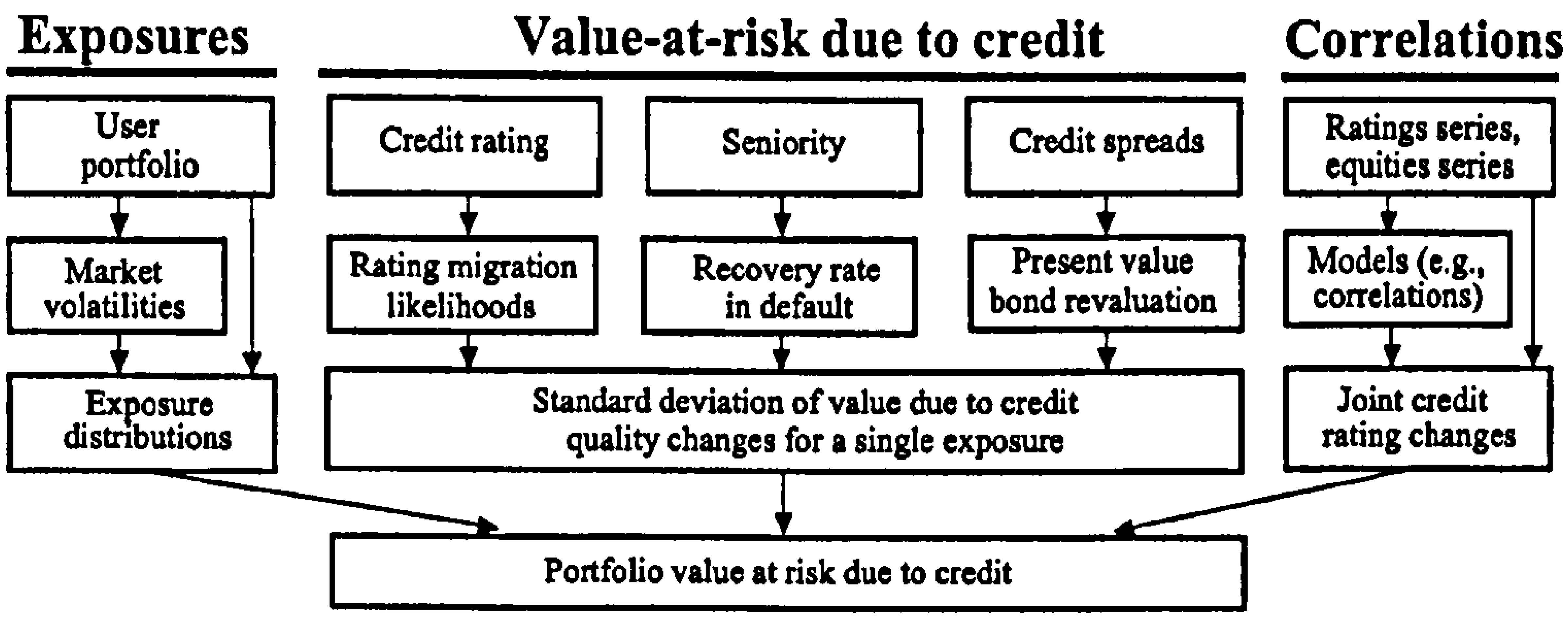


Figure 3.3 *CreditMetrics framework*

In the fourth step the forward distribution of the changes in portfolio value due to eventual changes in the credit quality is derived. Under the normality assumption, the α confidence level VaR for the bond/loan is obtained multiplying the z_α value and the standard deviation of loan value around its mean. However, we well know that credit distributions often exhibit long downside tails leading to a VaR measure that in fact underestimates the actual or true VaR. To overcome this problem, an additional "actual" VaR measure is computed using the actual distribution of bond values and transition probabilities. In either way, VaR measures the maximum loss of value on a given bond or loan (or a portfolio of bonds and loans) over the time period of 1 year at a given α confidence level.

Dealing with a portfolio of loans or bonds, joint default events amongst borrowers in the portfolio are related to the extent that the borrowers' changes in asset value are correlated (input in the form of a pairwise correlation matrix determined according to country and industry groupings). The accurate estimation of these correlations is determinant in portfolio optimization from a risk-return prospective. Equity prices are used as a proxy for the asset value of the firm[2] to estimate the correlations between the equity returns of various obligors. Correlations, like in KMV model, are derived from a structural model that links correlation to a set of fundamental factors that are systematic or common to all firms. The correlations between changes in credit quality are then inferred from the joint distribution of equity returns.

In the second building block the analysis carries on for large portfolios. The portfolio loss distribution is generated by a Monte Carlo simulation as follows. First, drawing random correlated

[2] Which is equivalent to assume that the firm's activities are all equity financed.

standard normal variables representing the change in asset value for each borrower. Second, comparing this standardized change in asset value to the pre-calculated critical value to determine which borrowers default. Third, summing the losses resulting from each borrower default to arrive at a total portfolio loss. Fourth, repeating thousands of times to build a distribution of portfolio losses.

In addition to the overall credit-VaR analysis for the portfolio, CreditMetrics calculate the marginal standard deviation, i.e. the marginal risk contribution of each individual asset on the overall portfolio standard deviation.

A few problems remain however with the VaR methodology employed in CreditMetrics. Specifically, the transition matrix is assumed to be a stable Markov process (Altman and Kao, 1992) meaning that movements between rating classes are independent. In contrast, the empirical evidence supports the hypothesis of autocorrelation in rating transitions, so that a bond or loan that has been previously downgraded is more likely to be downgraded in the current period (Nickell, Perraudin, and Varotto, 2000). The second weakness is related to the stability assumption of the rating transition matrix. That is, the same matrix is used for different borrower types, for different countries of the borrower, and for different points in time. Also in this case the evidence contradicts this assumption. Nickell et al. (2000) show how industry factors, country factors, and business cycle factors have a significant impact of rating transition.

An additional issue related to the rating migration computation is the impact of bond "aging" on the transition probabilities. Altman and Kishore (1998) show that significant difference are observed according to whether the transition matrix is computed on newly issued bonds or on all bonds outstanding in a rating class at a particular moment in time. Moreover, using bond transition matrices to value loans lead to ignore all the features that make loans behave differently from bonds, such as collaterals, covenants, etc. The assumption that recovery rates, interest rates, and credit spreads are all nonstochastic leads to the underestimation of the VaR and capital requirements. The underlying reason for this assumption lies in the controversial separation rather than integration of market risk and credit risk.

Finally, a key difficulty in the structural-based approaches of KMV and CreditMetrics is their estimation of the asset correlations from equity returns. Crouhy et al. (2000) show that credit VaR produced by these methodologies are sensitive to the correlation coefficients on asset returns and that small errors are important.

3.3.7. The Macro Simulation Approach and the McKinsey Model

The McKinsey's CreditPortfolioView model bases its strength on the clear evidence of a significant cyclic behaviour of downgrades and defaults. On the basis of this observation, CreditPortfolioView simulates the joint conditional distribution of both default and migration probabilities for various rating groups in different industries, for each country, conditional on the value of macroeconomic factors such as the unemployment rate, the rate of growth of GDP, the level of long-term interest rates, etc. The McKinsey multi-factor model links those macroeconomic factors to the default and migration probabilities.

The model starts with the empirical derivation of the relationship driving each borrower's (or "segment" of borrowers') default rate $p_{i,t}$, according to a normally distributed "index" of macroeconomic factors for that borrower (Wilson, 1997). The macroeconomic index $y_{i,t}$, is expressed as a weighted sum of macroeconomic variables $x_{k,t}$, each of which is normally distributed and can have lagged dependency.

$$x_{k,t} = a_{k,0} + a_{k,1}x_{k,t-1} + a_{k,2}x_{k,t-2} + \ldots + \varepsilon_{k,t} \tag{3.14}$$

$$y_{i,t} = b_{i,0} + b_{i,1}x_{1,t} + b_{i,2}x_{2,t} + \ldots + \upsilon_{i,t} \tag{3.15}$$

where the $\varepsilon_{k,t}$ and $\upsilon_{i,t}$ are normally distributed random innovations. The factor loadings $b_{i,k}$, for the index are determined by the empirical relationship between sub-portfolio default rates and explanatory macroeconomic variables, using logistic regression. The coefficients $a_{k,j}$ to the macro-economic variables can be determined by an appropriate econometric model. The index is successively transformed to a conditional default probability by a logit function:

$$p_{i,t} = \frac{1}{1+e^{y_{i,t}}} \tag{3.16}$$

The default probabilities are therefore determined by lagged macro variables, a general economic shock factor or innovation ($\upsilon_{i,t}$) and shock factors for each of the macro variables ($\varepsilon_{k,t}$). To calibrate the default probability model the system (3.14)-(3.16) has to be solved. The estimates of the fitted model are successively used to simulate the evolution of transition probabilities over time by generating macro shocks to the model. Structured Monte Carlo simulations are used to generate random values for both types of innovations according to their covariance structure. Macroeconomic variables outcomes according to their lagged past values and random innovations, on one side, and index values according to the macroeconomic values and the index random innovations, on the other side, are computed and the resulting default probabilities derived. The distribution of default outcomes for this iteration is calculated by successively convoluting each obligor's distribution of outcomes. All the previous steps are repeated thousands of times to build a distribution of portfolio losses. Simulated scenario values for each transition probability (each cell in the matrix) in the next periods are obtained. The new transition matrix will be conditional on the state of the economy and the ratio of the simulated probability values and the uncondional ones (based on Standard & Poor's or Moody's historical data) gives the percentage of the under- or over-estimation of the unconditional transition matrix. The new simulated matrix could be used to calculate VaR at the 1-year horizon in a way similar to the CreditMetrics framework. In this sense the macro simulation approach should be viewed as complementary to CreditMetrics, overcoming its biases resulting from its assumption of stationary transition probability matrix. Since $p_{j,t}$ can be simulated over any time horizon $t=1, \dots,$ T, this approach can generate multi-period transition matrices.

Although both KMV and CreditPortfolioView base their approach on the same empirical observation that default probabilities vary over time, the former links the probability of default to the market value of the obligor's assets (microeconomic approach), while the latter links the same probability to macroeconomic factors. Reliable data for each country and each sector within each country are necessary for the McKinsey model's calibration.

3.3.8. The Actuarial Approach: the Credit Risk+ Model

Credit Swiss Financial Products (CSFP) apply an actuarial approach to the derivation of the loss distribution of a bond/loan portfolio. Specifically Credit Risk+ makes use of mathematical techniques in loss distribution modelling common in the insurance industry (CSFP, 1997). Credit Risk+ is based on a portfolio approach to modelling default risk taking into account information relating to size and maturity of an exposure and the credit quality and systematic risk of an obligor. Credit spreads risk is viewed as part of market risk and the focus in on expected and unexpected loss calculations rather then expected and unexpected changes in value (VaR) as in CreditMetrics. Unlike the latter, Credit Risk+ model is a default mode (DM) model in that, in any period, it considers only two states of the world, default and non-default. The second major difference with CreditMetrics is that the default probability in any year is no longer discrete, but is modelled as a continuous variable with a probability distribution. Each individual loan is regarded as having a small probability of default that is independent of the default probability of other loans. As a result, the distribution of default probabilities of a loan portfolio during a given period of time resembles a Poisson distribution:

$$P(n\ defaults) = \frac{\mu^n e^{-\mu}}{n!} \quad for\ n = 0, 1, 2, \ldots, \tag{3.17}$$

where the annual number of defaults per year, n, is a stochastic variable with mean μ (average number of defaults per year) and standard deviation $\sqrt{\mu}$. As the mean default rate is expected to change over time depending on the business cycle, Credit Risk+ introduces the assumption that the mean default rate is itself stochastic with mean μ and standard deviation σ_μ. As a result the distribution of defaults is more skewed with a fat right tail.

In the extended model CSFP encompasses three sources of uncertainty: 1) the uncertainty of the default rate around any given mean default rate; 2) the uncertainty about the severity of loss; and 3) the uncertainty about the mean default rate itself. In the first step of the Credit Risk+ methodology, borrowers are allocated amongst "sectors" or "bands" ν_i, each of which is viewed as an independent portfolio of loans/bonds with an own mean default rate and a default rate volatility. The default rate volatility is the standard deviation that would be observed on an infinitely diversified homogeneous portfolio of borrowers in the band. Assuming the existence of k bands, each one represented by a random variable x_k, which is the number of defaults in the k^{th} sector, and which is assumed to follow a Gamma distribution with parameters α_k and β_k set to yield a given mean default rate μ_k and a default rate volatility of σ_k:

$$x_k \sim \Gamma[\alpha_k, \beta_k], \tag{3.18}$$

where $\alpha_k = \frac{\mu_k^2}{\sigma_k^2}$, and $\beta_k = \frac{\sigma_k^2}{\mu_k}$.

In the single-sector case, a borrower's default rate is scaled to this Gamma-distributed sector default rate. This analysis is repeated for each severity loss band ν_i taking into account the observed mean default rates for these different exposure bands. For multiple sectors, a borrower's default rate is scaled according to the weighted average of sector default rates:

$$p\,|_{x} = \bar{p}\sum_{k}\omega_{k}\frac{x_{k}}{\mu_{k}} \tag{3.19}$$

where $\bar{p}$ is the unconditional default rate, and ω_k is the weight in sector k, $\sum_{k}\varpi_{k} = 1$.

The next step would be aggregating the band exposures into a total loan loss distribution. Since borrowers' joint-default behaviors are independent conditional on fixed default rates, the unconditional default distribution for the homogeneous sub-portfolio can be obtained by "averaging" Poisson conditional default distributions according to default rates from the Gamma distribution – statistically, the convolution of the Poisson distribution with the Gamma distribution. This convolution leads to an analytic (closed form) expression for the resulting unconditional distribution of portfolio losses.

Dimensions from Comparison	Model 1 *CreditMetrics*	Model 2 *CreditPortfolio View*	Model 3 *Credit Risk Plus*	Model 4 *KMV*
Definition of Risk	Δ Market Value (MTM)	Δ Market Value (MTM or DM)	Default Losses (DM)	Default Losses (MTM or DM)
Credit Event	Downgrade/Default	Downgrade/Default	Default	Continuos Default Probabilities
Risk drivers	Asset values	Macro factors	Expected default rates	Asset values
Volatility of credit events	Constant (fixed or discrete value based on historic data)	Variable (logistic function of macro factors and shocks)	Variable (the pr.of default is a Poisson distribution; the mean default rate is modelled as a Gamma distribution)	Variable (varies with changes in stock prices)
Correlation of credit events	Multivariate normal asset returns	Factor loadings	Independence assumption	Multivariate normal asset returns
Recovery rates	Random	Random	Constant within band	Constant or Random
Numerical approach	Simulation or analytic	Simulation	Analytic	Analytic
Focus on exposures	Bottom-up model	Bottom-up model	Top-down model	Bottom-up model
Return Measurement	N/A	N/A	N/A	RAROC

Table 3.1 *Comparative analysis of credit models*

The major advantage of the Credit Risk+ methodology is the rather minimal data input and computation required (the probability of default and the loss given default). Moreover, no information is required about the term structure of interest rates or probability transition matrices. Its major limitation is that it is not a full VaR model since it focuses exclusively on loss rates rather then loan value changes. Additionally like CreditMetrics and KMV, Credit Risk+ assumes no market risk and does not deal with nonlinear products (options, swaps, etc).

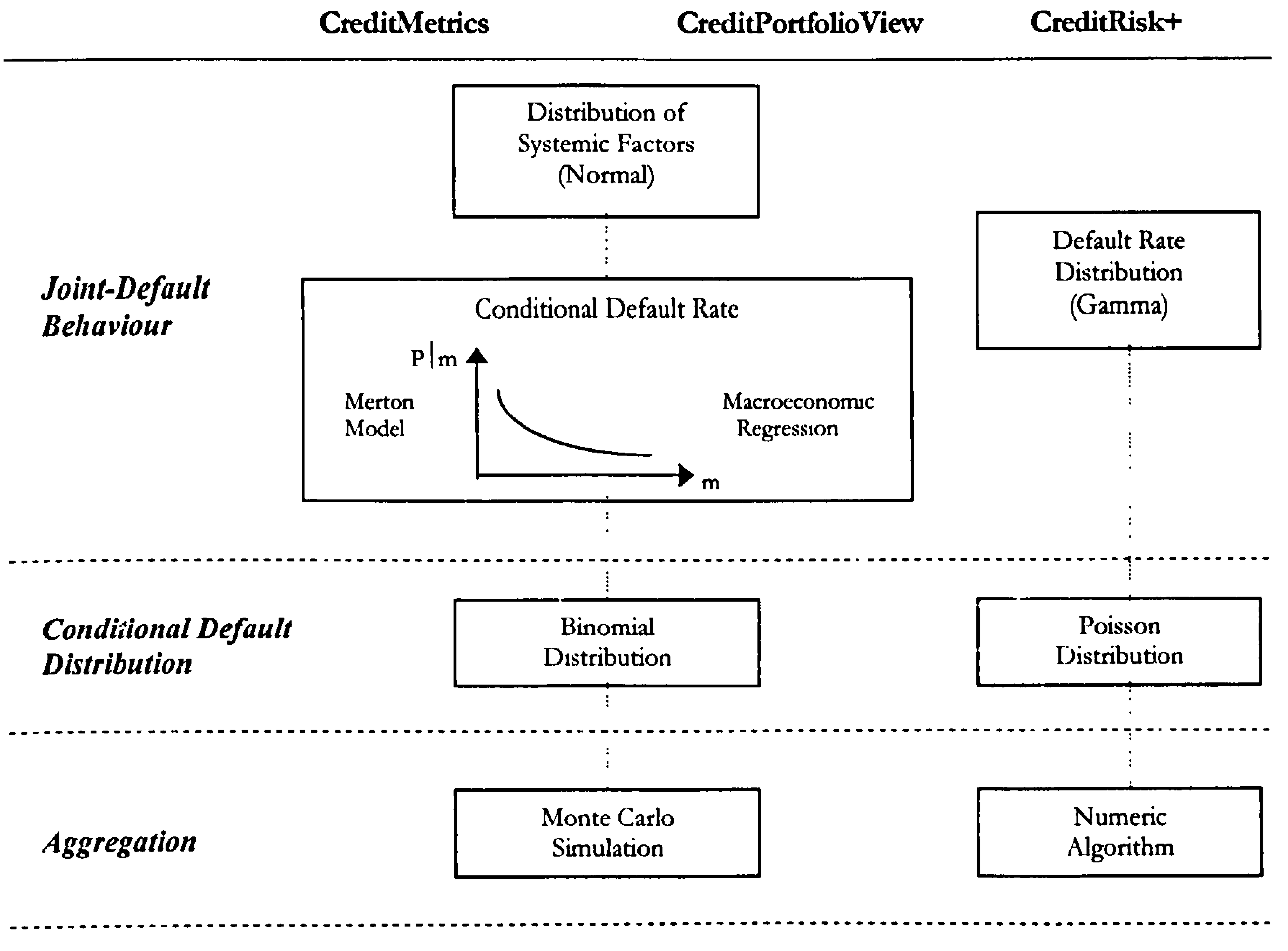


Figure 3.4 *Statistical features of credit models*

Table 3.1 and Figure 3.4 summarise the main features of some of the models presented above. Comparing credit risk models, strong statistical tests of effectiveness should be considered. The simplest test of the predictive accuracy of a model is to compare a specific prediction with the actual outcome. The forecast error, calculated from ex ante value (estimate) and ex post value (realisation), would be the best test of performance. As the absolute results of such tests depend on the particular sample used, the models we want to compare must use exactly the same sample population and include only firms for which all model values are simultaneously available. Models can also be compared from a different perspective in the context of portfolio risk and return framework. A more direct evaluation would be carried out through trading simulations based on consistent decision rules and constraints. The resulting profit and loss figures, rather than prediction error rates, could then be compared. This method, however, relies on good-quality debt price data, which are not always currently available.

Although practitioners and policy makers have invested in implementing and exploring each of these models individually, not much progress has been done with comparative analyses. Direct comparison of the models is not straightforward since the models are presented within rather different mathematical frameworks. We conclude this section saying that it is probably prudent neither to accept not to reject any of these approaches *in toto* but to subject them to objective examination and use them in combination with other sources of information in making credit risk decisions.

3.4. Model Validation

Given the extensive judgment required in specifying credit risk models, the need for effective *model validation* procedures is clearly important. The components of model validation can be grouped into a few broad categories: (a) backtesting; (b) stress testing; (c) structured Monte Carlo simulations; (d) assessing the sensitivity of credit risk estimates to underlying parameters and assumptions; (e) benchmarking; and (f) ensuring the existence of independent review and oversight of a model. At present, few banks possess processes that both span the range of validation efforts listed and address all elements of model uncertainty. This suggests that the area of validation will prove to be a key challenge for banking institutions in the foreseeable future. It remains that the validation of credit risk models is also fundamentally more difficult than the backtesting of market risk models. We present below the main reasons.

3.4.1. Backtesting

In many ways, the task of estimating the extreme tail of the PDF is comparable to predicting the frequency at which credit losses in any year will exceed many multiples of a normal year's losses. The only entirely objective method for evaluating the statistical accuracy of a credit risk model is to compare (over periods spanning multiple credit cycles) the model's *ex ante* estimates of

PDFs against *ex post* realizations of actual credit losses. That is, only the realization of more frequent, extreme credit losses (relative to the model's predictions) can provide a purely statistical basis for concluding a model is deficient.

The backtests must compare daily VaR measures calibrated to a one-day movement in rates and prices and a 98 percent confidence level for istance, against two measures of the profit and loss (P&L): a) the actual net trading P&L for the next day, and b) the theoretical P&L that would have occurred had the position at the close of the previous day been carried forward to the next day. Assuming that the risk factors are correctly modelled and that markets behave accordingly, we expect on average the absolute value of actual P&L to be greater than the VaR only 5 days over the last 250 days. Backtesting should be performed daily and net trading losses exceeding the corresponding VaR must be identified and reported.

However, while backtesting a VaR market risk model is relatively straightforward, the methodology is not easily transferable to credit risk models due to the data constraints noted above. The Market Risk Amendment (see section 3.6) requires a minimum of 250 trading days of forecasts and realised losses. A similar standard for credit risk models would require an impractical number of years of data given the models' longer time horizons. For these reasons, it is very difficult for users' own validation and for validation by third parties, such as external auditors or bank regulators, to conduct out-of-sample testing and statistical backtesting on the PDFs predicted by credit risk models.

These difficulties are the basic reason for the fact that a formal backtesting programme for validating estimates of credit risk – or *unexpected* loss – is not operational within most banks. Where analyses of ex-ante estimates and ex-post experience are made, banks typically compare estimated credit risk losses to a historical series of actual credit losses captured over some years. However, the comparison of *expected* and *actual* credit losses does not address the accuracy of the model's prediction of *unexpected* losses, against which economic capital is allocated. While such independent work on backtesting is limited, some literature indicates the difficulty of ensuring that capital requirements generated using credit risk models will provide an adequately large capital buffer.

In lieu of formal back-testing, credit risk models tend to be validated indirectly, through various market-based "reality" checks such as peer group analysis, rate of return analysis and comparison of market credit spreads with those implied by the bank's own pricing models. Peer group analysis is used extensively to gauge the reasonableness of credit risk models and internal capital location processes. Another market-based validation technique involves comparing the bank's hurdle rate with the expected risk-adjusted rate of return (i.e., the RAROC) that could be achieved by investing in corporate bonds or syndicated loans having a particular credit rating, say, BB. An implied RAROC well below (above) the bank's hurdle rate might be interpreted as evidence that the model's capital allocation for BB-rated credits was too high (low), possibly requiring some re-calibration of the model's parameters.

However, the assumption underlying these approaches is that prevailing market perceptions of appropriate capital levels (for peer analysis) or credit spreads (for rate of return analysis) are substantially accurate and economically well founded. Otherwise, reliance on such techniques could raise serious concerns regarding to the comparability and consistency of credit risk models over time, an issue that may be of particular importance from a supervisory perspective.

3.4.2. Stress Testing

Since credit data are scarce in the time dimension, but plentiful in the cross-sectional dimension, users of credit risk models have constructed alternative methods for validating these models. For example, credit risk models have been evaluated using "*stress testing*". Stress testing (ST) is a process which consists of generating market "extreme scenarios" for which key assumptions in the VaR model may be violated. We could say that while VaR considers unlikely events under normal market conditions, ST considers likely events in abnormal market conditions. ST should assess the impact of the major uncertainties in credit risk models – such as the estimation of default rates, the joint probability distribution of risk factors, correlations. ST should also investigate some causal relationships between market factors, between market and credit risks, and other exceptional relationships which may be triggered by abnormal events. In other words, stress testing allows firms to assess the impact of possible extreme "fat-tail" events. The model's performance and the adequacy of bank capital will be evaluated with respect to those event scenarios, regardless of the probability that such events may occur. Scenarios may be either artificially constructed or based on historical outcomes, and they may cover a wide range of events, including the performance of certain sectors during crises, the magnitude of losses at extreme points of the credit cycle, deterioration in credit ratings or market spreads, or shifts in default probabilities and changes in correlation structures. Although these scenarios generally do not occur, this practice may provide a consistency check regarding the model's assumptions.

In theory, a robust process of stress testing could act as a complement to backtesting given the limitations inherent in current backtesting methods. Stress testing is used routinely by the credit rating agencies, who often assign credit ratings on the basis of a security's ability to withstand various stress scenarios: to qualify for a AAA rating, the security would have to avoid defaulting under a AAA-scenario, to quality for a AA rating, the security would have to withstand a AA-scenario, and so forth. Similarly, with respect to banks' trading activities, stress tests designed to simulate hypothetical market disturbances (e.g., the October 1987 stock market crash) provide useful checks on the reasonableness of the required capital levels generated by banks' VaR models. In some ways, stress testing allows banks to derive some kind of confidence interval on its VaR numbers.

The advantage of this method is that it may cover situations completely absent from the historical data and that management might otherwise ignore. However, it does not appear that banks have dedicated a significant amount of resources to devising appropriate stress testing procedures. This might be due to the completely subjective nature of this approach with the possibility that bad or implausible scenarios may lead to wrong credit risk assessment. Moreover, the choice of scenarios may be affected by the specific portfolio position held. That is, scenarios change over time according to whether the portfolio is invested in national fixed-income rather than in currencies and measures of risk will change just because of changes between these positions. Finally, stress testing does not specify the likelihood of worst-case situations and poorly handles correlations by examining the effect of large moves in one financial variable at a time. We conclude saying that this method may be appropriate in situations where the portfolio depends primarily on one source of risk and that should be considered a complement rather than a replacement to other measures of risk.

3.4.3. Monte Carlo Simulations

In contrast to scenario analysis, structured Monte Carlo (SMC) simulations cover a wide range of possible values in financial variables and fully account for correlations. This method approximates the behavior of financial prices by using computer simulations to generate random price paths. It proceeds in two steps. In the first step a stochastic process for financial variables and process parameters is specified; parameters such as risk and correlations can be derived from historical or option data. In the second step, price paths are simulated for all variable of interest. At each horizon considered, the portfolio is marked to market and each realization is then used to obtain a distribution of returns, from which a VaR can be measured. Details of SMC simulations for credit risk are provided in Box [3.1]. This method is very expensive to implement in terms of systems infrastructure, computational cost and intellectual development, but is by far the most powerful. It is very flexible and can potentially account for a wide range of risks, including credit risk, nonlinear price risk, volatility risk, and model risk. It can also incorporate fat tails, time variation in volatility, and extreme scenarios. However, SMC relies on a specific stochastic model for the underlying risk factors as well as pricing models for securities such as options and mortgages. This suggests that simulation results should be complemented by sensitivity analysis to check if the results are robust to changes in the model.

Structured Monte Carlo Simulations. I) The first crucial step will consist of choosing an appropriate stochastic model for the behavior of credit spreads. For example the dynamics of credit spreads can be modelled as a mean reverting process of the form:

$$dcs_t = k(\theta - cs_t)\,dt + \sigma_t\, cs_t^{1/2}\, dz \quad \text{(Cox, Ingersoll and Ross, 1985)} \qquad (1)$$

An alternative way to the formulation of a stochastic process is forecasting credit spread changes through ARMA, ARCH, and GARCH models. Interactions with interest rate innovations can be introduced through correlation in the random terms. According to the simple formulation (1), the only source of uncertainty in the future value of the portfolio is due to credit quality changes –both up(down) grades, but it doesn't take into account the risk of default. A solution could be the introduction of a jump component. The variance of this process is proportional to the level of credit spreads. Additional factors can be eventually added (multifactor model).

In practice the process with an infinitesimally small increment dt is approximated by discrete moves of size Δt. Integrating $\Delta cs/cs$ over a finite interval we have approximately:

$$\Delta cs_t = k(\theta - cs_{t-1})\,\Delta t + \sigma_t\, cs_{t-1}^{1/2}\, \varepsilon\, \Delta t^{1/2} \qquad (2)$$

where ε is a standard normal variable with mean zero and variance one.

II) To simulate the credit spread path, we start from cs at time t and generate a sequence of ε for $1 = 1, 2, \ldots$ n scenarios. Then cs at time $t+1$ is set at

$$cs_{t+1} = cs_t + [k(\theta - cs_t)\,\Delta t + \sigma_t\, cs_t^{1/2}\, \varepsilon_1\, \Delta t^{1/2}] \qquad (3)$$

cs at time t+2 is similarly computed from cs at t+1, and so on for future values, until the target horizon is reached at which point $cs_{t+n} = cs_T$.

III) We can now calculate the value of the risky bond at the target horizon $P^*_t = P^*_{t+n}$ under this particular sequence of credit spreads.

Having previously modelled the price of the risk-free bond P_t using standard simulation models, we can now derive the ECL at each point in time and at the target horizon.

Repeating steps II) and III) as many times as necessary (10,000) we obtain a distribution of ECL from which the VaR can be reported. At the selected significance level c, the VaR is the ECL exceeded in c time 10,000 replications.

Box 3.1. *Structured Monte Carlo for modelling default on bonds*

3.4.4. Sensitivity Analysis

The following compensating controls may be employed to validate a credit risk model.

- *Historical backtest.* An historical backtest is a comparison of the capital that would have been calculated to the historic loss that would have occurred for a hypothetical portfolio over some past time interval. The hypothetical portfolio could either be randomly created by simulation or have been an actual loan portfolio of the bank at some past date. The historic loss in value could be ascertained from the defaults (and loss, given default) that actually occurred during the period and the loss in portfolio value that would have occurred from the historic changes in credit spreads and changes in credit ratings during the period. By choosing a severe economic downturn as a historic period, the robustness of the capital calculation could be tested.

- *Parameters.* A credit risk model's simulation of potential economic loss will depend on many parameters, such as the probability of default, given a risk rating, or the expected loss, given default. A model can be made more robust by taking into account the instability of the parameters it uses for simulation. For example, instead of using only an expected loss, given default, a credit model could use historical data to estimate the probability distribution of loss, given default and could draw from that probability distribution in its simulation. Alternatively, a model could use parameters that are dependent on a particular economic scenario. A first step in a simulation would be a draw from a probability distribution of potential economic scenarios over the coming year. Corresponding to the economic scenario that is drawn would be a set of parameters used for simulation.

- *Capital buffers.* Some additional controls that could be taken include identifying the uncertainty in capital corresponding to the uncertainty in the parameters used in simulation. An additional amount of capital could be allocated as compensation for the uncertainty in parameters. This analysis would depend on the sensitivity of the calculated capital to changes in the parameters and the degree of uncertainty in the parameters. The practice of testing the sensitivity of model output to parameter values or to critical assumptions is also not common. In the case of certain proprietary models, some parameter (and even structural) assumptions are unknown to the user, and thus sensitivity testing and parameter modification are difficult.

3.4.5. Benchmarking

Benchmarking is an efficient way of approaching the validation of internal ratings for publicly traded companies. It involves contrasting the output of an internal rating system against estimations of default/migration probabilities or losses obtained using other rating sources. For such comparison to be meaningful, the degree of conceptual consistency between the two systems being compared must first be assessed.

- *Using rating agencies.* It is common practice for banks to benchmark their ratings against those developed by agencies such as Moody's and Standard & Poor's in order to be able to use the relatively long time series of default/migration rates assembled by these agencies. Benchmarking against external ratings has potential limitations however. First, for banks whose portfolio contains a substantial proportion of externally rated assets, validating against external ratings may create a large selection bias. Including mostly publicly rated companies in the sample may lead to the development of internal models able to capture factors typical of such firms and leave out variables describing the features of non-rated companies. This in turn could compromise the reliability of the validation process itself, which can provide good results on a publicly rated sample, but not necessarily on a mixed or non-rated one. Second, rating agencies' default histories have tended to be US-focused, which may lead to question their relevance in countries where default patterns have been distinct from those observed in North America. However, most agencies are actively expanding their activities into Europe and Asia.

- *Using collective databases.* Collective databases offer another potential benchmark. Such databases exist in certain countries, where they have been assembled at the initiative of the industry, commercial firms or even the supervisors themselves. In the context of the Basle review, supervisors might need to consider the need for setting-up such databases, since these are a prime mean of checking the distribution of bank ratings across a sample of counter-parties. It is important to note in this respect that some supervisors may benchmark banks' ratings against their own rating systems (e.g., Banque de France).

- *Using other model outputs.* Banks may also assess the outcome of their internal rating models by running other models and comparing outputs. For this purpose, they may for example attempt to replicate any of the publicly available credit risk models (e.g. CreditMetrics, KMV, etc). They can feed the same data used in their internal model (and other pertinent information) to an alternative methodology. The study of differences in output between the internal rating system and the alternative method can reveal inconsistencies.

3.4.6. External assessment

Internal ratings can further be subjected to external type of assessments.

- *Assessment by rating agencies.* Banks may use external rating agencies to validate their own ratings. Public securitization involves precisely this process: rating agencies review the loss characteristics of the underlying portfolio in order to be able to rate the notes issued to investors.
- *Assessment by consultants.* Consultants can also play a role in validating internal systems, including the audit of the validation process itself.
- *Assessment by the supervisors.* In some countries, supervisors have already reviewed their banks' internal rating systems. This practice would become standard with the implementation of the proposed capital adequacy standards.
- *The market test.* One should not forget that a compelling validation process is already performed by the market. The price which investors are ready to pay for collateralised bond/loan obligations, CBOs/CLOs, is itself a function of the underlying portfolio's credit quality and may be used as a basis for assessing the underlying rating system.

All the methods we have presented have some advantages and all of them are related to each other. Perhaps the best we could do to measure credit risk is to check measures with different methodologies and investigate the sources of differences.

3.5. Capital-based pricing

Analogous to trading account VaR models, internal credit risk models are used in estimating the *economic* capital needed to support a bank's credit activities. By design, these systems create strong incentives for managers to economize on a bank's most expensive funding source: equity capital. Internal capital allocations are the basis for estimating the *risk-adjusted* profitability of various bank activities which, in turn, are used in evaluations of managerial performance and in determinations of managerial compensation. Credit risk models and economic capital allocations also have been incorporated into risk management processes, including risk-based pricing models, the setting of portfolio concentration and exposure limits, and day-to-day credit risk management.

It is complicated to define bank capital. A technical definition is that bank *capital* is the bank's net worth. More immediately, capital is the bank's cushion against possible losses due to various risks such as market, credit, and operational risk. This cushion capital is held mostly in the form of liquid, secure assets. When losses exceed the total amount of capital, the bank defaults and the excess loss is passed along to the creditors. Therefore it is important that a bank holds enough capital so as to have a small likelihood of default.

We ought to mention that in practice bankers speak of at least two kinds of capital: *regulatory capital* and *economic capital*. Regulatory capital is determined by rules set by the regulators. The estimated amount of capital needed to support a bank's risk taking activities is typically termed the bank's required or allocated "economic capital." Economic capital is determined by each bank's own internal policies. So it is customised to its own products and its own view of risk. The calculation of economic capital has generally been more scientific and has evolved to keep up with the new banking activities. It is sometimes calculated using some kind of actuarial method. This means the calculation of risk is statistical in nature and is based on historical experience.

Purportedly, both regulatory and economic capitals are a measure of the bank's risks. When banks where simply lending money, the two kinds of capital were nearly equal. At present, they are diverging. Indeed, banks are lobbying hard to convince regulators to adopt new rules to bring regulatory capital more in line with the banks' economic capital. Regardless of whether the two kinds of capital are the same, it is true that the capital concept is one kind of measure of risk and therefore is relevant to determining a fair price for that risk.

The systems for allocating economic capital against credit risk are based on the bank's estimate of the "probability density function" for credit losses ("PDF"). An important property of PDFs is that, for a hypothetical level of losses denoted by X in Figure 3.5, the estimated probability of actual credit losses exceeding this level is equal to the area under the PDF to the right of X. These systems generally assume that it is the role of reserving policies to cover expected credit losses, while it is the role of equity capital to cover credit risk. The precise definitions of "credit loss" tend to vary across banks depending on the conceptual frameworks underlying their risk measurement and management systems. Risk measurement systems generally "collapse" the estimated PDF into a single metric, termed the "economic capital" allocation for credit risk. Specifically, the economic capital allocation is determined in theory so that the probability of unexpected credit losses exhausting economic capital (i.e., the probability of insolvency) is less than some targeted level.

Once the parameters of the credit risk model have been specified, the bank must invoke a particular rule for determining how much economic capital should hold against this risk. As indicated above, at most institutions this "capital allocation rule" is expressed as the capital necessary to achieve some target insolvency rate (X) over the planning horizon. Note that the higher the target insolvency rate, the lower the allocated capital, other things the same. The portfolio's PDF generally is computed by one of two methods: (a) Monte Carlo simulation, or (b) approximations using a mean/variance methodology. In cases where the portfolio's PDF is estimated directly via Monte Carlo simulation, the economic capital allocation against credit risk is computed directly from the estimated PDF whose "shape" is consistent with the parameters of the underlying credit risk model. The Monte Carlo techniques employed in credit risk modelling are essentially identical to those used within VaR models in the trading account. Relatively few banks, however, currently use Monte Carlo methods to estimate PDFs. The vast majority use mean/variance approximations, which are viewed as computationally less burdensome. With mean/variance approximations, the general shape of the PDF is assumed, rather than inferred from the underlying credit risk model. In this case economic capital is generally calculated as some multiple of the portfolio's estimated standard deviation of credit losses, where this multiple is chosen to be consistent with the target insolvency rate and the assumed shape of the PDF. In practice, these multiples can vary widely (for example, between 3 and 7) depending on the target insolvency rate and on whether the "true" PDF is assumed to be beta- or normal-shaped. Final economic capital allocations, therefore, can differ considerably across banks owing to differences in their respective capital allocation rules (VaR, RAROC, ROE, ROA, etc).

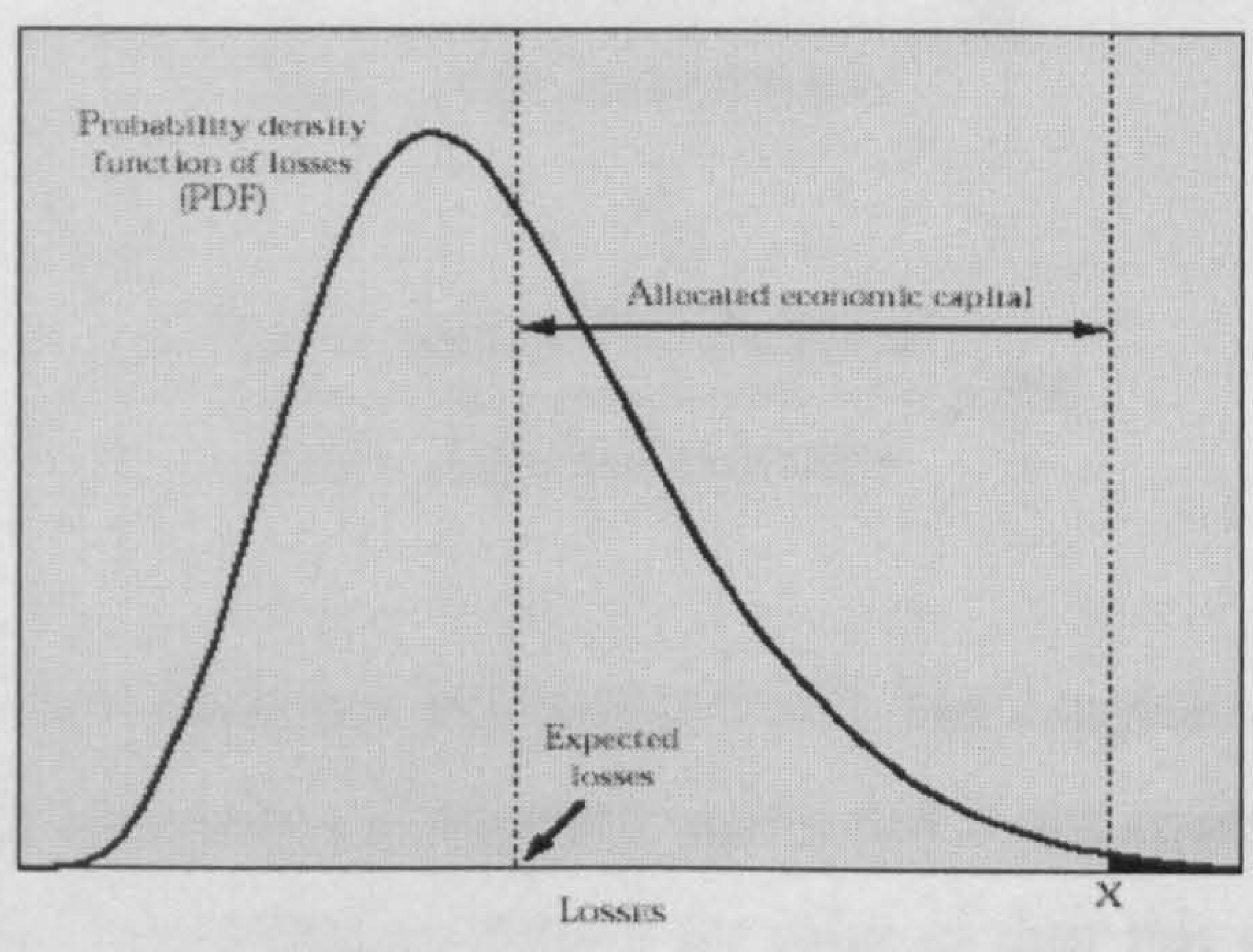


Figure 3.5 *The Relationship between PDF and Allocated Economic Capital Losses*

3.6. Credit risk and regulatory capital

Dealing with credit risk issues has become a major activity for both banks and bank regulators. The main concern of bank regulators is to ensure that a bank's capital reflects the risk it is bearing. The traditional approach they have adopted has been to specify minimum levels for balance sheet ratios. However, this became inappropriate in the late 1980s because of the rapid development of derivatives such as swaps and options, which do not appear on the balance sheet and that began to account for a significant proportion of the total risk. The Bank for International Settlement (BIS) proposed a first scheme in 1988 that was widely accepted by central banks worldwide.

3.6.1. The 1988 Basle Accord

The Basle accord (Basle, 1988) concluded on July 15, 1988, by the central bankers from the Group of Ten (G-10) countries was designed to ensure a minimum uniform capital standard applied to all financial institutions worldwide. Originally, the focus was on credit risk and only later the Accord was amended to capture market risk. According to the 1988 proposal, each on- and off-balance sheet item is assigned a weight reflecting its relative credit risk and minimum levels are set for the ratio of bank capital to total risk-weighted exposure. This ratio is known as the Cook ratio (eq. 3.21), fully implemented in 1993. Specifically, the following two capital requirements must be satisfied:

$$\frac{Tier1\,capital}{Risk\text{-}Adjusted\,exposure} > 4\% \tag{3.20}$$

$$\frac{Tier\,1\,capital + Tier\,2\,capital}{Risk\text{-}Adjusted\,exposure} > 8\% \tag{3.21}$$

where Tier 1 is shareholder's equity not including goodwill. Tier 2 capital consists of subordinated debt, loan reserves, and other sorts of long-term capital that is not equity. Therefore, banks are required to hold at least 8% of capital to support the value of their risk-weighted assets. Of this 8%, at least half has to be made of Tier 1 capital and at no time may the amount of Tier 2 capital exceed the Tier 1 level.

The novel feature of this regulation is that, for the first time, it recognises the risks associated with off balance sheet instruments such as swaps by converting them into on balance sheet risk-weighted asset equivalents. In determining the Cooke ratio it is indeed necessary to consider both the *on-balance* sheet as well as specific *off-balance* sheet exposures. On-balance sheet items have risk weightings from 0 percent for cash and OECD government securities, to 100 percent for corporate bonds and others. Off-balance sheet items are first expressed as a credit equivalent, and then are appropriately risk weighted by counterparty. The risk-weighted amount is then the sum of the following two components: i) the risk-weighted assets for on-balance sheet instruments and ii) the risk-weighted credit equivalent for off-balance sheet items. Table 3.2 gives the risk-capital weights (WA) by asset categories, and Table 3.3 shows the weights that apply to credit equivalents by type of counterparty (WCE).

$$\text{Risk-weighted amount} = \Sigma(\text{assets} * WA) + \Sigma\ (\text{credit equivalent} * WCE) \qquad (3.22)$$

The risk-weights for corporates are apparently inconsistent in Tables 3.2 and 3.3. The weight for off-balance sheet instruments is half what is required for on-balance sheet assets. BIS' rationale for this asymmetry is the better quality of the corporates that partecipate in the market for off-balance sheet products. In the case of off-balance sheet exposures, the first step is to calculate the credit equivalent as follows:

$$\text{Credit equivalent} = \text{Current exposure} + (\text{add-on factor}) \qquad (3.23)$$

The current exposure (CE) is the greater of the current value of the derivative and zero. The add-on factor (f) is a percentage of the notional principal according to the risk capital weights by asset categories as indicated in Table 3.4. The add-on factor differs quite substantially from one category to the other, although the rationale for such differences is not always clear. The sum of CE and f is then multiplied by the risk weight of the counterparty (Table 3.3) to give the risk-adjusted exposure. The result of this calculation is the final risk-weighted amount. It is important to realise that the capital requirement must be calculated not only at the time the contract is negotiated, but also during the life of the derivative. To this aim many financial institutions carry out Monte Carlo simulations to determine confidence limits for their regulatory capital at future times.

The BIS capital requirements do not distinguish between credit corporate counterparties wih different *credit ratings*. A counterparty with a AAA rating is treated as one with a BBB rating. For internal use, some financial institutions have developed more sophisticated capital allocation procedures. An amount of capital is allocated to each deal entered into by a financial institution and traders are evaluated on the basis of their return on capital employed. This has the advantage that motivates traders to take credit risk into account when quoting prices.

Basle regulations do not account for the *portfolio risk* of the bank. Correlations between components of the portfolio may significantly alter total portfolio risk. Credit risk can be in fact offset by diversification across issuers, industries, and geographical locations. The 1988 regulations actually raise the capital requirements from hedging operation.

Finally, the BIS 1988 proposal does not take into account what is known as *netting*. A bank that has offsetting open positions towards the same counterparty, may have a very small net exposure. Regulatory authorities have become progressively more sympathetic to the use of netting in the calculation of capital requirements.

Risk Weights (%)	Asset Category
0	Cash and gold bullion, claims on OECD goverments like Treasury bonds, insured residential mortgages.
20	Claims on OECD banks and OECD public sector entities like securities issued by US Government agencies, claims on municipalities.
50	Uninsured residential mortgages.
100	All other claims like corporate bonds and less developed country debt, claims on non-OECD banks, equity, real estate, premises, plant and equipment

Table 3.2 *Risk-capital weights by on-balance sheet asset category (WA)*

Risk Weights (%)	Type of Counterparty
0	OECD governments
20	OECD banks and public sector entities
50	Corporate and other counterparties

Table 3.3 *Risk-capital weights for off-balance sheet credit equivalent by type of counterparty*

Residual Maturity (years)	Interest Rate Contracts (%)	Equity (%)	Precious metals except gold (%)	Other commodities (%)	Exchange Rate Contracts (%)
<1	Nil	6.0	7.0	10.0	1.0
1-5	0.5	8.0	7.0	12.0	5.0
>5	1.5	10.0	8.0	15.0	7.5

Table 3.4 *Add-on factors by type of underlying and maturity*

3.6.2. The European Directives

The original Basle Accord, although it has been adopted across a wide number of jurisdictions, was not legally binding. Within the European Union, the substance of the Accord was incorporated into two key banking directives issued in 1989, the *Own Funds* and the *Solvency Ratio Directives*. These directives were legally binding and required the national regulators to amend their domestic legislation accordingly.

With minor differences, the process for determining capital requirements under the EU directives is the same as in the Basle Accord. However, the EU regulators were aware that the provisions of the Basle Accord applied only to credit-related activities and the EU directives were later extended to cover market risk as well. These were specified under the 1993 *Capital Adequacy Directive* (CAD) which came into force in 1996.

The first step under CAD is to analyse the types of financial activities undertaken by an investment firm or credit institution. CAD divides the activities of an institution into a *banking book* and a *trading book*. The trading book covers trading in short term instruments, positions in financial instruments arising from matched principal broking, instruments used to hedge elements of the trading book, exposures arising from unsettled transactions in debt and equity securities and OTC derivatives, and exposures from repurchase and securities lending/borrowing agreements. The trading book excludes activities such as deposits and loans, along with other traditional banking products, which are part of the banking book.

The main innovation in CAD was to regulate the capital provisions necessary to sustain the market risk on the institutions' trading books. The details of the CAD rules are very complex and the following is just an overview of some of the salient features:

- The risks on a trading book are analysed in terms of position risk, settlement and counterparty risk, foreign exchange risk and large exposure risk

- Position risks are further analysed in terms of their general and specific risks. Different risk conversion factors are applied under each of these risks, depending on the nature of the financial instrument
- In addition to the capital required to cover position risk, a basic capital requirement of 8% of risk-weighted assets is applied to cover settlement and counterparty risk. Additional limits are imposed on *large exposures* to specific counterparties, which must be reported to the national regulators. Large exposures in the trading books may exceed the approved limits but any excesses over the limits attract supplemental capital charges.
- A capital charge of one-quarter of an institution's administrative expenses during the preceding financial year is levied to cover all other types of risk, including operational risk.

Another innovation of CAD was to broaden the definition of capital to include Tier 3 capital. This includes certain types of short-term subordinated debt, as well as daily MTM profits of the trading book. This was a helpful addition in that it allowed institutions to offset some of the negative impact of profitable trading positions on their capital requirements.

One interesting feature of CAD is that it allows institutions to use their own proprietary value at risk (VaR) models to estimate the market risks on their positions, provided the models used come up with a capital requirement that is not less than the amount calculated using the regulatory approach.

3.6.3. The 1995 BIS market risk proposal: the 1996 amendment

The Basle 1988 proposal poorly accounts for market risk. Assets are in fact recorded at book values, which may substantially differ from their current market values. As a result, accounting lags may create a situation where an apparently healthy balance sheet hides losses in market values. In recognition of this drawback, soon after the introduction of CAD in Europe, the BIS published its Amendment to the Basle Accord to Incorporate Market Risk. The Basle Committee on Bank Supervision (1996) specifies qualitative and quantitative standards that institutions must observe in order to cover market risk, in addition to the existing provisions for covering credit risk. This proposal was implemented by the national regulators in 1998. To this aim a scenario analysis was suggested and the use of internal credit risk models allowed for the first time.

The initial accord still applies to the non-trading items both on-balance sheet and off-balance sheet. Market risk must now be measured for both on- and off-balance sheet traded instruments.

However, on-balance sheet assets are subject to market risk capital charge only, while off-balance sheet derivatives are subject to both market risk and credit risk capital charges.

	On-balance sheet	Off-balance sheet
Trading book	Market Risk	Market Risk + Credit Risk
Non trading book	1988 Accord	1988 Accord

Table 3.5 *The 1996 Amendment*

The initial BIS agreement was modified to allow banks to reduce their credit equivalent when bilateral netting agreements are in place. According to some surveys, netting reduces the banks' gross replacement (or current) value by half on average. The new BIS formula for add-on amounts is now:

$$\textit{Add-on amount} = \textit{notional} * (\textit{add-on factor}) * (40\% + 60\% * NPR) \qquad (3.24)$$

The add-on factors are the same as in Table 3.2. *NPR* denotes the replacement ratio which is the net replacement cost when positive, or zero otherwise, divided by the gross replacement cost calculated as before, without taking netting into account, i.e. the sum of the positive replacement cost for the transactions covered by the netting agreement. However, the new BIS formula does not allow for complete offsetting, even if netting agreements are in place.

In the 1996 Amendment to the original BIS Accord, a third tier of capital has been added only to meet market risk requirements. Tier 3, or sub-supplementary capital, consists of short-term subordinated debt with an original maturity of at least two years. It must be unsecured and fully paid up. It is also subject to lock-in clauses that prevent the issuer from repaying the debt before maturity, or even at maturity should the issuer's capital ratio become less than 8 percent after repayment. Banks will be entitled to use tier 3 solely to satisfy market risk capital charge, which in turn should be met also with tier 1 and tier 2 capital not allocated to credit risk.

According to BIS, market risk encompasses both "general market risk" and "specific risk". General market risk refers to changes in the market value of on-balance sheet assets and liabilities, and off-balance sheet instruments, resulting form broad market movements, such as changes in the level of interest rates, equity prices, exchange rates, and commodity prices. Specific risk refers to changes in the market value of individual positions due to factors other than broad market movements like liquidity, exceptional events, and credit quality.

BIS authorities recognise the complexity of correctly assessing market risk exposure, especially for derivative products. Flexibility in the modelling of the many components of market risk is thus allowed. The most sophisticated institutions that already have an independent risk management division in place will have the choice between their own "internal VaR model", referred as the internal approach, and the "standard model" proposed by BIS, referred to as the standardised approach, to determine market risk related regulatory capital.

The new capital requirement related to market risks should largely be offset by the fact that the capital charge calculated under the 1988 Accord to cover credit risk no longer need to be held for on-balance sheet securities in the trading portfolio. The capital charge for general and specific market risks should be, on aggregate, much smaller than the credit risk capital charge for large trading books. Then, banks adopting the internal models approach should realise substantial capital savings, probably of the order of 20-50 percent, depending on the size of their trading operations, and the type of instruments they trade.

The standardised approach. The standardised model uses a "building block" type of approach where VaR is first computed separately for portfolios exposed to interest rate risk, exchange rate risk, equity risk, and commodity risk. The bank's total VaR is then obtained from the summation of VaRs across the categories to obtain the global capital charge related to market risk. Although the objective is to identify banks with unusual exposures, this approach still have some problems. It applies the same capital charge to vastly different financial instruments. The duration of some instruments (i.e. mortgages) cannot be easily identified. The issue of diversification across risks and the interaction of credit and market risks, although difficult to deal with, remain still ignored. The capital charges are arbitrary as only loosely related to the actual volatility of each asset category, which would distort portfolio choices as banks will tend to move away from assets for which capital charge is particularly high.

The internal models approach. The internal models approach (Basle, 1995) remedies many of these criticisms, and attempts to improve the accuracy of the standardised approach. In particular, the committee recognised that many banks have developed sophisticated risk management systems, in many cases far more complex than what can be shaped by regulators. To be eligible to use its own internal model an institution must have a strong risk management group which is independent from the business units it monitors, and which reports directly to the senior executive management of the institution. Moreover, the internal models should be fully integrated in the daily risk management of the institution. In addition, the regulator requires that systematic backtesting and stress testing be conducted on a regular basis.

As far as the quantitative and modelling requirements is concerned, the latest "internal model" proposal suggests the computation of VaR with a horizon of 10 days, a 99 percent (one-tailed) confidence interval, an observation period of at least a year of historical data and updated once a quarter. The capital charge should be set at the higher of the previous day's VaR or the average VaR over the last 60 business days, times a multiplicative factor *k*, which normally should be equal to 3.

$$Market\ Risk\ Capital\,Charge\,(t) = max\left\{VaR_{t-1}, k * \frac{1}{60}\sum_{i=t-1}^{t-60} VaR_i\right\} \tag{3.25}$$

This factor intends to provide additional protection against environments that are much less stable than historical data would lead to believe. This multiplier should also be viewed as an insurance against model risk, imperfect assessment of specific risks, and other operational risks. A penalty component shall be added to the multiplicative factor if backtesting reveals that the bank's internal model incorrectly forecasts risks. Because of all these extra components, this proposal has been severely criticised as leading to capital requirements generally higher than the standard model and consequently discouraging the development of internal risk models.

Institutions are allowed to take into account correlations among risk categories. Volatilities and correlations should be estimated based on past historical data with a minimum history of 250 days. Market parameters should be updated at least once every three months. If empirical correlations are unavailable, then the aggregate VaR is calculated as the simple arithmetic sum of the VaR for each block, like in the standard approach.

The precommitment model. The Federal Reserve Board (1995) proposed a "pre-commitment" approach (PCA) to bank regulation. Under this alternative, the bank would pre-commit to a maximum trading loss over a designated horizon. This loss would become the capital charge for market risk. The supervisor would then observe periodically whether trading losses exceed the limit. If so, the bank would suffer a penalty in terms of a fine, regulatory discipline, or higher future capital charges. The PCA is an interesting initiative since it aims to replace regulatory capital requirements based on ex ante estimates of the bank's risks, with a capital charge that is set endogenously through the optimal resolution of an incentive contract between the bank and its regulators. It can be shown that the PCA takes the form of a put option written on the bank's asset and issued to the regulators. The value of this liability for the bank increases with the penalty rate, set by the regulator, and the riskiness of the bank's assets, while it decreases with the striking price of the put, i.e. the pre-commitment level. When the bank increases the risk of its assets it increases the value of its pre-commitment liability, which is more or less than offset by the increase in the value of the fixed-rate deposit insurance.

The main advantage of this "incentive-compatible" approach is that the bank itself chooses its capital requirement. The optimal design of the incentive contract becomes bank specific and should be such that the bank finds itself the right trade-off between the riskiness of its trading book and the level of pre-committed capital with the objective of maximising the shareholder value and of minimising the exposure of the deposit insurance institution (Kupiec and O'Brien, 1997). However, the PCA has been criticised by Gumerlock (1996) for the slow periodical verification in comparison to the real-time daily capital requirements of the Basle proposals. Moreover, there is some worry that dynamic portfolio adjustments to avoid exceeding the maximum loss could exacerbate market movements.

3.6.4. The proposed New Capital Adequacy Framework – BIS, 1999

In mid-1999 the BIS issued a consultative document acknowledging the need to revise the 1988 Accord principles. This new capital framework consists of three pillars: minimum capital requirements, a supervisory review process, and effective use of market discipline. The Committee believes that, taken together, these three elements are the essential pillars of an effective capital framework.

The BIS recognises that the world financial system has recently witnessed considerable economic turbulence and, while these conditions have generally not been focused on G-10 countries directly, the risks that internationally active banks from G-10 countries have had to deal with have become more complex and challenging. The review of the Accord is designed to improve the way regulatory capital requirements reflect underlying risks. It is also designed to better address the financial innovation that has occurred in recent years, as shown, for example, by asset securitisation structures.

The review is also aimed at recognising the improvements in risk measurement and control that have occurred. With regard to minimum capital requirements, the Committee recognises that a modified version of the existing Accord should remain the "standardised" approach, but that for some sophisticated banks use of internal credit ratings and, at a later stage, portfolio models could contribute to a more accurate assessment of a bank's capital requirement in relation to its particular risk profile. In so doing, the Committee proposes to clarify and broaden the scope of application of the current Accord. With regard to risk weights to be applied to exposures to sovereigns, the Committee proposes replacing the existing approach by a system that would use external credit assessments for determining risk weights. It is intended that such an approach will also apply, either directly or indirectly and to varying degrees, to the risk weighting of exposures to banks, securities firms and corporates. The result will be to reduce risk weights for high quality corporate credits, and to introduce a higher than 100% risk weight for certain low quality exposures. A new risk-weighting scheme to address asset securitisation, and the application of a 20% credit conversion factor for certain types of short-term commitments are also proposed. For some sophisticated banks, the Committee believes that an internal ratings-based approach could form the basis for setting capital charges, subject to supervisory approval and adherence to quantitative and qualitative guidelines. At a later stage those institutions may also be allowed to use probabilistic models to assess net credit exposures on a portfolio basis.

The existing Accord specifies explicit capital charges only for credit and market risks (in the trading book). Other risks, including interest rate risk in the banking book and operational risk, are also an important feature of banking. The Committee therefore proposes to develop a capital charge for interest rate risk in the banking book for banks where interest rate risk is significantly above average, and is proposing to develop capital charges for other risks, principally operational risk.

The second pillar of the capital adequacy framework, the supervisory review of capital adequacy, will seek to ensure that a bank's capital position is consistent with its overall risk profile and strategy and, as such, will encourage early supervisory intervention. Supervisors should have the ability to require banks to hold capital in excess of minimum regulatory capital ratios - a point underscored in the course of the Committee's discussions with supervisors from non-G-10 countries. Furthermore, the new framework stresses the importance of bank management developing an internal capital assessment process and setting targets for capital that are commensurate with the bank's particular risk profile and control environment. This internal process would then be subject to supervisory review and intervention, where appropriate.

The third pillar, market discipline, will encourage high disclosure standards and enhance the role of market participants in encouraging banks to hold adequate capital. The Committee proposes to issue later this year guidance on public disclosure that will strengthen the capital framework.

In summary, credit-risk models represent a substantial advance in the quantitative analysis of portfolios of credit exposures. Output from such models can help, for example, in identifying inadequate diversification, suggest hedging strategies and provide useful guidance for the allocation of economic capital. Questions remain, however, about the reliability of the risk measures they supply. These methods and models are still not sufficient for the pricing of credit derivatives. Moreover, in order to price a credit derivative one needs a model that describes the *dynamics* of credit risk, starting with modelling the considered measure of the firm (or industry, country, etc) and successively describing the possible ways the creditworthiness may evolve over time.

Chapter IV

LITERATURE REVIEW ON CREDIT RISK

This chapter provides a throughout review of the literature in the area of credit risk. It identifies several approaches used for the quantification, explanation, and pricing of credit risk. It also highlights the shortcomings associated with some of the methodologies and the unexplored topics from which our investigation originates.

4.1. Introduction

The literature relating to credit risk premia has focused on three main aspects: a) explanation of credit risk premia; b) specification of the risk structure of credit risk premia; c) valuation of risky debt. Section 4.2. will be dedicated to the first aspect, that is to the presentation of the main studies focused on the determinants of the bond yield or yield premium. Most of these works implement cross-sectional regression analysis in order to determine what are the factors that are significant in explaining credit risk premia. Among the most common factors we can mention: various proxies for the risk of default (earnings variability, time of no default, market equity value over par value of the debt), marketability, supply and demand factors, business cycle and macroeconomic variables (interest rates, inflation), specific features of the bond (callability, coupon rate, sinking fund, security status, recovery factor, industrial classification), actual default rates, returns on the firm's assets and the firm's capital structure.

Section 4.3. concentrates on the second topic, the term structure of credit spreads. The idea underlying the risk structure of credit risk is that spreads on corporate bonds vary with maturity holding all other characteristics of the bond constant. The idea reflects the fact that, in general, the market values bonds as if corporations have a higher probability of defaulting each year into the future. We will see that this is not always the case. Most of the theoretical and empirical works related to this topic present the consistent result of a mean reversion in the credit quality of the firms. High quality firms are unlike to default in the short term, but over the longer term might be facing a decrease in quality or ultimately default whereas lower quality firms face immediate prospect of default but over time can overcome their state of financial distress.

In Section 4.4. we present default risk pricing models. The basic idea of these models is that the inherent credit risk of any credit transaction should be compensated by way of return (calculated as the spread received) commensurate with risk as measured by the risk of default (both on expected and unexpected losses), the credit exposure and the recovery rate in the event of default.

The last sections are dedicated to more specific issues. In Section 4.5 the ideas of the CAPM are profitably applied in credit-selection decisions. Section 4.6 presents the first time series analysis applied to credit spreads. In Section 4.7 extreme value theory is implemented in order to estimate credit spread risk. Some conclusions are finally drawn in section 4.8.

4.2. Determinants of the credit risk premium

The basic theory and the idea underlying the concept of risk premium on loans was first introduced by McCullough (1830), which pointed out how risk premia have to be higher, the higher is the lender's risk of default and the more difficult is to turn the securities into cash. The first systematic treatment of the subject, however, will have to wait more than one century, till the contribution of Fisher (1959). Fisher (1959) defines the risk premium as the difference between the market yield on a bond and the corresponding pure rate of interest. Where, the market yield is given by the rate of interest at which the principal and interest payments must be discounted if their present value is to equal the current market price of the bond, and the pure rate of interest is given by the market yield on a risk-free bond with the same maturity as the bond under consideration.

The works presented below make abstraction from several market imperfections. Most importantly, they assume that the risky bond is identical to the risk-free bond, save for its default risk. In practice, government bond markets are larger and more liquid than corporate bond markets. This implies that in addition to the credit spread, investors will need to be rewarded for holding bonds less liquid than government bonds. The spread thus also contains a *liquidity premium*. Therefore, changes in the measured 'credit' spread may also be due to time-varying liquidity premia. In the theoretical analysis that follows, we will to a large extent ignore the liquidity premium. Also in the empirical analysis the distinction between pure credit spread and liquidity premium will not be made because of the difficulty to disentangle them.

4.2.1. Risk of default and marketability

Fisher (1959) develops a cross section analysis to find what are the main factors explaining the risk premium on US domestic industrial corporations. Public utilities and transportation companies were excluded from the sample as being subject to forms of regulation which prevent them from maximising profits, and that, other things being equal, make them less likely to default on their bonds than industrial companies with the same earnings variability. The factors under observation are: a) the risk of default of the firm, and b) the marketability of the bond.

The risk of default is estimated by a function of three variables:

i) the variability of earnings, measured by the coefficient of variation of the firm's net income over the last nine years (after all charges and taxes). This variable is expected to affect positively the risk premium as a firm with a small coefficient of variation of earnings is less likely to default on its bonds than a firm with a large coefficient – other things being equal.

ii) the length of time the firm has been operating without forcing its creditors to incur into losses. This variable provides a correction for the estimate of risk of default derived from earnings variability. In fact, the longer the solvency period of the firm, the less likely it is that the estimated coefficient of variation in earnings is much less than the coefficient in the hypothetical underlying population of annual net incomes.

iii) the ratio of the market value of the equity to the par value of the firm's debt. This is a measure of how much the firm's assets can decline in value before they become less than its liabilities.

The marketability of the bond can be estimated by a single variable, the total market value of all the publicly traded bonds the firm has outstanding. The smaller the amount of bonds outstanding, the less frequently we should expect bonds change hands, the thinner is the market, the more uncertain is the market price, the higher the expected risk premium.[3]

[3] Note that marketability influences the risk premium only if it measures the degree of imperfection of the market for a particular security. The degree of imperfection might be measured by the random fluctuations in the price of a bond over a short period, but if it is too short, the non random changes in bond prices are negligible and no random fluctuations can happen. The volume of trading can be a measure of marketability only for bonds listed on some securities exchange. The spread between bid and ask prices could be applied to both listed and unlisted securities, but published quotations for listed bonds are actual prices, and quotations for over-the-counter securities are generally nominal prices.

The hypotheses are tested regressing cross-sectionally the logarithm of the average risk premium on the logarithms of the following variables: earnings variability, period of solvency, equity/debt ratio and bonds outstanding. Fisher finds that a) for each cross section the four variables account for three-forts of the variance in the log of the risk premium; b) the elasticity of the risk premium with respect to each of the four variables is stable over time.

Fisher's paper is the first contribution to a structured approach in the area of risk premia, however, it presents some limitations as no macroeconomic factors are taken into considerations and variables like call provision, security status, and coupon level are omitted. The importance of indenture provisions such as call options is minimised. Also the effect of differential capital gains and taxation has been rationalised away. Finally, Fisher doesn't discuss the influence of term to maturity on the risk premium either through the level and shape of the underlying basic curve or more directly in its possible effect on the yield differential itself.

4.2.2. Demand and supply factors

Fair and Malkiel (FM, 1971) introduce demand and supply factors to explain risk premia. Investors may have different preferences for alternative types of bonds of the same risk level and maturity, or, in other terms, different types of bonds may not be perfect substitutes for one another because of one of the following factors:

i) legal restrictions which affect portfolio allocations of many investing institutions.

ii) the window dressing quality of bonds; government bonds may provide and enhance the public image of the financial institutions, especially of those who are subject to examination by public authorities.

iii) marketability, liquidity and transaction costs considerations. This attribute is partly a result of the existence of the former two attributes.

Monthly data -from January 1961 to June 1969- on the stocks of utility, industrial and government bonds are used to test the main hypothesis that yield differentials are determined by supply and demand factors. The analysis was applied to long-term US government, high quality utility, and high quality industrial bonds.

On the demand side of the FM model, since the different types of bonds are not perfect substitutes, each of them is characterised by a demand schedule that depends positively on its own rate of interest and on the stock of wealth to be distributed among the assets, and negatively on the rates of interest on the other assets. The supply side of the model assumes that supplies of government, utility and industrial bonds are exogenous.

Assuming that the securities markets are in equilibrium, so that each supply equals its demand, FM derive that the spreads between the assets yields are function of the relationship between the supplies of the assets themselves. The results, therefore, confirm that yield differentials are influenced by the stocks of bonds outstanding and by the relative flow of anticipated new financing during the future six-month period.

Jaffee (1975), developing a demand-supply model to explain cyclical variations in credit spreads, achieves different results from FM (1971). In his model the investor demand function for bonds of risk category depends positively on its own rate, negatively on the rates of the other categories, and also on a vector of exogenous variables. The supply function of issuing firms is negatively affected by their own rate, and depends, as the demand function, on a vector of exogenous variables, but is not affected by the other risk rates. Assuming the equilibrium in each risk market and equalling demand and supply, Jaffee obtains that interest rate for any risk category is a function of the risk-free rate and of the various exogenous demand and supply factors affecting the risk market. In the case of corporate bonds the demand and the supply variables are found not have a statistically significant effect on the risk structure.

4.2.3. Business cycle and confidence variables

According to finance textbooks, credit spreads behave cyclically over time (e.g., Van Horne, 1998). During periods of economic downturn credit spreads are expected to increase, as investors are more concerned with safety. On the other hand, during periods of economic expansion, investors are likely to seek the highest-yielding investments, implying reduced risk premia. Liquidity and marketability aspects might have an additional effect on the cyclical nature of credit spreads, to the extent that investors want to hold more liquid instruments in periods of recession, the spread will increase.

Jaffee (1975) was the first to introduce the idea that risk spreads between low and high quality bonds move with the business cycle. In particular, he suggests that top quality bonds might be risk-free regardless of the business cycle, while low rated bond quality are expected to deteriorate significantly during recessions. Hence, in recessions low quality bonds' credit spreads widen more than top quality bonds' credit spreads.

Assuming that the rating service can summarise the riskiness of a firm's debt issue in terms of a single grade at any moment in time, since a firm's risk is presumably varying over the business cycle while its rating is fixed, the risk associated with the rating must be changing. Changes in risk spreads, hence, are not the result of changes in the individuals' risk aversion or changes in the flow of funds to different investors in relation to the actual phase of the business cycle. Rather, risk spreads' changes are a technical feature deriving from the fact that rating agencies don't adjust their ratings in relation to short-run developments. Cohan (1973) had already raised this point stressing that the relative infrequency of changes in ratings for a particular company indicates that the risk associated with a given rating must vary over the business cycle.

The hypothesis is tested by Jaffee regressing each risk spread against a constant to account for the average level, and against different variables that are proxy of the business cycle to account for the cyclical variations. The data used in the analysis are quarterly risk spread indexes time series tabulated by Moody's Investor's Services for debt issued by corporate and municipal issuers (from Aaa to Baa ratings). The sample period covers the 1954-1969 period.

From the regression analysis it emerges that the variables correlated with optimism and peaks in the business cycle -the consumer sentiment, the growth of retained earnings of corporations, and the growth of investments- are negatively related to risk spreads. The unemployment rate and the growth of the output price index are positively correlated with spreads, since they are related with uncertainty and low levels of business activity. Changes in the level of interest rates show to have a negligible effect on changes in risk spreads.

The consumer sentiment variable plays by far the most important role and if we consider that this variable can be explained as a function of other economic variables, it's clear that this is important if rate spreads equations are used to forecast into future periods. The consumer variable has a particular explanatory power in the utility sector, and the most intuitive explanation for this would be to consider the utility sector's revenues less dependent on the general state of the economy and more dependent on the lags in regulatory price-settings than for industrial firms.

Fons (1987) tests for the impact of *macroeconomic surprises* on the credit spread by using deviations from expected inflation and industrial production. In periods of unanticipated rising prices, firms with fixed nominal financial obligations tend to benefit. In other words, the unanticipated part of inflation should have effect on the probability of default. Other indicators of macroeconomic activity correlated with default expectations are the industrial production index and the unemployment rate estimate. For various sample periods, the first difference of implied default rates is regressed on a constant, actual default rates, unanticipated inflation, unanticipated industrial production and unanticipated unemployment. Of all the macroeconomic indicators, deviations from expected inflation contribute the most to changes in expected default rates.

Fama and French (1989) show that the default spread seems to be related to long-term business episodes that span business cycles. In particular, they state that if bonds are priced rationally, the default spread is a measure of business conditions. In fact, although the default spread shows some business-cycle variation -low during periods of stronger and more stable economic conditions, and high during periods of general economic uncertainty-, its major swings seem to go beyond the business cycles measured by the NBER.

Moreover, business conditions are also likely to impact default risk: as debt-service becomes more difficult in periods of economic downturn, the required risk premium may increase. Arak and Corcoran (1996) find some empirical corroboration of the anticipated credit spread behaviour. They study yield spreads on privately placed issues, both investment-graded (A-rated) and sub-investment graded (Ba-rated) issues. They find that credit spreads are negatively correlated to economic activity as well as to the direction of change: when economic activity is high or expanding credit spreads tend to decrease. Finally, even if the probability of default remains constant for a firm, changes in credit spreads can occur due to changes in the expected recovery rate. The expected recovery rate in turn should be a function of the overall business climate.

As a result of the relationship between credit spreads and business cycle variables we would expect the rating transition probabilities to be "conditional" on macroeconomic variables (in addition to various firm-specific factors), such as the cyclical volatility of the firm's earnings and indicators of the current stage of the business cycle. In practice, however, there is generally insufficient data with which to estimate transition probabilities at such detail with reasonable precision. Thus, at most banks, the same rating transition matrix usually is applied to all borrowers, with no adjustment for business cycle effects. One potential implication of using "unconditional" transition probabilities is that estimates of expected losses and credit risk could be biased downward during the early stages of recessions, and biased upwards during the early stages of recoveries.

4.2.4. *Discounted certainty equivalent flows*

Silvers (1973) introduces a new measure of the bond incremental riskiness, *the certainty coefficient*, which is the ratio of certainty equivalent value divided by the promised payment. It is, therefore, a measure of overall reaction to a risky future prospects at a point in time, and it does not separate risk aversion from risk assessment as happens in the usual theoretical literature of finance and decision theory.

This approach differentiates from the traditional approach, the yield differential model. In the latter the bond price is represented as the sum of the promised payments discounted at a constant risk adjusted yield; in the certainty equivalent model the bond price is given by the sum of the discounted value of future certainty equivalent payments. In addition, in the yield differential model, a constant yield spread between the risky and the risk-less rate across all maturities would imply an identical adjustment for all promised payments in each period. However, in the certainty coefficient framework, a constant yield differential implies a non-uniform pattern of risk adjustment. In time of crisis, when default may be imminent, the certainty coefficient of near term prospects drops off very rapidly; but, because of the general lack of confidence, the absolute level of the curve will be lower as well. Hence, the certainty equivalent approach provides a more accurate picture of risk compensation in this extreme case. A decreasing pattern of yield spreads may indicate the presence of crisis at maturity, but it provides a poor measure of degree; while, the certainty coefficient precisely specifies the percentage reduction in payment assumed by the market.

In order to find the determinants of a corporate bond price, the market price of a corporate bond is regressed on discounted certainty equivalent flows, on marketability risk, and on call risk and capital gain effects. The vector of certainty coefficients is intended to capture the risk structure inherent in the evaluation of the cash flows.

Annual data are collected for the 1952-1964 period and the entire sample is divided into four investment-grade rating categories. Silvers concludes that each of the independent variables, with the exception of the marketability measure, are significant determinants of price. The overall explanation power of the regression is in the 0.92 to 0.97 range for high-grade bonds and in the 0.53 to 0.88 range for lower quality bonds. Most of this high correlation comes from the highly significant relationship between corporate bond prices and the underlying government structure.

Two are the main drawbacks of Silvers' work. First, the process of forcing a functional form onto the default risk structure may be too rigid; the data should have been tested unconstrained by any process and in a second step it should be observed how well the empirical results confirm the particular hypothesised relationship. Second, many other variables that have an impact on price -security status and price volatility- are not considered at all.

4.2.5. Coupon, sinking fund, security status, and price volatility

In Boardman and McEnally (1981) Silvers' constraints on the default risk structure are relaxed and additional variables are added to the regression in order to observe the role of these influences in different interest rates environments. The price of a bond is expressed as the present value of all future payments. Each payment is adjusted by a discount factor that has two components: one representing the impact of time and one representing the impact of default risk. In addition, the price is affected by the following factors: coupon rate, security status, sinking fund status, marketability, industry and price volatility.

All these factors constitute the independent variables of a regression where the bond's price is the dependent variable. The equation is estimated cross-sectionally for 515 randomly chosen seasoned corporate bonds[4] at four different points in time with a separate regression for each rating class. The bonds included in the analysis are those listed in Moody's Bond Record. The explanatory power of the regression tends to decrease with lower rating classes, which is consistent with the standard observation that lower quality bonds are less homogeneous than those in the higher quality groups.

The coupon rate

In general, credit spreads on coupon bonds are not equal to credit spreads on zero-coupon bonds because of either a non-flat term structure or a non-flat credit spread structure. To the extent that the credit-spread curve is upward sloping, higher coupon bonds will have lower credit spreads than lower coupon bonds with the same maturity (Litterman and Iben, 1991). Likewise, if the bond's duration shortens, e.g. because of an interest rate increase, the credit spread will decrease if the credit spread curve is upward sloping. Therefore, even if there is no relation between the interest rate level and credit spreads of zero coupon bonds, there still might be a relation between the former and the credit spread on coupon bonds. A smaller coupon rate relative to the yield implies a lower price, hence a larger capital gain on the bond (even if not held to maturity), and a higher present price.

---

[4] A seasoned corporate bond is one which has been available for trading long enough that its underwriters and initial purchasers have ceased to make an active market in it.

Sinking fund status

Sinking funds provide a means by which the issuer is forced to retire a part of the issue periodically or accumulate money to retire the bond at maturity. As a mean to resolve uncertainty with respect to eventual repayment, and as a mean to enter the market to buy the needed bonds through purchase rather than sinking fund call, a sinking fund should increase the bond's value. The sinking fund status is found to be significant only for the highest quality groups. This implies that the sinking fund provision is liked primarily for its effect on the after-market for the bonds.

Security status

The security status dummy variable measures the presence or absence of a claim on the asset. In the presence of a claim, the lender's control over the borrower is greater and she has a priority on assets proceeds in liquidation. For this reason we expect a positive relationship with the bond price. The dummy for security status is found to be significant in the higher groups, consistently with the suggestion of Cohan (1973) that security is demanded only when a credit is below average.

Price volatility

Bond beta coefficients are introduced to account for the bond's systematic price volatility. While duration measures the elasticity of a bond's price with respect to changes in its yields, beta is a more general measure because it reflects a bond's price sensitivity to aggregate market movements regardless of the source. The beta coefficient is estimated regressing bonds' holding period returns (HPR) on a constant and on a proxy for the market's beta – measures as a simple unweighted average of the HPRs on all the bonds. Standard pricing models hypothesize the beta coefficient to be negative. However, the beta variable is significant in half cases with a generally positive rather than the negative sign predicted by standard asset pricing models. This result might be due to the period (the preceding 12 months) over which the betas are estimated and that is not long enough to cover both bear and bull markets (60 months).

4.2.6. Actual default rates and macroeconomic variables

Fons (1987) is the first paper that tries to establish a relationship between the risk premium and the actual default experience. In order to test this relation, Fons develops a risk-neutral model of the expected probability of default for speculative grade bonds. Since the holding-period returns have shown to be poor indicators of expected default rates, he used an alternative "naïve" model of expected default rates in which the yield spread is taken as a measure of default risk.

An index of yields to maturity for low-rated bonds from 1979 to 1985 is obtained from Salomon Brothers' Corporation Bond Research department.[5] The yields to maturity for high-grade corporate bonds were taken from Salomon Brothers' New Medium Term Industrial index. This index is based on estimates of the required yields on issues coming to the market that are rated Aaa and that will mature in ten years. The Aaa/AAA-rated yields are chosen to represent the default-risk-free rates. Using the yields on long-term US Treasury issues would have introduced some difficulties because these securities lack call provisions, their returns are subject to a different tax treatment, and, finally, may have different marketability.

These data are used to test the correlation between yield spreads and actual default rates. The expected payment rate, P, was found to be negatively related with the risky rate of interest, r. The implicit function results to be convex over plausible values of r, so that cross-sectional average of P will be greater than or equal to the measured payment rate. The implication is that the implied expected default rate, $(1 - P)$, is biased downwards.

Additional insight is gained by using regression techniques. The expected default rates $(1\text{-}P)$ are regressed on a constant, on a raw default series, and on the smoothed default rates series. The null hypothesis that the market's estimate of default corresponds to actual default rate experience is rejected. Implied default rates exceed actual default rates by roughly five percentage points. As a consequence, holders of well-diversified portfolios of low-rated corporate bonds appear to be rewarded for bearing default risk.

The discrepancy between the two series suggests two possible conclusions. Either the market for low-rated debt is inefficient or the risk-neutral model is deficient. Fons tries to improve the model by introducing a simple rule of thumb[6] to use in the market for low-rated corporate debt. According to this model, the difference in the values of the indexes for the yields to maturity of low- and high-grade corporate bonds is a direct measure of expected default rates on low-rated debt and is regressed on a constant and smoothed actual default rates over the period 1980-1985. The results indicate that the rule of thumb model doesn't outperform the risk-neutral model as a predictor of actual default rates.

---

[5] Defaulting bonds are removed from the sample, as are issues that are upgraded to investment-grade status.

4.2.7. The term structure of interest rates

The relationship between credit spreads and interest rates is rather complex. Many are the articles focusing on the valuation of corporate securities that allow for both default risk and interest rate risk. These include Merton (1974), Ramaswamy and Sundaresan (1986), Hull and White (1992), Maloney (1992), Jarrow and Turnbull (1995, 1997, 2000), Kim, Ramaswamy and Sundaresan (1993), Ginzburg, Maloney and Willner (1993), Shimko, Tejima and Deventer (1993), Genotte and Marsh (1993), Nielsen, Saa-Raquejo and Santa Clara (1993), and Longstaff and Schwartz (1995a). While these works, by modelling risky debt, provide important conceptual insights, generally they have not provided empirical evidence to their theoretical implications. The comparative statics of these models predict that equilibrium credit spreads are negatively related to the risk free rate. Despite there are strong theoretical arguments to assume that there is a relation between credit spreads and the risk-free interest rate level, it is difficult to provide a convincing intuitive explanation for this negative relation.

While it is possible that a *'flight to quality'* could induce a temporary negative relation between corporate and government rates, it seems more likely that high nominal rates would be associated with a high risk premium for corporate debt. For example, the model in Bernanke and Gertler (1989) implies that higher interest rates, *ceteris paribus*, will raise agency problems for borrowers. This increases credit spreads because it widens the gap between internal and external financing costs.

In favour of a positive relationship is also a *mathematical argument*. Under the simplifying assumptions that investors are risk-neutral and the recovery rate given default is constant and known, a purely mathematical relation between credit spreads and the default-free rate can be derived. Consider for simplicity a one period risky bond and assume that the recovery rate given default is zero. If *EDF* denotes the expected default frequency (or the probability of default), market equilibrium implies

$$(1+i) = (1\text{-}EDF)\,(1+YTM) + EDF\,(0) \tag{2.1}$$

where i is the default-free one period rate and *YTM* the promised yield on the risky debt. This relation is fully derived by Bierman and Hass (1975). We can apply it to the computation of the credit spread σ as follows.

[6] If actual default rates are X percent, then the required yield to maturity on low-rated debt should exceed that on high-grade debt by X percent.

$$cs = YTM\text{-}i = (1+i)\ EDF/(1\text{-}EDF). \tag{2.2}$$

As long as *EDF* is a proper constant probability residing between 0 and 1, a positive relation exists between the default-free rate *i* and the spread *cs*. Of course, if investors are risk-averse, the reaction of the credit spread also depends on the risk premium the spread contains. If the risk premium decreases as the risk-free rate increases, this lowers the positive risk-neutral effect. Also, if the probability of default *EDF* is negatively correlated with the risk-free rate, the positive relation between the credit spread *cs* and *i* may be altered.

A positive theoretical relation between credit spreads and interest rates is also supported by a *fiscal argument*, which is based on the different tax rates applicable to corporate and Treasury bonds. If, as it generally happens, corporate bonds are more heavily taxed than Treasury bonds, an increase in bond yields amplifies the tax wedge between corporate and Treasury bonds. To offset this increased tax wedge, corporate bond yields should rise more than Treasury bond yields.

On the other hand, spreads and rates can be negatively related if we rely on the option framework of Merton (1974). According to this approach, a corporate bond can be seen as equivalent to a default-free bond and a short position in a put on the firm's assets. An investor who purchases the risky bond and then sells it prior to maturity will find that, if interest rates increase (decrease), the default-free component will decrease (increase) her wealth, while the short put will increase (decrease) her wealth. However, there is no holding period, short of maturity, that immunises since the investor will always be worse (better) off if interest rates increase (decrease). This is true also for default-free bonds, implying that the default-free component dominates the put component in terms of interest rate sensitivity.

Despite the relevance of the issue, few papers have empirically tested the interrelations between interest rates and credit spreads and the (scarce) empirical evidence documents generally a negative relationship. The empirical literature has focused and presented evidence about the time evolution of both corporate default spreads and interest rates in relation to business conditions, thus suggesting that default risk and interest rate risk are correlated.

Jaffee (1975) suggests that top quality bonds might be risk free regardless of the business cycle, while, one might expect low rated bond quality to deteriorate significantly during recessions. From their analysis it emerges that changes in the level of interest rates have a negligible effect on changes in risk spreads. Mella-Barral and Tychon (1996) carry on a sensitivity analysis of the term structure with respect to movements in various factors. They show that changes in the risk-less interest rate do not affect much the magnitude of credit spreads for short-term contracts. Credit spreads are only marginally increasing in the risk-less interest rate for longer maturities.

Nielsen, Saa-Requejo and Santa-Clara (1993) develop a model for the term structure of credit spreads that takes into account default risk, interest rate risk, and the interactions between the two. The interaction arises from two sources. Both the uncertainty of the value of the firm's assets and the default boundary are correlated with the interest rate uncertainty. In addition, both the rate of growth of the default boundary and the rate of return on the firm's asset depend on the level of the risk-less interest rate. They prove that the more negative is the correlation between the interest rate and the default risk, the smaller the spreads are, which is explained by the fact that the risk of default becomes easier to diversify.

Kim, Ramaswamy and Sundaresan (1995), following the suggestion given by Jones, Mason and Rosenfeld (1984), test whether the introduction of stochastic interest rates might improve the performance of contingent claims valuation frameworks for pricing corporate and Treasury bonds. They introduce a stochastic process for the evolution of the short interest rate and characterise the behaviour of yield spreads with respect to the parameters that govern the stochastic process that drives interest rates. Numerical solutions to the valuation equation show that default risk is sensitive to interest rate expectations –in terms of the location of the interest rate relative to its long-run mean rate- when default risk is relatively high (a high P/V ratio, where P is the face value of the bond and V is the value of the firm), but never to the volatility (uncertainty) of interest rates. Irrespectively of the debt ratio, the spreads decrease with the level of the interest rates.

Longstaff and Schwartz (LS, 1995a) provide a valuation framework for risky coupon bonds allowing also for empirical evidence supporting their theoretical implications. Their valuation framework differentiates from the traditional approach, which implies that credit spreads depend on only an asset-value factor, while the interest rate is assumed to be constant. In contrast LS state that credit spreads are driven by an asset-value factor, an interest rate factor, and by the correlation between the two factors. Specifically, the static effect of a higher spot rate is to increase the risk-neutral drift of the firm value process. A higher drift reduces the incidence of default, and in turn, reduces the credit spreads. To examine whether the properties of credit spreads are consistent with the implications of their two-factor framework, they regress changes in credit spreads on proxies for the two factors. Changes in the 30-year Treasury yield is used as a proxy for the changes in the interest rate and returns from Standard & Poor's industrial, utility and railroad stock indexes as a proxy for the return on the underlying assets. The empirical investigation confirms that credit spreads are strongly negatively related to the level of interest rates, credit spreads narrow as interest rates increase –as implied by the model. An increase in the short-term interest rate tends indeed to reduce the probability of default because of the effect on the drift of the risk-neutral process that drives the total value of the assets of the firm. The second result is that credit spreads are negatively related to returns on the firm's assets. The reason for this is simply that an increase in the value of a firm's assets decreases the probability that the default boundary will be reached. As a third result, the magnitude of the decrease in the credit spread, however, depends on the value of the correlation coefficient between the risk-free interest rate process and the total value of the assets process. The interest rate sensitivity of credit spreads increases as the correlation coefficient increases. The intuition for this is similar to the intuition why the credit spread itself increases with the correlation. When the correlation is positive, changes in interest rate are reversed by changes in the default risk of the firm. Conversely, when the correlation is either negative or zero the total effect on credit spreads is higher.

The LS correlation argument in fact interacts with a *coupon effect argument*, which can also explain a negative strong relation between credit spreads and the slope of the Treasury yield curve. Corporate bonds have higher coupons than Treasury bonds, implying that a corporate bond that has the same maturity as that of a Treasury bond will have a shorter duration. Short-duration instruments are more sensitive to short-maturity discount rates than are long-duration instruments. Therefore an increase in the slope of the Treasury yield curve, raises the yields on Treasury bonds more relatively to yields on corporate bonds of equal maturity and hence decreases the yield spreads of corporate coupon bonds over Treasury coupon bonds. This "coupon effect" is stronger for long-maturity bonds than for short-maturity bonds because coupon-induced differences in duration are larger for bonds with more coupon payments (Duffee, 1998).

Duffee (1998) investigates the relation between yields on noncallable Treasury bonds and spreads of corporate bond yields over Treasury yields. This relation conveys information about the covariation between default-free discount rates and the market's perception of default risk. Yield spreads on both callable and noncallable corporate bonds fall when Treasury yields rise; specifically this relation is much stronger for callable bonds. In the case of noncallable bonds, for every combination of maturity and credit rating an increase in the level of the Treasury term structure corresponds to a decline in yield spreads. This relation strengthens as credit quality falls. Also the relation between yield spreads and the slope of the Treasury term structure is generally negative. Empirical results for noncallable and callable corporate bonds are found regressing monthly changes of credit spreads on changes in the three-month Treasury bill yield and changes in the slope of the term structure, as measured by the difference between the thirty-year constant-maturity Treasury yield and the three-month bill rate. The period spans from February 1985 through March 1995 and month-end data are collected for the bonds that make up the Lehman Brothers Bond Index. In the case of callable bonds, the negative relation between yield spreads and Treasury yields is more strong but the differences across credit ratings are substantially smaller than those for non callable bonds. Duffee (1998) investigates also the persistence of changes in corporate bond yield spreads associated with changes in Treasury yields using vector autoregressions (VARs) of the 3-month Treasury bill yield, the slope of the Treasury term structure, and corporate bond yield spreads. Changes in yield spreads appear to persist for more than a year, but the VARs' coefficients result to be too uncertain to draw any firm conclusions about the persistence of changes in yield spreads in response to innovations in Treasury yields.

Malitz (1994) documents that firms tend to issue less debt when interest rates are high, suggesting that stochastic interest rates are a relevant factor in determining credit spreads. Arak and Corcoran (1996) also find a negative relation between yield spreads on privately placed issues and risk-free rates when all variables are measured in levels. The relation is significant for A and Baa-rated paper, at least when influences of other economic variables are taken into account, but not for Ba-rated paper. Fridson and Jónsson (1995), however, report that they did not find any relation between the level of Treasury rates and the spread on high-yield bonds, which are also below-investment grade.

The empirical studies presented above focus on the short-term behaviour of corporate spreads and Treasury rates while failing to incorporate information on the co-movement of these two variables over time. In other words, the empirical specifications in these studies focus on changes and do not incorporate equilibrium relationships between the variables. This is important because the predictions of the theoretical models are long run or equilibrium predictions. Since the models do not specify the transition path from one equilibrium to another, it is questionable to draw inference about the equilibrium spread from the short-run dynamics. Moreover, if corporate spreads and Treasury rates are cointegrated, the estimated coefficients relating changes in yields and changes in spreads are biased and inconsistent unless the level of the variables is also considered in the econometric analysis.

Morris, Neal and Rolph (1998) point these statistical pitfalls in previous studies and show that the relation between corporate bond spreads and Treasury yields depends on the time horizon.

Using 10-year constant maturity Treasury bonds and Moody's Aaa and Baa seasoned indices over the period January 1960 to December 1997, they find that each of the corporate yield series is cointegrated with Treasury rates. In both cases the long-run relationship turns out to be positive. When Treasury rates increase by 1% point, Aaa (Baa) rates increase by 1.028 (1.178)% points, implying that credit spreads increase. Using more appropriate first difference regressions, however, they show that in the short-run the relationship between Treasury rates and corporate spreads reverses and becomes negative. As time progresses, an initial rise in Treasury yields translates into proportionately greater increase in corporate bond rates, widening the credit spread.

This leaves us with some apparent contradictions. Firstly, although the negative relation seems at odds with the simple mathematical argument, a sufficient condition for consistency is a negative correlation between interest rate risk and default risk, implying a decrease in the probability of default when the interest rate increases. This is actually what follows in the model by Longstaff and Schwartz (1995a). Moreover, their model entails that the higher the value of the company is correlated with changes in interest rates, the stronger the rate sensitivity of the credit spread will be. The Arak and Corcoran (1996) and Fridson and Jónsson (1995) can therefore be made consistent with those of Duffee (1998) if below-investment-grade issuers were more negatively correlated with interest rate changes than investment-grade issuers.

Secondly, the cointegration results of Morris, Neal and Rolph (1998) imply that bond yields are non-stationary, which seems hard to explain economically, as this would imply that yields may grow to infinity. Structural breaks in the series under study, which may hamper correct statistical inference of cointegration models, may be an explanation for their results. Morris et al.'s (1998) results have important implications for models of capital structure and for models of pricing corporate debt and for managing the interest rate risk of corporate bonds.

Chance (1990) and others have argued that the presence of default risk shortens the effective duration of corporate bonds. The duration of a default-free zero coupon bond can be seen as the maturity multiplied by the present value of the face value divided by the price. When the bond is subject to default, a similar representation can be given, but expected values are replaced with certain values. The duration is, thus, the maturity multiplied by the present value at the default-free rate of the face value times the probability of solvency, divided by the price.

Comparative static analysis are performed by Morris et al. (1998) to examine the behaviour of duration in light of changes in the underlying variables. In particular, duration was found to decline steeply at low debt ratios and levels off at higher debt ratios irrespectively of the time to maturity. This reflects the fact that at high debt ratios the put has little time value, as default is likely, and the put price is primarily driven by the difference between the asset value and the face value of the bond. Duration was also studied in relation to the level of the default-free interest rate. Duration showed to increase with the level of the interest rate as it does for default-free coupon bonds; however, for short-maturity bonds, duration increases at much lower rate, but the duration of all bonds asymptotically approaches the maturity. While the negative short-run relation between α and the risk-free rate is consistent with Chance's logic, the positive long-run response of Morris et al. (1998) implies that corporate bonds are eventually more sensitive to interest rate movements than otherwise similar Treasury bonds.

Finally, it has been indicated that the spot rate process itself may depend upon other factors. For instance, Brennan and Schwartz (1979) introduce a model where short rate dynamics depends upon the long rate. Extending the logic of Longstaff and Schwartz (1995a), if the short rate is expected to mean-revert about the long rate, then an increase in the slope of the treasury curve should increase the expected future short rate, again leading to a decrease in credit spreads. From a different perspective, a decrease in yield curve slope may imply a weakening economy and it is reasonable to believe that the expected recovery rate might decrease in times of recession. Once again, theory predicts that an increase in the treasury yield curve slope will create a decrease in credit spreads.

4.2.8. Marketability

Marketability should also be related to a bond's price. Marketability depends upon the elasticity of the demand curve the bond faces, but the lack of means to estimate the demand curve drives scolars to use a proxy variable. The most common proxy is a size variable, which could be: a) the total market value of all the issues the firm has outstanding; b) a dummy variable to indicate if a bond is traded only over the counter or is also traded on one of the major exchanges as well. When liquidity is measured as the issue's size, many authors find a negative relation between spread and size: the larger the size, the larger the issue's liquidity, the lower the required yield and therefore the spread.

Marketability was first introduced by Fisher (1959) as the natural logarithm of the dollar par value of bonds outstanding. According to Fisher, the smaller the amount of bonds outstanding, the less frequently we should expect bonds change hands, the thinner is the market, the more uncertain is the market price, the higher the expected risk premium. Fisher's results support the relevance of the factor "marketability". Later on, Crabbe and Turner (1995) will show that size does not necessarily proxy for liquidity. To investigate whether issue size is a significant determinant of liquidity, they test for yield differences between medium-term notes and bonds of the same corporate issuers. If investors would value large offerings for their greater liquidity, then large issues will have lower yields than small issues. The yield difference is found not significant and no relation is found between the face amount of an issue and its yield. Their evidence therefore implies that the liquidity of a security reflects both the characteristics of the borrower and the features of the security.

Successively, Silvers (1973) states that marketability (defined as in Fisher's work) will be independent of default expectations if it has a significant explanatory power when risk of default is held constant. However, if marketability is not significant within a risk class, it can be either that the bond market is efficient (differently from Fisher's research), or that the variable used as a proxy for marketability is misspecified. In fact, the volume outstanding as a measure of marketability results to be insignificant within a homogeneous risk sample. Therefore Silvers can imply either that the proxy used for marketability is in fact proxy for another measure of default risk, or that marketability may still be important but it is collinear with measures of risk, or that marketability is not a relevant factor and the bond market is efficient.

Boardman and McEnally (1981) find a negative relation between size and yield for Baa or better-rated US corporate bonds, consistently with Silvers' but not with Fisher's results. The difference in significance between Fisher's and Silvers' quantity variable might be dependent upon the formulation of the estimating equation and the empirical procedure. Also for highly levered transaction loans Angbazo, Mei and Saunders (1998) find a negative relationship between size and spread. This corroborated by Shulman, Bayless and Price (1993) who report a significantly negative relation between several spread and liquidity proxies for individual high-yield bonds.

Besides the liquidity of a specific issue market-wide 'liquidity events' may also impact credit spreads. Cornell (1992) reports large abnormal returns on low-grade bonds due to changes in liquidity in the junk bond market. First, the bonds experienced positive abnormal returns (resulting in higher prices and hence in lower spreads) when Drexel Burnham Lambert exponentially increased the issuance of low-grade bonds, and then abnormal negative returns (higher spreads) when the market collapsed after Drexel's default in 1989. This is confirmed by Patel, Evans and Burnett (1998) and the same observation is made by Arak and Corcoran (1996) related to yield spreads on privately placed issues: investment grade issues had lower spreads than expected in late 1989 and early 1990, whereas sub-investment issues yielded less than expected according to economic conditions.

Similarly, after the Russian moratorium in August 1998 credit spreads rose sharply in the international secondary debt markets, at a moment when liquidity dried up, which reinforced the credit spread increase. Fridson and Jónsson (1995) also find significant relations between the high-yield spread and liquidity proxies. These proxies include the net inflows to high-yield bond mutual funds (negative relation), cash proportion held by these funds (positive), and the three-month moving average price of the high-yield index (positive).

It may be argued that these market-wide changes in spreads due to changes in liquidity do not really belong in a report on credit risk. Nevertheless, it is not always clear whether in all liquidity-induced changes credit risk is not involved. It may be the case that due to dramatically altered risk perceptions, credit spreads explode or tighten. At the same time the changes in risk perception may equally impact the volume investors want to trade. The Bank for International Settlements, for instance, links both the sharply increased risk and liquidity premia in the wake of the Russian debt moratorium in 1998 to the drying-up of securities issuance. Both are "... suggestive of a large-scale retrenchment in the supply of risk capital" (Basle, 1999:93). In any case, when the focus of interest is the credit spread (e.g. because of the fact that the pay-off of a credit derivative is related to the credit spread, or because the bond portfolio is marked to market), models should take into account that the level of the credit spread may dramatically wander through time regardless whether this is due to changes in liquidity or changes in risk perception.

4.2.9. Other factors

Callability

Callability or other option features may be important as well. In efficient markets the value of these options is embedded in the bond's price and thus in the credit spread. The results in Duffee (1998) clearly indicate that the call feature can dramatically change the spread behaviour. He finds that spreads are negatively related to changes in risk-free rates. However, the relationship is stronger for callable bonds as the call feature's value is obviously related to interest rate level. If rates increase, the calls move further to the out-of-the-money range. This implies that prices of callable risky bonds do not drop as much as those of non-callable bonds, therefore lowering the credit spread stronger for callable bonds. On the other hand, Boardman and McEnally (1981) find that callability is significant only in the higher rating classes since it is much less frequent among lower quality bonds. Also Kim, Ramaswamy and Sundaresan (1995) focus their attention on the call future which is found to have a differential effect in Treasury issues relative to corporate issues and it is relatively more valuable in the Treasury issues. Interactions between default risk and the call provision play an important role in explaining the observed yield spreads between noncallable corporate bonds and straight Treasuries on one side and callable corporates and callable Treasuries on the other side.

Credit rating

As the credit spread compensates the holder of the debt instrument for expected losses, there should be a link between the credit spread and the credit rating class, given the fact that there exist ample evidence that rating categories indeed entail an indication of relative credit risk. Researches have indeed shown that there exists a close relationship between credit rating classes and subsequent default experience. This is mirrored in empirical studies where it is always found that the credit spread widens at an increasing rate as the credit rating worsens. This is for instance depicted by Duffee (1998) for US investment grade corporate bonds.

Moreover, the standard deviation of individual bonds' credit spreads *within a given rating category* increases as the credit rating worsens. This indicates that not all bonds within the same rating class are assumed to bear the same credit risk. Apparently, the higher cross-sectional standard deviation in the lower rating classes indicates that rating agencies allow for more heterogeneity in these classes. By re-valuing the debt instrument assuming a transition to a given credit rating class and then taking expectations, the mark-to-market mode of credit risk management models effectively take this empirical evidence into account. However, the relatively large standard deviations should also be taken into account when computing unexpected losses.

Seniority and collateral

Both the seniority of a bond or loan and the collateral attached as security to it, have an impact on the credit spread because, arguably, both kinds of provisions will increase the recovery rate in case of default. Indeed, Izvorski (1997) finds that for defaulted US bonds debt seniority is one of the most important determinants of the recovery ratio, thus implying a lower yield for senior issues. This is also the case for syndicated bank loans: a study by FITCH IBCA showed that while distressed bank loans recovered 82%, senior subordinated debt of the same issuers recovered 42% and subordinated debt only 39% (Grossman, Brennan and Vento, 1998).

In some papers, however, the reverse relationship is reported: within a rating class security covenants actually *increase* the issue's yield (e.g. Angbazo, Mei and Saunders (1998) for highly leveraged transaction loans). Roberts and Viscione (1984) explain this anomalous finding by differences in credit risk within the same rating category. Relatively risky bonds are more likely to have covenants, which in turn may lead to higher credit ratings for the issue than it would have without covenants. To eliminate this bias Roberts and Viscione (1984) study the yield difference between bonds issued by the same company, with similar features except for seniority/security covenants. In their sample, they do find lower yields for higher security bonds.

Changes in leverage and asset volatility

In the Merton model corporate bond spreads widen as the firm's leverage increases. The latter is defined as the ratio of the present value of the nominal amount of debt outstanding to the market value of the firm's assets. The intuition for this direct proportionality is that increased gearing heightens the probability that the firm may be unable to make its promised payments. However, recent empirical evidence of Hotchkiss and Ronen (1999) and Collin-Dufresne, Goldstein and Martin (1999) finds small explanatory power of changes in leverage for changes in credit spreads.

Moreover, according to the Merton model, a rise in the volatility of the firm's value increases the probability of default, thus widening the credit spreads. In fact, in the context of option pricing, an increase in the volatility of the underlying asset raises the price of the put option, thus reducing the value of the corporate debt and increasing the yield spread relative to a risk-free asset.

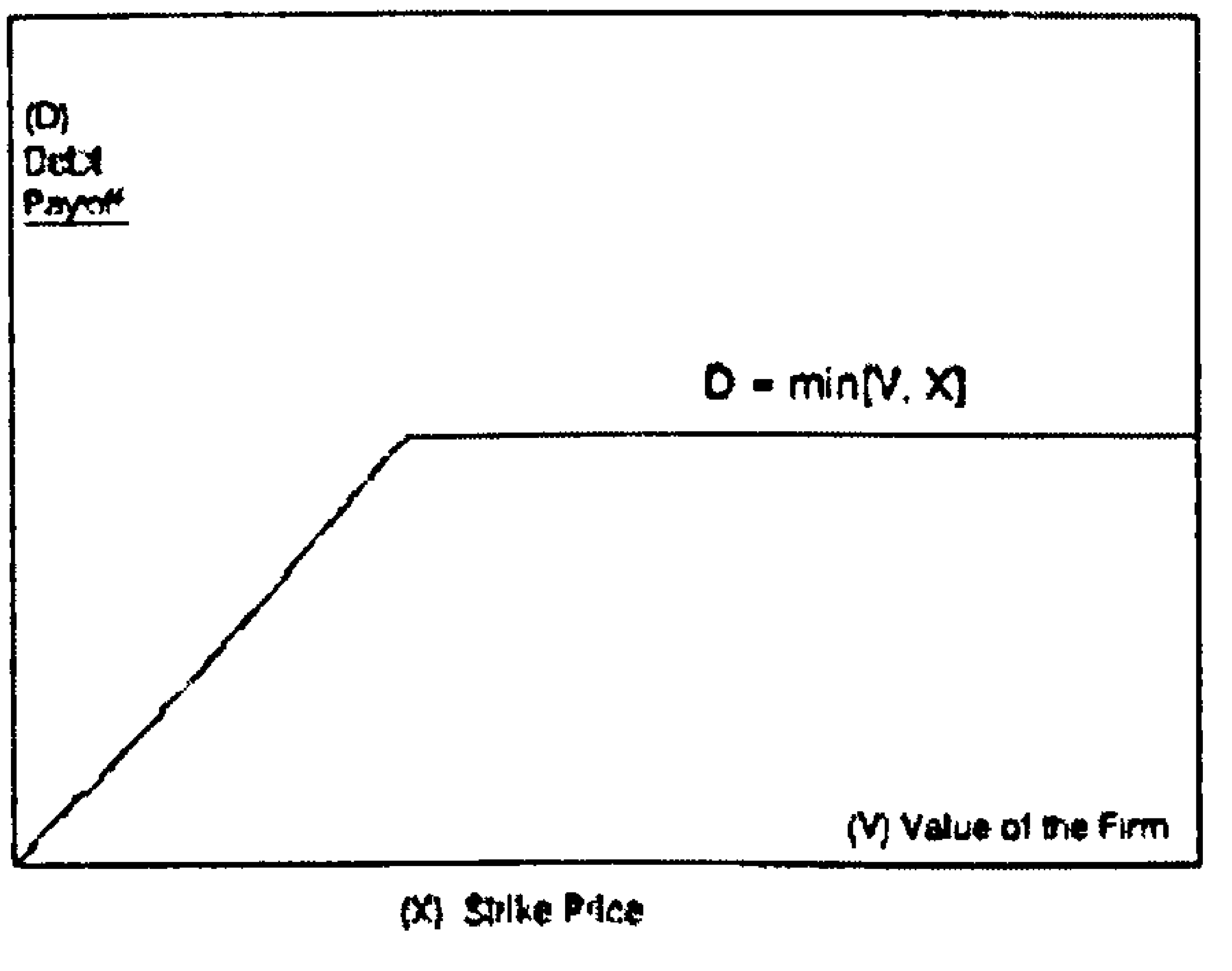


Figure 4.1 *Valuing Risky Debt*

4.2.10. Do Credit Spreads differ by Type of Obligor?

Distinctions are frequently drawn between exposures to sovereigns, banks and industrials. Of particular interest are the questions: (i) are exposures to sovereigns less risky than those to non-sovereigns with the same rating, and (ii) are exposures to banks less risky than those to industrials?

Jackson and Perraudin (1999) show the amount by which average daily Bloomberg spreads for US dollar denominated sovereign debt exceeded those on US corporate debt of a similar rating. Average credit spreads were significantly wider for BBB-and BB-rated debt issued by governments than for US industrials with the same rating. However, the relatively small number of sovereigns in the sample (6,6 and 8 for the categories BB, BBB and AA, respectively) make it difficult to draw firm conclusions. The higher spreads may in part reflect market concerns about the outcome of problems on sovereign exposures. When a corporate defaults, its assets can be attached and it can be declared bankrupt, enabling legal action to be taken. This may mean that recovery rates on sovereign exposures are typically lower and less timely than those on corporates. Some rating agencies take loss-given default into account in the ratings but not all do so.

Another way to investigate the relative riskiness of different types of obligor is to study the behaviour of ratings transitions. Standard &Poor's one-year transition matrices, calculated on ratings data from 1975 to 1998, suggest that exposures to sovereigns and non-sovereigns differ (see Standard &Poor's (1999a) and (1999b)) but in the opposite way from that indicated by the spread data of Jackson and Perraudin (1999). No rated sovereigns defaulted in this period although some renegotiated their external debt, or needed emergency IMF packages. And, in general, sovereign ratings appear more stable. One-year transition matrices calculated by Bank of England staff from Moody's data covering the period 1970 to end-1997 also indicate that changes in ratings are less frequent for sovereign than for corporate obligors although the difference is less pronounced than in the case of the Standard & Poor's transitions. These differences in ratings transitions partly reflect the fact that only a few sovereigns were rated in the earlier part of the sample period and all these were high quality. For example, in 1975, Standard & Poor's rated only seven countries: Australia, Austria, Canada, France, Japan, New Zealand and the United States. Even by 1990, there were only thirty-one sovereigns rated by Standard & Poor's, of which only nine were from the emerging markets.

There is some evidence that rating agencies find sovereign exposures more difficult to rate than industrials, perhaps indicating that there could be more uncertainty surrounding risk assessments for sovereigns and providing some justification for stickiness in ratings. Cantor and Packer (1995) find, when comparing Moody's and Standard & Poor's ratings, that there are greater differences in the ratings given by the two agencies to particular low credit quality sovereigns than is the case for low-quality corporates. This may reflect the short track record in rating lower quality sovereign exposures and the greater subjectivity in sovereign measurement – countries do not fail as such and whether payments are met depends in part on political will. There are also questions over adequacy of information released by some governments.

On the relative riskiness of *banks and industrials*, Nickell, Perraudin and Varotto (1998) look at the ratings transitions for types of obligor. Data on default probabilities over ten year horizons for US obligors, calculated from the data used in the study, indicate that banks in all ratings categories down to B are significantly less likely to default than non-banks. For AAA-rated obligors the default probabilities are 0.09 percent for non-banks and 0.02 percent for banks and for BBB-rated obligors the figures are 9.6 percent for non-banks and 4.6 percent for banks.

Nickell, Perraudin and Varotto find that the volatility of ratings changes is higher for banks than for industrials but large movements in ratings are just as likely if not more likely for industrials. When they focus on just US industrials and banks they find that, in a business cycle trough, highly-rated banks (AAA, AA and A) are more subject to downgrades than industrials. However, the opposite is true of banks rated BBB and below. These are more likely to experience an upgrade than would be the case for a corporate of the same rating. This may reflect the influence of regulation. Whereas all obligors face market pressure to deal with problems, banks also face pressure from regulators. As a bank became weaker, so some kind of regulatory action would become likely. For example in the United States, if a bank had many problem loans, and losses were likely, formal or informal action could be taken including discussions with management over the extent of any problems and following these the bank might be required to increase its provisions against future loan losses. A bank would not be able to pay dividends if that would leave it under capitalised relative to the regulatory minimum after taking into account any need for higher provisions. This would make it more likely that the decline in the bank would be arrested or turned round.

Data on spreads on bonds issued by US banks, industrials and utilities with particular ratings, taken from Bloomberg, point to a rather different conclusion on the market's assessment of relative riskiness. For all ratings categories average spreads on bonds issued by banks are higher than spreads on industrial bonds or utilities. In part this will reflect the fact that many bank bond issues are subordinated. Because subordinated debt can count in Tier 2 capital under the Basle Accord, banks have an incentive to issue this kind of paper.

The Bank of England has a large database of bonds put together from Reuters data and this shows a much higher use of subordination by banks than other types of obligor and a much lower use of guarantees for bank-issued bonds. Both factors would tend to imply higher spreads on bank bonds. In their study of US dollar denominated international bonds, Perraudin and Taylor (1999), however, find that bank spreads are slightly higher even when allowance is made for seniority. The spread difference is small (eg 6 basis points for AA), but it does appear to be statistically significant. This may reflect perceptions about relative recovery rates. Altman and Kishore (1996), in a study of 700 US corporate bonds in default, find that financial institutions have lower recovery rates (36 per cent) than the average (42 per cent). The difference remains even after allowing for subordination.

Summarising, the evidence on whether exposures to banks are less risky than exposures to non-banks is therefore rather mixed. The evidence for the United States is that banks do have lower probabilities of default than non-banks. In terms of ratings transitions, bank ratings are in a sense mean-reverting: highly-rated banks are more likely to be downgraded and low-rated banks are more likely to be upgraded than industrials. The evidence from spreads is, however, that banks are regarded as somewhat more risky than industrials perhaps because of perceived recovery rates.

4.2.11. Bond spreads versus loan spreads

So far, little is known about differences between the credit risk of relatively liquid exposures (bonds) and illiquid exposures (loans). It is only during the last years that some research on the loan market has been done, spurred by the fact that secondary markets for loans start to develop and financial institutions realising the importance of this kind of research have started to make data available to researchers. The general conclusion of these studies is that spreads on loans are different from spreads on comparable bonds, but that they do show co-movement to some extent. Therefore, care should be taken when bond market data are applied in risk management tools for loan portfolios.

Arak and Corcoran (1996) use data on privately placed debt yields. They find that these yields do not closely follow yields of comparable-quality public debt issues, although there is more similarity for A-rated paper than for sub-investment grade issues (Ba-rated). Moreover, privately issued lower rated issues have a considerably lower spread compared to their publicly issued counterparts. Both observations are explained by the fact that lower rated private issues include more covenants than similarly rated bonds, which implies lower default losses for the former and therefore a lower spread and less co-movement between the series as the credit risk profile is dramatically changed. They also find that public issue yield spreads are far more volatile than privately placed issue yields.

Similar results are found by Angbazo, Mei and Saunders (1998) who study highly leveraged transaction loans. Spreads on these loans are stickier than spreads on Baa- rated bonds as well as spreads on junk bonds. Nevertheless, the series do show some relation with each other although much less strong than a one-to-one relation. They estimate that when loan yields increase by 1 percentage point, loan spreads increase by some 30 bp.

Altman and Suggitt (2000) examine ratings transitions for US-syndicated loans and conclude that they behave very like bonds issued by similarly rated obligors. Their finding is not surprising, however, since the loan ratings are generally identical to those of bonds issued by the same companies; and in cases where Altman and Suggitt cannot obtain a rating for the loan, they actually infer it from the same obligor 's bond rating.

There is reason to believe that credit risk in private debt portfolios is not entirely similar to credit risk in public debt portfolios. An interesting study by Carey (1998) examines default histories of a large sample of US privately-placed bonds over the period 1986 to 1992, arguing that such private placements resemble loans in that they are monitored quite actively by lenders as is bank debt. Carey (1998) finds that especially for sub-investment grade issues credit risk for private debt is lower. This is both due to lower default rates and lower losses given default. Carey suggests that this is evidence of private debt being better monitored by lenders.

Kamin and von Kleist (1999) focus on spreads of primary issues of emerging market debt instruments, both bonds and loans. They find that both types of debt instruments react similarly to a number of issue-specific and general items, but that bond spreads are generally double as high as loan spreads with comparable characteristics. However, it is not clear whether this is due to the mere difference between loans and bonds or to the fact that all loans studied have a floating rate whereas all bonds have a fixed interest rate.

Finally, Carey (1994) examines the consistency of pricing in the bond and loan markets by comparing the new issue terms of loans with spreads on bonds issued by the same obligor. He finds that, adjusting for the fact that loans are generally floating rate whereas bonds are generally fixed-rate obligations, differences between bond and loan pricing are not larger than could plausibly be attributed to contractual features of the debt. Nevertheless, he stresses that the standard errors associated with his estimates are too large for confident statements to be made about loan and bond market consistency.

The evidence reviewed above suggests that the pricing of exposures and the probability of changes in credit standing are broadly similar in the bond and loan markets. However, there have been too few comparative studies of liquid and illiquid exposures for one to be confident of these conclusions and more research in this area is needed.

4.2.12. Limitations of credit spreads as indicators of credit risk

Credit spreads are only one indicator of risk and are not ideal. Kiesel, Perraudin and Taylor (1999a) dealt with a number of the drawbacks of spread data by calculating VaR measures for portfolios of exposures. Kiesel, Perraudin and Taylor generalise CreditMetrics by allowing spreads for different ratings categories to change randomly. VaRs are calculated for a one-year holding period and a confidence level of 99.7% for portfolios of 500 exposures, each of equal face value. They focus particularly on VaRs for an "average portfolio", the credit quality profile of which mimics that of the average portfolio of large US banks surveyed by the Federal Reserve Board (see Gordy (1999)). They also examine VaRs for a "high quality portfolio" which resembles that of more conservative lending institutions included in the same Federal Reserve survey. Each VaR is divided by the expected value of the portfolio and multiplied by 100 and so is in the same units as a percentage capital requirement. Under reasonably standard assumptions about correlations between different exposures, VaRs for the average portfolio are close to the 8% capital charge specified by the 1988 Basle Accord. The VaRs are slightly higher if spread risk is included as well as rating change and recovery risk. For the high quality portfolio, VaRs are rather lower, being around 5%.

Kiesel, Perraudin and Taylor find that VaRs depend markedly on the average duration of the exposures included in a portfolio. This maturity effect is greater for high credit quality portfolios. For the average-quality portfolios, their calculations yield VaRs for exposures of two and ten-year maturity of 5.4 and 10.0, respectively. For high credit quality portfolios, the corresponding VaRs are 2.7 and 7.6.

An explanation for the somewhat flatter maturity profile of VaRs for lower credit quality exposures is a kind of survivorship bias. If low-rated obligors survive in the near term, their credit standing is likely to have risen, in which case the market may believe that they will remain solvent for a long time. Another reason for the steeper profile for the high-quality exposures may be that the VaRs are an estimate of the likelihood that there will be a change in credit standing during the next year. With a prime-quality credit, it is more likely that information released within the year would point to problems at a later date rather than immediately. This would make a change in value of longer-term exposures more likely than shorter term.

The spreads they obtain may be regarded as average spreads for obligors from particular ratings categories. By analysing the errors from the spline fits, one may gauge whether the debt of obligors of different types is priced differently from the debt of the average obligor from the same rating category. Regressing the errors from the spline fits on a range of variables including dummies for different obligor domiciles, Perraudin and Taylor find that, allowing for rating, liquidity, seniority and some tax effects, spreads do appear to be affected by the domicile of the borrower. The effects are small, however. Bonds issued by AA-rated Japanese and European obligors are priced at a 10 basis point discount and a 4 basis point premium respectively compared with those of AA-rated US obligors. AAA-rated European bonds are priced at a 4 basis point premium compared with US AAA 's while Japanese AAA-rated bonds are rated at a 4 basis point discount 9.

4.3. The specification of the term structure of credit spreads

Economists have paid a great deal of attention to the term structure of interest rates. However, relatively little is known about the term structure of credit risk, defined here as the behaviour of credit spreads as maturity varies. In other terms, the risk structure of interest rates may be defined as the interest rate differentials that exist between securities that are identical in all relevant aspects except for the likelihood of default on the payment of interest or principal. The risk structure of interest rates is thus directly analogous to the term structure of interest rates, in which term to maturity is the differentiating characteristic. The key difference between term and risk structure works is related to their distinguishing characteristics. While the term to maturity is explicit and well defined, the risk of default is not directly and objectively measurable.

An important question for banks and regulators assigning capital to credit exposures is whether there is a significant maturity structure to credit risk and in particular whether shorter-maturity exposures should carry less capital than longer-maturity exposures. The current Basle Accord has a maturity dimension for interbank exposures but not for other types of exposure. If the horizon over which one wishes to evaluate risk coincides with the maturity of the debt then a reasonable measure of risk is the credit spread times the maturity of the exposure in question. The fact that the spread is multiplied by maturity means long-maturity exposures are likely to be riskier than short maturity. If the spreads themselves are on average upward (or downward) sloping in maturity, this would accentuate further (or mitigate) the effects of maturity.

4.3.1. Term structure of interest rates for default-free bonds

The available theory and empiricism pertaining to the shapes of the basic yield term structure, have provided three main explanations: liquidity, expectations and institutional influences. According to the liquidity preference theory, long-term bond prices fluctuate over wider ranges than their short-term counterparts in response to changes in the level of basic interest rates. Investors that are afraid of having losses of principal value and are subject to the danger of forced sales, will sacrifice yield to obtain liquidity offered by the short-term bonds. Short-term bond yields have shown to be more volatile, so that if investors desire stability of income and are not subject to a forced sale risk, they will have a preference for long-term bonds. Ultimately, if the relative importance of investors seeking liquidity is greater than investors seeking stability of income, the term structure will result to be upward-sloping.

According to the expectation hypothesis, current long-term yields can be derived from a series of expected future short-term yields; so that if short-term yields are expected to increase in the future, current long-term yields will be greater than current short-term yields and the result will be an upward-sloping term structure.

More often the expectation hypothesis and the liquidity argument are combined together to explain the term structure. As a result, the term structure will slope upwards steeply when interest rates are expected to rise in the future, amplifying the desire and need for liquidity of investors and speculators, who will avoid long-term bonds. The opposite will occur when there are strong expectations that interest rates will fall in the future. In absence of strong expectations about the direction of interest rates movements, the shape of term structure would be determined by the net importance of investors requiring liquidity *versus* those needing income stability.

Finally, the monetary authority could determine, by itself, the term structure through money and debt management operations that alter the outstanding supply and demand for bonds at each term to maturity (institutional influences hypothesis). Commercial banks also can influence the term structure by liquidating or buying short-term government bonds in response to changes in demand for bank loans. Depending on whether the business improves or declines bankers will sell or buy short-term bonds in order to meet the strong or weak loan demand respectively.

Hence the term structure would slope upwards or downwards if we are in the unfavourable or favourable phase of the business cycle.

These theories are groundwork to go beyond and analyse the influence of term to maturity upon yields and performances of bonds not free of risk of default. Term to maturity has a potential influence upon financial risk of bonds and upon the probability of default.

4.3.2. The term structure of interest rates for risky bonds

From a theoretical perspective, the credit spread should increase in line with increasing default risk and maturity, that is financial risk premia should be greater for bonds of longer terms to maturity. According to this view, the more distant the maturity, the greater the range of unforeseen difficulties that the obligor may face. Robinson (1960) and Hayes (1956) suggested that this time-function financial or credit risk should be greater for the intermediate quality than for high quality bonds.

In practice, the observed behaviour of credit spreads show that credit spreads increase with maturity only for higher credit quality bonds, while they decrease for lower credit quality bonds. Hence the nearness of maturity does not insure repayment of the principal (Graham, Dodd and Cottle, 1962). Harold (1938) disputes the time-function risk argument by claiming that although short maturities are an element of strenght in good times, they become an element of weakness in crisis periods. No explanation is offered as to why, but most probably we think he is referring to potential difficulties in refinancing during times where earnings are low, interest rates are high and credit is simply not available. Risk premia are thus expected to be greater for shorter-term bonds. The behaviour of credit spreads reflects the impact of the crisis at maturity –predicated on the risk generated by the liquidity pressures created by the need to refinance near-term maturing debt which is often confronted by lower credit quality and highly leveraged firms- and the pattern of marginal default risk for lower credit quality firms. While higher in absolute terms, the marginal default risk for lower rated firms decreases with maturity. In contrast, the marginal default risk of higher rated firms increases with maturity. The pattern of marginal default risk for lower credit quality firms is consistent with the life cycle of ratings outlook, whereby lower rated firms face higher short-term risk which is resolved by survival of default and with mean reverting processes in ratings outlook, where lower rated issuers improve, middle rated issuers stay the same and higher rated firms tend to decline on average.

4.3.3. Estimation and measurement of the term structure of credit spreads

To identify relative value among corporate bonds, it's necessary to understand the relationship between the default risk and the yield spreads over Treasuries. The spread of a corporate bond reflects default risk, but as we have seen, the magnitude of the spread for a given corporation depends also on the bond's maturity and coupon, its degree of subordination, its call structure, and the expected future volatility of interest rates. Thus, one corporation might have a number of bonds outstanding, each with its own spread.

The basic principle is that price of coupon bond is lower than price of a government bond because the former reflects default risk, that is the probability that the issuer will default. For the same expected return to result by holding either bond, the price of the corporate bond, assuming a zero recovery rate, must be equal to the price of the government bond times the probability of solvency:

$$\textit{Price of Corporate Zero} = \textit{Price Government Zero} * \textit{Probability of Solvency} \tag{2.3}$$

Or equivalently, since the probability of solvency is equal to one minus the probability of default:

$$\textit{Price of Corporate Zero} = \textit{Price of Government Zero}\ (1 - \textit{Probability of Default}) \tag{2.4}$$

Solving for the probability of default, we obtain:

$$\textit{Probability of Default} = 1 - (\textit{Price of Corporate Zero})/(\textit{Price of Government Zero}) \tag{2.5}$$

Applying this procedure to bonds maturing in different years, we can determine the conditional probability of default in each year, given that the corporation doesn't default in the previous year. We refer to this probability as *the forward probability of default*.

Given the assumption that the expected return from holding a government zero for two years must equal the return from holding a corporate zero for two years times the probability of solvency, the forward probability of default can be calculated. Repeating this procedure for the following years, we derive a term structure of credit spreads for zero coupon corporates for a given corporate issuer.

In practice, the difficulty of applying this technique is that there are no issuers that offer a sufficiently wide range of corporate coupon securities to construct a zero-coupon spread curve.

The model developed in Litterman and Iben (LI, 1991) is able to measure the effective spread curve implied in the price of each bond, isolating the impact of credit risk, and facilitating the analysis of the sources of value in corporate bonds.

The procedure used by LI is to construct a generic-zero spread curve by credit rating and industry using actual trading data. The first step is to estimate the term structure of Treasury interest rates from the prices of non-callable Treasury coupon bonds. Assuming there is a common shape of the spread curves of corporations with similar credit quality and within a given industry, for a particular industry we will have a *generic par spread curve*, derived from trader quotes for spreads of par coupon newly issued non-callable corporates of the specified industry and rating, with maturities corresponding to those of the current Treasury issues. From the generic par spread curve zero curve spreads are inferred.

The generic zero and par spread curves provide a natural index of credit quality through which we can compare the default risks of corporate bonds. In order to summarise the size of the credit spread through one number and to facilitate this comparison we search for each bond along curves interpolated between the generic zero curves for the appropriate industry, until we find the unique zero spread curve, *the effective zero spread curve*, that prices the bond with no error. We then generate the par coupon curve associated with it. The height of the par coupon curve over Treasuries at the maturities of the two Treasury benchmarks -whose durations bracket the duration of the bond- constitute the effective par spreads. The *effective par spread curve* will be given by the set of different effective par spreads function of maturity.

The result is an upward-sloping term structure of credit spread –credit spread increases with maturity- and the lower the credit rating, the steeper the curve. One implication of this term structure is that it is inappropriate to discount the cash flows from a corporate bond at a constant spread to the Treasury spot rate curve. The shorter-term cash flows will be undervalued, and the long-term cash flows will be overvalued.

4.3.4. Evidence of independence between default risk differential and bond's maturity

Bierman and Hass (1975) present the first systematic treatment of the importance of default probabilities in determining risk differentials. They attempt to reinforce and extend Fisher (1959) by specifying the process and variables that determine the risk differential assigned by the market to the debt of a given firm with a given capital structure.

Bierman and Hass first look from the investor point of view and define *the contractual rate* as the interest rate needed in order for the risky bond to have the same expected present value as a default free bond. The investor-required contractual interest rate decreases as the probability of survival increases. From the perspective of the firm issuing the debt, for a given level of outstanding debt, the probability of survival is inversely related to the contractual interest rate paid on the debt. The intersection of the two functions gives the minimum interest rate required by the market for a given amount of debt. Subtracting the risk-free interest rate from this amount we obtain the default risk differential.

The risk differential is invariant with the life of the bond when investors maximise expected net monetary value and the probability of survival is a constant over time. The explanation is grounded on the consideration that the risk differential does not change as maturity changes since the change in the expected present value of the principal repayment is exactly offset by the change in the expected present value of the interest payments. On the other hand, when the probability of survival changes over time and, in particular, when it is revised upward, the risk differential decreases as maturity increases.

The drawback of this method is that investors may use more complex decision criteria than the simple expected net present value. In addition factors that affect the likelihood and size of debt obligation payments cannot be summarised into well-behaved probability series. Factors as risk aversion and portfolio effects must be considered in the modelling of the investor behaviour. Furthermore, the characterisation of the survival process and how it changes over time must be enlarged upon in order to better ascertain the cost and the limit of debt for a firm.

Yawits (1977) extends the analytical model presented by Bierman and Hass (1975) and demonstrates that their conclusion that risk differentials are independent of maturity for par bonds actually holds for premium and discount bonds also. Yawits starts from the definition of the value of a bond as the summation of values of a series of discount instruments, each of which carries a claim on a single payment in the future. The bond's risk differential is simply the weighted average of the risk differential on each of the discount instruments, where the weights are determined by each instrument's portion of the bond's value. Showing that the risk differentials are equal for every discount instrument composing the bond, he can conclude that the bond's risk differential will have this same value. The second step is to broaden the Bierman-Hass model to include the effect of a second parameter –in addition to the default probability-, the terms of settlement in the event of default. The main result is that the addition of this new factor doesn't alter the independence between a bond's risk differential and its maturity. For a multi-period extension of Bierman and Hass (1975) see Jonkhart (1979).

4.3.5. Financial risks and the shape of the term structure

Johnson (1967) studies the influence of term to maturity upon losses on corporate bonds. Losses can be a result of two types of financial risk: they can be due to a default event, or they can be losses of market value due to apparently increased danger that the bond will default. According to Johnson, term structures may be determined not only by time-function credit risk, but also by:

a) financial illiquidity as a positive function of term to maturity. Prices of longer-term bonds may fluctuate more than shorter-term counterparts (of the same quality) in response to identical changes in absolute abilities of obligors to pay.

b) expectations about directional movements in premia for financial risk. Movements in financial risk premia influence term structures of corporate bond yields; if they are expected to fall (optimistic market) there may be a tendency for financial risk premia to be smaller the longer the term to maturity.

In order to test for the different hypotheses, data are collected from the Corporate Bond Project of the National Bureau of Economic Research covering the period 1900-1944.

Crisis at maturity. Bonds maturing during the test holding period experience greater default frequencies than bonds of the same quality which do not come to maturity. Crisis at maturity is important for bonds of the lowest qualities during both optimistic and pessimistic market conditions. In periods of strong business, crisis at maturity exists only for the lowest qualities bonds; in periods of market pessimism, it becomes relevant for bonds of successively higher quality ratings.

Bond lifetime performance. In order to capture default frequencies, losses on interest payments and the proceeds received after default, and average annual losses on control groups of bonds are computed. A strong positive relationship between loss rates and term to maturity are observed only for the three best qualities, while no consistent relationship exists for the lowest qualities bonds. Hence the positive time-function credit risk argument found in the literature is applicable only to the high quality bonds. Term to maturity allowed time for degeneration of quality and for improvement in quality.

Financial illiquidity. To test whether financial illiquidity might be a function of term to maturity, average performances of bonds purchased, held and liquidated over various periods are computed. The potential losses as a result of changes in basic interest rates and changes in abilities of obligors to pay are calculated for each quality group and each term to maturity group.

The general result is that average potential loss rates –as the net result of declining basic yield components and increasing financial risk premium components of total yields- are greater the longer the term to maturity. The strong implication is that financial illiquidity is a positive function of term to maturity. Hence, in a liquidity preference market, an upward-sloping term structure would be the result of financial illiquidity and interest rate illiquidity for corporate bonds. This result adds substance to the theory that optimistic or pessimistic expectations will influence term structures of corporate bond yields.

In fact, the final shape of the term structure will be the result of the various combinations of these risk phenomena, and in particular we can have one of the following:

- *Downward-sloping and U-shaped yield curves*. The crisis at maturity –which is correlated with rating quality and economic conditions- combined with an optimistic or pessimistic expectations function, gives as a result a negative and an U-shape, respectively, function of financial risk premia against term to maturity.
- *Upward-sloping yield curve*. In the absence of crisis at maturity, maturity values become certain and pricing decisions are based upon expectations of receiving face values at maturity. In a liquidity preference market, an upward-sloping curve is the manifestation of a pessimistic expectations function and a financial illiquidity function increasing with term to maturity.
- *Hill-shaped yield curve*. This type of curve occurs occasionally for lower qualities bonds and is the result of the summation of an optimistic expectation function (downward-sloping) and an increasing liquidity preference function (upward-sloping).
- *Inverted-S-shaped yield curve*. This type of curve occurs between upward-sloping and U-shaped curves. Bonds of this transitional quality are considered to have either little trouble refinancing at maturity so that at the very short maturities.

Johnson (1967) is the first to assemble and interpret data on the structure of bond yields classified by a measure of risk status. His interpretation should be regarded as exploratory, and its limit lies on the lack of consideration of approaches to interest rate theory alternative to the expectation one. In particular, more explanatory role could have been given to variations in the structure of supply of securities and general dynamic theories.

4.3.6. The credit yield curve and the leverage factor

Merton (1974) represents the first systematic theory of the risk structure of interest rates, defined as "the possible gains or losses to bond holders as a result of (unanticipated) changes in the probability of default" (Merton, 1974, p. 449). Along the line of Black and Scholes (1973) he derives a pricing theory to value a zero-coupon corporate bond with a face value of B, a term to maturity T, issued by a firm with value V. The price of the bond can be expressed as a function of T and d, the "quasi-debt ratio" of the firm (Be^{-rt}/V), and also as a premium over the risk-free rate. In this way Merton shows that the premium increases with leverage (d) and the volatility of the firm's earnings, but can either increase or decrease with maturity depending on the risk of the firm.

The commonly used measure of the risk premium on debt, H, is given by the yield to maturity (R) in excess of the riskless rate (r). ($R - r$) is a valid measure of the riskiness of the bond under the necessary condition for the premium to move in the same direction as the standard deviation of the returns on the bond does to changes in the underlying variables: leverage, maturity and firm's returns standard deviation.

Note that the risk premium and the earnings standard deviation change in the same direction in response to a change in the "quasi-debt" to firm value ratio, in the business risk of the firms or in the riskless rate of interest. However, they need not change in the same direction with a change in maturity. For values of d greater than or equal to one, the premium over the risk-free rate decreases with maturity. For lower values of d, the credit yield curve is either strictly upward sloping or hump-shaped (see Figure 4.2). Hence, the term premium on bonds of the same maturity is a valid comparison of the riskiness of such bonds, but we cannot conclude that a higher term premium on bonds of different maturities implies a higher standard deviation.

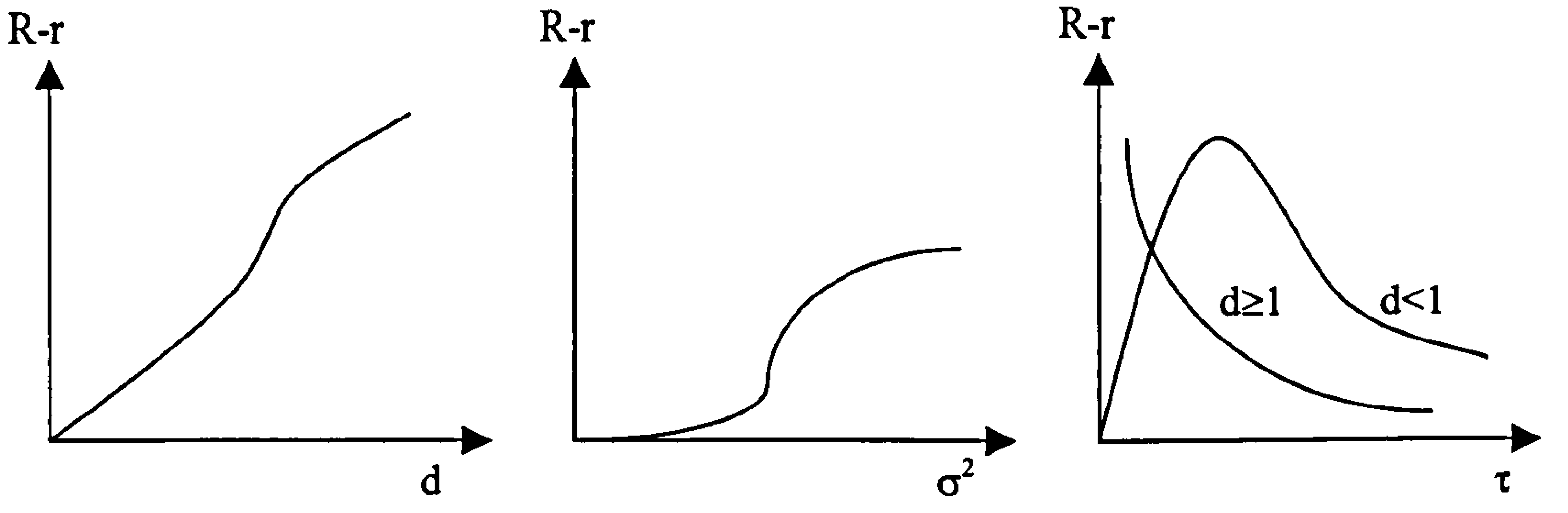


Figure 4.2 *Merton (1974)'s implications*

The intuition behind these results is that the value of the bond depends on the probability of default, which varies with the value of the firm. The highest quality bonds face a probability of default that is very small at issuance and a possibility of substantial downward movement in credit quality is quite high after some time. Thus the credit yield curve is upward-sloping for high-grade firms. Speculative-grade bonds, however, are very risky at issuance, but the longer the maturity, the more time the bonds have to improve and the value of the firm to rise. The credit yield curve will be strictly downward sloping if the bond at issuance cannot go but up over time; for firms a bit less risky, the yield curve will be hump-shaped because in the short term the potential to deteriorate dominates, but in the longer term it's offset by the upside potential.

The limit of the Merton's approach is that default occurs only at maturity, when the default event is defined by the condition that the firm value falls short of the promised payment and occurs if and only if this condition is met.

Lee (1981) disputes Merton's results, claiming that an increasing function of the term premium with respect to leverage is not consistent with the downward and hump-shaped yield curves for low-rated bonds. The explanation is that if the risk premium is a monotonically increasing function of the leverage ratio, for any given maturity, a discount bond with a higher leverage ratio pays a higher risk premium. Hence the hump-shaped curve should be no higher than the downward sloping curve.

The term structure curves in terms of the leverage ratio have a different shape depending on the vale of the parameter d. The term structure curve with a unitary leverage ratio marks the borderline of two distinctive cases. When the maturity approaches to zero, those risk premia with $d > 1$ approach infinity; those with $d < 1$ approach zero. When the maturity approaches infinity, the whole family of curves approaches zero. For a leverage ratio close to zero, the term structure curve would asymptotically approach the horizontal axis.

Despite Lee (1981) eliminates a source of confusion present in Merton's model, his re-examination is still partially incorrect, and his graphic representation of the risk premium, H, is not correctly depicted for small values of time to maturity. Pitts and Selby (1983) prove mathematically two properties of the risk premium which settle the disparities and give the final graph of H as a function of time: a) when $d = 1$, H tends to infinity as time to maturity approaches zero; b) when d is between zero and one, and time to maturity tends to zero, the partial differentiation of H with respect to time to maturity is zero.

Kim, Ramaswamy and Sundaresan (KRS, 1995) examine an expanded model for the valuation of corporate debt. In their model, the issuing firm pays a dividend, the holders of the bond receive a continuous stream of "coupon" payments, default is possible prior to the maturity of the bond, and the return on the firm's assets is correlated with the stochastically varying instantaneous risk-free rate of return. Using numerical analysis, KRS find that the capital structure has a significant effect on the shape of the term structure of credit spreads only in the case of non-callable bonds. In particular, they obtain that the term structure of total yield spreads on a callable corporate bond is hump-shaped regardless of the debt ratio values, although the level of yield spreads is high when the debt ratio is high. This result is in contrast to the results for non-callable bonds. For firms with a low debt ratio, the yield spread increases with maturity. In this case, long-term bonds are riskier than short-term bonds because more coupons are subject to default risk. With a high debt ratio, the spreads increase in the first place and then decrease as time to maturity increase. As a consequence, short-term corporate bonds are priced to provide a higher yield than long-term bonds. This results in a humped risk structure of interest rates. The levels of credit spreads, however, decline significantly with reduced debt ratios across all maturities. This suggests that the relation between time to maturity and risk premia is not confined to the simple world modelled by Merton (1974) and Lee (1981).

Longstaff and Schwartz (1995) present a model for coupon bonds in which firm value is correlated with the risk-free rate. According to their model, the credit yield curve may be upward-sloping or hump-shaped, but not strictly declining. The peak spread for the hump-shaped curve occurs at the third year, however, so that most of the credit yield curve facing very risky issuers is negatively sloped. Given the appropriate parameter values, this model could also generate a downward-sloping curve for speculative-grade firms. Wei and Guo (1997) apply the LS model to Eurodollar spreads in 1992 and show that the credit term structure is mostly downward sloping for the values of credit risk observed in their data.

From the comparison between LS (1995) and Merton (1974) it emerges that although the LS model is less general in terms of default probability, as it permits default only at the maturity date; the Merton model is more general in terms of the recovery rate. When the time to maturity goes to infinity, numerical calculations in LS (1995) show that the credit spread converges to zero, while in Merton (1974), it converges to a constant. As a result, for a solvent firm, which is the most common case in practice, the LS model can generate a hump-shaped credit structure that starts from zero and eventually converges to zero. Finally, both models are restrictive because of the predictability of the arrival times of default, which implies that the credit structure has to start from zero.

The empirical findings: Sarig and Warga (1989)

Previous empirical studies had focused on the difference between yields on coupon-paying corporate bonds and yields on coupon-paying government bonds of the same maturity. Problems coming from using these data are related to the feature that most corporate bonds promise more than a single payment. As a consequence, it's not possible to estimate the default-risk premium for a single future date, because the price of a coupon-paying bond is the sum of the values of all of its cash flows components. In addition most of these bonds have sinking fund provisions and some are callable, which make their price depend on all these characteristics. It would therefore be impossible empirically to isolate the effect of default risk alone on the yields of these bonds.

Considering these difficulties, Sarig and Warga (SW, 1989) investigate the risk structure of interest rates using *pure discount bonds*. The prices of pure-discount corporate bonds of various rating and maturities are analysed and their yields are compared to the yields of similar maturity pure-discount government bonds. The data set is obtained from Shearson Lehman Brothers for the period February 1985-September 1987. The set contains 137 corporate zero issues of 42 companies rated AAA to C, and 119 strips of US government bonds. The yield spreads for each rating group are averaged to produce the risk structure. These data allow us to compare observed default risk premia to the theoretical premia suggested by Merton (1974), Lee (1981) and Pitts and Selby (1983).

Each month, SW subtract the yield of a zero-coupon government from the yield of each zero-coupon corporate bond with identical maturity. These yield differences are then averaged across bonds in a given month and then across time to produce the following results. Striking is the close resemblance to the theoretical plot obtained by Merton (1974) and the other contingent claims models that followed. The estimated term structures of the risk premia is upward sloping for high rating pure discount bonds, humped for medium rating bonds, and strictly downward-sloping for low rating bonds. However, the small number of observations doesn't allow an extensive and more formal study of default premia, and cannot sufficiently prove that the risk structure is upward sloping for investment grade and downward sloping for speculative bonds. Nevertheless, it is encouraging to see the theoretical model and the empirical results match up.

Merton's results are based on the assumption that each firm has only one type of debt outstanding, the pure discount bonds. In order to see the shape of the risk premia for firms that have a series of pure discount bonds outstanding, Sarig and Warga look also at two firms in their sample who have issued large series of pure discount bonds. The result shows that the high rating firm's risk premia profile is relatively flat, while the low rating counterpart is downward sloping. This can be considered as an empirical demonstration that Merton's results hold even when more than a single bond is outstanding. This is also a reaffirmation of the similarity between the profiles obtained by Merton (1974) and by Kim, Ramaswamy and Sundaresen (1987).

4.3.7. Interaction between interest rate risk and default risk

The empirical literature has presented evidence that the time evolution of both corporate default spreads and interest rates are related to business conditions, thus suggesting that default risk and interest rate risk are correlated. On this line, Nielsen et al. (1993) develop a model for the term structure of default spreads taking into account default risk, interest risk and the interaction between the two.

The interrelation between default risk and interest rate risk arises from two sources. First, the uncertainty of the value of the firm's assets and the default boundary are both correlated with the interest rate uncertainty. Second, the rate of growth of the default boundary and the rate of return on the firm's asset depend on the level of risk-less interest rates. Both sources of correlation are shown to affect the term structure of default spreads.

The model for determining the default premium is developed for non-callable corporate zero-coupon bonds. The model assumes that trading occurs continuously in perfect and frictionless financial markets with no taxes, transaction costs or informational asymmetries. The results show that an increase in the payoff in case of default leads to an important decrease in the risk spread for all maturities. Second, the term structure of risk spreads is highly sensitive to changes in the volatility of the assets of the firm (a small increase in the volatility increases substantially the spread). Third, the solvency of the firm powerfully determines the height and the slope of the term structure of default spreads. When the firm is solvent at the time the bond is priced, the spread on very short-term bonds is always close to zero. When the time to maturity is short but greater than zero, the probability of default is very high for firms with a low leverage ratio, since negative shocks on the value of its assets can easily lead to default before the maturity of the bond. For longer maturities this effect becomes less important since the probability of default in some years decreases through time due to the positive drift in the value of the firm. Fourth, the more negative is the correlation between the interest rate risk and the default risk, the smaller the spreads are, which is explained by the fact that the risk of default becomes easier to diversify.

Finally, the model produces a variety of shapes for the term structure of the probability of default: it can be increasing, decreasing or humped, and so can be the shape of the present value of the expected writedown through time.

4.3.8. The recovery rate and the term structure of credit spreads

Fons (1994) provides a simple numerical model of bond pricing in which the value of the bond depends on the probability of default each period and the recovery rate if default occurs. Based on Moody's default data by rating over the period 1970-1993, Fons (1994) tests for the shape of risk structure of various rating groups.

Marginal[7] and cumulative[8] default rates from 1 to 20 years for broad rating categories were estimated. The cumulative default rates show a clear pattern of increasing risk as rating quality declines over any time horizon. In general for investment-grade marginal default rates they observe a rising trend as the time horizon lengthens, while the trend is declining for speculative-grade marginal default rates. This pattern of marginal default rates by risking category indicates an underlying mean reversion in the company credit outlook. Over the long term, then, surviving low-rated issuers tend to rise to the middle ratings, middle-rated firms tend to stay middle-rated, and top-rated firms tend to slip to the middle ratings.

Within the framework of a risk-neutral bond pricing model[9], and using historical default and recovery rates, theoretical credit spreads are modelled. A steady upward trend with respect to maturity is observed for risk-neutral spreads of investment-grade bonds. At the Ba rating level, however, credit spreads rise through the fifth year but then slowly taper off. At the single B rating, spreads fall from year 1. Despite the theoretical spread behaviour and the corresponding marginal default rates show similar pattern, it's surprising to find that spreads might actually narrow as maturity increases –especially for the lowest rating categories.

Finally, risk-neutral credit spreads are quite sensitive to the recovery rate estimate. They increase as the recovery rate lowers, and they narrow as the recovery rate increases. In contrast, the model is much less sensitive to changes in the level of the risk-free yield.

Yield spreads calculated using market data show patterns consistent with the modelled behaviour. No clear trend emerges in the plot of Aaa spreads. Bonds rated Aa and A, however,

[7] The marginal default rate d_t (R) is the average issuer-weighted default rate for R-rated issuers in their t-th year.
[8] The cumulative default rate D_t (R) is the probability that a bond rated R will default by year t.
[9] The following assumption are introduced to use the default data to compute a yield spread over a comparable-maturity: a) bonds are priced at par; b) investors hold bonds until maturity or default; c) investors are risk-neutral; d) capital markets are arbitrage free.

exhibit a significant positive relation between spread and maturity. Bonds rated Baa also show a positive relationship, although not as strong as that for bonds rated A. Consistent with the modelled behaviour, credit spreads for bonds rated Ba decline only slightly as maturity increases. Furthermore, a negative spread-maturity relationship was found for B-rated bonds.

Eventual discrepancies between the model estimates and market credit spreads are explained in terms of:

1) Liquidity factor. Investors in less liquid issues may require a premium as compensation for liquidity risk.
2) Risk-neutral behaviour. Although individuals may exhibit risk-neutral behaviour with small portions of their wealth, they are likely to be risk-averse when large sums are concerned, requiring a higher premium.
3) Tax considerations. Individual investors are often willing to accept a lower yield on securities exempt from income taxes.
4) Residual call provision effects and risk for which investors will demand compensation in the form of a higher yield.

El-Jahel (1998) sets up a model of default where credit spreads depend on the level of the discount bond price and indirectly on the level of interest rates. This result is supported by Duffee (1997) and Das and Tufano (1995), and credit spreads generated within this framework are consistent with the empirical findings of Sarig and Warga (1989), Longstaff and Schwartz (1995), Kim et al. (1993), and Nielsen et al. (1993).

The bond price, the credit spreads, and the term structure of credit spreads all depend on the percentage recovery rate. The *recovery rate*, in turn, usually depends upon the existence of an equity committee, the strenght of ties between managers and shareholders, the outcome of the bargaining process between bondholders and the issuers of the debt and is also particular to each bond issue and class of security in the firm's capital structure.

Estimates of the recovery rates are derived from historical data on default recovery rate values. As the recovery rate increases, the bond price increases, the credit spreads decrease, and the risk term structure can take on different shapes. High and medium quality firms have an upward sloping credit spreads term structure. Lower quality firms, have humped-shaped or downward-sloping term structure. Also this result is consistent with the general empirical findings.

Changes in the *volatility of the assets* of the firm process are found to have a relevant impact on the term structure of credit spreads. A small increase in the volatility from 15 to 30 per cent increases the spread for a four years maturity bond from 150 to nearly 300 basis points. Changes in the volatility parameter and in the hazard rate process parameters seem to widen the spreads for medium and long term maturity bonds.

Modelling the term structure of credit risk spreads as a Markov model, Jarrow, Lando and Turnbull (1997) can give an explicit representation for the credit risk spreads in terms of the recovery rate and the transition matrix for credit classes. Assuming risk neutrality and a zero recovery rate, credit spreads are plotted against maturity and for some parameter values, credit yield curves are similar to those in Merton (1974). Most investment-grade bonds have upward-sloping risk term structures, while B-rated and most BB bonds face downward-sloping credit yield curves, and CCC-rated firms curves are strictly downward-sloping.

4.3.9. The impact of different parameterisations of the event of default

Mella-Barral and Tychon (1996) illustrate how differences in the parameterisation of the event of default – the total value of the firm's assets or the firm's operating earnings as the economic fundamental, default triggers or the total value of the firm in default - affect not only the valuation of bonds, but also the implied term structure of credit spreads. Adjusting the expected bankruptcy scenario to the specificity of the firm and its economic context is therefore of crucial importance.

Assuming that the whole firm is financed with a single debt contract, Mella-Barral and Tychon illustrate the impact of a particular choice of i) underlying economic fundamental, and ii) default trigger rule, on the value of debt, and on the term structure of credit spreads. In case i) the economic fundamental is the total value of the firm's assets and the debt is protected. In case ii) the economic fundamental is the firm's operating earnings and the bankruptcy is triggered by a strict liquidity constraint.

The term structure corresponding to the second set of assumptions is much more hump-shaped. The spreads increase until an intermediate maturity of either 8 or 4 years and then decrease as the maturity increases. This is the result of a trade-off between the exposure to credit risk and the expected present value of the coupon payoff stream, which both increase with maturity.

The fact that the first set of assumptions generates much smaller credit spreads is explained observing that when the total value of the firm's assets is the economic fundamental, the chances that the process hits a barrier from above are lower than when the dynamics are driven by the operating earnings.

A sensitivity analysis of the term structure of credit spreads with respect to a 10% upwards or downwards movement in i) initial face value of the debt contract, ii) volatility; iii) interest rate, and iv) bankruptcy costs, is carried out. A rise in face value, volatility, and bankruptcy costs increases credit spreads. Changes in the safe interest rate do not affect much the magnitude of credit spreads for short-term contracts. Credit spreads are only marginally increasing in the risk-less rate for long maturities.

4.3.10. Alternative models for the term structure of default risk

Cumby and Evans (CE, 1997) examine alternative methods for making inferences about the value and dynamics of credit quality from market prices. In doing so they ask if the time series behaviour of the prices of risky debt is consistent with five models of the time series behaviour of credit risk.

Models of the term structure of default risk are applied to a sample of risky Brady bonds issued by the governments of Mexico, Venezuela and Costa Rica in 1990. These bonds are considered an ideal vehicle with which to examine the dynamics of credit quality. They are risky, and judging from the large fluctuations in their prices, they have experienced large movements in their perceived credit risk. Moreover, the market for Brady bonds is large and highly liquid.

In the first model, the probability of a borrower defaulting at any future time is assumed to be constant (geometric term structure of credit risk). The term structure of credit risk is monotonic and approaches one as the time horizon increases. Although this assumption results in attractive simplifications, it implies that current and anticipated future credit quality are identical.

In the other models -that we indicate as Model II, III, IV, and, V, respectively- creditworthiness is treated as an unobservable variable that follows a specified stochastic process. Model II assumes that credit quality follows a continuous-time diffusion process. Although this provides scope for anticipated changes in credit quality, the long run behaviour of default risk is constrained to be either one or zero. With model III, IV and V CE move to discrete time and allow respectively for a random walk with drift, a mean-reverting stationary autoregressive process, and a random walk with drift and stationary higher-frequency dynamics ARIMA(1,1,1). This last process has the advantage of imposing fewer restrictions on the dynamics of credit quality and can therefore produce a wider range of term structures of credit risk.

Specification tests are applied to the first model in order to see whether the estimated probabilities evolve randomly as the model assumes. Model I is found to be dynamically inconsistent in that changes in the default probabilities are predictable. The runs test confirms this result: too few runs are found to be consistent with randomness. The data are also inconsistent with model IV. The models allowing for non-stationary dynamics, and in particular Model V provides a better fit for the bonds in the sample.

Maximum likelihood estimates, diagnostic tests for serial correlation in the levels and the squared innovations show that model V has the best overall fit. The differences in the models can yield significant divergences in the term structures of credit quality that they imply. As expected, the term structure computed from the constant conditional probability model shows a gradually declining survival probability. The ARIMA model yields a greater variety of term structure shapes than any other model. Note that the differences in the term structures can in turn lead to substantial differences in the valuation of new debt instruments.

4.3.11. Implications of imperfect accounting data

Duffie and Lando (1998) provide a simple model of the implications of imperfect accounting data for the term structure of credit spreads on corporate bonds. The model of Leland (1994) is extended assuming that outside investors cannot observe the issuer's assets directly, and receive instead only periodic and imperfect accounting reports. For a setting in which the assets of the issuer are a diffusion process satisfying technical conditions, a formula for the hazard rate process for default is provided in term of the conditional distribution of the assets of the issuer, conditional on accounting data and on survivorship.

A numerical illustration is implemented and the theoretical shape of the term structure of credit spreads is compared for firms of various credit qualities and various levels of precision of accounting data. It emerges that in the presence of perfect accounting data credit spreads go to zero as maturity goes to zero, regardless of the level of assets. For lower-credit quality firms, credit spreads would widen sharply with maturity, and then typically decline. With imperfect accounting data, however, the model implies that credit spreads remain bounded away from zero as maturity goes to zero.

Moreover the term structure is plotted for various lagged accounting reports; with perfect accounting information, the previous accounting report would have no impact, given the current report. Hence the shape of term structure of credit spreads may provide some indication of the quality of accounting information assumed by investors.

So far we have seen that academics and market practitioners tend to agree that the risk structure is upward-sloping for high quality credits. As far as the slope of the curve for high-yield issuers is concerned, practitioners usually do not agree it is negative. From this perspective Helwege and Turner (1998)'s investigation provides some empirical support for the practitioners' view: contrary to many bond pricing models' predictions, the credit yield curve for most speculative-grade firms appears upward-sloping.

4.3.12. An upward-sloping credit yield curve for speculative-grade firms

Helwege and Turner (1998) criticise the empirical studies done so far because of sample selection bias associated with maturity choice and due to the lack of control for credit quality. Credit ratings wouldn't reflect fully the differences in credit quality across firms that belong to the same rating category and this is particularly true for the high-yield universe. "This statistical error in ratings can lead to a sample selection bias in the estimated slope of the credit yield curve because of the endogeneity of bond maturity" (Helwege and Turner, 1998: 5). The more creditworthy firms in a given rating category are most likely to issue long-term bonds. This causes the average yield spread to decline with maturity, even though for an individual firm the spread typically might increase with maturity.

Helwege and Turner correct for this bias by looking at pairs of BB- and B-rated bonds issued by the same company at the same moment, having the same seniority but having different maturities. Differences in credit spread (computed using the primary market offerings) are therefore only due to maturity (and also potentially different call features). The database is composed by all non-investment-grade bond offerings listed in the Securities Data Company (SDC) from 1977 to 1994. The sample is restricted to straight public bonds sold in the US on the same day as other bonds of the same company (multiple bond offerings). In a large majority of cases, these comparisons point towards upward sloping credit spread curves and noncallable bonds provide the most reliable information in the sample and these also point to an upward-sloping credit curve.

The shape of the credit curve is tested further by applying t-tests and rank tests. The two-tailed t-test tests whether the average change in the spread is significantly different from zero; the signed rank test is non parametric and tests whether the spread rises or falls as maturity lenghtens, giving higher weights to observations with large differences in spreads. Both t-test and the rank test indicate that the credit curve facing high-yield issuers is positively sloped.

To check whether the difference between their results and those of previous studies is due to the method of analysis, Helwege and Turner estimate the regressions of spreads on maturity without holding constant issuer quality. In all but the highest rating class, the coefficients tend to be negative, consistently with the findings of Sarig and Warga (1989) and Fons (1994) that are based on secondary markets prices.

The analysis is extended to secondary bond price data from Lehman Brothers Fixed Income Database. The results are similar to those reported for the SDC data. The majority of the firms face yield curves that are strictly or mostly upward sloping. Moreover the cases that are not upward-sloping are not necessarily downward sloping or hump-shaped as the theory predicts.

This does not necessarily imply that the theoretical pricing models are wrong. It may be the case that for the bonds in the sample, the probability of an improvement of credit conditions is insufficiently high (due to low earnings volatility or a too low a debt-to-equity ratio – both are important factors in the theoretical models). In any case, many other authors also fail to find other than positively sloped credit spread curves. Litterman and Iben (1991) indicate that in their sample the credit spread curve is upward sloping, although they only study BBB or higher rated bonds. Ma, Rao and Peterson (1989) report a positive relation between yield spread and duration and Duffee (1996) also finds (using investment-grade bonds that for typical firms the term structure of yield spreads is upward sloping, with a slope which is positively related to the level of the spread. Fons (1994) computes credit spreads using historical default rates and assuming risk-neutrality. Although the credit spreads increase with term to maturity for investment-grade bonds, the credit spread curve for Ba-rated bonds is slightly humped, whereas the credit spread curve for B-rated bonds is negatively sloped. In contrast, Angbazo, Mei and Saunders (1998) find a positive relation between term to maturity and credit spreads on loans for highly leveraged transactions. It is remarkable that even for these highly risky loans no humped or downward sloping curve is found.

Explanations of the discrepancy between predicted and actual yield curves might be due to:

1) the parameterisation of the corporate bond pricing models. The downward-sloping credit yield curve occurs in the models because the equity-like optionality of the bond eventually

dominates the pricing. If the actual corporate bond market includes few bonds with such upside potential, the observed yield curve will not be downward-sloping.

2) the speculative-bonds included in the sample may be not sufficiently risky on average to exhibit a downward-sloping curve.

3) corporate bond pricing models may suffer from inappropriate assumptions about parameter values, such as incorporating an excessively high volatility of operating earnings to boost the spreads on high-grade bonds.

4.4. Valuation of risky debt

The default pricing models seek to combine the loss exposure, recovery rate and default probability into a quantification of the credit risk of transaction and the fair value that compensates for that risk. Models for valuing defaultable bonds can be divided in the following groups: proprietary models (sections 4.4.1), structural models (section 4.4.2), intensity based models (section 4.4.3), credit-spread based models (section 4.4.5). and rating-based models (section 4.4.6).

4.4.1. The proprietary models

Proprietary default prediction models are typically based on the original thesis by Black and Scholes (1973) that the equity in a risky firm is equivalent to a call option on the net asset value of the firm. The net asset value is calculated as the market value of the firm's assets minus the claims on the assets which include traditional financial claims such as debt and other claims including erosion of asset values which may result upon default. Another way of restating this is to view the position of the bond holder as a combination of the long position in the underlying bond plus the sale of a put option on the company's assets where the option has a strike price equal to the value of the debt.

On this line Merton (1974) used the option theory to price defaultable bonds. Apart from the standard assumptions of continuous time no-arbitrage models (continuous costless trading and short-selling, no taxes, perfectly divisible assets, price-taking investors, no borrowing-lending spread), additional assumptions are: a) constant interest rate; b) the default event occurs at the maturity if the value of the firm falls short of the face value of the debt at that time; c) the loss distribution conditional on default is endogenously determined; d) bankruptcy is cost-less; e) the debt has a zero coupon; f) firms have very simple capital structures with only one type of debt; g) firm's assets trade in the secondary market.

Given these assumptions, the firm's liabilities are viewed as contingent claims issued against the firm's underlying assets[10], with the payoffs to the various debt-holders in bankruptcy completely specified in terms of seniority and covenants. Bankruptcy is determined via the evolution of the firm's assets in conjunction with the various debt covenants. This model allows derivation, calculated from the distribution of asset values, of the default probability that asset values will be lower than the value of the claims on the asset.

All the assumptions of the model are rather crude description of reality. They largely concern the nature of the debt contract and the way that bankruptcy is triggered and settled. As a result, this approach is difficult to implement in practice. Firstly, all of the firm's assets are not tradable nor observable. Secondly, to utilise this technique, the complex priority structure of the payoffs to all the firm's liabilities need to be specified and included in the valuation procedure (Jarrow et al. 1997). Thirdly, the market value of the real assets, the volatility of the asset values and the measurement of liabilities are difficult to estimate. Furthermore, since this approach does not use credit rating information, it cannot be used to price credit derivatives whose payoffs depend directly on the credit rating. Also from the point of view of valuing corporate debt, these models have not had much support from empirical evidence. They indeed generate default premia smaller than those observed in practice (Jones, Mason and Rosenfeld (1984), Franks and Torous (1989)). In addition, since the above models assume that firms have a simple capital structure, their approach becomes intractable when applied either to more complicated capital structures, or to more complex securities like coupon bonds.

In order to generate credit spreads that were similar to those observed in reality, much of the subsequent effort in this area has been directed at relaxing the assumptions underlying the Black and Scholes (1973) and Merton (1974) models. A "perfect" version of the model would require at least the following extensions: multiple classes of coupon-bearing debt with realistic covenants, stochastic interest rates, the inclusion of taxes, costly bankruptcy and financial distress that can occur throughout the life of the debt, and possible violation of strict priority rules.

A number of papers have extended Merton's approach. Geske (1977) extends the analysis of Merton (1974) to risky coupon bonds that have a finite time to maturity and discrete coupon

[10] The value of a corporate discount bond is equal to an equivalent riskless discount bond minus the value of a put option on the value of the firm with strike price equal to the face value of the debt.

payments. Black and Cox (1976) extend Merton (1974) to the study of safety covenants, subordination arrangements, and limits on the financing. A distinct feature of this latter model is the possibility that default could occur before the maturity date. Brennan and Schwartz (1977) model convertible debt with stochastic interest rates. Mason and Bhattacharya (1981) also extend the analysis to firm value that follows a discontinuos process and to more complex boundary conditions. Turnbull (1979) generalises Merton (1974) from a different perspective. In a study of debt capacity, he extends the Merton's mode to an economy with both corporate tax and bankruptcy costs. He derives closed-form solutions for a firm's common stock and pure discount bonds. On the same line is the work by Leland (1994) which makes it possible to work with notions of optimal capital structure. Kim, Ramaswamy and Sundaresan (1989) extend Merton (1974) by assuming that the riskless interest rate follows the square root process of Cox, Ingersoll and Ross (1985) and is correlated with the firm value process. Cooper and Mello (1991) and Rendleman (1993) demonstrate the insight provided by Merton (1974) into the valuation and analysis of risk sharing in swaps with default risk. We finally mention other contributions: Brennan and Schwartz (1980), Shimko, Tejima, and van Deventer (1993), and Merton (1977). The subsequent literature on defaultable bond pricing has taken two approaches: the structural approach and the reduced form approach.

4.4.2. The structural approach

The structural models (or models based on the value of the firm) view risky debt as payoff an exogenously given fraction of each promised unit of currency in the event of default. In these models bankruptcy is allowed to occur at a random time and the causality of default is directly linked to information on the asset of the firm -the total value of the firm's assets is employed as the economic fundamental. In other words, default time is determined by an underlying process describing the value of the firm and default will occur when this process hits a some boundary which may be either deterministic or random.

This approach is used in Hull and White (1995) and Longstaff and Schwartz (1995), Kim, Ramaswamy and Sundaresan (1992), and Nielsen, Saa'-Raquejo, and Santa-Clara (1993). These models -as Merton, 1974- assume that the value of the firm follows a diffusion process; and in contrast to Merton's allow for stochastic interest rates and for the correlation between interest-rates and firm value. The latter two allowing also for deviation from strict absolute priority rule, they are able to generate realistic credit spreads, although the payment upon default is exogenously defined.

While this approach is convenient in the presence of scarce data, it has the drawback that firms whose assets are modelled by a diffusion process will have a defaulting probability on short-term debt equal to zero. In addition, even if it simplifies computation by avoiding the need to understand the complex priority structure of payoffs to all the firm's liabilities in bankruptcy, it still requires estimates for the parameters of the firm's asset value, which is a somewhat abstract quantity typically not observable. Even if many quantities are observable which could lead to sensible estimates of firm value, it would seem to be a formidable task for a financial institution dealing with thousands of default-prone counter-parties to work out and update these estimates for each counter-party. Some sort of easily observed proxy for firm value might be preferable.

Also, as noted in Kim et al. (1993), realistic values of leverage and volatility of the value of the firm seem incapable of producing the yield spreads observed in the market. Moreover, it may be unrealistic to assume that default is equivalent to a situation in which the market value of assets is reduced to or below that of liabilities. Finally, this framework still cannot handle various credit derivatives whose payouts depend on the credit rating of the debt issue.

4.4.3. The reduced form approach

The reduced form models or intensity based models, as the structural models, view debt as paying off a fraction of each promised unit of currency in the event of default; but the time of default is now given as an exogenous hazard rate process and does not explicitly depend on the firm's underlying assets. Contrary to the previous approach, the default event is not defined and occurs at a random time. The default time is specified in terms of a hazard rate, within a Poisson process -like environment to describe the idea that the timing of default takes the bond-holders by surprise. These models allow one to derive the term structure of default probabilities from credit spreads, while assuming an exogenous and somewhat arbitrary recovery rate.

The simplest cases is considered in Jarrow and Turnbull (1995) where the recovery rate is constant and the default process is modelled as a jump process and the default time is exponentially distributed. This assumption for the default process achieves two effects. The first is that it removes the dependence on the value of underlying assets, so that the model may be applied to situations where this is not observable. Secondly, it cures a technical problem with models of the Merton type. The assumption of a jump process makes the default time unpredictable and avoids the implausible behaviour of credit spreads for short maturities (Pitts and Selby, 1983) due to the fact that default becomes predictable when the value of the underlying assets approaches the default boundary.

On the other hand, the assumption of a constant default intensity is too simple and effectively imposes the independence of the bankruptcy process from the default-free interest-rate process. The default intensity of a highly rated firm would be expected to be low in the near future, but increase in the distant future as the effects of a possible worsening of the firm's conditions come into play. This is one motivation behind the work of Jarrow, Lando and Turnbull (1997).

Jarrow, Lando and Turnbull (JLT, 1997) model default time as the first time a continuous time Markov chain hits the absorbing state represented by the default event. With enough securities trading one could in principle imply out the relevant parameters of this Markov chain from market prices, but in reality this will be difficult. Furthermore, since there is a lot of empirical data on the transition matrices it would seem natural to use this information. JLT (1997) relied on the transition probabilities reported in Standard and Poor's Credit Review, 1993; the recovery rates were found in Moody's Special Report of 1992 and risk premia were estimated using yield-to-worst data for coupon bonds with varying maturities and credit ratings.

Using credit ratings is a controversial issue since it is debatable to what extent prices react to rating changes. The overall conclusion of Hand, Holthausen and Leftwich (1992) is that there are stock and bond price effects associated to up-and downgrading, but the evidence is mixed. Clearly if ratings are slow to react to information about firms it poses a problem for pricing. A comforting property of the credit ratings is the property of stochastic monotonicity: default probabilities do seem to decrease with better ratings.

A formulation involving credit ratings is necessary for the pricing of credit derivatives. An application of the Markov model, modified to have random recovery rates, can be found in Das and Tufano (1995). Lando (1995) describes default as the first jump time of a Cox process which can be thought of as a Poisson process with a random intensity and it remedies to the problem of deterministic credit spreads –as long as there are no rating changes.

Another early use of stochastic intensity is in Madan and Unal (1995). The intensity is modelled as a function of the excess return on the issuer's equity, and the recovery rate is specified as a random variable independent of the recovery rate process. A key question is whether it is possible to imply out the relevant intensities and the recovery rate from observed market prices. If the recovery rate is zero, intensities can be implied out from market prices under technical conditions (Artzner and Delbaen, 1995). If the recovery rate is not zero, and all one observes is the price of the bond, it is impossible in general to imply the hazard and the recovery rate distribution separately. For other works in which the independence assumption appears in some form, see Johnson and Stulz (1987), Litterman and Iben (1991), and Hull and White (1995).

Intensity based approaches that relaxed the independence assumption, or in other words, that addressed the correlation between default risk and yields on default-free bonds are presented in Duffie and Singleton (1999) and in Duffie, Schroder and Skiadas (1995) using recursive methods and backward stochastic differential equations and in Lando (1994b) using Cox processes. Among many authors, we can mention Madan and Unal (1993), Martin (1997), Nielsen and Ronn (1995), Pye (1974), Schonbucher (1998), and others.

The advantage of this approach is that it allows exogenous assumptions to be imposed only on observables and the derived pricing formulae can be calibrated to market data. The behaviour of the hazard-rate process might be fitted to market data and allowed to depend on firm specific or macroeconomic variables; on the other hand, the default time is not modelled directly in terms of the issuer's incentives or ability to meet her obligations. Also this approach can easily be modified to include credit rating information in the bankruptcy process, and used to price credit derivatives. Moreover, these models are more flexible than the first ones as all parameters may be inferred from market data and, since the default event is a jump-event, credit spreads at short maturities differ from zero.

The main disadvantage is that the hazard rate is not linked to the value of the assets of the firm which allows for the possibility that default will not occur despite very low asset values. Still this approach is difficult to implement in practice, and in some instances, the model calibration yields negative default probabilities. This is because the recovery factors do not only vary over time, but also should be endogenously determined in the model, since the loss incurred by the debt-holders should depend on the value of the firm's assets.

It should be noted that the distinction between the structural approach and the reduced form approach is not clear cut. Models which use the value of the firm could easily be intensity based by describing the value of the firm as a jump process, and intensity based models could easily incorporate the value of the firm by using it as a variable affecting the default intensity. So, perhaps, the distinction could be portrayed also as follows: the structural models typically result in problems similar to those encountered when extending the Black-Scholes model to include American options, dividends, stochastic interest rates, and exotic features; whereas the reduced form models result in setups which more closely resemble term structure modelling. But again, the classification wouldn't be precise.

4.4.4. The middle-way approach

The middle-way approach attempts to combine the two previous approaches. The main aim is to allow for positive credit spreads at short maturities without neglecting the causality of default, which is in relation to the firm's resources. Madan and Unal (1998) model the hazard rate as a linear function depending on the level of the interest rates and the logarithm of the value of the firm's assets. Zhou (1997) models the firm's assets value process by including a jump component. Cathcart and El-Jahel (1998) allow for expected an unexpected default by introducing a stochastic hazard rate that admits a lower boundary at which default becomes a certain event. Duffie and Lando (1998) derive a hazard rate process based on an unobservable value of the firm. In El-Jahel (1998) the boundary of default depends on the level of the discount bond price and the hazard rate depends on the level of the stochastic variable, that is assumed to follow a mean reverting square root process –precluding, hence, the possibility of a negative hazard rate-. Credit spreads generated within this framework will depend on the level of the discount bonds and indirectly on the level of interest rates.

All pricing in this arbitrage-based framework is linear and whether linearity is a feasible approximation to reality is difficult to say. Certainly, if a derivative is a very small part of the firm's operations it may be reasonable to assume that the value of the contract does not really influence the default probability. On the other hand there is the limit that if a bond issue heavily influences the cash-flow of a firm, it may be necessary to include the non-linear effect. Although Modigliani-Miller I claims that firm value does not depend on the method of finance, in the presence of 1) bankruptcy costs (lawyers, agency, underinvestment, reputation); 2) agency costs in terms of the shareholders' incentive to take on risky but not necessarily positive NPV investments; and 3) tax shield effect in terms of a corporate tax advantage to debt and a tax disadvantage to the debtholders, the irrelevance proposition does not hold any longer. Finally, as the models give an arbitrage-based valuation of default risk they can be used to price default risk independently of the risk preferences of investors.

4.4.5. Credit spreads based models

Credit spread models focus on the modelling of the stochastic process driving credit spreads. This approach was introduced by Ramaswamy and Sundaresan (1986). Due to credit risk, corporate bonds will sell at a discount relative to government bonds, the size of which depends on the probability of default, the contractual provisions that define payoffs contingent on default and the premium demanded in the market for similar instruments. Ramaswamy and Sundaresan propose, as instrumental variables, default premia on newly issued instruments with the same maturity and from the same risk class required by investors. Since these instruments are close substitutes for the newly issued risky bonds, it is argued that the premia observed in the market should provide good proxies for the required premium on the risky instrument which has already been trading for some time.

Assuming that both the risk-free and the expected market premium follow a mean-reverting square-root process, the required return differential on default-risky bonds is obtained by solving a valuation equation under a boundary condition. Both the boundary condition and the pricing equation have been criticised. The former as it is not adequate for instruments whose payoff will be reduced by default. The latter as it implies that a risky bond should yield the same return as a newly issued bond of the same type; this is cleary contradictory when applied over the whole life of the instrument.

Solnik (1990) argued that at the time of issue, the spread is added to the risk-free rate to compensate both for the expected capital loss due to default and to provide a higher expected return on a risky bond due to risk aversion and can thus be written as the sum of these two components. If investors could diversify the default risk, risk premia should be expected to be zero but the premium required due to the possibility of default should remain. For the case of risk neutrality, the expected return on the bond should thus be risk-free interest rate. If agents were risk-averse and the risk could not be diversified Ramaswamy and Sundaresan's approach would hold.

Similar in spirit is the approach of Longstaff and Schwartz (1995b) where the risk-adjusted process for the log of the credit spread is modelled as an Ohrnstein-Uhlenbeck process, and the risk-less interest rate is as Vasicek (1977). The model is then used to value credit derivatives.

The limitations of these models that make direct assumptions about the spread is that they are not generally derived by writing down the true process that rates follow and then showing how the no-arbitrage condition may be used to switch this into a risk-adjusted form. Instead, a risk-adjusted process for the spread and a risk-adjusted valuation procedure are simply used. This means that the models are not derived from fundamental assumptions about the default process itself and, as such, the link with the pricing of other securities that depend on this process is necessarily complete. Thus, the models may be viewed as extremely partial relative pricing models which could, in principle, be made consistent with a more general representation of the default process. They do, however, have the merit that they can be parameterised fairly directly to match the actual process followed by credit spreads, thus overcoming a fundamental weakness of many of the other default risk models (see Longstaff and Schwartz, 1995a)

4.4.6. Credit-Rating Models

Rating models are used to identify the risk of default for a counterparty with a *known* current rating. These models use historical default experience to estimate the probability of a change in value of the security resulting from a change in the credit spread as a result from a change in rating (ratings migration) or default. These models also incorporate macro-economic cycles specific default risk as a function of two primary factors: current rating and time to maturity of the obligation.

Rating based models predict two types of default risk:

- Cumulative risk of default - measures the total default probability of a counterparty over the term of the obligation;
- Marginal risk of default - measures the *change* in the default probability of a counterparty over a sequence of time periods.

Note that where a firm or entity is not rated is still possible to utilise rating-based models and statistics. This will usually entail a three-step process. First, the firm's financial data are used to calculate key accounting ratios, which are the same as those computed by the rating agencies. Second, the accounting performance as captured by the ratios is compared with the comparable median for rated firms in both the industry and the universe of rated entities. The comparison is designed to allow a rating equivalent to be determined. Third, based on the theoretical rating, the default probabilities appropriate for that particular rating categories is then utilised.

This approach raises two issues. The default probability is sample specific and there may be significant differences between markets. Moreover, pricing is based on aggregate statistics and issuer level information is lost.

An example of this alternative way of modelling spread behaviour has been pursued by Jarrow et al. (1997) and Fons (1994). This involves characterising rating changes as Markov transitions between categories. With appropriate assumptions, the true probabilities of the transitions may be transformed into risk-adjusted probabilities and used to value contingent payoffs. The weakness of the approach is, however, that ratings categories do not represent homogeneous discrete groups of bonds. There is considerable variation in the credit quality within a rating group, so that this type of model assumes too much discreteness in the structure of creditworthiness.

4.5. The CAPM and credit selection decisions

From a different perspective the analysis of the spread risk involved in corporate bond investing allows one to estimate the fair value of corporate sector spreads. This is the approach of Karagiannis (1994), that shows how the ideas of the CAPM may be profitably applied in credit-selection decisions.

The paper attempts to apply the CAPM to the various sectors of the corporate credit market in order to develop a strategy that capitalises on deviations from equilibrium excess returns. In other terms, a strategy capable of identifying relative value in the corporate credit market is showed to offer investment results superior to those attainable by passive investment in a single sector or mix of sectors. Note that CAPM techniques are infrequently mentioned and used in the fixed-income market, in this way Karagiannis' work is innovative.

A simple comparison of the current with the historical spread in a given credit sector is often used by investment managers to allocate assets and by brokerage firms as an indication of relative value. This analysis is however incomplete if the investment decision does not take into account the risk of investing in a specific sector and its changes over time. Each sector spread is showed to be proportional to the sensitivity of its changes to changes in the market spread. Hence, the risk actually experienced by an investor in a corporate sector involves two sources of risk -the interest rate risk and the spread risk- and the correlation between the two –pronounced for lower ratings. Karagiannis (1994) focuses on the spread risk, which is the most important in the credit-sector selection, and maintains a neutral stance on interest rates.

Changes in credit spreads are derived for January 1974 to December 1992 from the Lehman Brothers Corporate Index data. Changes in each sector's spread are regressed on changes in the corporate market monthly spreads (beta), and for every regression the constant is zero and the beta coefficient significantly positive and increasing as the sector rating declines. Beta represents the volatility in spreads that can be attributed to factors such as default probabilities, economic conditions, perceptions of the credit quality of the sector, supply and demand, and liquidity. A shift in the sector weighting within the overall market would also cause the sector's beta to change.

Differently from the contingent claims-based approach, Karagiannis (1994) uses the average spread over the past three years as a proxy for the theoretical (or fair) value of a sector's credit spread. As the financial markets can be out of equilibrium, and investors can have different expectations, actual spreads can deviate from their theoretical values. A strategy that capitalises on such deviations is developed through a coupon adjustment, so that the total sector fair value is given by the sum of the excess spread (current minus historical sector spread) and the coupon component (sector minus the market average coupon). The former captures only the price-appreciation component; the latter takes into account also the coupon income. The total sector value is plotted against sector beta to identify mispricings.

The sector selection is made by choosing the sector that at the end of the year is undervalued.[11] If no undervalued sector exists they select the sector that offers the best value, provided it's not overvalued. Only one sector is selected each period, as the various credit sectors are highly correlated, and there is hence no benefit to diversifying across the sectors.

The total sector value strategy results are compared with a) the widest spread and no coupon strategy -investing in the sector with the widest spread relative to its historical average-; and b) the widest spread with coupon -based only on identifying sector value regardless of risk-. The total-return strategy results to be the most efficient in a long-term view and as a part of overall allocation within the corporate sector.

4.6. The empirical distribution of credit spread changes

Pedrosa and Roll (PR, 1998) represents the first study focused on a time series analysis of credit spreads and in particular on the empirical distributions of systematic credit spread changes. The data are provided by Bloomberg Financial Services and are daily credit spreads on dollar-denominated bonds, categorised by industry, maturity and rating. PR (1998) provide evidence about the nature of the intertemporal instability of credit spreads and evidence of cointegration among credit spread time series, suggesting that the observed non-stationarity is attributable to common underlying influences.

[11] To determine the optimal rebalancing period, Karagiannis checks to see if the historical evidence indicates reversals in the time series of returns. They chose the minimal holding period for which mean reversion appears. The variance ratio is a statistical test that checks for the presence of trends or reversal in series of price returns. If the ratio equals 1, the series follows a random walk; otherwise trends (Ratio > 1) or reversal (Ratio < 1) are present. The variance ratio of one-year return variance divided by 12 times the one-month return variance is found to be the lower closest to 1.

The distribution of changes in credit spreads exhibits substantial departures from the Gaussian distribution, especially due to high kurtosis. Gaussian mixtures appear to provide reasonably good models for the thick-tailed distributions of credit spread changes. Most credit spreads series behave as if they were generated by two or three distinct regimes that occur randomly on a daily basis.

4.7. Credit spreads and the extreme value theory

Phoa (1999) estimates credit spread risk using extreme value theory, whose applications to financial risk management are relatively recent. The failure of many internal risk management models in occasion of the recent dramatic widening in credit spreads, stressed the importance of correcting assumptions like normal distribution of the innovations and making use of insufficient historical data. The extreme value theory focuses on the estimates of the probability distribution of the maxima or "extreme" events, rather than of the individual events (Embrechts, Kluppelberg, and Mikosch (1997), Adler, Feldman, and Taqqu (1998)). From the Fisher-Tippett theorem, we know that, under mild conditions, one can approximate the probability distribution of the maxima by the distribution of the individual observations. If the latter have a normal or lognormal (leptokurtic) distribution, the maxima will have a Gumbel (Frechet) distribution.

Phoa (1999) shows that the Frechet distribution, consistent with GARCH models of financial time series, works well for the case of the Australian dollar swap spread data. Phoa finds also evidence of the possibility of asymmetric distributions. Extreme spread tightenings are generally greater in magnitude than extreme spread widenings. A possible explanation is that daily spread shifts tend to be negatively correlated with shifts in Treasury yields, and sharp rises in Treasuries yields have been more common than sharp falls. He, then, suggests deriving quantile estimates for spread tightenings separately.

4.8. Conclusions

In this chapter we have seen how many micro and macroeconomic factors have been found to influence directly or indirectly the level of credit spreads. We have also seen showed credit spreads themselves are not constant over time and the reasons for their changes may lie in market supply and demand factors, in federal budget financing needs, or in the outlook of the economy.

Economic conditions have a direct influence on the shape and spread of default risk structures. As economic conditions change, investors may place differing emphasis on the risk of default. In the good economic years, the spreads between the certainty coefficients is small across all payment periods and the decrease in the certainty coefficients with increasing futurity of payment is very small. The opposite is observed in recession periods.

Early studies of the term structure of credit risk note an upward-sloping risk structure for highly rated bonds. Conversely, when credit quality is low, researchers find a downward sloping risk structure. A crisis at maturity model is used to explain this unusual pattern. The crisis at maturity hypothesis assumes that highly leveraged firms with debt maturing over the near term may encounter refinancing problems. The higher default risk associated with debt maturing in the near term is reflected in higher spreads at shorter maturities. More recent theoretical models of credit risk, based on contingent-claims models of debt pricing, take a much more sophisticated approach to this question.

Significant progress has been made in modelling credit risk since the pioneering work of Black and Scholes and Merton. The early models based on underlying asset value are now giving way to models based upon more direct assumptions about the default process. These models can be used to value derivative products that are affected by default risk simultaneously with the default risk itself. Most importantly, they can be parameterised to fit the current structure of prices of risky bonds. Considerable challenges remain, however. The numerical implementation of these models often requires an independence assumption. Either risk-free interest rates are assumed to be independent of the process driving default or the process driving the incidence of default is independent of the write-down in default. Both these assumptions are unsatisfactory.

Another concern is the inability of the models to explain the time-series behaviour of credit spreads or the relative levels of spreads in different parts of the market (Cooper and Mello, 1988). Many of these models cannot generate sufficient time-series variability in the spread to match actual rates. The behaviour of actual spreads is very complex and, as yet, no model adequately captures this complexity (Brown et al. 1994). Unless a model can do this, it will not be useful in determining the relative prices of the new credit derivatives, some of which are extremely sensitive to the time-series properties of the spread.

PART TWO

ALL MISSING PAGES ARE BLANK

IN

ORIGINAL

Chapter V

MODELLING CREDIT SPREADS

5.1. Introduction

Financial institutions around the world are investing heavily in systems for measuring market and credit risks, responding to the request of better information by regulators and investors on one side, and to the internal risk monitoring needed by senior executives on the other side. The need for a deep understanding of credit risk is growing and will be further stimulated by several trends -financial market integration, privatisation, and disintermediation. Credit analysis is also likely to become more complex as new types of securities are continuously created by financial engineering.

As debt markets grow more complex, they are also becoming more volatile. In an environment of increasing economic volatility, the task of forecasting credit risk is becoming more central to investment decisions and more resources will have to be committed to credit analysis. Investors will require access to timely and adequate information regarding the true nature of the credit risk to which they are exposed. This will enable them to take advantage of new opportunities, compare relative risks across new ranges of debt instruments and cross-border debt issuers, maximise yields and diversify investment risk. In brief, a better understanding of credit risk will contribute to stabilise the access to capital markets by helping both issuers and investors.

The traditional credit risk analysis, mainly a "straight ratios-based" analysis, is unlikely to be the answer to the current urgent needs. This type of approach was indeed appropriate when interest rates were stable and investors bought bonds to hold them to maturity. Bonds are nowadays traded with the purpose of making profits on interest rates movements or changes in the absolute or relative credit quality of the issuer. In this new environment a new modern approach is taking place, focusing on changes in the perceived credit risk.

** Part of this chapter is forthcoming in a Special Issue of the Review of Financial Analysis dedicated to Credit Derivatives.

Changes in the credit quality of a firm have been estimated inspecting the counterparty's financial statements, or analysing financial history, historical default rates and rating migrations from similar credit risk. However, financial statements are reports of the past and are therefore inherently backward looking. Moreover, traditional methods of adjusting exposure levels would entail participation in the secondary loan market and boosting credit-asset origination efforts in the relevant markets. Nevertheless, the illiquidity of the loan market, the possibility of damaging the relationship with the client, and the difficulty to originate assets in non-traditional markets, may all in fact make difficult the application of the traditional approaches.

The need to find viable alternatives to old mechanisms for adjusting credit-risk profiles have lead to adapting to credit risk variants of theories and methodologies previously used to address other financial risks. According to this new approach, changes in the market's expectations of default are directly recovered from the observation of price changes or credit spread changes. Alike in previous credit-risk management methodologies, looking at prices or yields that, by their nature, are inherently forward looking, will involve a more quantitative analysis of credit quality characteristics. In particular, credit risk can be measured as the fraction of price volatility that is related to the issuer itself and that differentiates from the price volatility generated by general market movements, namely market (general) risk. Alternatively, credit risk can be measured by credit spreads, which, theoretically, are attributable entirely to the corporation's default option.

This chapter can be considered as a new perspective to analyse credit spreads. Within the credit spreads literature works have so far focused on three main areas: cross-sectional explanation of credit spreads and yield changes, specification of the risk structure of credit spreads, and valuation of risky debt. By contrast, we will follow a time series approach. In fact little is known about the forces driving credit spread changes and volatility. Moreover, we think that the identification of a process that describes the dynamic evolution of credit spreads is of great interest both to practitioners and academicians and needs to be explored more deeply. Specifically, we apply our analysis to the sterling Eurobond market and in particular we intend to identify what macroeconomic and financial factors have driven changes in the sterling Eurobond credit spreads in the period from January 1991 through May 1999. To our knowledge this is the first study of its kind on the Eurobond market.

One way of posing this issue will be to ask whether changes in credit spreads reflect economic fundamentals, or whether they represent a self-generated force bearing little relation to fundamentals. Credit spreads, like default rates, have shown to be not constant over time and there is general agreement on the direct impact that the state of the economy has on them. A report by Standard and Poor's (1997) states that "*A healthy economy in 1996 contributed to a significant decline in the total number of corporate defaults. Compared to 1995, defaults were reduced by one-half...*". Another report by Moody's Investors Service (1996) argues that "*The sources of [default rate volatility] are many, but macroeconomic trends are certainly the most influencial factors*". We, therefore, expect credit spreads to adjust as general macroeconomic and regulatory variables, business environment, conditions in firms' factor, and output markets unexpectedly change altering firms' credit outlooks.

The remainder of the chapter is structured as follows. Section 2 presents an overview of the literature of credit spreads. Section 3 describes the data and extensively presents the time series properties of credit spreads. An appropriate model to explain the behaviour of changes in credit spreads is derived and estimated in Section 4. Section 5 summarises and concludes the main findings of the chapter.

5.2. Literature Review

As mentioned in the previous section, the main studies and key findings related directly or indirectly to credit spreads have so far focused on three main areas: a) explanation of credit spreads; b) specification of the risk structure of credit spreads; c) valuation of risky debt.

Most works focused on the determinants of bond yields and yield premia -obtained by subtracting from the corporate bond yield the yield observed on a risk-less security of the same maturity- use cross-section regression analysis to determine the variables significant in explaining credit risk premia. The most common factors are: i) proxies for the default risk -earnings variability, time of no default, market equity value over par value of debt- (Fisher, 1959; Boardman and McEnally, 1981; Nielsen et al.1993; El-Jahel, 1998); ii) supply and demand factors (Fair and Malkiel, 1971); iii) bond specific features -callability, marketability, coupon rate, sinking fund, security status, recovery factor, industrial classification- (Fisher, 1959; Silvers, 1973; Duffee, 1998; Boardman and McEnally, 1981); iv) actual default rates (Fons, 1987); v) returns on the firm's assets (Longstaff and Schwartz, 1995); vi) firm's capital structure (Leland, 1994); vii) business cycle and confidence variables –consumer sentiment, returns on stock indices, industrial production, inflation, unemployment- (Jaffee, 1975; Longstaff and Schwartz, 1995; Fons, 1987) and viii) interest rate variables –short- and long-term rate, term spread, interest rate volatility and expectations- (Mella-Barral and Tychon, 1996; Fons, 1994; Kim et al., 1995; Duffee, 1998).

Another large part of the literature deals with the term structure of credit spreads. The idea underlying the risk structure of credit quality is that spreads on corporate bonds vary with maturity, *ceteris paribus*. The idea reflects factors such as the crisis at maturity and the pattern of marginal default risk. The crisis at maturity hypothesis assumes that highly leveraged firms with debt maturing over the near term may encounter refinancing problems, which is reflected in higher spreads at shorter maturities. The marginal default risk is observed to increase with maturity for higher rated firms and decrease with maturity for lower rated firms (Fons, 1994). This pattern is consistent with two strongly linked observed phenomena: the mean-reverting process in credit quality and the life cycle of ratings outlook. Most theoretical and empirical works infer that high quality firms are unlike to default in the short term. Over the longer term, however, they may experience credit quality deterioration or ultimately default. Middle-rated firms tend to maintain their rating, and lower quality firms while facing immediate prospect of default, they are likely to overcome their state of financial distress in the long period. From the credit quality mean-reverting feature the life cycle of ratings outlook can be inferred and explained in terms of different shapes of the term structure of credit spreads. Specifically, the term structure of credit risk is upward-sloping for highly rated bonds, hump-shaped for middle-rated firms, and strictly declining for low-rated firms (Johnson, 1967; Merton, 1974; Kim et al., 1995; Sarig and Warga, 1989; Jarrow, Lando and Turnbull, 1997). Nielsen et al. (1993) and El-Jahel (1998) extend previous works showing how the term structure of credit risk is highly sensitive to changes in the volatility of the firm's assets. Mella-Barral and Tychon (1996) illustrate how differences in the parameterisation of the event of default affect not only bond valuation, but also the implied term structure of credit spreads. Helwege and Turner's (1999) investigation provides some empirical support for the practitioners' view of an upward-sloping credit yield curve for most speculative-grade firms.

The third approach of the literature concerns the valuation of risky debt. The basic idea underlying risky bond pricing models is that the inherent credit risk of any credit transaction should be compensated by a return (calculated as the spread received) commensurate with the risk of default (both on expected and unexpected losses), the credit exposure, and the recovery rate in the event of default. Models for valuing defaultable bonds have developed and significant progress has been made in modelling credit risk since the pioneering work of Black and Scholes (1973) and Merton (1974), both based on option theory. A number of papers (*proprietary models*) have used and extended the option-based approach and removed in turn some of its strong assumptions. Geske (1977) extends the analysis to risky coupon bonds that have a finite time to maturity and discrete coupon payments. Black and Cox (1976) extend Merton (1974) to the study of safety covenants, subordination arrangements, and limits on the financing. Brennan and Schwartz (1977) model convertible debt with stochastic interest rates. Mason and Bhattacharya (1981) study the firm value as a discontinuos process and with complex boundary conditions. Turnbull (1979) extends the Merton's model to an economy with both corporate tax and bankruptcy costs. On the same line is the work by Leland (1994) which involves notions of optimal capital structure. Cooper and Mello (1991) and Rendleman (1993) apply Merton's model to the valuation and analysis of risk sharing in swaps with default risk.

The subsequent literature on defaultable bond pricing has taken two approaches: the structural approach and the reduced form approach. *Structural models* (or models based on the value of the firm) specify a particular firm value process and assume that default is triggered when firm value hits some specific threshold. The latter is typically a function of the amount of bond outstanding. In these models bankruptcy is allowed to occur at a random time and the causality of default is directly linked to information on the asset of the firm –the total value of the firm's assets is employed as the economic fundamental. This approach is used in Hull and White (1995), Longstaff and Schwartz (1995), Kim, Ramaswamy and Sundaresan (1992) and Nielsen, Saa'-Raquejo, and Santa-Clara (1993).

In *reduced form models* or intensity based models, alike in structural models, the default process is directly specified and is represented by a Poisson or "jump" process –to describe the idea that the timing of default takes the bond-holders by surprise- not explicitly depending on the firm's underlying assets. The default event is not defined and occurs at a random time and an exogenous and somewhat arbitrary recovery rate is assumed. The simplest model is presented in Jarrow and Turnbull (1995) where the recovery rate is constant, the default process is modeled as a jump process, and the default time is exponentially distributed. Jarrow, Lando and Turnbull (1997) model default time as the first time a continuous time Markov chain hits the absorbing state represented by the default event. An application of the Markov model, modified to have random recovery rates, can be found in Das and Tufano (1995). Lando (1995) describes default as the first jump time of a Cox process which can be thought of as a Poisson process with a random intensity. Another early use of stochastic intensity is in Madan and Unal (1995) where the intensity is modeled as a function of the excess return on the issuer's equity, and the recovery rate is specified as a random variable independent of the recovery rate process. Although this class of models is widely used in practice because of its analytical tractability, the abstraction from the underlying firm value makes it less useful for suggesting determinants of credit spreads.

It should be noted that the distinction between the structural approach and the reduced form approach is not clear-cut. Models which use the value of the firm could easily be intensity based by describing the value of the firm as a jump process, and intensity based models could easily incorporate the value of the firm by using it as a variable affecting the default intensity. A summary review of the default risk literature is contained in Sundaresan (2000), where the various models are compared and their impact in the industry discussed.

Alongside the literature on corporate credit spreads a number of papers have focused on government and emerging market credit spreads. As it is beyond the scope of this work to analyse directly the empirical evidence on credit spreads in these markets, we briefly present the main line of research in this area. Globalisation, country performance variables (GDP growth, per capita income, inflation, external and internal balance, etc.), currency denomination, rating, default history, and maturity have been the explanatory variables generally investigated to explain sovereign spread changes. However, the role of industrial countries short-term interest rates and its linkage with government spreads has received most of the attention. The presence of a positive relationship between interest rates and credit spreads is generally explained either in terms of a creditworthiness effect or through the "appetite for risk" hypothesis. Kamin and von Kleist (1999) find little evidence of a short-term relationship between industrial country interest rates and emerging market bond spreads. This result confirms findings in previous works: both the long-term US Treasury bond interest rate (Cline and Barnes, 1997) and the short-term US Treasury bill rate (Min, 1998) are found to be positively but not significantly related to credit spreads on new bond issues.

Much work has been done in the credit risk field, but considerable challenges remain. The numerical implementation of the models described above often requires unsatisfactory assumptions on the independence between the risk-free interest rate and the process driving default. Another concern is the inability of the models to explain the time-series behaviour of credit spreads and the relative level of spreads in different parts of the market (Cooper and Mello, 1988). Moreover, most of these models cannot generate sufficient time-series variability in the spreads to match actual rates. Concluding, the behaviour of actual spreads is very complex and, as yet, no model adequately captures this complexity (Brown et al. 1994). Unless a model can do this, it will not be useful in determining the relative prices of new credit derivatives, some of which are so extremely sensitive to the time-series properties of the spreads.

5.3. Time series properties of credit spreads

5.3.1. The Data

We focus on the Eurobond market, which, we believe, has not received by the academic financial literature the attention commensurate with its size and importance. In particular, we model credit spreads on the ISMA sterling Eurobond index, which is a market-value weighted, redemption yield index of straight Eurobonds, calculated by ISMA Ltd, London, from December 31, 1990, and made available on a daily basis through Datastream International. The daily data set extends from December 31, 1990 to May 26, 1999 for a number of 2193 observations and includes such extreme events as the European exchange rate mechanism crisis in 1992.

ISMA indices are provided for three different life-to-maturity bands: over 1 year –i.e. all maturities-, 1 to 5 years and over 5 years. We decided to use the index associated to the larger maturity band. The rationale underlying our choice was to match as much as possible the maturity of the Eurobond index with the maturity of the UK-government bond index used as a benchmark. Both indices are indeed characterised by an average life to maturity of 10 years.

Though this index suffers from the aggregation problem typical of index data. It is an aggregate of bonds of different maturities, coupons, and credit ratings. In order to maintain the desired characteristics of the index it is periodically adjusted causing discontinuity in the data series. We are therefore aware that the results and statistical properties of the data that we detect later on may be affected by the shifting composition of the index. Despite these pitfalls, we believe that ISMA is a very reliable source of data and they used the best procedure to build this index, which we briefly present.

The bonds used in calculating the index are selected once a month for inclusion throughout the following month. The universe of bonds from which the selection is made consists of those bonds for which ISMA has adequate prices on the last Friday of the month. An adequate price is a price averaged from a minimum number of market makers with a maximum price spread. Bonds must be fixed rate "bullet" bonds. That is, they must not have a sinking fund or a call or a put option. Bonds will be rejected if: i) they have special features, for example dual currency options and index linking; ii) they are partly paid, in default; iii) they have a maturity yield vastly different from other bonds in the same category; iv) they are new issues, and the closing date is after the end of the month; v) they are fungible into another bond before the end of the next month; vi) zero coupon bonds are also rejected because they yield less than conventional bonds of similar duration.

Table 5.1 shows the general composition of the ISMA Eurobond index. Eurobonds included in the index and issued in the period 1992-1999 have been classified according to the country (or origin) of the issuer, the issuer credit rating, and the issue credit quality. Over the 8-year period, on average 59 percent of the total volume of new issued and outstanding Eurobonds was from UK, 16 percent from a European country, 6 percent from USA, Canada and Latin America, and 5 percent from Japan, Asia and Oceania. The share of UK borrowers in total issuance has fallen over time, while European and USA borrowers have increased their participation in the Eurobond market. As far as the maturity structure of the Eurobonds is concerned, 32 percent are characterised by a life to maturity between 7 and 10 years, 26 percent between 3 and 7 years, and 20 percent between 20 and 30 years. Most important is the average credit rating of the index. Specifically, AAA- and AA-rated bonds constitute on average 40 and 42 percent, respectively, of the total market value of the issues. The stake of most creditworthy borrowers (AAA) has not revealed any trend over the period, while AA-rated bonds are characterised by a decreasing trend alongside with an increasing trend for the A-rated bond fraction. As we expected the quality of the bonds in the sample is generally high. The investment-grade bias reflects the fact that issuers traditionally need to be a high credit standing to be able to raise capital in the Eurobond market, together with a regulatory bias (Dale and Thomas, 1991). Our analysis will benefit from this feature in the sense that yields on investment-grade bonds will have relatively more of their volatility attributable to credit spread movements than sub-investment grade credits, which will be primarily driven by potential company-specific default events.

Credit spreads (CS) are defined as the continuously compounded yield differencial between the ISMA index and the UK long-term (10 year) government bond index. The latter is provided by Datastream too[12]. From Favero et al. (1996) we know that the simple difference between rates (discrete time compounding) is affected by the *level* of the reference rate. This argument might be termed as the "mathematical" effect and in our case it implies that credit spreads would be an increasing function of the level of the benchmark index yield. In the simplest case of two one-period interest rates, r^{EB} and r^{TB}, which are the rate on a risky instrument (with probability of being repaid $p<1$) and the rate on a safe instrument, respectively, in equilibrium the following equality holds:

[12] The Datastream codes for the ISMA index and for the Benchmark index are respectively: ISMSTG5(RY) and BMUK10Y(RY). The datatype RY stands for gross redemption yield and is a good approximation to the average yield of a portfolio. The RY of the index is obtained by weighting the individual bond yields by the size of the holding multiplied by the duration.

	1992	1993	1994	1995	1996	1997	1998	1999
Panel A: Origin of Issuer								
UK	69%	68%	62%	59%	61%	54%	51%	50%
Euro	12%	14%	16%	17%	17%	19%	18%	18%
Non-Euro	1%	1%	2%	2%	1%	1%	2%	1%
Japan, Asia & Oceania	6%	5%	5%	6%	5%	5%	4%	4%
USA, Canada & Latin America	3%	3%	4%	4%	3%	8%	10%	10%
Other Internationals	8%	9%	11%	13%	12%	14%	16%	18%
Panel B: Maturity Structure								
[0, 3)	-	-	-	-	-	3%	11%	16%
[3, 7)	-	4%	14%	21%	32%	46%	37%	30%
[7, 10)	43%	46%	42%	39%	29%	19%	20%	18%
[10, 15)	9%	14%	17%	12%	11%	8%	6%	8%
[15, 20)	15%	9%	9%	9%	10%	8%	8%	6%
[20, 30)	33%	27%	17%	18%	18%	13%	11%	19%
> 30	-	-	1%	1%	1%	3%	6%	3%
Panel C: Rating								
AAA	39%	40%	37%	39%	34%	42%	46%	44%
AA	48%	47%	48%	45%	47%	37%	32%	29%
A	12%	13%	14%	15%	17%	20%	20%	21%
BBB	-	-	-	-	-	1%	-	4%
BB	-	-	-	1%	1%	-	-	1%
B	-	-	1%	1%	-	-	1%	1%
Panel C: Industry								
FINANCIAL	37%	45%	45%	45%	46%	47%	45%	45%
GOV & SUPRANATIONALS	13%	14%	17%	17%	17%	18%	20%	21%
INDUSTRIAL	43%	35%	31%	31%	32%	28%	27%	26%
PAUT & ABS	7%	5%	5%	5%	4%	6%	6%	5%
Other	0%	1%	1%	1%	1%	1%	2%	2%

Table 5.1 *ISMA Eurobond Index composition over time, 1992-1999.*

The ISMA Eurobond Index has been broken down by country of the issuer, maturity of the issue, and credit rating of the issuer. The data are expressed as percentages of the total market volume of Eurobonds issued in the respective year.

$$(1+r^{TB}) = p(1+r^{EB}) + (1-p)0, \tag{5.1}$$

from which we can derive the formula for the spread as

$$r^{EB} - r^{TB} = (1+r^{TB})(1-p)/p \tag{5.2}$$

As long as p<1, increases in the risk-free interest rate lead to an increase in the amount that has to be repaid by the risky borrower. However, as it is not certain that the risky borrower will be able to repay its additional debt, the yield on the risky instrument must rise more than proportionately respect to the safe instrument. Hence an increase in the risk-free rate is likely to raise the spread only for "mathematical" reasons (Kamin and von Kleist, 1999).

To eliminate the mathematical effect and the effect of discrete time compounding, credit spreads are converted to become continuous compounding by the transformation:

$$cs_t = ln(1+r^{EB}) - ln(1+r^{TB}) \tag{5.3}$$

and changes in credit spreads at time *t* are defined as:

$$dcs_t = cs_t - cs_{t-1}, \tag{5.4}$$

with t = 1, 2, ... , 2193 days.[13]

Note, however, that despite the fact that credit spreads are obtained by subtracting a risk-less rate of interest from a yield on a corporate bond, they are not a spread that is the result of the interaction between two assets. In fact, in the remainder of the chapter credit spreads will be considered an independent financial asset.

5.3.2. Credit Spreads Stylised Facts

In this section we will look at the time series pattern of both credit spread levels and changes. Figure 5.1 plots credit spread levels over the entire sample period. We can recognise a rather cyclical behaviour over the period with a decreasing trend from the beginning of 1991 to the end of 1992. From 1997 the series appears to trend steeply upward until the end of 1998 and then stabilise around the same mean level it had experienced before 1992.

---

[13] Note that the natural logarithm specification is generally preferred as it captures the nonlinear relationship between yields and ratings (Kan, 1998; Cantor and Packer, 1996; and Kamin and von Kleist, 1999).

Figure 5.1 plots also credit spread changes over the same sample period and shows credit spread volatility fluctuations over time. Credit spread volatility appears high at the end of 1992 and in 1994, and very high from late 1998. In addition, from the plot of the absolute changes in credit spreads (Figure 5.1), it emerges that large absolute changes are more likely than small absolute changes to be followed by a large absolute change. The evidence of volatility clustering suggests that a suitable model for the data should capture this time varying volatility structure.

It is worth focusing for a while on the recent remarkable rise in volatility observed after May 1997, when the Thai baht was subject to severe speculative attacks and finally devaluated. The crisis subsequently spread to other emerging and developed markets. Until July 1998 –Russia's financial crisis- however, the mature financial markets in the United States and Europe were generally buoyant and little affected by the Asian crisis. However, the crisis in Russia sparked a broad-based reassessment and repricing of risk, especially regarding emerging market investments, and a large-scale of portfolio rebalancing across a range of global financial markets. We can therefore explain the reflection of the Asian crisis on the Eurobond market in terms of "contagion" effect. As the crisis was worsening, the global credit crunch caused by investors' loss of appetite for risk began to drive up the yield spreads in the whole fixed-income universe, apart from the treasury markets of the strongest economies. The crisis was to a large extent a liquidity shock rather than a real credit event, especially for highly rated firm. One way to validate this hypothesis is to look at spreads within the Treasury bond market. Clearly default is not an issue here since the spread is generated by the extremely strong demand for liquidity. In other words, the huge credit spread widenings in the last two years is mainly due to the large fall in the government bond yields rather than to a rise in actual borrowing costs.

Main descriptive statistics for the CS series are presented in Table 5.2. Credit spreads present positive skewness (sk = 2.035), and since price changes present skewness in the opposite direction than that of yield changes, positive credit spreads skewness implies that the left tail of the loss distribution (for a long position) contains more probability than a normal one. Credit spreads are also leptokurtic (k = 7.734) and therefore characterised by a fairly large likelihood of small credit spreads, coupled with a small chance of large credit spreads. This is in line with the specific feature of credit risk to be subject to small frequent variations and rare large variations. Table 5.2 reports also various descriptive statistics for the series in differences, dCS. The series while is roughly symmetrically distributed, it presents fat tails (k = 8.79). Summarising, credit spread levels and changes present signs of the typical fat-tailed behaviour and in both cases the Jarque-Bera χ^2 statistic for the null hypothesis of normality is far beyond the critical value at the 1 percent level, which suggests that the two series are far from a normal distribution. The significant deviation from normality can be a symptom of dependence or nonlinear dynamics (Fang et al. 1994). Before going into any further discussion, we have first to identify the process generating credit spreads.

5.3.3. The Variables

As the risk of a change in credit quality varies over time, we collected a set of variables in order to test for their correlation and influence on the time series of Eurobonds credit spread levels and changes. Since the credit spreads we are using are computed on an index, we expect them to be affected mainly by financial and macroeconomic variables, rather than by firm-specific factors. We present the variables below.[14]

- R^{FTSE} and DY^{FTSE} are the return and the dividend yield series on the FTSE All Share index, respectively. The former is a proxy for the economic confidence and we would expect credit spreads to narrow as R^{FTSE} increases. The correlation of credit spreads to equity indices is consistent with the Black and Scholes model (Black and Scholes, 1973) of firm capital structure.

The higher the leverage of the firm (larger CS), the lower is the positive difference between the value of the firm and the value of the bonds, and in turn the lower correlated are changes in bond value and in the risk-free bond values. Moreover, while considering constant the firm's probability of default, changes in credit spreads may occur due to changes in the expected recovery rate. The expected recovery rate, in turn, is likely to be a function of the general business climate (Altman and Kishore, 1996). As a result, in a poor economic climate investors will move to a more conservative credit risk exposure (*flight to quality*), and credit spreads will widen. Following the same logic, we expect credit spreads to narrow in periods of boom. As far the DY^{FTSE} is concerned, we expect a positive relation with credit spreads. Increases in the dividend yield make indeed the equity market more as a yield-bearing investment.

[14] All the variables are available from Datastream International.

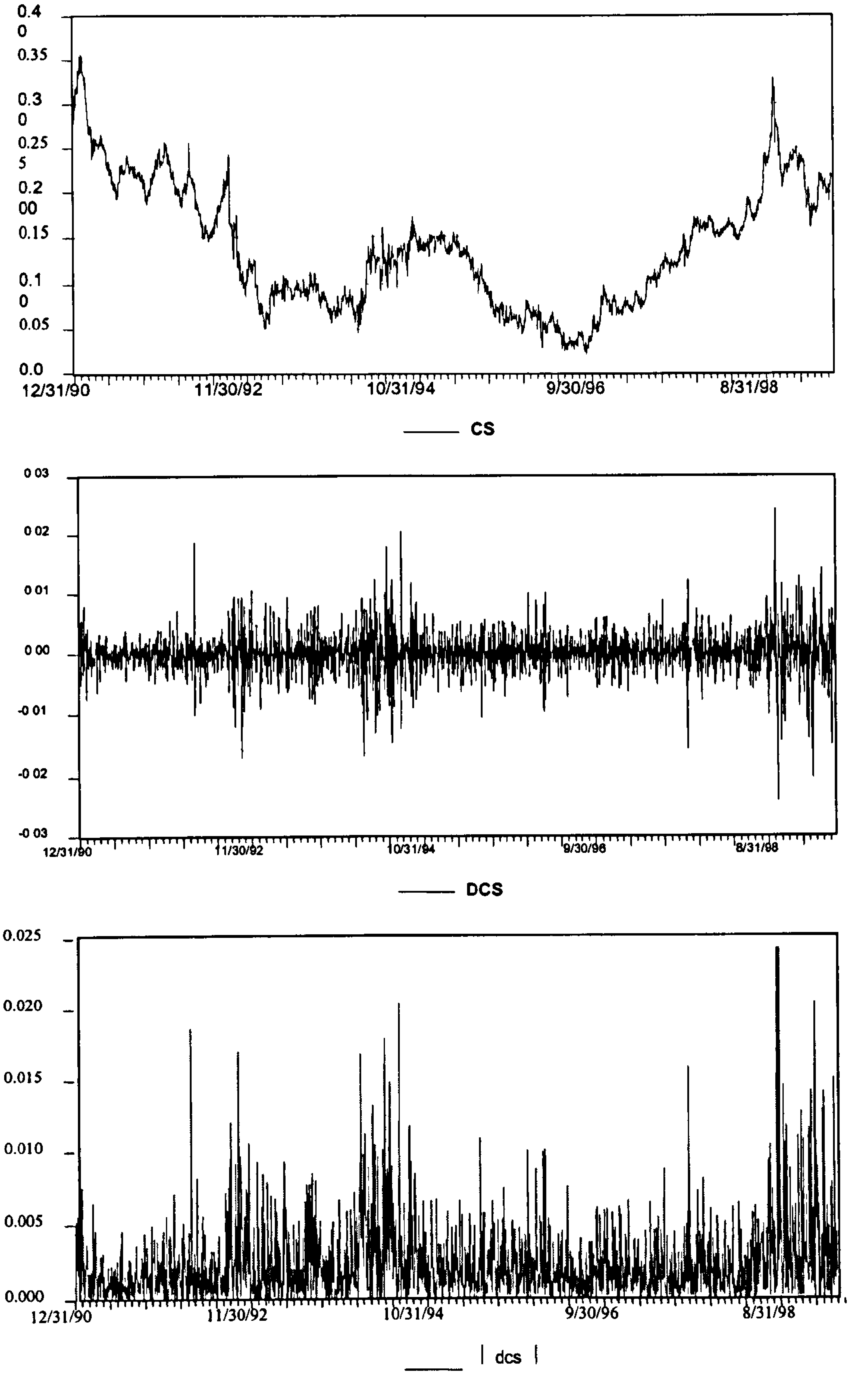


Figure 5.1 *Time Series of Daily Credit Spread Levels, Changes and Absolute Changes*

Credit spreads, defined as the continuously compounded yield differencial between the ISMA Eurobond index and the UK long term (10 year) government bond index, are plotted over the period from 31/12/1990 to 26/5/1999. The time series pattern is also presented for credit spread changes and absolute changes, over the same sample period.

	Mean	*Median*	*Max*	*Min*	*St. Dev.*	*Skewness*	*Kurtosis*	*N*
CS	.074 (3.083)	.070	.199	.039	.024	2.035	7.734	2193
ΔCS	.000027 (0.007)	.000	.024	-.024	.004	-.070	8.791	2192
ΔDOLLAR	.000 (0.000)	.000	.047	-.061	.010	-.337	6.948	2192
ΔSHORT	-.004 (-0.054)	.000	.531	-.844	.074	-2.392	36.61	2192
ΔLONG	-.003 (-0.048)	-.001	.333	-.556	.063	-.065	8.383	2192
ΔTERM	.001 (0.011)	-.001	.756	-.775	.093	.524	15.75	2192
R^{FTSE}	.001 (0.125)	.000	.059	-.035	.008	.156	6.794	2192
$RY^{EUROBOND}$	8.381 (5.298)	8.410	11.89	5.100	1.582	-.009	2.460	2192
ΔMARK	.000 (0.000)	.000	.055	-.110	.013	-.509	7.856	2192
ΔLT_DY	.000 (0.000)	.000	.125	-.106	.018	-.081	6.885	2192
ΔDY^{FTSE}	-.001 (-0.032)	.000	.180	-.280	.031	-.677	1.26	2192

Table 5.2 *Unconditional Daily Distributions*

The table summarises the daily distributions of the main variables. The sample covers the period from January 1, 1991 through May 26, 1999, for a total of 2193 observations. Yields on the Eurobond Index are from ISMA Ltd. All the other data are from Datastream International. T-statistics are presented in paretheses.

- *SHORT* and *LONG* are the interest rate on the 3-month Treasury bill and the redemption yield on the UK government bond index with 15 years life to maturity, respectively. While the short-term interest rate should reflect the stance of monetary policy and hence the country (UK) liquidity, the long-term interest rate should capture the expectations of future UK inflation. If we consider a corporate bond as being equivalent to a portfolio composed of a risk-free asset and a short position in a put option on the value of the firm (Merton, 1974), a rise in the default-free rate of interest would reduce the value of the put option that bondholders have granted to shareholders. This, in turn, increases the value of corporate bonds and reduces their yield.

Longstaff and Schwartz (1995) reach the same conclusion pointing out that the static effect of a higher spot rate is to increase the risk-neutral drift of the firm value process. A higher drift reduces the incidence of default, and in turn, reduces the credit spreads. From the demand and supply perspective, a decline in interest rates may cause the supply of corporate bonds to increase which lowers their price and hence raise their spreads. On the other hand, a positive relationship between interest rates and credit spreads may be explained in terms of a creditworthiness effect and through the "appetite for risk" hypothesis. According to this hypothesis, an increase in the interest rates increase the debt burden by borrowers, thereby reducing their ability to pay and lowering their creditworthiness. Moreover, in front of a general reduction in interest rates investors will enhance portfolio returns by increasing their risk exposure, the demand for corporate and higher yield bonds will raise and credit spreads in turn will narrow. The final and net impact of interest rate changes on spreads is therefore a matter of empirical evidence. A weak but significant negative relationship between changes in credit spreads and interest rates is found by Duffee (1998) on a sample of non-callable bonds. A negative short-term relationship is also found in Morris, Neal and Rolph (1998) and Bevan and Garzarelli (2000) who explain that in the short-term spreads narrow because a given rise in Treasuries produces a proportionally smaller rise in corporate rates. However, cointegration analysis shows that over the long run this relation is reversed.

- *TERM* represents the term spread, calculated as the difference between the long-term interest rate and the three-month interest rate (LONG-SHORT). The slope of the Treasury yield curve is a proxy for the real interest rate risk. This measure has been used in many bond and interest rate studies (see Clare et al. 2000, Nelson and Schaefer, 1983). If the short rate dynamics depend upon the long rate (Brennan and Schwartz, 1979), we can here extend the logic of Longstaff and Schwartz (1995). If the short rate is expected to mean-revert to the long rate, then an increase in the slope of the Treasury curve should increase the expected future short rate, again leading to a decrease in credit spreads. From a different perspective, we would expect the flattening of the benchmark curve imply a weakening economy on one side and a steepening of generic and individual issuer yield curve on the other side. Moreover, the expected recovery rate might decrease in times of recessions and corporate investors presumably would demand a higher risk premium (more long spreads) to extend the maturity from 10 years to 30 years with a flatter underlying yield curve. All these factors therefore support a negative relationship between credit spreads and the slope of the Treasury yield curve.

- *LT_DY* is the bond to equity yield ratio. Specifically, it is the ratio of the yield on UK long-term government bonds to the dividend yield on the FTSE All Share index. This has been formalised for the UK equity market in a predictive time series sense by Clare, Thomas and Wichens (1994) and as a macroeconomic-financial source of risk priced in the UK equity market by Clare and Thomas (1994). From this perspective, the ratio can be interpreted as reflecting a substitution effect between the bond and the equity markets within the current economic-financial outlook. In an increasingly risky environment, we expect investors to move from the equity to the gilt market, and for demand and offer laws bond prices will rise, lowering credit spreads. As a result a negative relationship is likely to be observed between the two variables.
- *DOLLAR* and *MARC* are the US dollar and German mark to UK sterling exchange rates, respectively. They are a measure of the relative strenght of the UK sterling and are expressed as US dollars or German marcs per unit of sterling. Since the bonds pay UK sterling, the stability of the exchange rate helps to support the sterling Eurobond market by limiting the currency risk faced by overseas borrowers. Moreover, in the event of an increasing strenght of the sterling, overseas issuers will face a higher price of their debt. This heavier debt burden might compromise their ability to repay the debt and their creditworthiness, raising the bond yields. We would therefore expect an increase in the exchange rate to lead to a widening of credit spreads. The existence of a relationship of this kind is supported by Clare et al. (2000), where a positive risk premium on Eurodollar bonds is found attached to the rate of change in the US effective exchange rate.

Descriptive statistics for the variables discussed above are presented in Table 5.2. We can generally see that most of the variables in differences present means not statistically different from zero. However, despite low skewness values, the unconditional distributions of all series show high kurtosis, and are therefore non-normal.

Table 5.3 presents the correlations between credit spreads and the financial variables presented above. Credit spreads are significantly and positively correlated with changes in credit spreads and with the exchange rate against the dollar. The higher the exchange rate, that is the stronger the sterling, the larger the credit spreads. Moreover, credit spreads are strongly negative correlated with the term spread and with the long-term rate, but positively correlated with the short-term interest rate level. Finally a negative correlation is measured against the dividend yield of the FTSE All Share Index; while credit spreads are positively correlated with the FTSE All Share Return index and the long-term interest rate to dividend yield on the FTSE All Share Return index ratio.

Table 5.3 presents also correlations for credit spread changes. We can see how changes in credit spreads are negatively correlated with changes in the interest rate variables –especially high is the correlation coefficient with changes in the term spread and in the long-term interest rate. Positive correlation is found with the return on the FTSE All Share index. Finally negative correlation is observed with changes in the long rate/dividend yield ratio and with changes in the dividend yield of the FTSE All Share index.

	CS		DCS
ΔCS	0.083** (0.00) N=2191	CS	0.083** (0.000) N=2191
DOLLAR	.230** (0.00) N=2193	ΔDOLLAR	-.032 (0.148) N=2191
PRICE^{FTSE}	.357** (0.00) N=2193	R^{FTSE}	0.161** (0.00) N=2191
DY^{FTSE}	-.171** (0.00) N=2193	ΔDY^{FTSE}	-.161** (0.00) N=2191
LONG	-.445** (0.00) N=2193	ΔLONG	-.676** (0.00) N=2191
LT_DY	-.672** (0.00) N=2154	ΔLT_DY	-.474** (0.00) N=2152
SHORT	.122** (0.00) N=2193	ΔSHORT	.009 (0.674) N=2191
TERM	-.577** (0.00) N=2193	ΔTERM	-.462** (0.00) N=2191

Table 5.3 *Bivariate Unconditional Daily Correlations*

Bivariate correlations between CS and ΔCS and basic financial variables are computed and measured as Pearson's correlation coefficients with their significance levels in parenthesis. Note: **, * Correlation is significant at the 0.01 and 0.05 level, respectively (2-tailed).

5.3.4. Autocorrelation Structure

We proceed now to explore the time-series properties of credit spreads employing the Box and Jenkins (1976) methodology for appropriate model selection. In a first step, identification stage, we address the question of dependence in credit spreads. Since a series cannot be independently distributed if any of its autocorrelation coefficients are non-zero, we compute the autocorrelation function (ACF) of CS and dCS series followed by tests that the serial correlation coefficients are zero. The pattern of autocorrelations and partial autocorrelations (PACF) is also important in indicating the plausible structure and nonlinear dynamics of the CS process.

In Panel A of Table 5.4 we present the sample autocorrelations from lag 1 to 5 and 10, 20, 40, 70 and 100 for CS, $|CS|$, and $(CS)^2$. In addition, the autocorrelogram of CS, $|CS|$, and $(CS)^2$ from lag 1 to lag 100 is plotted in Figure 5.2 with the dotted lines representing the 95 percent confidence interval for the estimated sample autocorrelations if the CS process was independently and identically distributed (*i.i.d.*). The sample correlogram shows a smooth decay for the CS series, and the sample partial correlogram in Figure 5.3 shows two significant spikes in correspondence of the first two lags, suggesting a simple second-order autoregressive model. The first lag autocorrelation for CS is 0.988, which indicates the presence of a unit root for credit spreads.

Panel B in Table 5.4 exhibits the sample autocorrelations for dCS, $|dCS|$, and $(dCS)^2$, and the autocorrelograms of dCS, $|dCS|$, and $(dCS)^2$ are plotted in Figure 5.2. Firstly, we note that about one sixth of the sample autocorrelations within lag 100 are outside the 95 percent confidence interval. Secondly, if dCS was as an *i.i.d.* process then any transformation of it should also be an *i.i.d.* process. In other words, if the dCS series had a finite variance, then the standard error of the sample autocorrelations of $|dCS|$ would be still within the confidence interval and the same standard error would be applicable for the sample autocorrelations of $(dCS)^2$, providing that CS has also finite kurtosis. From Figure 5.2 it emerges that not only most of the autocorrelations of $|dCS|$ and $(dCS)^2$ are outside the confidence interval, but also that they are all positive, which suggests that dCS^2 series might be characterised by a long-term memory structure. In other words, the dependence between close observations may not necessarily be stronger than that one between distant observations, or the most recent market information may not necessarily be more useful than past information.

	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_{10}	ρ_{20}	ρ_{40}	ρ_{70}	ρ_{100}	Q(5)	Q(20)
Panel A												
CS	.988	.983	.977	.971	.965	.940	.879	.776	.719	.547	10482	38624
											[.00]	[.00]
|CS|	.988	.983	.977	.971	.965	.940	.879	.776	.719	.547	10482	38624
											[.00]	[.00]
CS²	.989	.982	.974	.965	.956	.924	.839	.713	.689	.471	10409	37126
											[.00]	[.00]
Panel B												
ΔCS	-.32	.024	.007	.019	-.006	.040	.025	-.002	.013	-.009	227.33	259.59
											[.00]	[.00]
|dCS|	.323	.179	.191	.142	.127	.133	.107	.098	.087	.002	46.28	1098.8
											[.00]	[.00]
ΔCS²	.237	.121	.169	.085	.078	.095	.075	.061	.064	-.001	247.51	578.65
											[.00]	[.00]
Panel C												
ε	-.003	-.002	-.004	.021	-.024	.043	.015	-.025	.01	.001	2.27	31.22
											[.81]	[.05]
$\|\varepsilon\|$	.212	.179	.189	.138	.118	.149	.101	.081	.076	.005	319.73	886.54
											[.00]	[.00]
ε^2	.135	.131	.172	.081	.052	.116	.057	.048	.036	.001	162.9	516.6
											[.00]	[.00]

Table 5.4 *Autocorrelation structure*

Autocorrelation coefficients for lags up to 5, and for lags 10, 20, 40, 70 and 100 are presented for daily CS, |CS| and $(CS)^2$ in Panel A); for daily ΔCS, |ΔCS| and $(\Delta CS)^2$ in Panel B and for the realised, absolute and squared daily residuals from the model:

$$\Delta cs_t = a + \beta_1 \Delta cs_{t-1} + \beta_2 \Delta cs_{t-2} + \varepsilon_t$$

in Panel C. The last two columns reported are the Ljung-Box Q-statistics with their p-values in brackets. The Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. Under the null hypothesis, Q is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of lags. The null hypothesis is rejected at a significant level of less than 1 percent for all lags for both the series CS and ΔCS.

In order to provide a more robust test for long term dependence in the daily credit spread changes, we used the R/S methodology that looks at the scaling behaviour of the rescaled cumulative deviations of dCS^2 from the mean. We estimated the Hurst exponent (Hurst, 1951), which is expected to be between 0.5 and 1 if the long memory structure exists. The sample period has been split into sub-samples according to the pattern of the volatility as resulting form the CUSUM square test for variance stability (see Section 5.4.1). Specifically we have identified five sub-periods as follows: 2 January 1991 to 15 October 1991 (205 obs), 16 October 1991 to 21 June 1994 (700 obs), 22 June 1994 to 25 April 1995 (220 obs), 26 April 1995 to 26 February 1999

(1003 obs), and 27 February 1999 to 26 June 1999 (63 obs). The Hurst coefficient (H) was computed for the whole sample period and for each sub-period (with their respective expected values in brackets). Results indicate significant positive long-term memory for the whole sample (H=0.85, R^2=0.99), the third (H=0.684, [0.587]), and marginally the second periods (H=0.576, [0.574]). The null hypothesis of no long-term dependence could not be rejected for the first (H=0.578, [0.591]), fourth (H=0.551, [0.574] and fifth sub-periods (H=0.573, [0.616]). In conclusion the evidence so far is not in favour of an *iid* process for the credit spread changes process.

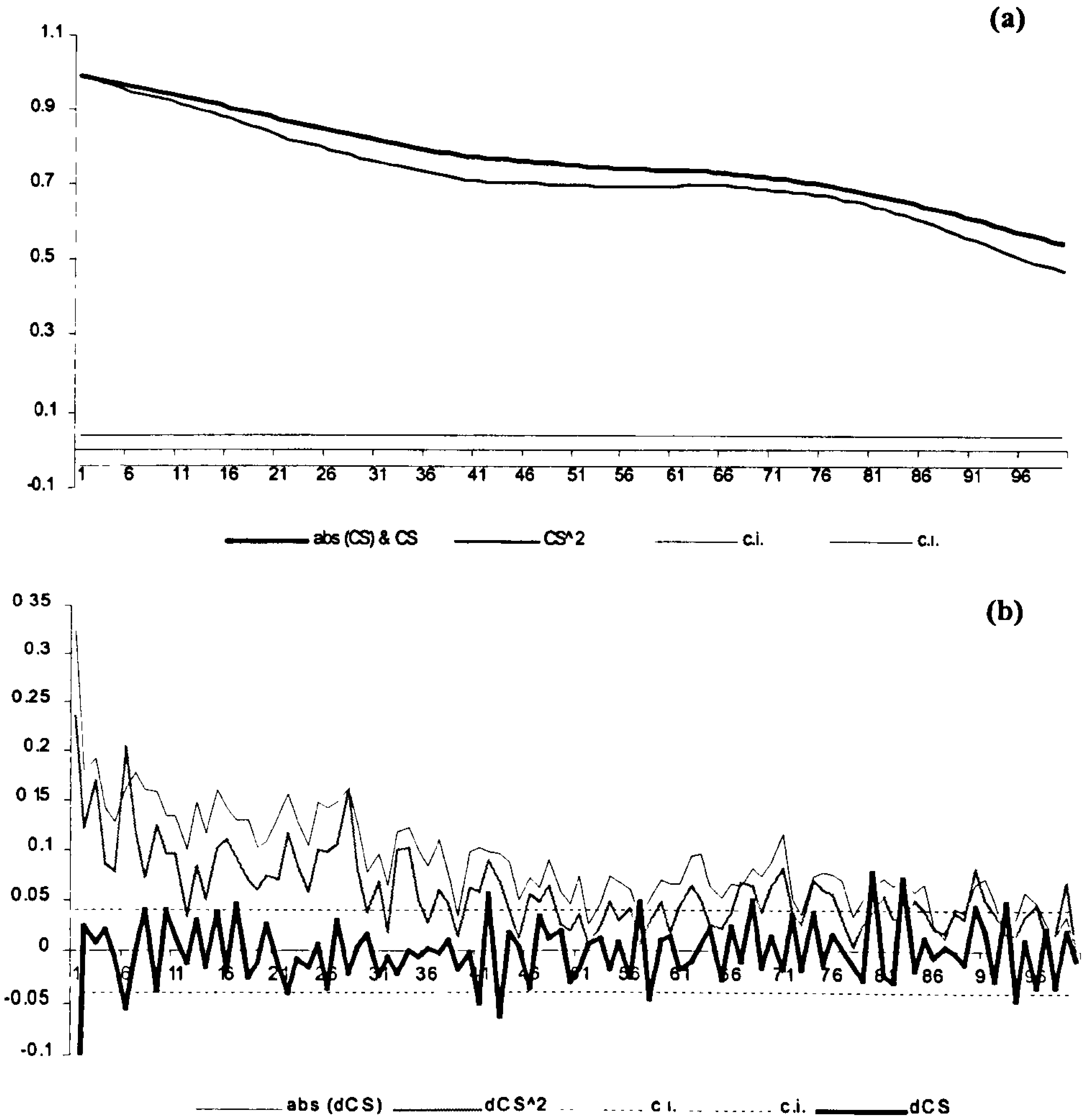


Figure 5.2 *Sample Autocorrelation Function for daily (a) CS, /CS/ and (CS)^2 and (b) dCS, /dCS/ and (dCS)^2*

The autocorrelation function of CS, absolute CS and CS squared is plotted up to lag 100 in part (a). The autocorrelation function for ΔCS, absolute ΔCS and ΔCS squared is also presented in part (b). The dotted lines (c.i.) in the plots of the autocorrelations are the approximate two standard error bounds computed as $\pm\ 1.96/\sqrt{T}$. Autocorrelation coefficients within these bounds are not significantly different from zero at (approximately) the 5% significance level.

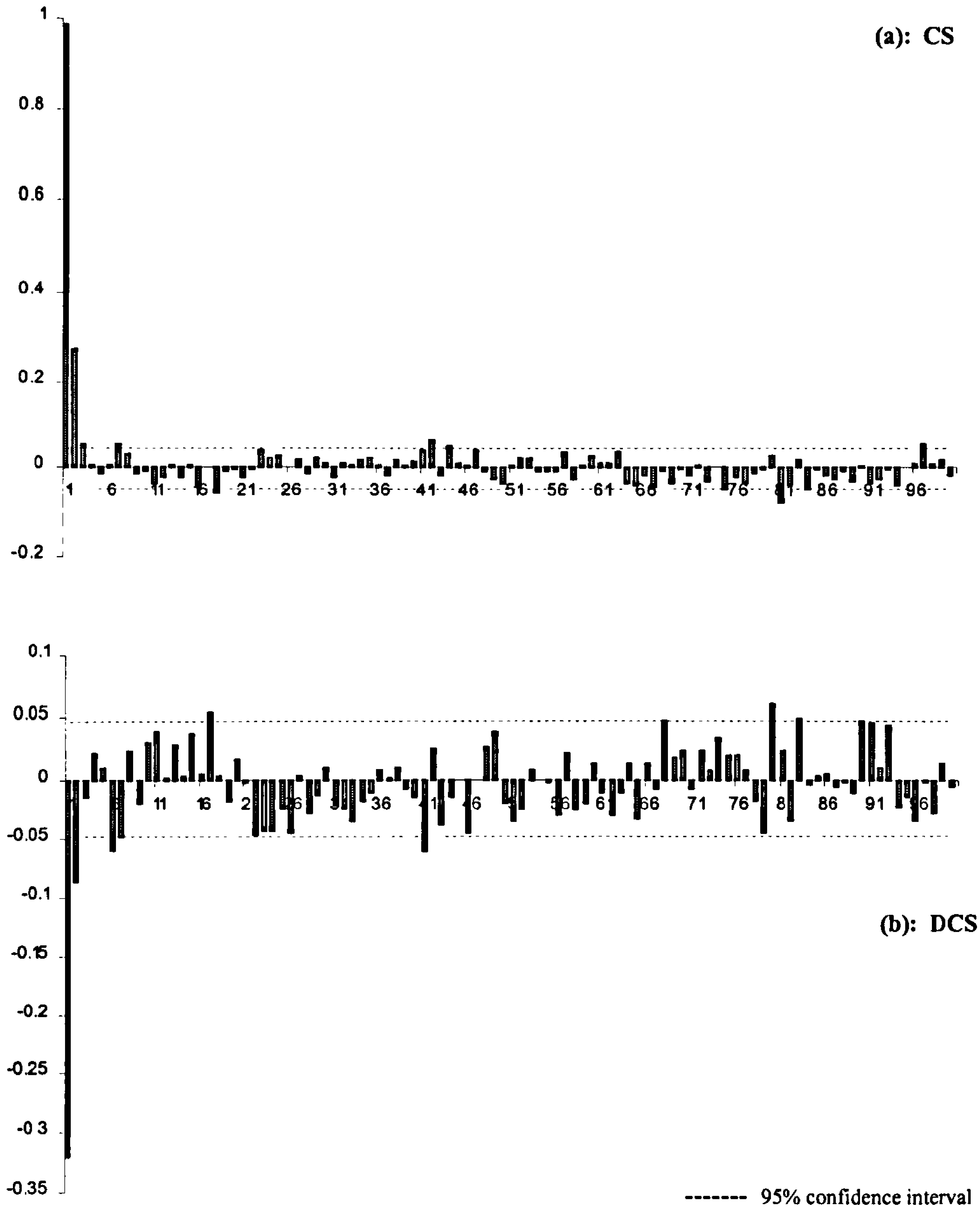


Figure 5.3 *Sample Partial Autocorrelation Function (PAF) for CS and ΔCS.*

The partial autocorrelation at lags from 1 to 100 is plotted both for CS and ΔCS. The PAF measures the correlation of values that are k periods apart after removing the correlation from the intervening lags. If the pattern of autocorrelation can be captured by an autoregression of order less than k, then the partial autocorrelation at lag k will be close to zero. The dotted lines in the plots of the partial autocorrelations are the approximate two standard error bounds computed as $\pm\ 1.96/\sqrt{T}$. Partial autocorrelation coefficients within these bounds are significantly different from zero at (approximately) the 5% significance level.

Despite the strenght of the evidence in favour of long memory, we should take into account that this result may be due to the aggregation effect deriving from the use of a bond index. The key idea is that the aggregation of weakly dependent series can produce a strong dependent series (Lobato and Savin, 1996). This possibility could be examined at a later stage in two ways: analysing the long memory properties of a subsample of individual bonds included in the index, and applying the modified R/S analysis to produce a new R/S statistic (Lo, 1991) robust to short-term dependence, heterogeneities and nonstationarity.

From the observation of the correlogram for dCS it is clear that both the ACF and the PACF are close to zero after two lags. The negative sign of the first autocorrelation coefficient (=-0.32) suggests a mean-reverting behaviour of credit spreads. We presume an AR(2) specification is a parsimonious representation of the process governing the residuals and we consequently present in Panel C of Table 5.4 autocorrelations of the residuals, squared and absolute residuals of an AR(2) model for dCS:

$$\Delta cs_t = \alpha + \beta_1 \Delta cs_{t-1} + \beta_2 \Delta cs_{t-2} + \varepsilon_t \tag{5.5}$$

An AR(2) specification was selected as the best specification. Despite this specification was able to remove all serial correlation in the residuals up to lag 5, the correlograms of the absolute and squared residuals display a very similar pattern to their counterparts in the dCS series. The Box-Pierce *Q* statistics for all lags up to 100 are much higher than the critical values, rejecting the null hypothesis of zero autocorrelation. This implies that the residuals exhibit high levels of intertemporal dependence and suggests the need of a model able to capture all the stylised facts emerged so far: lack of independence, nonlinearities in the series, implied persistence in conditional variance and excess kurtosis.

5.3.5. Credit Spreads Stationarity

The second step towards the identification of the best model fitting the data consists in recording evidence about credit spreads intertemporal stationarity in order to avoid any potential spurious regression problem. The autocorrelation functions were examined and the Augmented Dickey-Fuller (ADF) test for the presence of a unit root was implemented to determine the integration order of the series. The ADF test was first applied to credit spread levels. Since, the CS series does not exhibit any trend and has a mean close to zero, neither a trend nor a constant were introduced in the test regression. Both Akaike and Schwarz's information criteria selected an autoregressive model of order (2). For the ADF test, the test statistic is the *t*-statistic for the lagged dependent variable in the test regression. As the *t*-statistic is 0.029 and lower (in absolute terms) than the 95 percent MacKinnon critical value (-1.93), the test fails to reject the null hypothesis of a unit root in the CS series at any significance level. The ADF test was successively applied to the first difference of the CS series and in this case the null hypothesis of non-stationarity could be rejected (*t*-statistic=-41.48, critical value=-1.93). The dCS series is found to be stationary at any significance level. In conclusion, the CS series is integrated of order 1, I(1).

As the ADF test assumes a moving average process for the error series (Said and Dickey, 1984), we implemented also the Phillips-Perron (PP, 1988) test, which is a semi-parametric (Z-statistic) method that allows for higher-order serial correlation and heteroskedasticity in a series. The PP test results to be desiderable for its weaker set of assumptions concerning the error process and for its greater power to reject a false null hypothesis of a unit root.[15] The PP Z-statistic is -0.018 and -67.43 for CS and dCS, respectively, and the critical value at the 95 percent level is still -1.93. The null hypothesis of a unit root is rejected only for the dCS series. The results obtained performing the PP test are therefore totally consistent with those provided by the ADF test.

An alternative way to test for stationarity is to focus on the nature of the variance of the CS series, that is implementing the variance ratio test (Poterba and Summers, 1988). If the CS series is I(1) taking

$$\underset{k}{\Delta} cs_t = cs_t - cs_{t-k}, \tag{5.6}$$

$$\underset{l}{\Delta} cs_t = cs_t - cs_{t-l}, \tag{5.7}$$

and the ratio

$$\lambda = \frac{var \underset{k}{\Delta} cs_t}{var \underset{l}{\Delta} cs_t}, \tag{5.8}$$

[15] The cost of weaker assumptions lies in the fact that in the presence of negative moving average terms, the P-P test tends to reject the null of a unit root whether or not the actual data-generating process contains a negative unit root. Hence, it is preferable to use the ADF test when the true model contains negative moving average terms and the Phillips-Perron test when the true model contains positive moving average terms.

a plot of λ against k should be an increasing (straight) line. If CS does not have a unit root both Δ_k CS and Δ_1 CS will be constant, so that the ratio λ does not change after k becomes large enough. However, as Figure 5.4 shows, the variance ratio is increasing with k, suggesting the presence of a unit root and confirming the results from the ADF and PP tests. The variance ratio test has also been applied to credit spread changes. The value of the ratio displays an oscillating behaviour around its mean value of 0.756 for any value of k (Figure 5.4), which is evidence of stationarity for the dCS series. According to Poterba and Summers (1988), the fact that the variance ratios lie below unity is also evidence of mean reversion.

5.3.6. Cointegration Analysis

The ADF test was also applied to all the macroeconomic and financial series in levels presented in Section 5.3.3 and all of them were found to be non-stationary and I(1). In this section we are interested in determining whether the CS series is cointegrated with any of the financial variables, and if it is, in identifying the cointegration or long-run equilibrium relationship. Two previous studies estimated the long-run relationship implied in the yield premium using cointegration analysis. A cointegrating vector was found between Treasury yields, noninvestment grade bond yields, and default rates by Barnhill, Joutz, and Maxwell (2000). Moreover, Morris, Neal and Rolph (1998) show that corporate rates are cointegrated with government rates and the relation between Treasury rates and credit spreads on Moody's seasoned bond indices is negative in the short-run and reverses to be positive in the long-run.

The Johansen's cointegration methodology was employed as it has been proven to be more powerful respect to other alternative techniques (Gonzalo, 1994). Furthermore, the Johansen approach offers a test statistic for the number of cointegrating vectors and allows direct hypothesis tests of the coefficients entering the cointegrating vector.

The only variable that showed to be cointegrated with credit spreads is the FTSE All Share Price index. We now turn to see how the test develops. In the Johansen procedure, maximum likelihood is applied to an autoregressive representation of the form given by the following equation:

$$\begin{bmatrix} \Delta CS_t \\ \Delta P^{FTSE}{}_t \end{bmatrix} = \Gamma(L) \begin{bmatrix} \Delta CS_{t-1} \\ \Delta P^{FTSE}{}_{t-1} \end{bmatrix} + \Pi \begin{bmatrix} CS_t \\ P^{FTSE}{}_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{CS} \\ \varepsilon_t^{P^{FTSE}} \end{bmatrix} \tag{5.9}$$

where $\Gamma(L)$ is a 2×2 matrix of polynomials in the lag operator. The Johansen test is on the rank of the long-run impact matrix Π. In the absence of cointegration, Π is a singular matrix (rank = 0). Hence, in our case, the rank of Π could be between zero and two, the number of variables in the system. The appropriate lag structure to use in the VAR was determined from the log-likelihood, Akaike and Schwarz's information criteria, and the F-statistic for comparison of the restricted and unrestricted models. We selected an autoregressive model of order (3) as the appropriate lag structure. The maximum eigenvalue statistic for no cointegrating vector (rank =0) was 0.0058 and the trace statistic was 15.93. The 95 percent critical value for the trace statistic was 12.53, implying that the null hypothesis of no cointegrating vector could be rejected. Successively, the null hypothesis of at most 1 cointegration relation (rank = 1) was tested. The maximum eigenvalue for r=1 was 0.0014 and the trace statistic (3.04) was lower than the 95 percent critical value (3.84), indicating that the null hypothesis could not be rejected. We concluded that there is one cointegrating vector between credit spreads and the FTSE All Share Return index and the normalised cointegrated relation can be written as follows:

$$CS + 0.003165 * Log(P^{FTSE}) = 0. \tag{5.10}$$

As cointegrated variables CS and P^{FTSE} are characterised by time paths influenced by any deviation from the long run equilibrium. If the sum of CS and P^{FTSE} is large relative to the long run relationship, either the FTSE must fall ultimately relative to the CS, or CS must fall relative to the FTSE. Without a full dynamic specification of the model, we cannot determine which of the two possibilities will eventually occur. But we know that the short run dynamics must be influenced by the deviation from the long run relationship. According to this result, we will add an error correction variable (ECM) to the dynamic models we will present later on, so that they will actually be error correction models. If the error correction component will result to be statistically significant, this will consolidate the cointegration analysis results and demonstrate the importance of the long-run relationship. We conclude this section, focusing the reader's attention on Figure 5.5 and, in particular on the clear change in the slope of the long run relation around mid eighties, which suggests the possibility for a further investigation about the presence of a nonlinear cointegration relationship.[16]

---

16 For the interested reader we recall that the basic concept underlying this theory is that the error correction term derives from the nonlinear combination of two or more integrated variables. For details on nonlinear cointegration we advice to see the pioneer work in this field by Granger and Hallman (1991),

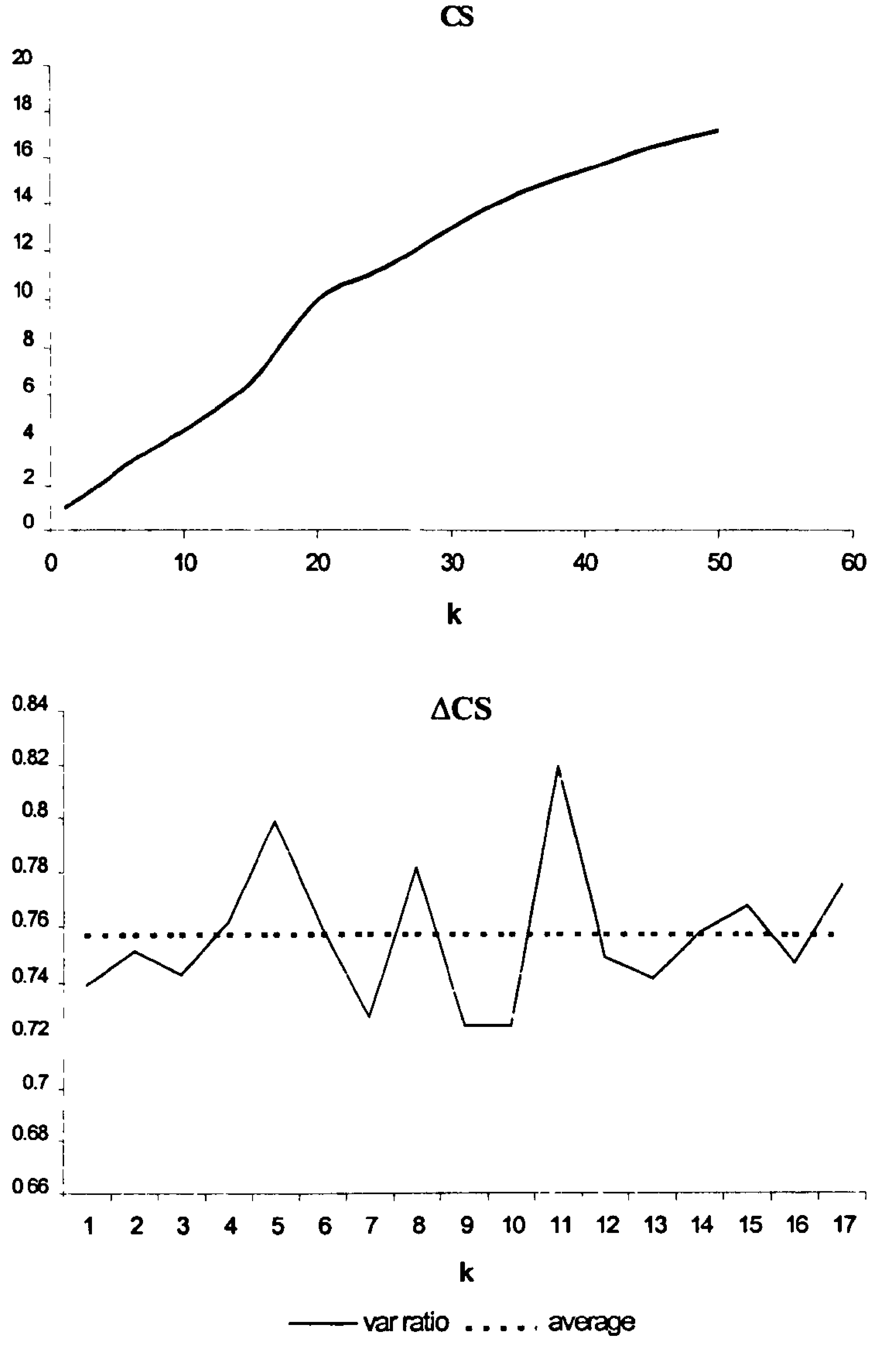


Figure 5.4 *The variance ratio test for stationarity*

The variance ratio λ is plotted against k periods ahead both for CS and ΔCS and is computed by dividing the variance of CS (ΔCS) estimated from longer intervals by the variance of CS (ΔCS) estimated from shorter intervals, (for the same measurement period), and then normalizing this value to one by dividing it by the ratio of the longer interval to the shorter interval. The variance ratio is an increasing (straight) line if the series presents a unit root. In the absence of a unit root the value of the ratio oscillates around a mean value for any value of k We can also infer evidence of mean reversion if the variance ratio lies below unity.

successively extended by Haekfe and Helmenstein (1996), Escribano and Granger (1998), and Markellos (1998).

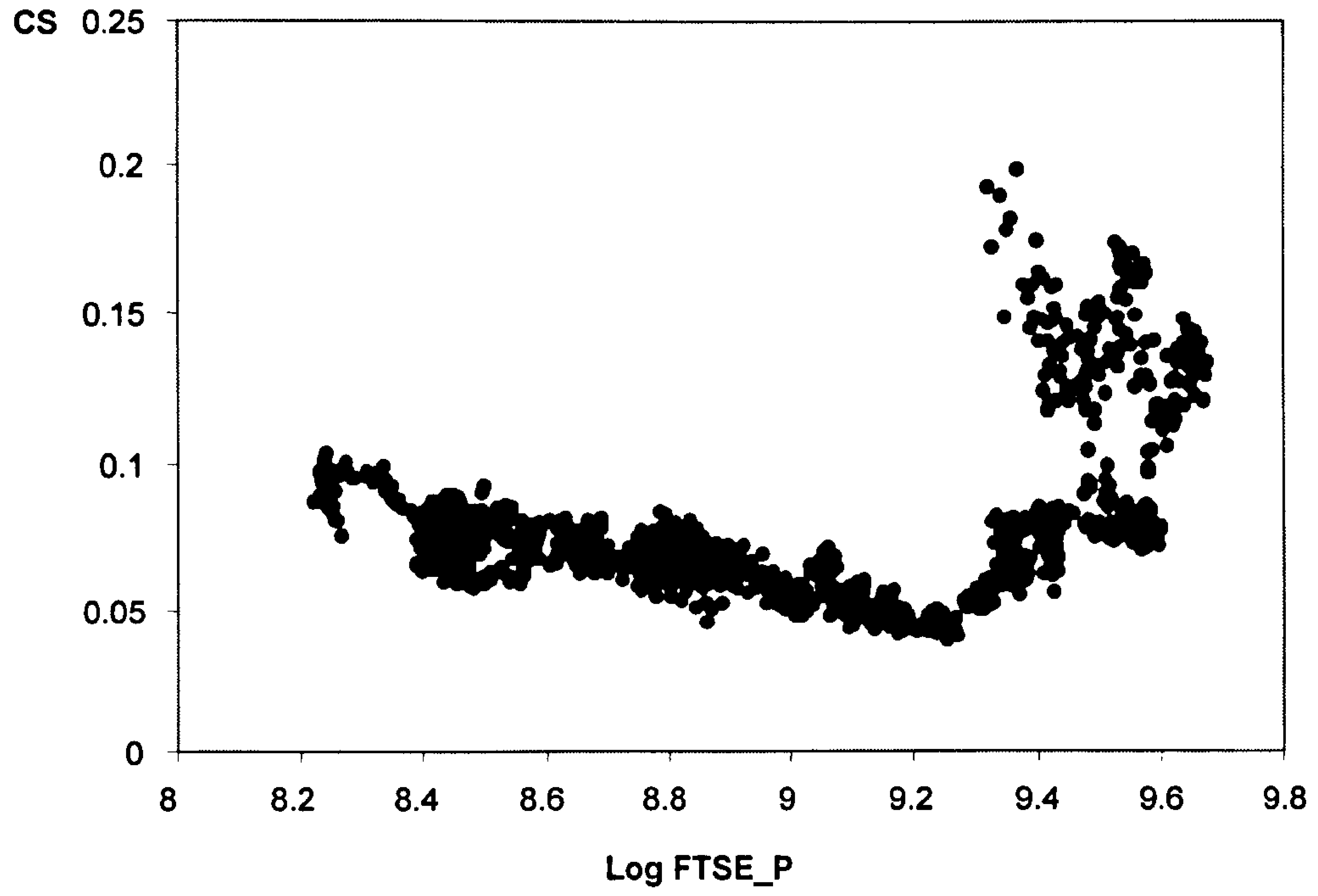


Figure 5.5 *Cointegration between credit spreads and the FTSE All Share Price Index*

The CS series is plotted against the Log(FTSE Price) series. A linear negative relationship between the two series is apparent for values of the Log(FTSE Price) series up to 9.3, or in other words up to May 1997, which is also the starting date for the Asian crisis. After this period the relation seems to invert to become positive

5.4. Modelling Credit Spreads

The time-series properties of credit spreads broadly discussed in the previous section provide strong evidence for nonlinear dependence, changing volatility, and high levels of intertemporal dependence in the credit spreads generating process. We will carry on our analysis on the basis of these results by modelling the credit spreads process as time dependent. As credit spreads are proved to be non stationary, and since in this case asymptotic distributions are never achieved, they would produce not reliable statistical results. For this reason we will concentrate on the behaviour of credit spread changes.

In this section we will proceed going through the last two stages of the Box-Jenkins methodology, the estimation stage and the diagnostic checking stage. In the estimation stage different models are fitted and parameters estimated. In the diagnostic checking stage models are compared using the parsimony principle (AIC, SBC tests...), *t*-statistics, stationarity and invertibility tests. We will start with modelling credit spread changes as a simple OLS model and its unability to account for some important features of the data will lead us to introduce more complex models, namely autoregressive heteroskedastic models.

ARCH techniques to model interest rate data have been applied to the term structure of interest rates. In particular ARCH models were estimated on corporate bond yields (Weiss, 1984) and on the differential returns between bills with different maturities (Engle, Lilien and Robins, 1987; Engle, Ng and Rothschild, 1990), while ARCH-M specifications were applied to the term premium by Engle, Lilien and Robins (1987). However, applications of ARCH or GARCH models to credit spreads have never been implemented so far.

5.4.1. The OLS model

The first model we introduce for credit spread changes is a simple homoskedastic model:

$$dCS_t = c + \beta_1 * dCS_{t-1} + \beta_2 * dCS_{t-2} + \beta_3 * R_{t-1}^{FTSE} + \beta_4 * dTERM_t + \beta_5 * dDOLLAR_{t-1} + \varepsilon_t$$

After taking into consideration all the financial variables presented in Section 5.3.3, we used the adjusted R^2 criterion, the Akaike and Schwarz information criteria, and the likelihood ratio (LR) test to select the most parsimonious model. The White (1980) heteroskedasticity consistent method was used to estimate the coefficient covariance matrix. The results and the main diagnostic tests are presented in Tables 5.6 and 5.7, respectively. The first and the second order autoregressive parameters are estimated to be -0.31 and -0.074, respectively, and both are significantly different from zero at the 1 percent significance level. Credit spread changes are negatively and significantly influenced by the return on the FTSE All Share index lagged one period ($R^{FTSE}{}_{t-1}$) with a coefficient of -0.021 and by the contemporaneous change in the term spread ($\Delta TERM_t$) with a coefficient of -0.017. The change in the exchange rate against the dollar ($\Delta DOLLAR_{t-1}$) lagged one period has a positive impact, with a parameter estimate of 0.011. All the signs are as expected.

We first test for *parameter estimates stability*. The plot of the recursive coefficient estimates -which shows the evolution of estimates for any coefficient in the OLS model as more and more of the sample data are used in the estimation- produces no indication of instability. None of the coefficients displays significant variation or jumps typical of a structural break. We notice, however, that most of the coefficients show either a small drop or a spike in correspondence of the end of 1992. The Chow's breakpoint test was implemented in order to see whether the event of the exit from the EMS on September 16, 1992 represents a structural break. The idea of this test is to split the sample in correspondence of the potential break, fit the equation separately for each subsample and chech for any significant difference in the estimated equations. The results of the test are presented in Table 5.5. Neither the *F* test nor the Loglikelihood Ratio statistic rejects the null hypothesis of no structural change. Moreover, to reflect a possible structure break, a dummy variable was included for September 1992, and lagged one month to encompass any anticipation effect. The dummy coefficient estimate was positive (0.0011) but not significant (t=1.22), confirming the absence of any structural break.

Chow Breakpoint Test: 16/9/1992			
F-statistic	1.204	Probability	0.30
Log likelihood ratio	7.244	Probability	0.29

Table 5.5 *The Chow's breakpoint test*

The breakpoint Chow test is performed to test for the presence of a structural break. Two test statistics for the Chow test are reported. The F-statistic has an exact finite sample F-distribution if the errors are independent and identically distributed normal random variables. The log likelihood ratio statistic is based on the comparison of the restricted and unrestricted maximum of the (Gaussian) log likelihood function. The LR test statistic has an asymptotic distribution under the null hypothesis of no structural change.

Two additional tests for parameter stability are developed: the CUSUM test based on the cumulative sum of the recursive residuals, and the CUSUM of squared residuals (see Figure 5.6). The first test indicates no parameter instability as the cumulative sum of the recursive residuals lays always within the 5 percent critical lines. The CUSUM of squared residuals is suggestive of residual variance instability since the cumulative sum of the squared residuals periodically lies outside the area between the two (parallel) critical lines. Specifically significant departures from the confidence intervals are observed in the October 1991-June 1994 and April 1995-February 1999 periods.

Serial Correlation tests. From the autocorrelation and partial autocorrelation functions of the standardised residuals, we observe that the OLS model is able to remove serial correlation in the residuals only up to lag 5 (Table 5.7). The Breusch-Godfrey Lagrange multiplier test for serial correlation was also implemented. The null hypothesis of no serial correlation in the residuals up to lag 20 could not be rejected.

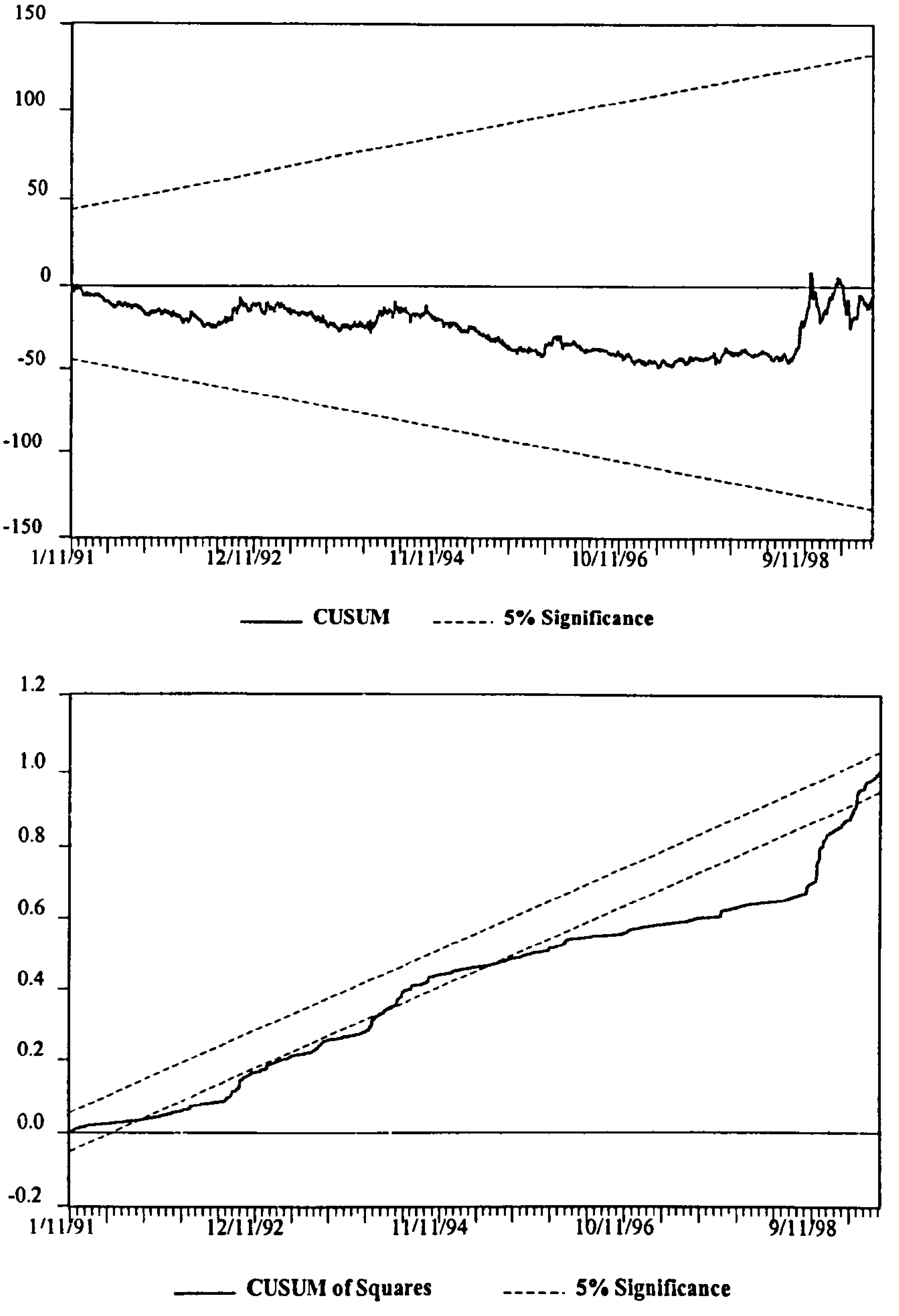


Figure 5.6 *The CUSUM test for OLS residuals and squared residuals*

The CUSUM test is based on the cumulative sum of the recursive residuals. The test finds parameter instability if the cumulative sum goes outside the area between the two 5% critical lines, the distance between which increases with t. Movement of the statistic outside the critical lines is suggestive of coefficient instability. For the CUSUM of squares the significance of the departure of the statistic from its expected value is assessed by reference to a pair of parallel 5 % critical straight lines around the expected value. Movement outside the critical lines is suggestive of parameter or variance instability. We present (a) the CUSUM test and (b) the CUSUM of squares test for residuals from the OLS regression

The White's test for heteroskedasticity in the residuals was also applied. The test statistic was equal to 287, which is significantly higher than the critical value at any significance level. This implies that the null hypothesis of no heteroskedasticity is to be rejected. However, as the null hypothesis assumes that the errors are both homoskedatic and independent of the regressors, and that the linear specification of the model is correct, the high value of the test statistic might be due to the failure of any one of these conditions.

ARCH effects tests. Both the Ljung-Box Q-statistic for the squared residuals and the ARCH-LM test up to lag 20 in Table 5.7 indicate the presence of strong ARCH effects in the residuals. This may lead to serious model misspecification if it is ignored. As with all forms of heteroskedasticity, the analysis will result in inappropriate parameter standard errors, which will be typically too small. As a consequence the equation for credit spread changes should be re-specified.

5.4.2. GARCH Models

Generally, it is argued that the lack of independence arises from the presence of nonlinearities in the series. The dependence between the series and its past history raises the issue of how to summarise such dependence in a useful way. One way is to treat functions of ΔCS as being determined by models such as ARMA, ARCH or GARCH. Defining the expectation of a random variable conditioned upon its past history as E_{t-1}, these models make E_{t-1} $(g(\Delta CS_t))$ a function of ΔCS_{t-1}. When $g(\Delta CS_t) = \Delta CS_t^2$, and E_{t-1} $(\Delta CS_t) = 0$, E_{t-1} $(\Delta CS_t^2) = \sigma_t^2$ which we indicate as the conditional variance of ΔCS_t. Having generated ΔCS_t^2 by such models makes σ_t^2 potentially dependent upon the past.

As we have seen in Table 5.4 the squares of credit spreads are correlated and the slow decline in the autocorrelation coefficients may be used to argue that the correlation is very persistent, and that ΔCS squared possess long-memory. In order to capture the ARCH effects and to represent the observed autocorrelation structure in daily credit spread changes, we estimate a number of conditional heteroskedastic time series models. GARCH (p, q) models with different values of p and q are tested from 1,0 to 3,3 applying likelihood ratio tests until the improvement in the likelihood function becomes insignificant.

Non linear optimisation techniques are used to calculate the maximum likelihood estimates based on the Berndt-Hall-Hall-Hausman (BHHH) algorithm. Since we suspect the residuals are not conditionally normally distributed, the quasi-maximum likelihood covariances and robust t-statistics are calculated using the Bollerslev and Wooldridge (1992) procedure.[17]

5.4.2.1. ARCH(4) Model

A simple ARCH(4) process is firstly fitted to daily credit spread changes (see Table 5.7). The fourth order of the process is found by using the information criteria mentioned above (the Schwarz information criterion and the Likelihood Ratio test). The mean equation does not differ from the mean equation in the OLS and all the variables maintain the same sign as before. The variance equation is as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \alpha_3 \varepsilon_{t-3}^2 + \alpha_4 \varepsilon_{t-4}^2 + \upsilon_t$$

The estimate of the constant term (α_0) is positive and smaller than the sample variance obtained in the OLS model. This is due to the changing conditional variance over time and its eventual contribution to the unconditional variance. The sum of the other ARCH parameters ($\alpha_1+\alpha_2+\alpha_3+\alpha_4$) is substantially smaller than unity (0.67), indicating that the fitted model is second-order stationary and that at least the second moment exists (Bollerslev, 1986). Finally, the ARCH model is able to totally remove the serial correlation in the residuals but not in the squared residuals. The Q^2 stats and the Lagrangean multiplier reject the presence of significant ARCH effects left only up to lag 5.

5.4.2.2. GARCH (1,1)

In order to find a more parsimonious specification for the dCS process we model credit spread changes as a GARCH process. Within the class of GARCH processes, we first estimated a simple GARCH (1,1) incorporating first-order GARCH effects in the residuals ε_t. While the mean equation is similar to the OLS and ARCH(4) specifications, the structure of the variance equation is

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1} + \upsilon_t$$

[17] Non robust standard errors would tend to under-estimate the true parameter estimator uncertainty and in the case of GARCH-M models, the GARCH-M parameter would tend to become significant.

The GARCH persistence parameter (β) and the ARCH parameter (α_1) are estimated to be 0.826 and 0.115, respectively, with their sum slightly below unity –necessary condition for stability to hold. So the stationary GARCH formulation seems adequate to model the time variant credit spread changes volatility. However, the degree of persistence in shocks to volatility -given by the sum of the coefficients $\alpha_1 + \beta$ - is quite high, which implies that shocks to the Eurobond market have highly persistent effects and the response function of volatility decays at a relatively slow pace. The volatility of credit spread changes is driven mainly by the variance observed in the previous trading day –as indicated by the size of the GARCH coefficient, which measures the long-term persistence in volatility[18]. With respect to the estimates of the other parameters in the model, all the variables mantain the same sign and approximately the same magnitude as before except for the return on the FTSE index and the exchange rate parameters which become significant at the 1 percent level. The maximised loglikelihood showed an increase of 214 points over the homoskedastic model and the loglikelihood ratio (LR) strongly rejects homoskedasticity at better than the 1 percent level. Being able to remove the ARCH effects also after lag 5, the GARCH model represents an improvement over the ARCH model, with generally better diagnostic tests.

5.4.2.3. GARCH (1,1)-Component

We proceed introducing additional variables in the variance equation of GARCH (1,1) in order to test whether they are helpful in reducing the degree of persistence of volatility. In particular we found that the credit spreads level is good for our purpose. We leave the mean equation unchanged as before and we focus on the variance equation parameter estimates:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma CS_t + \upsilon_t$$

Small credit spreads are associated with low risk and reduced default frequency and thus to low volatility in the corporate bond market. Conversely, when the economy is in a downturn and defaults become more and more frequent, spreads are high and tend to react significantly to every new default in the market. Thus high credit spread levels are naturally associated with high

[18] Note also that only persistent changes in volatility are associated to an adjustment in the risk premium.

volatility. Credit spreads level is proven to be an important source of time variation in volatility and volatility itself shows to be directional, rising in periods of rising spreads. Respect to the previous GARCH models, this new model shows to have a better goodness-of-fit, lower kurtosis in the standardised residuals, and higher loglikelihood value. The sum of the ARCH and GARCH coefficients decreases to 0.87. The tests for serial correlation and for ARCH effects are even more strongly rejected. Despite these improvements, non-normality in the residuals is still quite strong.

To corroborate our general results we finally have replaced changes in credit spread as defined in Eqs. (5.3)-(5.4) with changes in relative credit spreads (ΔrCS) following the methodology in Longstaff and Schwartz (1995). We have run the same regressions introducing this new dependent variable and we compared the new estimates with the previous ones. The signs and the magnitude of the new coefficient estimates are similar to the previous parameter estimates. The R^2s of the new specification are generally slightly lower than those presented in Table 5.6, ranging from 0.272 to 0.289. The DW values also appear to be lower in the new regression specifications. The standardised residual mean and kurtosis coefficients result to be larger when taking into considerations relative CS. We can generally conclude that changes in credit spreads and changes in relative spreads lead to similar results. However the presence of slightly better diagnostic statistics in the "simple" model specification might be a reasonable argument to prefer it to the "relative" counterpart.

	Exp. Sign	OLS	ARCH(4)	GARCH(1,1)	GARCH(1,1) Comp
Mean Equation:					
$C*10^5$		6.850	-6.730	6.730	3.890
		(.00006)	(.00005)	(.00005)	(.00005)
ΔCS(-1)		-.310***	-.385***	-.307***	-.331***
		(.02865)	(.02395)	(.02246)	(.02221)
ΔCS(-2)		-.074***	-.133***	-.078***	-.082***
		(.02810)	(.02419)	(.02274)	(.02163)
R^{FTSE}(-1)	-	-.021*	-.021**	-.035***	-.030***
		(.01202)	(.00859)	(.00843)	(.00835)
ΔTERM	-	-.017***	-.015***	-.015***	-.015***
		(.00151)	(.00106)	(.00117)	(.00115)
ΔDOLLAR(-1)	+	.011	.013**	.017***	.016***
		(.00701)	(.00535)	(.00555)	(.00571)
Variance Equation:					
$C*10^6$		-	3.470***	.376***	-.815***
			($3.53*10^{-7}$)	($1.28*10^{-7}$)	($3.15*10^{-7}$)
Arch(1)		-	.247***	.115***	.121***
			(.06196)	(.02932)	(.02846)
Arch(2)		-	.108**	-	-
			(.04850)		
Arch(3)		-	.168***	-	-
			(.05757)		
Arch(4)		-	.145**	-	-
			(.05231)		
Garch (1)		-	-	.826***	.754***
				(.04184)	(.05069)
CS	+	-	-	-	$2.53*10^{-5}$ ***
					($7.44*10^{-6}$)

Table 5.6 *Linear and nonlinear estimates for daily credit spread changes*

The summary parameters and statistics for the linear and nonlinear models for credit spread changes are presented. The sample period is from January 1991 to May 1999 for a total of 2192 observations. The dependent variable is the daily change in the credit spread. In the OLS model the coefficient covariances are corrected for the presence of heteroskedasticity using the White (1980) covariance estimator. All the nonlinear models are estimated under the assumption of not conditionally normally distributed residuals. Robust t-statistics (in parenthesis) are obtained using the method presented in Bollerslev and Wooldridge (1992). NOTE: ***, **, * Significantly different from zero at the 0.01, 0.05 and 0.1 level, respectively (using a two-tailed test).

Diagnostic Checks	OLS	ARCH(4)	GARCH(1,1)	GARCH(1,1) Comp
$\alpha s + \beta$	-	0.67	0.93	0.87
Adj. R^2	0.307	0.297	0.304	0.303
Log. Lik.	9668	9882	9915	9943
Mean	-7.64E-20	0.038	-.00067	0.00069
St. Dev.	0.0029	0.999	1.057	0.995
Skewness	0.177	0.217	0.24	0.19
Kurtosis	11.91	7.76	7.53	7.04
Jarque-Bera	7267 (0.00)	2085 (0.00)	1892 (0.00)	1508 (0.00)
DW	2.00	1.85	2.00	1.96
Q(5)	4.558 (0.47)	2.721 (0.74)	5.275 (0.38)	6.324 (0.27)
Q(20)	42.46 (0.00)	23.72 (0.25)	26.75 (0.14)	27.712 (0.11)
LM Arch Test $_{20\ lags}$	13.32 (0.00)	2.338 (0.00)	0.999 (0.45)	0.717 (0.81)
$Q^2(5)$	136.94 (0.00)	3.976 (0.55)	3.065 (0.69)	2.8747 (0.72)
$Q^2(20)$	424.92 (0.00)	47.86 (0.00)	20.50 (0.42)	14.719 (0.79)
Akaike I.C.	-8.82	-9.015	-9.046	-9.072
Schwartz I.C.	-8.80	-8.987	-9.023	-9.046
N	2190	2190	2190	2190

Table 5.7 *Residuals Diagnostic Checking*

Q(5), Q(20) and $Q^2(5)$, $Q^2(20)$ are the Box-Pierce portmanteau test statistics, with 5 and 20 degrees of freedom, applied to the standardised and squared standardised residuals, respectively. They provide a test for the presence of autocorrelation and ARCH effects, respectively. Their P-values are reported in parentheses. In addition the Durbin Watson statistic (DW) for first-order serial correlation and the LM statistic test for the presence of remaining significant ARCH effects are presented. Skewness, kurtosis and the Jarque-Bera test statistic for normality of the standardised residuals are also reported.

5.4.2.4. Additional Tests

Summarising, we have found that estimates of the variance equation provide strong evidence of changing conditional volatility for credit spread changes. In all the models presented the estimated sum of the GARCH coefficients $(\alpha_1+\beta)$ provides a measure for the persistence of volatility since expected future volatility decays towards the unconditional variance σ_e^2 according to the equation:

$$\sigma_e^2 = \frac{\alpha_0}{1-(\alpha_1+\beta)} \tag{5.11}$$

The sum $\alpha_1 + \beta$ results to be very close to one. This means that multi-step forecasts from the model will approach the unconditional variance quite slowly: the estimated mean lag of this variance expression, $1/(1-\beta)$, ranges between 4 to 6 days. Another way to view the volatility persistence is by calculating the half life of volatility shocks, which is computed as $\ln(0.5)$ over $\ln(\alpha+\beta)$. The half-life of volatility shocks ranges from 2 to 10 days.

We tested if the second-order system admits periodic solutions, that is if the following relation holds:

$$\alpha_1 < -\beta^2/4 \tag{5.12}$$

Substituting the paramer estimates we obtain $-0.082 < -0.027$, which is a standard result implying periodic cycles (Bidargota, 1996). Further and more formal tests might be applied to confirm this preliminary piece of evidence.

As a final comparison of the performance of the various models, we analysed the residuals from the various models and their 95 percent forecast intervals $\pm$ 1.96 $(h_t)^{1/2}$. Residuals appear to be almost indistinguishable, indicating that any model may not provide a significant improvement over the others in terms of point forecasts. The forecast intervals, however, are very different. In particular, it emerges that the conditional variance derived from the GARCH (1,1)-component model seems to reflect more accurately the behaviour of the series. During periods of low volatility, such as before 1992 and from 1996 to 1997 the forecast intervals of the ARCH model frequently decline to the lower bound $\pm 1.96\ (\alpha_0)^{1/2}$. However, for both the GARCH models, during the same periods, the forecast intervals become smaller than $\pm 1.96\ (\alpha_0)^{1/2}$. As we should expect from a good conditional variance model, the series can be predicted with higher confidence during less volatile periods. Therefore, from the confidence intervals analysis, the GARCH(1,1) models appear to be most attractive, confirming results in Table 5.7.

5.4.3. Asymmetric Analysis

The main limitations of the GARCH model derive from the property of linearity and from the quadratic form of the conditional variance that this model displays. The impact of past values of the innovation on the current volatility is only a function of their magnitude and not of their sign. However, we might expect bad news to have a bigger impact on the predictable volatility of CS than good news of similar magnitude, we therefore proceed testing this hypothesis.

The simplest approach to examine the eventual dependence of the conditional volatility of $\Delta CS(t)$ upon the past is to plot $(\Delta CS_t - \mu)^2$ against CS_{t-1}, which is done in Figure 5.7.a. The evidence of a level effect it's not very clear. Alternatively, we can look at the cross correlation between the squared standardised residuals and lagged standardised residuals. These cross correlations should be zero for a symmetric GARCH model and negative for asymmetric GARCH models (TARCH or EGARCH). From Figure 5.7.b it emerges that volatility does not depend upon the sign of credit spread changes; in fact, neither the magnitude of the correlations is high, nor the sign is persistent over time. However, the cross correlation only picks up linear associations between the two series and may miss nonlinear dependence between the two series.

As an alternative approach to check for any level effect we can investigate if the observed conditional heteroskedasticity in the data might be better accounted for by an asymmetric GARCH process -TARCH or EGARCH. The Threshold GARCH (TARCH) model, introduced by Zakoian (1990) and Glosten, Jagannathan and Runkle (1993), differentiates from a GARCH model since the quadratic form of the residuals in the standard GARCH is replaced by a linear function, allowing for different reactions of volatility to the sign of the past errors. Another useful parameterisation is the exponential GARCH (EGARCH) proposed by Nelson (1991):

$$log(\sigma_t^2) = \alpha_0 + \beta_1 log(\sigma_{t-1}^2) + \alpha_1 \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{5.13}$$

where the parameter γ is essentially the parameter that allows for asymmetry. If γ is not significantly different from zero, then a positive surprise has the same effect on volatility as a negative surprise of the same magnitude. If $\gamma > 0$, a negative surprise ($\varepsilon > 0$) increases volatility more than a positive surprise ($\varepsilon < 0$). Note that a bad news in the case of credit spreads is identifiable by a positive shock $\varepsilon > 0$. If $\varepsilon > 0$ the credit spread level increases and the credit risk as well. For this reason we expect $\gamma > 0$ if volatility increases with bad news ($\varepsilon > 0$). From the estimation of the TARCH (1,1) and EGARCH (1,1) we obtain values for the leverage effect parameter γ not significantly different from zero.

A graphical and more intuitive presentation of these results is offered by the news impact curve. This curve relates past credit spread changes shocks (news) to current volatility and measures how new information is incorporated into volatility estimates. In other words, the curves show whether the volatility of the two subsets reacts in the same manner after a bad or good unexpected event. The news impact curve for a TGARCH (1,1), for example, is given by:

$$\sigma_t^2 = A + \alpha_1 \cdot \varepsilon_{t-1}^2, \text{ for } \varepsilon_{t-1} < 0 \tag{5.14}$$

$$\sigma_t^2 = A + (\alpha_1 + \gamma) \cdot \varepsilon_{t-1}^2, \text{ for } \varepsilon_{t-1} > 0 \text{ where} \tag{5.15}$$

$$A = \alpha_0 + \beta_1 \cdot \sigma_{Un}^2 \tag{5.16}$$

where σ_{Un}^2 is the unconditional variance. From our estimates we obtain that:

$$\sigma_t^2 = -1.93E-06 + 0.203 \cdot \varepsilon_{t-1}^2 \text{ for } \varepsilon_{t-1} < 0 \tag{5.17}$$

$$\sigma_t^2 = -2.71E-06 + 0.206 \cdot \varepsilon_{t-1}^2 \text{ for } \varepsilon_{t-1} > 0. \tag{5.18}$$

Eqs. 5.17 and 5.18 are represented in Figure 5.7.c and 5.7.d equivalently. We can see how bad news ($\varepsilon > 0$) have just slightly bigger impact on conditional volatility as indicated by the steeper slope for the positive side.

5.4.4. Summary results

The explanatory power of linear and nonlinear models is very similar with adjusted R^2 around 30 percent. The variables able to explain changes in credit spreads are the two autoregressive terms, the return on the FTSE All Share index (lagged one period), the change in the exchange rate against the dollar (lagged one period), and the contemporaneous change in the TERM spread. The signs of the estimated coefficients are all consistent with our expectations. Credit spread changes are mainly explained by autoregressive components, which present a negative sign implying mean reversion in the credit spread process. Moreover, credit spreads increase as the slope of the term structure decreases and increase as the sterling appreciates. The return of FTSE in the previous period has a negative impact on credit spreads in the current period. The coefficient of changes in the risk-free short-term rate is negative but not significant either statistically or economically. Finally, credit spreads volatility is increasing with credit spreads level.

A GARCH-M (1,1) model was also estimated with a mean equation similar to the mean equation of previous models except for the presence of an additional term, h, representing the impact of the conditional standard deviation on the conditional mean. The trade-off parameter γ, which is the estimated coefficient for the h term, can be interpreted as the coefficient of relative risk aversion according to Merton (1980) and Campbell and Hentschel (1992). The sign and the magnitude of this parameter depend on the utility functions of the agents and the supply conditions of the assets. Hence, γ can take a positive, negative, or a zero value (Engle et al. 1987). Note also that γ is the price for systematic risk, that is the price for the risk component that cannot be diversified. If fluctuations in volatility are mostly due to shocks to the unsystematic risk, γ can have any sign. In other words, an increase in the conditional variance, which is a measure for the total risk, does not need to be accompanied by an increase in the risk premium. The GARCH-M parameter is positive but not significant. Volatility, therefore, does not contribute to the premium for credit risk.

We also tested whether among the other explanatory variables the error correction mechanism (ECM) is significant and if its coefficient is negative as we expect in accord with convergence toward the long-run equilibrium. To this aim we included the ECM in the mean equation interpreting its coefficient as a speed of adjustment parameter. If credit spreads start to increase more rapidly than is consistent with the steady state solution, the term $\{cs(-1 +0.003165*Log(P_{FTSE}(-1))\}$ increases. However, since the coefficient is less than zero, the overall effect is to slow down the short-term growth in credit spreads, forcing credit spreads at time t

back towards their long run growth path. In other words, changes in credit spreads partially correct last period's disequilibrium and move towards the new equilibrium in response to movements in its determinants (long-term interest rates, return index on the FTSE All Share index and short-term interest rate conditional volatility). In fact we found that the estimated ECM coefficient in the mean equation is actually negative but not significant. This does not convalidate the cointegration analysis before developed, confirming that a more appropriate methodology should be applied to shed some light on credit spreads long-term relationships.

5.5. Conclusions

The main results of our investigation about the behaviour of credit spreads on the sterling Eurobond index can be summarised as follows. Credit spreads show to be characterised by a cyclical behaviour and by a clustering of outliers across time, which is symptomatic of a persistent volatility process. This argues against homoskedastic models for credit spreads in favour of conditionally heteroskedastic models. The unconditional distribution of both credit spread levels and changes is more peaked and displays fatter tails than a normal distribution. Short-run co-movements with the main financial and economic variables are measured by correlation coefficients. Changes in credit spreads appear to be negatively correlated with interest rates variables, and with the exchange rate against the dollar. On the other hand, credit spreads are positively correlated with variables proxy for the consumer confidence or business cycle. From the intertemporal stationarity analysis credit spreads result to be integrated of order 1, and long-run comovements (cointegration) are weakly observed with the FTSE All Share Price index. Moreover, credit spread levels and changes are proved not to be an *i.i.d.* process and from the autocorrelation structure analysis a few stylised facts emerged: short-term dependence, nonlinearities, and persistence in the conditional variance. The evidence, hence, suggests nonlinear dynamics and time-varying volatility structure.

We estimated linear and nonlinear models to identify the factors driving changes in credit spreads. Our results show that the factors suggested by traditional models of default risk explain 30 percent of the variation in credit spreads as measured by the adjusted R^2. We find that the signs of the coefficients of the explanatory variables are in line with what the analysis would predict. An increase in the return on the FTSE leads to a contraction in credit spreads. Moreover, Eurobond spreads are positively related to the exchange rate and negatively related to the slope of the term structure. The ECM, as derived from the cointegration analysis, was also added in the model, but its estimate was found not significant.

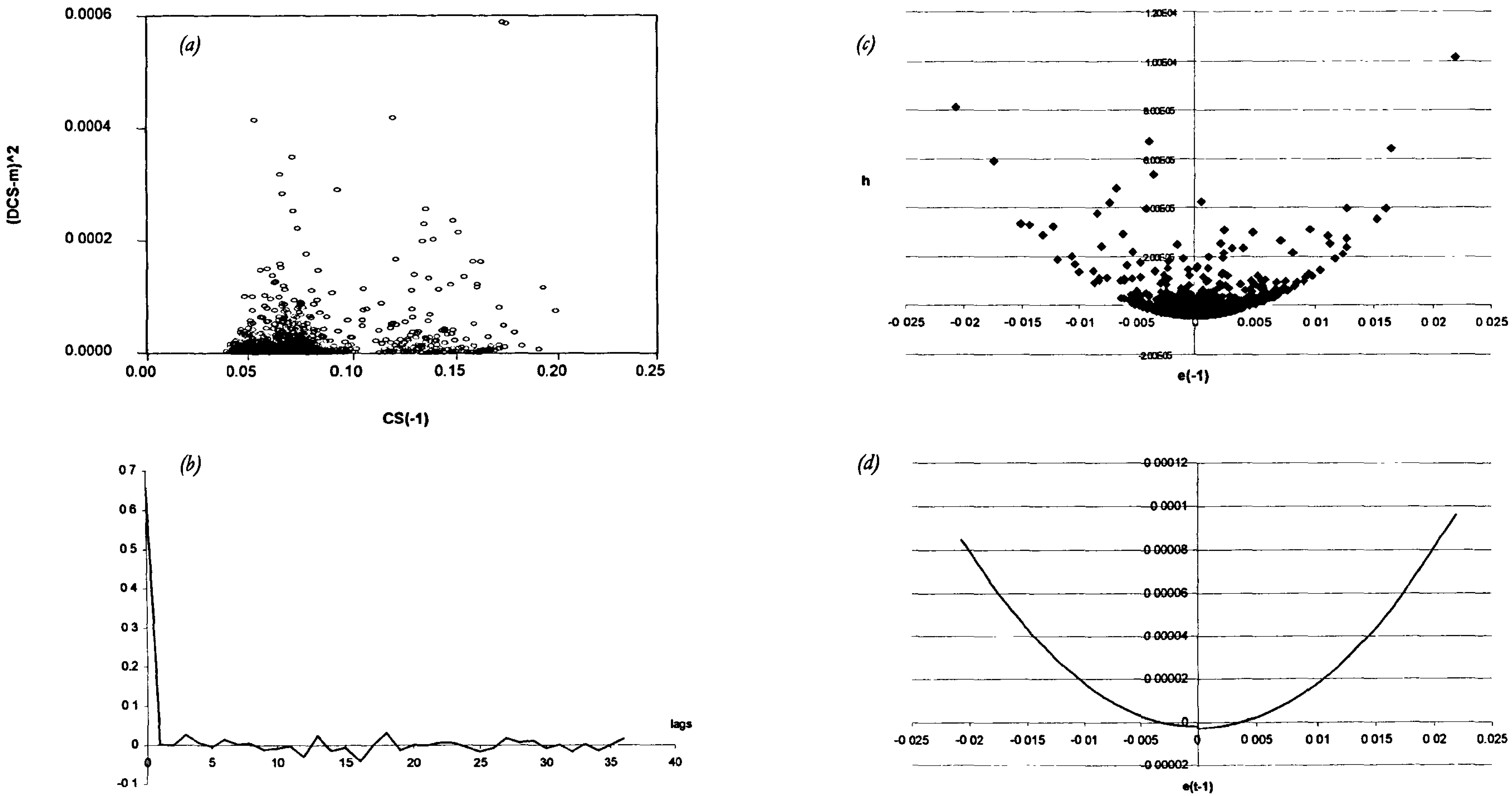
The analysis of the residuals shows that nonlinear models remove the autocorrelation but cannot fully account for the leptokurtosis they reveal. The study also finds a preliminary piece of evidence in favour of periodicity in the time series of changes in credit spreads. Finally, no statistically significant evidence of asymmetries in the persistence of positive and negative shocks is documented.

Our empirical results contribute to understanding the time series process of credit risk. This has implications for term structure models of corporate yields, the pricing of credit derivatives, and methods for measuring credit risk. Our investigations can be refined by further exploring the long memory structure of credit spreads in the presence of nonlinearities and by a future investigation about the presence of periodic cycles, which might be exploited for forecasting purposes. It remains also to be investigated whether GARCH models with thick-tailed errors can account for *all* the leptokurtosis observed in the data. The hypothesis of a mixture of normal distributions - that might explain both the shape of the densities and the excess kurtosis of the data- and the nonlinear cointegration hypothesis might also be the focus of new research in the field of credit spreads.

Figure 5.7 *Asymmetric Responses and News Impact Curves*

(a) To examine the dependence of the conditional volatility of $\Delta CS(t)$ upon the past we plotted $(\Delta CS_t - \mu)^2$ against CS_{t-1}. (b) Alternatively, we can look at the cross correlation between the squared standardised residuals and lagged standardised residuals. These cross correlations should be zero for a symmetric model and negative for asymmetric models. Note that the cross correlation only picks up linear associations between the two series and may miss nonlinear dependence.

(c) and (d) We present the news impact curves, which are curves that relate past credit spread changes shocks (news) to current volatility and measures how new information is incorporated into volatility estimates. We can see whether the volatility of the two subsets reacts in the same manner after a bad or good unexpected event. We can see how bad news (ε>0) have just slightly bigger impact on conditional volatility with steeper slope for the positive side.



changes in the variance of abnormal yields will provide results different from those obtained using a standard event-study methodology.

The remainder of the chapter is organised as follows. In Section 6.2, we review the evidence to date on this topic. Data and methodology are explained in Section 6.3. In Section 6.4, we document and present the results regarding the effect of corporate and government rating revision announcements on daily spread mean and volatility. Conclusions are drawn in the last section.

6.2. Literature Review

Research on the information value of bond-rating revisions has produced mixed results so far. Two ways to approach the question have been explored in the literature. The first is to examine whether bond yields are related to rating information. The second is to examine price reactions to rating changes. Using the first approach, West (1973), Liu and Thakor (1984), Ederington, Yawitz and Roberts (1984, 1987) and others relate yield spreads (i.e., the difference between corporate bond yields and the yields of equal maturity default risk-free bonds) to ratings, controlling for firm and issue characteristics. In general these studies find that credit ratings help explaining cross-sectional differences in yield spreads, and have a statistically significant independent effect on yields. In other words, ratings seem to convey pertinent information to investors in addition to what they can deduce from publicly available data.

It is not clear, however, whether rating information is pricing relevant per se or merely proxies for omitted, publicly available, variables that affect yield spreads. This is investigated by studies taking the second approach and examining the reaction of bond and stock prices to announcements of rating changes. The advantage of this approach is that each firm serves as its own control, which means that all pricing-relevant factors are controlled for. We briefly present below the main works related to rating revisions and stock price reaction. We look more extensively at rating changes and bond prices reaction.

[21] See, for example, Foster et al. (1984), "Earnings Releases, anomalies and the behaviour of security returns", *The Accounting Review*, 59, 4, p. 574-603; and Bernard and Thomas (1989), "Post-Earnings Announcements", Journal of Accounting Research, 27, Suppl., p. 1-36.

6.2.1. Stock Market Reaction

Most of the literature has focused on the adjustment of equity prices to the release of new rating information. Griffin and Sanvincente (1982), Holthausen and Leftwich (1986), Hand, Holthausen and Leftwich (1992), Wansley and Clauretie (1985), Cornell, Landsman and Shapiro (1989), Matolcsy and Lianto (1995), Ederington and Goh (1998) have all established that stock market reacts negatively to bond downgrade announcements, while upgrades are not found to be associated with significant abnormal returns. Clark, Dellva and Foster (1993), through the use of influence statistics, find a positive relationship between bond rating changes and changes in the beta of the firm. Cornell, Landsman, and Shapiro (1989) examine whether the response of stock prices is affected by the nature of the firm's assets and suggest that the impact of new information on a firm's value is likely to depend on the firm's net intangible assets. Goh and Ederington (1993) find evidence supporting the hypothesis that the reaction to downgrades depends on the exact reason for the downgrade. The market reaction is sizeable and significant only when rating changes are related to the performance or deterioration in the firm' financial prospects. On the other hand, rating downgrades due to an increase in leverage have positive implications for stockholders, but as they are generally in response to past known leverage increases, no equity market reaction is observed for them. Finally, Akhigbe, Madura and Whyte (1997) find significantly negative valuation effects for rating downgrades, and they show how this effect is transmitted throughout the whole industry. Dichev and Pietroski (1998) find that stocks with upgrades outperform stocks with downgrades for up to one year following the announcement. Further evidence suggests that this divergence between upgrades and downgrades is primarily due to the returns of small firms and firms with non-investment grade debt.

The general consensus is that the market for common stocks is relatively efficient. However, much less is known about bond market efficiency mostly because of the lack of data on bond pricing. We proceed introducing and briefly discussing the main empirical works focused on bond market reaction to rating change announcements.

6.2.2. Bond Market Reaction

Weinstein (1977) uses 132 rating changes from 1962 to 1974 to examine the difference between the holding period return both on utility and industrial bonds with changed ratings and on bonds with the original unchanged rating. He finds marginal evidence of a price reaction in the period 18 months to 6 months before the rating change and no evidence of abnormal returns in the period from 6 months before to 6 months after the event. However, none of the 23 excess holding period return averages that Weinstein presents in the paper are significantly different from zero. Moreover, the use of non-transaction-based monthly prices raises questions about the study's findings.

Wakeman (1978) uses weekly bond returns and confirms Weinstein's results in not finding any price reaction at the time of a rating change. On the same line Hettenhouse and Sartoris (1976) and Pinches and Singleton (1978) report that rating changes for investment-grade public utility bonds provide little or no information of value to shareholders. They state there is a lag that ensures that any information content is fully discounted by the month of the change. Wakeman (1981) argues that rating changes, which lag rather than lead security price changes, provide a code that incorporates all the major ingredients of the bond's risk. Moreover, since rating changes are triggered by economic events, it is not clear how much of the price reaction is due to the rating announcement and how much is due to the triggering economic event itself.

McCarthy and Melicher (1988) introduce a constrained optimisation approach using a mean-variance framework to examine bond-rating changes in the context of a bond portfolio. The bonds with rating changes are matched with bonds that have not been re-rated. The relative demand for two closely matched bonds is expected to be similar under conditions of equilibrium. Changing conditions should alter this relationship. In particular, the relative demand for a bond is expected to rise if its risk-return attributes and rating are improving and to decline in the opposite case. As a consequence, divergence in investment proportions between matched change and non-changed bonds is used to identify market anticipations. The results show that in over two-thirds of the cases, the market anticipated the formal announcement of a rating change. Furthermore, the average market adjustment occurred earlier for downgraded bonds than for upgraded bonds.

However, a number of studies do find significant bond price reactions after the ratings announcement. Katz (1974) collects monthly bond yields for electric utility companies spanning the 1966-1972 period. The purpose of the study is to test the hypothesis of a semi-strong efficient bond market. The change in yield to maturity is taken as measure of market adjustment. Regression models are developed to forecast the expected yield to maturity of a reclassified bond for both its old and new rating class in the twelve months prior to and five months after the rating change. The actual yield is then compared to the two expected yields to determine to what degree an adjustment has taken place. The empirical results indicate that no anticipation existed prior to a public announcement of reclassification. In addition a slight lag is found to exist in the adjustment process subsequent to the announcement, and 100 percent adjustment prevails only 6-10 weeks after a reclassification.

Grier and Katz (1976) examine 96 industrial and utility issues down-rated by S&P between 1966 and 1972. In this case average monthly dollar and percentage changes in market prices are used as measure of market adjustment. Re-rated bonds are compared with single issues with approximately the same coupon and maturity. They conclude that the market reacts after, not before, a rating change, thought no formal statistical analysis is performed to sustain this conclusion.

Ingram, Brooks and Copeland (1983) examine the information content of municipal bond rating changes by evaluating monthly price adjustments during the period surrounding the rating change. Subtracting from the yield to maturity of each municipal issue the estimated yield to maturity of a US Treasury bond with similar maturity and coupon, a yield premium for each municipality for each month is derived. The effect of bond rating changes is assessed by comparing the average yield premium for municipalities that experienced a rating change with the average yield premium for equivalently rated municipalities that experienced no rating change. Rating changes were limited to the period May 1977 through April 1978 to enable the derivation of yield premia for a minimum of 8 months prior and 8 months after the rating change. Test statistics on yield premium differentials show that the impact of rating changes occurred during the month of the change. The yield premium differential does not appear to anticipate the impending rating change.

Wansley, Glascock and Clauretie (1992) use institutional bond weekly prices from Merrill Lynch Bond Pricing Service instead of listed quotes, which are infrequently traded. From this study the bond market appears to be highly efficient with respect to changes in bond rating grades. A strong negative announcement effect is found during the week of bond rating reductions and no price reaction is observed during the weeks after the rating change. While bond downgrades convey considerable information, bond-rating increases are not associated with announcement effects. Additionally, this study, breaking down the sample according to the industry sector, provides evidence that industrial bonds may be more sensitive to rating changes than utilities.

Hand, Holthausen and Leftwich (1992) is the first study that uses daily data to examine the price reaction of bonds to rating changes between 1977 and 1982. Pricing information was collected from 60 days before to 60 days after rating change announcement. Hand et al. use exchange transactions data and find that anticipated rating changes produce no reaction in either the bond or stock markets. By contrast, *unexpected downgrade* announcements cause significantly negative bond and stock returns; and *unexpected upgrade* announcements cause relatively little positive movement in bond prices. Moreover for downgrades, the average excess bond returns result to be stronger for below investment grade bonds than for investment-grade bonds. However, we recall that exchange-traded debt instruments suffer of a sample bias toward non-investment grade debt in the dimensions of listing, volume, and frequency of trade. In addition the irregularity of trading and the thinness of the market made it infeasible to investigate the issue of when a bond began to exhibit abnormal returns.

Hite and Warga (1997) use a database of more than 1500 industrial firms' trader quotes. The time period spans from March 1985 through March 1995 and all S&P and Moody's rating changes are analysed from 12 months before to 12 months after the rating change. Their findings reveal a significant announcement effect (in terms of abnormal bond returns) to downgraded firms in both the announcement month and pre-announcement period The magnitude of the downgrading effects increase dramatically moving from investment-grade to non-investment grade firms. Also in this study upgrades effects are much weaker in magnitude and significance than downgrade effects. The evidence for downgrades is generally stronger in terms of event-month and pre-event price reactions if the sample is restricted to events that are uncontaminated (i.e., not preceded by a rating change in the six-month pre-event period) and in which both agencies simultaneously re-rate.

Kliger and Sarig (1999) collect monthly information on bonds included in the Lehman Brothers Bond Indices. Their objective is to test if the release of new rating information affects both the value of the firm as a whole, as well as its division between stockholders and bondholders. They find that bond and stock prices and yield spread information provided by Moody's is valuable. They find no evidence of any impact on the firm value as a whole and they interpret this explaining that bankruptcy costs are small and that the incremental information of bond rating is largely about diversifiable risks. This is because if bankruptcy costs are significant or if default risk is systematic, the rating information that affects debt and equity values will also affect firm value. Lastly, they find that the effect of rating information on bond prices is monotonic in firm leverage: the more levered the firm is, the stronger is its bond-price reaction to new rating information.

Clark, Foster and Ghani (1997) focus on the information effect of bond rating changes by examining financial analysts' reactions rather than the market reaction. The specific focus is on the effect of firm size on the short-term forecasts. Large firms are expected to provide significantly more information to the market than small firms. This is because of a belief that the benefit of such information sharing exceeds the cost and because they have fewer competitive concerns than small firms. Their sample consists of 440 corporations downgraded by S&P between 1986 and 1992. Firms are split in two groups on the basis of market capitalisation. Average earnings forecast revisions and abnormal earnings forecast revisions for small and large firms are estimated and tested for significance in the months -6 to +6 respect to the event month. Results indicate that rating information is value-relevant with respect to small firms. The evidence does not support similar value-relevance for large firms. This would imply that rating agencies diminish information asymmetries in the capital markets by communicating valuable new information about firms that tend to operate in less precise information environments.

6.2.3. Event studies and Event-Induced Variance

Although most traditional event-study methods assume a constant variance through both pre- and post-event periods, a number of studies have documented that the classical event study methodology exhibits a bias toward detecting "effects", irrespective of whether such effects actually exist.[22] Brown and Warner (1985) verify that event studies work well when an event has an identical effect on all firms. They also warn that when an event has different effects on firms, the variance of the variable we are considering (returns, yields, etc.) will increase -due to a temporary change in the firm's systematic risk. Moreover if variance is underestimated, the test statistic will lead to rejection of the null hypothesis more frequently than it should, even when the average performance is zero.

The first paper that takes into consideration variance aspects is Hettenhouse and Sartoris (1976). They construct an F-ratio of the variance of yield differentials six months before and after the revision, and one month before and one month after. The results don't allow them to reject the hypothesis of no difference in the variance before and after the revision. In other words rating changes showed to be not useful to homogenize investor opinion. One additional possibility examined is that the conformity of opinion on yields would be greater closer to the rating revision. F-ratios are then calculated by dividing the variance for the six-month time period by the variance for the one-month time period. The data, however, provide little support for the hypothesis that the variability is reduced by proximity to the revision date.

[22] See, for example, the papers by Boehmer, Musumei and Poulsen (1991), Brown and Warner (1985), and Frankfurter and McGoun (1993).

More recently, a number of papers dealing with stock market reaction to various events, have analysed the importance of adjusting for autoregressive conditionally heteroskedastic (ARCH) effects in the residuals obtained from the conventional market models. This adjustment has been motivated by the idea that the ability to reliably form statistical inferences can be seriously compromised by failing to consider the ARCH error structure (Connolly, 1989; Schwert and Seguin, 1990). Brockett, Chen and Garven (1998), for example, use a market model that incorporates ARCH effects, time-varying systematic risk parameter (beta), and time-varying conditional variance. With this new methodology they reach exactly the opposite conclusion of previous empirical studies regarding the effects of a significant regulatory event (specifically, the passage of California's Proposition 103).

Since ARCH effects have been shown to be generally significant in financial time series and specifically significant in the Eurobond yields series, we take this into consideration in our model by applying GARCH models to the abnormal yield series. No previous work has modelled bond yields or prices reaction taking into consideration both cross-sectional and time series changing variance.

6.3. Data and methodology

We collected data on all sterling Eurobonds rating revisions by Standard and Poor's between January 1992 to December 1999. From Datastream International we retrieved the daily time series of ratings for each bond starting from the date it was issued. Credit rating information was available for 477 fixed coupon straight Eurobonds. The data were screened using the following process. The whole sample was split on the basis of rating migrations during the life of the issue. 313 Eurobonds were not re-rated over the sample period, while 164 experienced a rating revision, of which 123 downgrades and 41 upgrades. Eight bonds were re-rated within 60 days from a previous revision and therefore excluded from the sample as causing overlapping observations. After this first screening, the data set reduces to 117 downgrades and 39 upgrades.

In order to separate the effect of a downgrade upon a bond's yield from the effect of a change in the general credit market conditions we collected a control group of bonds similar in all respects to the group of re-rated bonds. The sole difference being that the control group did not experience a rating change. We successively matched individually each re-rated Eurobond with a Eurobond in the non re-rated sample with similar characteristics in terms of original rating, industry sector, time to maturity on the date of the rating's change, coupon and market value. For the bonds that have been re-rated over the period and for the matched (control) bonds we collected daily time series of redemption yields and maturity dates. Coupon rates and number of days accrued towards the coupon payment date were also collected. The last screening step was to select issues for which two or more features -among rating, maturity, and industry- could not be properly matched. These issues were dropped from the sample with the resulting data set finally consisting of 107 downgraded and 29 upgraded bonds. While we were able to match exactly the original ratings, 105 bonds were not matched on one criterion –maturity or industry. Average absolute differences in maturities are 1.85 years and industry is matched 80% of the times.

6.3.1. *Rating Transition Matrix*

Table 6.1 presents the rating transition matrix defined over the whole sample period 1992-1999 and for all the bonds (477) for which rating information is available. It depicts the size and the direction of typical rating changes. The rows of the matrix indicate the rating at the time the bond is issued. The columns relate to the new rating in correspondence of each first re-rating of each bond. The number in each cell represents the number of observations that have the respective old and new rating.

The upper left-hand corner of Table 6.1 indicates that 90% of AAA-rated bonds have remained at that level over the period from 1992 to 1999. In other words, AAA-rated issues have the greatest stability, in terms of retaining their initial rating. This is not surprising as a triple A bond can change in only one direction. The next cell to the right indicates that 10% of AAAs have been downgraded to AA+. Moreover, the table indicates that 10% of all AA- rated companies experienced an improvement of one letter rating (to AA). The vast majority of across-rating changes occur within one class (within-one-class changes are on the two diagonals immediately above the and below the main diagonal). Only 39 observations, or about 8% of the sample, are across two or more rating classes.

Cells along the main diagonal of the matrix contain the number of bonds in each correspondent rating category that remained unchanged over the whole period. Unchanged bonds account for 313 observations, or about 65% of the sample, indicating that the most likely rating for an issuer is the original rating the issuer was assigned when issued. As we move off of the diagonal values are generally lower. This is simply explained by the infrequent large changes in credit quality over the period. Cells above and below the main diagonal provide number and percentage of bonds that have been downgraded (sum equal to 123) and upgraded (sum equal to 41), respectively.

In the next steps we will examine how the observed credit quality and magnitude of rating changes in our sample are related to the strenght of the information effect of bond rating changes.

	AAA	AA+	A	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	Total
AAA	130 (0.9)	15 (0.10)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	145
AA+	-	20 (0.49)	10 (0.24)	8 (0.20)	-	-	1 (0.02)	-	-	2 (0.05)	-	-	-	-	-	-	41
AA	-	9 (0.19)	26 (0.54)	8 (0.17)	1 (0.02)	1 (0.02)	2 (0.04)	1 (0.02)	-	-	-	-	-	-	-	-	48
AA-	-	-	6 (0.10)	37 (0.59)	20 (0.32)	-	-	-	-	-	-	-	-	-	-	-	63
A+	-	-	-	5 (0.09)	20 (0.36)	24 (0.44)	6 (0.11)	-	-	-	-	-	-	-	-	-	55
A	-	-	-	-	1 (0.03)	25 (0.66)	5 (0.13)	7 (0.18)	-	-	-	-	-	-	-	-	38
A-	-	-	-	-	-	8 (0.22)	25 (0.68)	3 (0.08)	-	-	-	-	-	1 (0.03)	-	-	37
BBB+	-	-	-	-	-	-	3 (0.21)	11 (0.79)	-	-	-	-	-	-	-	-	14
BBB	-	-	-	1 (0.09)	-	-	-	1 (0.09)	8 (0.73)	1 (0.09)	-	-	-	-	-	-	11
BBB-	-	-	-	-	-	-	-	-	2 (0.40)	1 (0.20)	1 (0.20)	1 (0.20)	-	-	-	-	5
BB+	-	-	-	-	-	-	-	-	-	2 (0.50)	1 (0.25)	1 (0.25)	-	-	-	-	4
BB	-	-	-	-	-	-	-	-	-	-	-	2 (0.67)	-	1 (0.33)	-	-	3
B-	-	-	-	-	-	-	-	-	1 (0.50)	-	-	-	-	1 (0.50)	-	-	2
B+	-	-	-	-	-	-	-	-	-	-	1 (0.25)	-	1 (0.25)	1 (0.25)	1 (0.25)	-	4
B	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2 (0.67)	1 (0.33)	3
B-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4 (1.00)	4
Total	130	44	42	59	42	58	42	23	11	6	3	4	1	4	3	5	477

Table 6.1 *Rating Transition Matrix, 1992-1999.*

The rating transition matrix is defined over the whole sample period 1992-1999. The size and the direction of typical rating changes are presented. Rows indicate the rating at the time the bond is issued. Columns correspond to the new rating in correspondence of each first re-rating of each bond. In each cell we report the frequency and the probability in brackets. Along the diagonal there is the probability for a bond in each correspondent rating category to remain unchanged over the whole period.

6.3.2. *Standard Event Study*

We first conduct a standard event study of the bond market (price) reaction to the announcement of a rating change. We use an event window of (-60; + 60) days around the event day (day zero). The event window is split in five sub-periods, T_j, with j=1, 2, ..., 5. T_1 (T_5) includes the period - (+)60 to - (+)16 days before (after) the event; T_2 (T_4) includes the period - (+)15 to - (+)2 days before (after) the event (pre-announcement and post-announcement periods); and T_3 is the small -1 to +1 event window (announcement period). Daily returns for changed and non changed bonds are computed as follows:

$$R_{it} = \frac{(P_{it} - P_{i,t-1}) + \dfrac{n}{360}C - \dfrac{n-1}{360}C}{P_{i,t-1} + \dfrac{n}{360}C} \qquad (6.1)$$

with n = days accrued towards the next coupon payment and C = coupon payment.

Abnormal Returns (*AR*s) are successively measured by subtracting from the return on a changed bond the return on a non-revised bond having the same rating, industry and maturity classification as the bond in question. Cumulative Abnormal Returns (*CAR*s) are successively computed for various event windows and for downgrades and upgrades separately. Their magnitude is tested in order to see if the adjustment lag for bonds is of economic significance. In other words, we want to provide preliminary evidence about the possibility for a trader to make a profit upon announcement of a rating change by selling the reclassified bond and later repurchasing it.[23]

Besides splitting the sample in positive and negative revisions, downgraded bonds are broken down into various categories on the basis of industry, rating, guarantee, country of origin of the borrower, coupon, marketability, maturity on the day of rating change, and the presence of a previous rating change (rating history). We aim to test for the existence of profitable trading rules and significant differences among the various categories of bonds. A simple t-test and one-sample signed rank test are used to test the null hypothesis that the mean and the median, respectively, of the population from which the data sample is drawn is equal to zero.

[23] The current analysis does not take into account commission fees.

6.3.3. Asymmetric Responses

In the second step, we use the same event study methodology to examine the impact of rating changes announcements on bond yields. The first hypothesis we want to test is the different response of bond yields to positive and negative rating revisions. Empirical evidence occasionally has revealed that both the stock and bond market react to downgrades but not to upgrades (Holthausen and Leftwich, 1986; Cornell and Shapiro, 1987; Wansley et al., 1992; Hand, Holthausen and Leftwich, 1992; Hite and Warga, 1997). The hypotheses that may help explain this asymmetric response are the following: i) companies voluntarily may release favourable information but may be reluctant to release unfavourable information; ii) rating agencies may spend more resources in detecting deterioration rather than improvement in credit quality (Ederington and Goh, 1998); or iii) bondholders (stockholders) may be more concerned with increases (downgrades) rather than decreases (upgrades) in risk.

An alternative explanation is provided by the stakeholder hypothesis (Cornell, Landsman and Shapiro, 1989). Implicit claims have components that are analogous to bonds in that the maximum payout is fixed. A firm that has been performing well is unlikely to improve its performance significantly in the regard of default risk if its financial conditions strengthen. On the downside, however, stakeholders face significant risk. If a company runs into financial difficulties, the payouts on implicit claims may be cut substantially. The exception is a firm whose rating is already low that its stakeholders are not expecting payments on many implicit claims. If such a firm experiences an upgrade, the price of its implicit claims could rise substantially.

We want to test also for different responses between groups of bonds according to various factors whose impact on bond value is well understood. To this aim observations have been classified into different groups according to maturity, original rating, coupon, industrial secor (financial/industrial), country of the issuer, guarantee attached, liquidity, and rating history. We discuss them below.

Industrial Sector. We have split our sample in industrial and financial bonds to compare the magnitude and the volatility of their yield adjustments to rating reclassification. While some evidence exists which suggests that industrial bonds are more sensitive to rating changes than utilities (Grier and Katz, 1976; Wansley and Clauretie, 1985), no empirical evidence has ever been provided regarding any different behaviour between industrial and financial bonds. We will provide an important piece of evidence regarding this matter.

Coupon. Bonds have been split into low-coupon bonds and high-coupon bonds on the basis of the median coupon rate. The higher the coupon rate, the larger will be the amount of obligations the firm will miss in case of default. For a given yield change, higher coupon bonds are inherently riskier than lower coupon bonds, so that a change in their rating represents a significantly higher increase in the default risk. On the other hand, bond price theorems indicate that bonds with lower coupon rates are characterised by more price volatility than similar bonds with higher coupon. As we are dealing with rating revisions rather than with default events, the latter hypothesis may be more appropriate.

Country of the Issuer. As we are dealing with the Eurobond market, and in particular, with Eurobonds issued in sterling, we expect bonds issued by non-UK borrowers to bear a higher risk component compensating for the exchange rate risk they are subject to. Evidence of the existence of a positive relation between yields on Eurobonds and the exchange rate risk is provided in Clare et al. (2000) and in Chapter V. In the event of an appreciation of the sterling, overseas borrowers face a higher price of their debt. This heavier debt burden might compromise their ability to repay the debt and their creditworthiness, raising their bond yields. According to this interpretation non-UK issues should be inherently riskier and a bigger reaction is expected in case a rating revision occurs.

Guarantee. We distinguish between bonds with attached negative pledge guarantee (NP) and bonds with no such guarantee attached. In the presence of a negative pledge clause, if the company issues new debt, the old debt must be secured as the new one. It is designed to protect the bondholder from credit deterioration as a result of the issuer's actions. The breach of the clause may accelerate the date for the repayment of the principal and put into place procedures to enforce repayment. As the presence of this indenture should reduce the credit risk for bondholders, we expect the yield effects of bond rating changes to be stronger for bonds with a negative pledge. This can be explained in terms of the relation between the probability for a bond to be downgraded with the attachment to the bond of a NP guarantee. Anticipating here a result obtained in the next chapter, bonds with NP clause are less expected to be downgraded. Their yields therefore will react more in case of an unexpected change in the rating.

Liquidity. The amount of bonds outstanding can be viewed as a proxy for the marketability of the bond. The smaller the amount outstanding, the less frequently we expect the bonds to be traded and the thinner their market. The uncertainty and the scarce disclosure of information associated to the lower marketability would make the market less efficient. However, if marketability results to be not significant, this might be due to the bond market efficiendency or to a misspeciification of the variable used as a proxy for marketability.

Rating History. Bonds having experienced a rating revision in the past have been classified as PC, while bonds never re-rated since they have been issued have been classified as NPC. It has been observed a serial correlation in the rating changes (Dichev and Piotroski, 1998), according to which a rating change is expected be followed by a new change in the same direction later on. Following this logic, the surprise of a rating change for a PC bond should be smaller than the surprise associated to a re-rating of a never revised bond, NPC. In other words, we expect higher yield jumps for non-previously re-rated bonds than for previously re-rated bonds.

6.3.4. OLS Panel Estimation

In order to be able to test for the market reaction, daily yield spread data are computed as the difference between the yield on a re-rated bond and the yield on the correspondent matched bond for the window-spanning period -60 to +60 days. To test our hypotheses abnormal yields daily time series/cross-section data from January 1992 to December 1999 have been pooled to estimate a least squares model (LS) where the dependent variable is the abnormal yields series. This methodology, although fails to account for the information related to the sample outside the (-60; +60) data window, it has the advantage that any general change in bond prices (or yields) caused by a change in the general credit market conditions is captured by the control group of bonds. Rating changes are therefore assumed to be only relevant factor affecting the life of the bond over the selected time window.

We indicate the abnormal yield series as AY. We plot the average movements in yield spreads around the time of negative and positive announcement in Figure 6.1. The plot shows the pattern of spreads (AY) sixty days before and after rating changes. The shaded area in the figure highlights the event window (-1; +1). During the forty-five days preceding negative rating announcements, yield spreads show a stable pattern around a mean value of 6-7 basis points (bps). In the next fifteen days (prior to the announcement), the yield spread level increase of 1 bp and increases 3 bps further to reach a 10 bps level during the announcement period. The upward trend continues also in the last two time windows with an increase of 2 bps in each of them. As far as the spread mean dynamics before, during, and after an upward rating revision is concerned, we observe a generally stable 15 bps level in the days before the pre-announcement period. Spreads successively tend to fall fairly smoothly of about 0.8 bps during the pre-announcement period and further decrease of 2 bps in the event window. The negative drift is still discernible in the post-announcement period after which the adjustment seems complete and the mean level finally stabilises around a mean level of -20 bps in the last time interval.

Summary statistics for the pooled AY series are provided in Table 6.2. Abnormal yields both for downgrades and upgrades are negatively skewed and slightly leptokurtic, as indicated by the skewness and excess kurtosis statistics. The null hypothesis of normality is rejected at the 0.01 level in both cases as indicated by the Jarque-Bera χ^2 statistic. Average and variance figures for time interval sub-samples provide a first general idea of the mean and volatility patterns over time for the AY series.

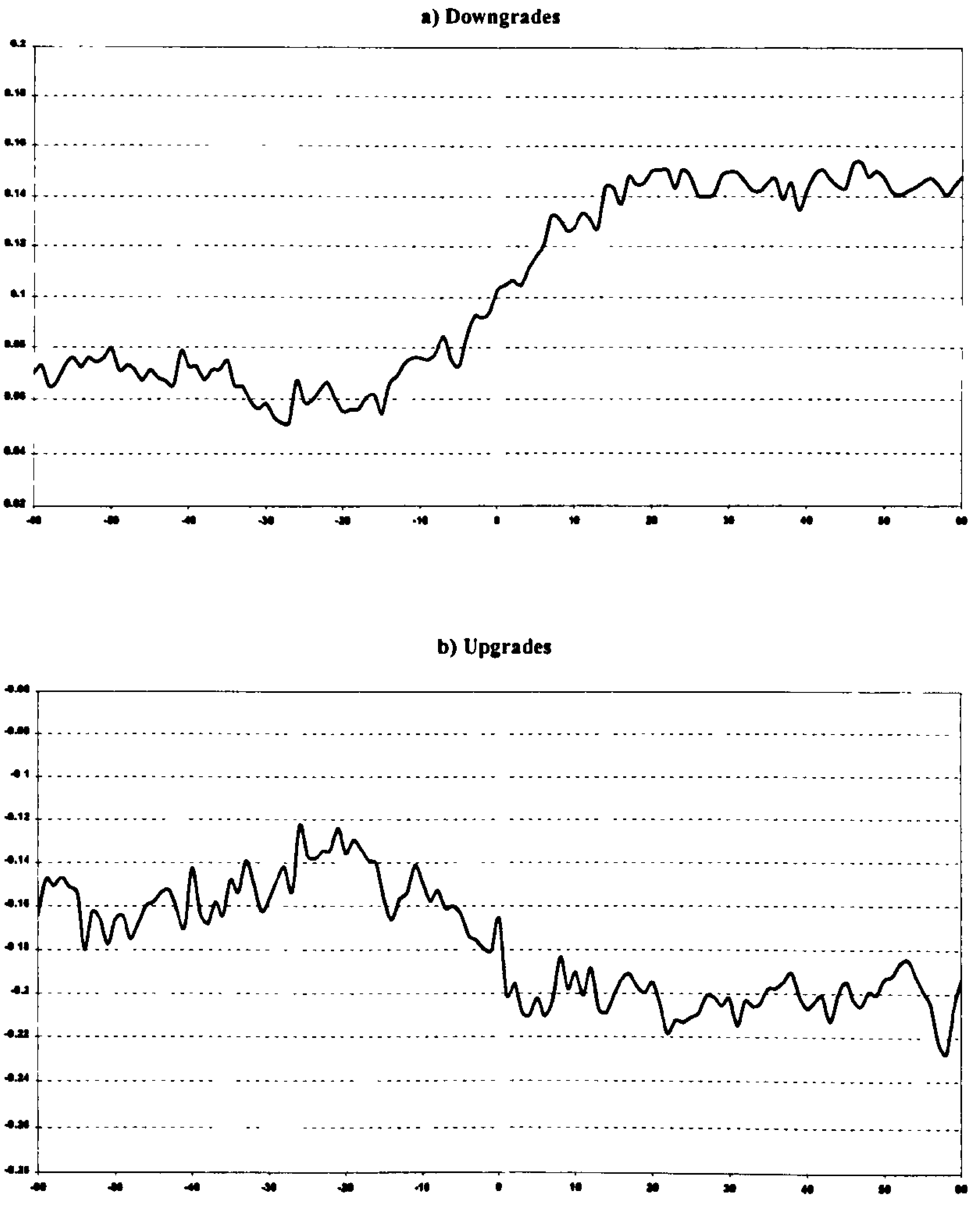


Figure 6.1 *Abnormal Yields for Downgrades and Upgrades*

Abnormal yields were computed as difference between yields of re-rated bonds and yields of matched bonds. We present graphs both for downgraded bonds (N=107) and upgraded bonds (N=29). The event window spans from –60 days before the announcement of the revision of the rating to +60 days afterwards. The –1; +1 event window is shadowed to allow a clearer comprehension of what is happening closely around the event day.

		Average	Median	Variance	Skewness	Kurtosis	Jarque-Bera	VR
Panel A: **Downs** (N=107)								
Total		0.064	0.062	0.094	-0.117	4.595	1375 (0.00)	
	T_1	0.048	0.048	0.005	0.109	0.091		1.000
	T_2	0.042	0.045	0.003	-0.036	0.193		0.635
	T_3	0.063	0.063	0.001	-0.011	-		0.178
	T_4	0.076	0.077	0.002	-0.128	0.013		0.394
	T_5	0.076	0.078	0.005	-0.021	-0.122		1.216
Panel B: **Ups** (N=29)								
Total		-0.178	-0.171	0.111	-0.319	3.089	61 (0.00)	
	T_1	-0.152	-0.155	0.007	-0.125	-0.024		1.000
	T_2	-0.161	-0.157	0.005	0.049	-0.007		1.142
	T_3	-0.182	-0.177	0.003	-0.129	-		0.699
	T_4	-0.200	-0.201	0.002	0.206	0.588		0.539
	T_5	-0.193	-0.204	0.004	0.161	-0.173		0.837

Table 6.2 *Descriptive Statistics for Abnormal Yields (AY)*

Descriptive statistics for abnormal spreads (AY) are computed as average values across all the firms and are reported separately for downgrades and upgrades, for the whole time window (-60; +60), and for each time interval T_j (j= 1, 2, ..., 5) . Variance ratios are also presented in the last column of the table.

A preliminary analysis to test for differences in the *AY* variance over time is performed comparing variance ratios computed in the various time intervals. Firstly, we have computed the variance of *AY* in each event window for each issue *i* (σ^2_{iT}, with T= 1,2,3,4, and 5). Then, ratios of each variance (σ^2_{iT}) over the variance in the first time period (σ^2_{i1}) are computed (VR_{iT-1}) for each issue *i*. The VR_{iT-1} ratios are pooled across firms in each sub-sample of downgraded and upgraded bonds. Both parametric (*t-test*) and non-parametric (the *Wilcoxon signed ranks test* and the *sign test*) tests are used. The results are quite strong and indicate a significant decline in downgraded bond volatility over the period -15 to +15. After day +15, volatility starts rising to go back to the initial level.[24] Mean volatility in the last period is indeed not significantly different from its mean level as before the pre-announcement period (mean difference = -0.049 and p-value = 0.85). As far as the

[24] Both mean and median paired differences are significant different from zero. Because of the non-normality of the data, we report only the Wilcoxon signed ranks Z-values for each paired period with their significance in parentheses: [-15; -2 and -1; +1] = -5.44 (0.00); [-1; +1 and +2; +15] = -4.66 (0.00); [+2; +15 and +16; +60] = -6.80 (0.00); [-15; -2 and +16; +60]=-6.01 (0.00).

volatility pattern for upgrades is concerned, volatility declines during the announcement and post announcement periods and starts rising up after day +15.[25] These preliminary findings suggest evidence of resolution of uncertainty around the event window.

We attempted to provide more accurate and formal evidence about the different bond yields reaction between downgrades and upgrades (and between the other categories mentioned above) introducing a pooled Least Square (LS) estimation. Before estimating the model, univariate time series analysis of the dependent variable, AY_{it}, was performed to determine the order of the autoregressive and moving average processes. We recall that estimators that ignore autocorrelated errors are biased, inconsistent and inefficient[26]. The number of statistically significant partial correlations suggests an autoregressive process of order two, with the first and the second lag partial autocorrelation coefficients are 0.98 and 0.17, respectively. An ARMA(2,0) model was selected on the basis of likelihood ratio tests and the principle of parsimony.

To identify the different effects of negative and positive rating revisions, issues were classified as downgrades and upgrades and two dummy variables were introduced which take value 1 or 0 depending on whether the bond has been downgraded (*DOWN*) or upgraded (*UP*). Additionally, we built a set of dummies (D_i with i=1, 2, ..., 136), each one for each of the bonds, able to capture the presence of potential heteroskedasticity across firms. Moreover, in order to test for a pre-rating and post-rating drift we split our event window in five sub-periods, T_j, with j=1, 2, ..., 5. As we mentioned above, T_1 (T_5) includes the period – (+)60 to – (+)16 days before (after) the event; T_2 (T_4) includes the period – (+)15 to – (+)2 days before (after) the event (pre-announcement and post-announcement periods); and T_3 is the small –1 to +1 event window (announcement period). We refer the reader to the classic paper by Gujarati (1970) on using dummies to test for equality between coefficients.

The general linear regression takes the form:

$$AY_{it} = \sum_{i=1}^{107} a_i D_i + \sum_{i=108}^{136} a_i D_i + \beta_1 AY_{i,t-1} DOWN_i + \beta_2 AY_{it-2} DOWN_i + \beta_3 AY_{it-1} UP_i + \beta_4 AY_{it-2} UP_i + \\ + \sum_{j=2}^{5} \delta_j T_j DOWN_i + \sum_{j=2}^{5} \varphi_j T_j UP_i + \lambda \sigma_t + \varepsilon_{it} \qquad (6.2)$$

[25] The Wilcoxon signed ranks Z-values for each paired period with their significance in parentheses are as follows: [-15; -2 and 1; +1]= -1.67 (0.09); [-1; +1 and +2; +15] = -2.21 (0.02); [+2; +15 and +16; +60] = -2.75 (0.00); [-15; -2 and +16; +60]=-2.54 (0.01).

[26] See Greene (1993, p. 419)

where AY_{it} is the abnormal yield for issue i at time t and ε_{it} is a white noise error with mean zero and variance h. Assuming independent, normally distributed and homoskedastic error terms, we will interpret the linear regression coefficient estimates as follows. $\sum_{i=1}^{107}\alpha_i$ and $\sum_{i=108}^{136}\alpha_i$ will be the average abnormal yield over the period (*-60; -16*) for downgraded and upgraded bonds, respectively; β_1 and β_2, and β_3 and β_4 are the estimated coefficients of the first and second autoregressive terms for downgrades and upgrades, respectively. The coefficients δ_j (with j=2, 3, 4, and 5) represent the difference of the average AY for downgrades in periods T_2, T_3, T_4 and T_5 respect to the average AY in the first time window, T_1. By the same logic, ϕ_j coefficients will have the same interpretation but with respect to upgraded bonds. According to this, if we want to know the absolute level of AY in the event window (T_3) for downgraded bonds we will have to sum up $\sum_{i=1}^{107}\alpha_i$ coefficients and the estimate for δ_3. The *t-test* will directly give the significance of the differences respect to the initial window.

Successively dummy variables were introduced to represent each of the previously formed groups and were combined both with the time dummy variables for the five windows around the event date (T_js) and with *DOWNS* and *UP* dummy variables. The total panel (unbalanced) observations are 16433.

6.3.5. *Event-Related GARCH*

The simple OLS estimation with pooled data models the mean of AY in the different time-windows without taking into consideration the possibility that the variance of AY may change over time. Ignoring any event-induced changes in the variance of the AY series may of course lead to biased and unreliable results. The effect of rating changes announcements on abnormal yield volatility may also be of interest.

For these reasons we introduce a GARCH model, which is able to model simultaneously the mean and the variance of AY series. From the autocorrelation of squared AY for each class of bonds we cannot reject the hypothesis of serial correlation. This preliminary test of ARCH-effects supports the introduction of a GARCH model. The model for abnormal yields incorporates the temporal information diffusion from lagged abnormal spreads, the effect of news on conditional volatility and autoregression in conditional volatility. The mean equation in the GARCH model is the same as in the OLS model. The mean and the variance equations are similarly structured as follows:

$$AY_{it} = \sum_{i=1}^{107} a_i D_i + \sum_{i=108}^{136} a_i D_i + \beta_1 AY_{i,t-1} DOWN_i + \beta_2 AY_{it-2} DOWN_i + \beta_3 AY_{it-1} UP_i + \beta_4 AY_{it-2} UP_i + \\ + \sum_{j=2}^{5} \delta_j T_j DOWN_i + \sum_{j=2}^{5} \varphi_j T_j UP_i + \lambda \sigma_t + \varepsilon_{it} \tag{6.3}$$

$$h_{it} = c + \sum_{i=108}^{136} a_i D_i + \sum_{j=2}^{5} b_j T_j DOWN_i + \sum_{j=2}^{5} d_j T_j UP_i + \theta_1 h_{it-1} + \theta_2 h_{it-2} + \xi \varepsilon_{it}^2 + \upsilon_{it} \tag{6.4}$$

$$\text{with } \varepsilon_{it} \sim N(0, h_{it}) \tag{6.5}$$

where ε_t is a white noise error with conditional variance h_{it}. According to Equations (6.4)-(6.5), the variance is allowed to differ across bonds and events (subscript i) and also across days within each time window (subscript t). We are therefore able to take into account all the three sources of heteroskedasticity explained above.

The specification in Equations (6.3)-(6.5) is therefore ARMA(2, 0) for the mean equation and GARCH(1, 2). The GARCH(1, 2) specification was selected as the best specification according to the parsimony principle (AIC and SBC criteria, and Likelihood Ratio test) as shown in Table A9. The variance on day t is conditional on the variance on the two previous days, according to the θs parameter estimates, and on the most recent squares shock, according to the estimate for ξ. The constant term c captures the average level of volatility in the first period among downgraded bonds; Σa_i provides the average level of volatility in the (*-60; -16*) period among upgraded bonds; b_js and d_js represent the difference in the volatility level in the various time windows relatively to the initial time window for downgrades and upgrades. As in the case discussed for the mean equation, the absolute level of volatility that downgraded bonds experience for instance in the event window (T_3) is found simply summing up the constant term with the estimate for b_3.

Moreover, the GARCH-type methodology allows us to test for the persistence of announcement shocks. On one side, the lack of persistence would imply that bond prices (yields) quickly incorporate public information and that the trading process does not generate persistent volatility in response to news. On the other hand, strong persistence would suggest that either information-gathering or some feature of the trading process itself would cause volatility to be autocorrelated.

6.4. Empirical Results

Tests on mean and median CARs. Table 6.3 presents mean and median coupon adjusted cumulative abnormal returns for the whole sample and for different time windows. Our statistical inference is based on simple *t-tests* and *one-sample signed rank tests* to test the null hypothesis that the mean and the median, respectively, of the population from which the data sample is drawn is equal to zero. Results for downgrades and upgrades are presented in Panel A of Table 6.3. Downgraded bonds experience significantly negative mean *CARs* of 98 bps from –15 to +15 days around the event day; 56 bps from -5 to +5 days; 78 bps from +2 to +15 days and 91 bps from +2 to +60 days. Upgraded bonds don't show *CARs* significantly different from zero in any of the time windows.

For comparative purposes, Panel B splits the downgraded bonds in various categories (as described above). As we want to find out if a profitable trading rule exists, for which category, and if it is of some economic significance, we are particularly interested in bond returns after the event. Bonds with a negative pledge clause attached (NP) behave significantly different from bonds with no negative pledge guarantee. In particular, NP bonds experience a significant negative return of 165bps in the window +2 to +15. Financial bonds and UK-firm bonds show a significant return decrease of 196 bps and 130 bps, respectively, in the period +2 to +60 days. Low coupon bonds, high maturity bonds and previously downgraded bonds show relevant negative returns of 145 bps, 134 bps, and 172 bps, respectively, from day 2 to day 15 after the event day. As far the various rating categories is concerned, returns were significantly negative only for AA-rated bonds (92 bps and 154 bps in the windows +2, +15 and +2, +60, respectively), which are also the bonds most likely to be re-rated (see Chapter VII).

OLS Panel Estimation. Table 6.4 presents coefficient estimates from Eq. (6.2). The autoregressive terms at lag 1 and 2 are both positive and highly significant with their sum equal to 0.86 and 0.73 for downgrades and upgrades, respectively.

While we observe a significant negative bond market reaction to downgrades, upgraded bonds seem not to show any relevant reaction, with the coefficient estimates all not significantly different from zero. The lack of response following positive rating revision confirms the general previous evidence, implying that the market apparently views downgrades but not upgrades as informational events. We will then focus on downgrades. The small positive increase in the pre-announcement period is not significant, implying the absence of any relevant anticipation of the rating event. Abnormal yields significantly increase in the three days around the event date, after which they quickly adjust to the new significantly higher equilibrium level.

Additional regressions were run to test for differences in the reaction of various sub-samples. Due to the small number of observations among the upgraded bonds, we will not comment our results with respect to this category, which was however included in the estimation. To save space, OLS estimates are not presented for all the categories, but main results are mentioned below. Mean abnormal yields among downgrades are significantly higher for longer maturity issues, financial issues, lower coupon bonds, issues accompanied by a negative pledge guarantee, non-UK issues, more liquid issues (in terms of larger amount of bonds outstanding), and AA-rated bonds. For these same categories a significant positive post-announcement drift is generally observed in both the (+2; +15) and (+16; +60) periods. These results confirm the findings for the whole sample and provide a robustness check. We, now, proceed to analyse the results of the pooled GARCH model.

GARCH Panel Estimation. Simple OLS estimates are inefficient because they fail to account for conditional heteroskedasticity. We therefore present results from the maximum likelihood estimation of model (6.3)-(6.5) using the Berndt-Hall-Hall-Hausman (BHHH) iterative optimisation algorithm.

There is still a significantly asymmetric pattern of response to downgrade and upgrade announcements. While positive rating news releases have still no impact at all on bond yields, rating downgrades drive yields to rise within the small event window. However this increase becomes more strongly significant after properly allowing for heteroskedasticity. The Wald test indicates a 5 percent significance level in contrast to a previous weak 10 percent level. In addition, no significant pre- or post-announcement drift is found, and the weak evidence of a small overreaction in the event period is also found to be not significant.

Variance coefficient estimates are presented in Table 6.5[27] and pattern of volatility over the whole time interval (-60; +60) is depicted in Figure 6.2. The null hypothesis of homoskedastic errors is strongly rejected. The α and β coefficients are significantly positive, with the direct effect of a shock on tomorrow's conditional volatility being around 0.18. This effect decays at rate 0.6 subsequently. That is, about one sixth of the most recent squared error is incorporated in the subsequent volatility estimate, while lagged volatility has a weight of about two-thirds. The sum of

α and β is 0.68, well below unity, necessary condition for variance stationarity. We can therefore measure the volatility persistence as a half-life, that is, as the time it takes on average for the conditional variance to revert halfway to its unconditional value. This is computed as $-\ln(2)/\ln(\alpha + \beta s)$ and yields a value of approximately 1.8 (days).

The variance profile depicted in Figure 6.2 seems to present particular and separate shapes to the spread series surrounding positive and negative revisions. The impact of a rating decrease on volatility around the event date is strongly depressing in the pre-announcement period reaching its minimum right in the event window. Once the disclosure is made, and its effects assimilated, volatility starts rising up over time to reach and exceed its "normal" or long run level. In the case of a rating increase, volatility falls in the pre-announcement and post-announcement periods, but peaks in the 3-day event window to approach the initial level during the (+16; +60) days period after the announcement. In both cases, the effect on volatility seems to dissipate substantially after the post-announcement interval. Volatility for downgraded bonds stabilises around a mean level significantly higher than the long-run level before the announcement. This is consistent with the increase in risk that the event itself has brought to the downward revised bonds. No relevant effect is observed for the volatility of upgraded bonds.

Individual autocorrelations of the residuals and squared residuals (not shown) are small, the highest being 0.031 at lag ten for the standardised residuals and 0.005 at lag twenty-one for the standardised squared residuals. The model is able to remove serial correlation only up to lag four. The Ljung-Box Q statistic for the standardised residuals is indeed significant at the 1 percent level at lags 10 and 20. The Ljung-Box Q statistic for the squared standardised residuals is not significant at lags 10 and 20. The standardised residuals have a skewness coefficient of -0.07, which although statistically significant, does not indicate severe skewness. They are also leptokurtic, with a kurtosis coefficient of 16. This latter finding supports the need to model the errors as t-distributed.

[27] To save space coefficients for first time interval dummy variables D_{it} ($i = 1, 2, \ldots, 136$), are not shown.

Table 6.3 *Mean and Median CAR tests developed for Downgrades, Upgrades and various categories of Downgrades*

Returns for changed and non changed bonds were computed as follows:

$$R_{it} = \frac{(P_{it} - P_{i,t-1}) + \frac{n}{360}C - \frac{n-1}{360}C}{P_{i,t-1} + \frac{n}{360}C}$$

with n = days accrued towards the next coupon payment and c = coupon payment.

Abnormal Returns (AR) were computed as the difference between returns for changed bonds and returns for matched bonds. Cumulative Abnormal Returns (CARs) are presented below for various event windows. Panel A presents results for downgrades and upgrades. Panel B splits the downgraded bonds in various categories on the basis of industry, rating, guarantee, country of origin of the borrower, coupon, liquidity (AOS), maturity on the day of rating change, and the presence of a previous rating change (rating history). A simple t-test and one-sample signed rank test are used to test the null hypothesis that the mean and the median, respectively, of the population from which the data sample is drawn is equal to zero. Probabilities are presented in brackets for mean and median CARs. The number of positive observations (N>0) within each class is also presented. The independent-samples t-test procedure was used to compare means for two groups of cases. In addition the Wilcoxon two-sample paired signed rank test was used to test the null hypothesis that the population median of the paired differences of the two samples is 0. We presented only the mean and median differences with asterisks for the level of significance.

			-60; +60			**-15; +15**			**-5; +5**			**-1; +1**		
Panel A		*N*	*Mean*	*Median*	*N>0*	*Mean*	*Median*	N>0	*Mean*	*Median*	*N>0*	*Mean*	*Median*	*N>0*
Downgrades		107	-1.06	-0.34*	52	-0.98**	-0.08	55	-0.56*	-0.04*	52	-0.04	-0.01	50
			(0.10)	*(0.06)*		*(0.03)*	*(0.14)*		*(0.07)*	*(0.06)*		*(0.73)*	*(0.14)*	
Upgrades		29	-2.33	0.38	20	1.23	0.16	21	0.016	0.04	19	-0.12	0.02	20
			(0.33)	*(0.70)*		*(0.18)*	*(0.22)*		*(0.96)*	*(0.21)*		*(0.71)*	*(0.57)*	
Panel B														
	NP	40	-2.32**	-0.54**	18	-2.91***	-0.30***	18	-1.40**	-0.13***	20	-0.33	-0.02*	19
			(0.04)	*(0.04)*		*(0.00)*	*(0.00)*		*(0.03)*	*(0.00)*		*(0.20)*	*(0.10)*	
Guarantee	*No Guar*	66	0.047	-0.10	29	0.40	0.06	31	0.085	-0.02	27	0.235	0	28
			(0.95)	*(0.64)*		*(0.37)*	*(0.40)*		*(0.73)*	*(0.66)*		*(0.11)*	*(0.80)*	
	Diff.		-1.67*	-1.20		-3.47***	-3.04***		-2.13**	-1.62*		-1.95**	-1.46	
	Financial	30	-2.83***	-0.62**	12	-0.46	-0.03	14	-0.12	-0.02	11	-0.12*	-0.01	12
			(0.01)	*(0.02)*		*(0.29)*	*(0.56)*		*(0.69)*	*(0.52)*		*(0.09)*	*(0.27)*	
Industry	*Industrial*	68	-0.63	-0.32	31	-1.14*	-0.16*	30	-0.74	-0.05*	34	-0.07	-0.02	30
			(0.43)	*(0.26)*		*(0.08)*	*(0.08)*		*(0.12)*	*(0.08)*		*(0.74)*	*(0.28)*	
	Diff.		-1.49	-1.35		0.87	-0.70		0.80	-0.57		-0.21	-0.07	
	UK	72	-0.46	-0.40	32	-0.26	-0.14	30	-0.14	-0.04	36	0.12	-0.02	31
			(0.54)	*(0.17)*		*(0.55)*	*(0.25)*		*(0.50)*	*(0.25)*		*(0.35)*	*(0.36)*	
Country	*Non UK*	35	-2.08*	-0.13	17	-2.20**	0.04	22	-1.28*	-0.04*	13	-0.33	0.00	16
			(0.09)	*(0.21)*		*(0.02)*	*(0.69)*		*(0.09)*	*(0.9)*		*(0.25)*	*(0.27)*	
	Diff.		1.12	-0.30		1.88*	-0.16		1.47	-0.64		1.67*	-0.18	

			-60; +1			-15; +1			**+2; +15**			**+2; +60**		
Panel A		*N*	*Mean*	*Median*	*N>0*	*Mean*	*Median*	*N>0*	Mean	*Median*	*N>0*	*Mean*	*Median*	*N>0*
Downgrades		107	-0.15	0.085	63	-0.20	-0.05	52	-0.78***	0.00	60	-0.91*	0.00	61
			(0.81)	*(0.99)*		*(0.53)*	*(0.34)*		*(0.01)*	*(0.45)*		*(0.07)*	*(020)*	
Upgrades		29	0.92	-0.26	16	0.58	0.16	21	0.65	-0.07	17	1.33	-0.07	18
			(0.51)	*(0.74)*		*(0.43)*	*(0.32)*		*(0.11)*	*(0.90)*		*(0.28)*	*(0.60)*	
Panel B														
	NP	40	-1.52	-0.19	23	-1.25**	-0.08*	20	-1.65***	-0.11***	18	-0.79	0.05	61
			(0.13)	*(0.20)*		*(0.05)*	*(0.07)*		*(0.00)*	*(0.01)*		*(0.41)*	*(0.61)*	
Guarantee	*No Guar*	66	1.01	0.25	34	0.72**	-0.01	29	-0.31	0.12	33	-0.96*	-0.04	28
			(0.22)	*(0.30)*		*(0.05)*	*(0.48)*		*(0.29)*	*(0.61)*		*(0.06)*	*(0.23)*	
	Diff.		-1.96**	-1.56		-2.83***	-1.66*		-2.10**	-2.31**		0.155	-0.17	
	Financial	30	-0.87	-0.10	14	-0.12	-0.05*	12	-0.34	0.003	17	-1.96**	-0.07	14
			(0.16)	*(0.36)*		*(0.70)*	*(0.09)*		*(0.26)*	*(0.58)*		*(0.04)*	*(0.21)*	
Industry	*Industrial*	68	0.33	0.23	41	-0.31	-0.09	29	-0.83**	-0.09	33	-0.97*	-0.16*	34
			(0.70)	*(0.31)*		*(0.53)*	*(0.40)*		*(0.05)*	*(0.23)*		*(0.09)*	*(0.07)*	
	Diff.		-1.12	-1.23		0.32	-0.05		0.94	-0.87		-0.91	-0.47	
	UK	72	0.08	0.21	41	0.17	-0.09	31	-0.43	-0.06	34	-1.30***	-0.21***	32
			(0.22)	*(0.40)*		*(0.59)*	*(0.58)*		*(0.18)*	*(0.43)*		*(0.01)*	*(0.01)*	
Country	*Non UK*	35	-1.84*	-0.03	19	-0.84	-0.01	18	-1.36**	0.06	23	-0.24	0.14	26
			(0.09)	*(0.46)*		*(0.23)*	*(0.55)*		*(0.02)*	*(0.99)*		*(0.82)*	*(0.35)*	
	Diff.		2.19**	-1.20		1.49	-0.22		1.36	-0.20		-0.90	-1.90**	

Table 6.3 continued

		N	-60; +60 Mean	Median	N>0	-15; +15 Mean	Median	N>0	-5; +5 Mean	Median	N>0	-1; +1 Mean	Median	N>0	-60; +1 Mean	Median	N>0	-15; +1 Mean	Median	N>0	+2; +15 Mean	Median	N>0	+2; +60 Mean	Median	N>0
Coupon [c]	*Low C*	58	-0.064 *(0.92)*	0.035 *(0.96)*	29	0.088 *(0.80)*	-0.08 *(0.50)*	26	-0.045 *(0.85)*	-0.02 *(0.57)*	25	0.12 *(0.28)*	-0.02 *(0.27)*	22	1.07*** *(0.01)*	0.27** *(0.02)*	36	0.48 *(0.11)*	-0.05 *(0.55)*	24	-0.39* *(0.06)*	0.00 *(0.72)*	28	-1.14** *(0.04)*	0.00 *(0.20)*	29
	High C	49	-1.96* *(0.07)*	-0.96** *(0.01)*	23	-1.95** *(0.01)*	-0.08 *(0.13)*	29	-1.02** *(0.06)*	-0.05** *(0.03)*	27	-0.20 *(0.39)*	0.00 *(0.30)*	28	-1.25 *(0.24)*	-0.52 *(0.11)*	27	-0.82 *(0.14)*	-0.045 *(0.32)*	28	-1.12** *(0.04)*	0.00 *(0.41)*	32	-0.70 *(0.37)*	0.015 *(0.60)*	32
	Diff.		1.48	-1.95**		2.38***	-0.69		1.66*	-1.05		1.26	-0.16		2.03**	-2.64***		2.01**	-0.55		1.26	-0.20		-0.43	-0.65	
AOS [c]	**Low AOS**	81	-1.52* *(0.09)*	-0.40* *(0.09)*	23	-0.81 *(0.17)*	-0.03 *(0.48)*	28	-0.21 *(0.35)*	-0.02 *(0.59)*	26	0.035 *(0.60)*	0.00 *(0.87)*	26	-0.79 *(0.20)*	-0.11 *(0.17)*	26	-0.15 *(0.59)*	-0.04 *(0.63)*	26	-0.65 *(0.17)*	0.06 *(0.60)*	34	-0.73 *(0.32)*	0.13 *(0.99)*	31
	High AOS	26	-0.65 *(0.48)*	-0.28 *(0.37)*	13	-1.13* *(0.09)*	-0.12 *(0.23)*	11	-0.87 *(0.11)*	-0.13** *(0.04)*	10	-0.11 *(0.63)*	-0.07 *(0.11)*	8	0.42 *(0.67)*	0.28 *(0.18)*	18	-0.24 *(0.66)*	-0.07 *(0.50)*	14	-0.88** *(0.02)*	-0.09 *(0.12)*	14	-1.07 *(0.12)*	-0.19* *(0.08)*	15
	Diff.		-0.66	-0.59		0.35	-0.37		1.17	-1.26		0.59	-1.45		-1.01	-1.66*		0.13	-0.46		0.38	-1.20		0.34	-1.01	
Maturity [c]	*Low Mat*	48	-0.64 *(0.40)*	-0.17 *(0.36)*	26	0.08 *(0.82)*	-0.01 *(0.82)*	31	0.04 *(0.73)*	-0.02 *(0.22)*	26	-0.02 *(0.76)*	0.00 *(0.36)*	26	-0.14 *(0.78)*	-0.01 *(0.42)*	29	0.32 *(0.27)*	-0.02 *(0.76)*	29	-0.23 *(0.32)*	0.04 *(0.84)*	33	-0.49 *(0.38)*	0.01 *(0.87)*	36
	High Mat	49	-1.49 *(0.17)*	-0.96* *(0.06)*	26	-2.08*** *(0.01)*	-0.19* *(0.07)*	24	-1.18* *(0.06)*	-0.05* *(0.09)*	26	-0.07 *(0.78)*	-0.01 *(0.35)*	24	-0.15 *(0.89)*	0.27 *(0.60)*	34	-0.74 *(0.21)*	-0.13 *(0.34)*	23	-1.34** *(0.02)*	-0.09 *(0.21)*	27	-1.35 *(0.11)*	-0.30* *(0.08)*	25
	Diff		0.66	-0.93		2.48***	-1.42		1.99**	-0.85		0.21	-0.71		0.05	-0.55		1.68*	-1.23		1.80*	-0.74		0.81	-1.10	
Rerating	*PC*	30	-1.51 *(0.31)*	-0.98 *(0.11)*	15	-1.87* *(0.09)*	-0.18 *(0.18)*	15	-1.09 *(0.22)*	-0.09 *(0.28)*	15	-0.016 *(0.96)*	-0.001 *(0.97)*	18	-0.11 *(0.94)*	0.28 *(0.70)*	22	-0.15 *(0.86)*	-0.03 *(0.98)*	17	-1.72*** *(0.01)*	-0.13* *(0.06)*	15	-1.40 *(0.16)*	-0.21 *(0.13)*	17
	NPC	77	-0.84 *(0.21)*	-0.13 *(0.28)*	37	-0.56 *(0.15)*	-0.03 *(0.28)*	40	-0.30 *(0.11)*	-0.002 *(0.38)*	37	-0.06 *(0.52)*	-0.02** *(0.04)*	32	-0.16 *(0.72)*	0.00 *(0.65)*	41	-0.22 *(0.34)*	-0.005 *(0.31)*	35	-0.33 *(0.27)*	0.006 *(0.63)*	45	-0.68 *(0.23)*	0.007 *(0.67)*	44
	Diff.		-0.41	-1.20		-1.10	-3.04***		-0.87	-1.60		0.11	-1.46		0.03	-1.56		0.07	-1.66*		-1.87*	-2.31**		-0.67	-0.17	
Rating	*AAA*	15	0.75 *(0.55)*	0.00 *(0.72)*	7	0.46** *(0.03)*	0.31** *(0.02)*	12	-0.04 *(0.69)*	0.05 *(0.42)*	8	0.00 *(0.99)*	0.015 *(0.54)*	7	-0.57 *(0.64)*	-0.15 *(0.51)*	6	0.015 *(0.91)*	0.075 *(0.21)*	9	0.45 *(0.14)*	0.14*** *(0.00)*	13	1.33 *(0.22)*	0.22*** *(0.01)*	12
	AA	51	-1.22 *(0.12)*	-0.56 *(0.13)*	23	-1.00** *(0.04)*	-0.14** *(0.03)*	19	-0.21 *(0.53)*	-0.13*** *(0.00)*	14	0.17 *(0.36)*	-0.05 *(0.21)*	19	0.31 *(0.51)*	0.19 *(0.49)*	29	-0.081 *(0.77)*	-0.22** *(0.04)*	17	-0.92*** *(0.01)*	-0.04 *(0.30)*	24	-1.54** *(0.02)*	-0.19** *(0.04)*	22
	A	41	-0.35 *(0.76)*	-0.16 *(0.39)*	20	-0.41 *(0.62)*	-0.12 *(0.73)*	21	-0.69 *(0.28)*	0.085 *(0.76)*	26	-0.37 *(0.16)*	-0.01 *(0.20)*	19	0.53 *(0.63)*	0.21 *(0.66)*	26	0.27 *(0.58)*	-0.00 *(0.59)*	22	-0.68 *(0.23)*	-0.09 *(0.25)*	18	-0.88 *(0.21)*	-0.00 *(0.38)*	22
	Diff	All [b]	4.40			8.81** A/AA***			6.76*			1.24 AA/A**			4.52			4.99 AA/A*			4.23 AAA/A**	A/AA***		4.87 AAA/A**	A/AA**	

[a] *NOTE: ***, **, *: Significantly different from zero at the 1%, 5% and 10% level, respectively, using a two- tailed test.*
[b] *We report the χ^2 statistics for differences among all the rating groups.*
[c] *Observations are classified as Low or High according to whether they are below or above the median value, respectively.*

Time Window	DOWNS (N=107)		UPS (N=29)		Autoregressive Terms	
	Coefficient	Cumulative	Coefficient	Cumulative		
-60; -16	0.0065	0.0065	-0.0279	-0.0279	β_1	0.7485*** (0.0091)
-15; -2	0.0009 (0.0016)	0.0073	0.0002 (0.0031)	-0.0277	β_2	0.1216*** (0.0088)
-1; +1	0.0071** (0.0031)	0.0135*	-0.0058 (0.0060)	-0.0337	β_3	0.6563*** (0.0143)
+2; +15	0.0047** (0.0016)	0.0111	0.0037 (0.0031)	-0.0315	β_4	0.1889*** (0.0138)
+16; +60	0.0056*** (0.0011)	0.0120	-0.0032 (0.0021)	-0.0311		
Total Ch. (-60; +60)		0.0056 (86%)		-0.0032 (-12%)		

Table 6.4 *OLS Pooled Estimation for Abnormal Yields (AY) around event dates, 1992-1999.*

Daily data from January 1992 to December 1999 have been pooled to estimate a least squares model (LS). The total panel (unbalanced) observations are 16433. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression equation is structured as follows:

$$AY_{it} = \sum_{i=1}^{107} a_i D_i + \sum_{i=108}^{136} a_i D_i + \beta_1 AY_{it-1} DOWN_i + \beta_2 AY_{it-2} DOWN_i + \beta_3 AY_{it-1} UP_i + \beta_4 AY_{it-2} UP_i + \sum_{j=2}^{5} \delta_j T_j DOWN_i + \sum_{j=2}^{5} \varphi_j T_j UP_i + \varepsilon_{it}$$

Notes: Regression statistics: Adj. R^2=0.9727, SE=0.0546, DW=1.91

We also tested for the significance of a risk pricing term (λ) in eq. (6.3). The sign of λ is of special interest since time series analyses of securities returns have produced both positive and negative relationships between conditional returns and conditional variances. In our application we would expect a negative sign as suggested by the risk aversion hypothesis. As we are modelling abnormal yields, a positive shock (in terms of good news) would be in this case represented by a negative error (ε>0), which would indeed represent a decline in the bond risk (yield) and in tuin an increase in bond returns. An AR(2)-GARCH-M (1, 2) model was estimated. The risk premium term was indeed found to be significantly negative (λ = -0.127, t = -2.269). All the other parameter estimates were consistent with previous results.

Time Window	DOWNS (N=107)		UPS (N=29)		Autoregressive Terms	
	Mean Equation					
	Coefficient	Cumulative	Coefficient	Cumulative		
-60; -16	0.0086 [t=0.17]	0.0086	-0.0363 [t=-0.61]	-0.0363	β_1	0.6808*** (0.0163)
-15; -2	-0.0034 (0.0022)	0.0053	0.0078* (0.0032)	-0.0285	β_2	0.1651*** (0.0155)
-1; +1	0.0062* (0.0036)	0.0148**	-0.0033 (0.0085)	-0.0396	β_3	0.5869*** (0.0152)
+2; +15	0.0041** (0.0020)	0.0128	0.0032 (0.0033)	-0.0332	β_4	0.2348*** (0.0183)
+16; +60	0.0072*** (0.0019)	0.0159	-0.0037 (0.0031)	-0.0400*		
Total Ch. (-60; +60)		0.0072 (84%)		-0.0037 (-10%)		
	Variance Equation [a]					
-60; -16	0.0978*** ($7.15\cdot10^{-5}$)	0.0978	0.3985	0.3985	ε^2_{t-1}	0.1395*** (0.0068)
-15; -2	-0.0409*** ($5.53\cdot10^{-5}$)	0.0569	-0.0392*** ($3.88\cdot10^{-5}$)	0.3593	h_{t-1}	0.4819*** (0.558)
-1; +1	-0.0569*** ($12.5\cdot10^{-5}$)	0.0409	0.0584** ($23.8\cdot10^{-5}$)	0.4569***	h_{t-2}	0.1613*** (0.0449)
+2; +15	-0.0442*** ($5.21\cdot10^{-5}$)	0.0536	-0.0430*** ($2.58\cdot10^{-5}$)	0.3555***		
+16; +60	0.0383*** ($4.89\cdot10^{-5}$)	0.1361***	0.0084 ($6.32\cdot10^{-5}$)	0.4069***		
Total Ch. (-60; +60)		0.0383 (39%)		0.0084 (2%)		

Table 6.5 *GARCH Pooled Estimation for Abnormal Yields (AY) around event dates, 1992-1999.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 2) type model. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{i=1}^{107} \alpha_i D_i + \sum_{i=108}^{136} \alpha_i D_i + \beta_1 AY_{it-1} DOWN_i + \beta_2 AY_{it-2} DOWN_i + \beta_3 AY_{it-1} UP_i + \beta_4 AY_{it-2} UP_i + \sum_{j=2}^{5} \delta_j T_j DOWN_i + \sum_{j=2}^{5} \varphi_j T_j UP_i + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=108}^{107} a_i D_i + \sum_{j=2}^{5} b_j T_j DOWN_i + \sum_{j=2}^{5} d_j T_j UP_i + \theta_1 h_{it-1} + \theta_2 h_{it-2} + \xi_{it} \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

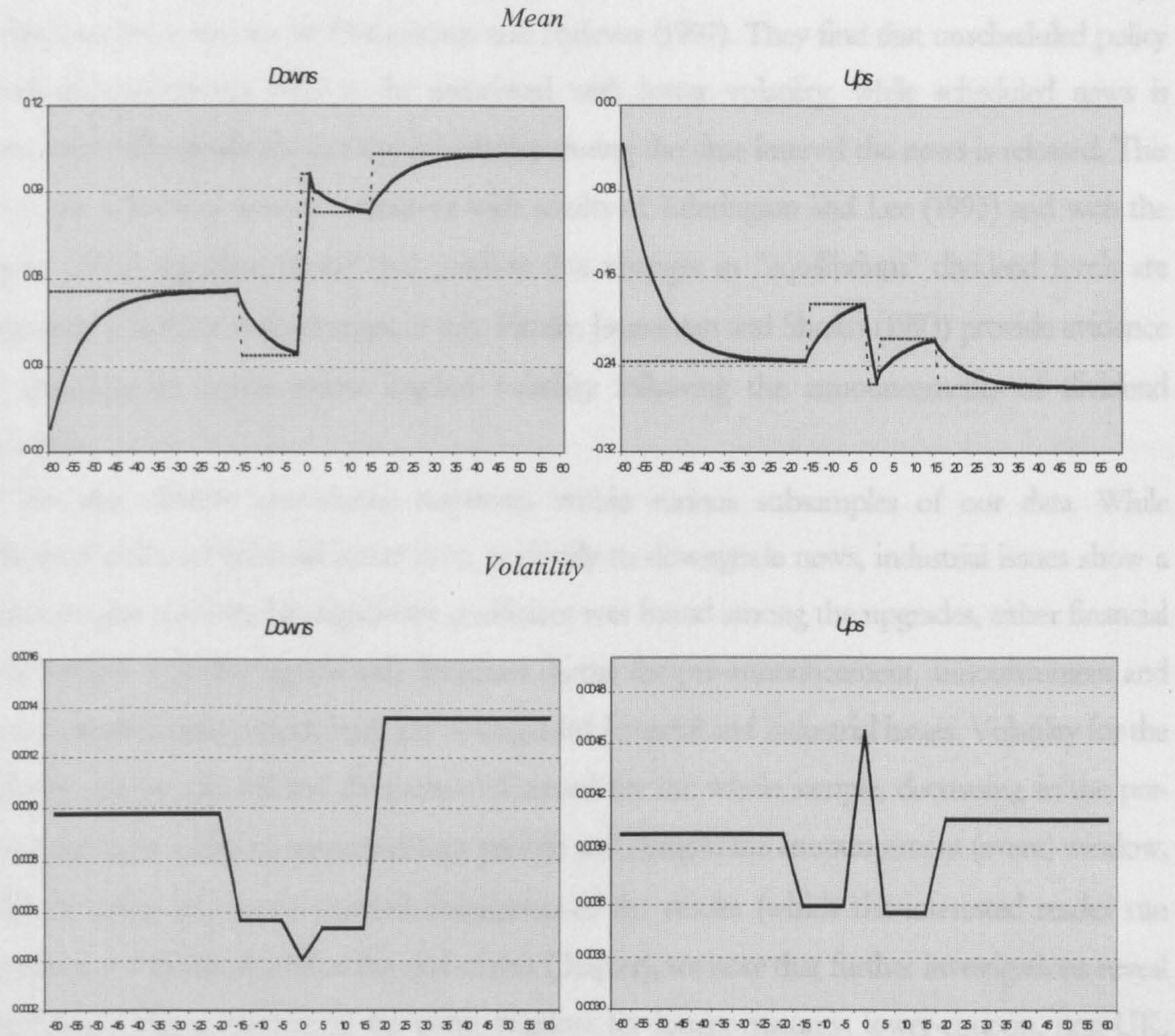


Figure 6.2 *The impact of rating revision announcement on Eurobond mean and volatility spreads*

Mean and variance abnormal spreads (AY) are reported over the observation period of -60; +60. The figures on the x-axis are time periods (days) relative to the announcement time (day zero). The asymptotes, represented by the dashed line, have been built as $\left(\sum_{i=1}^{107}\alpha_i + \beta_j T_j\right)/(1-\beta_1-\beta_2)$ (for the downgrades, and similarly for the upgrades) according to the GARCH model coefficient estimates. The continuous lines were plotted adjusting each daily observation for the autoregressive part of the change.

The conclusion we draw is that rating announcements in our sample seem to have negatively impact on the yield volatility of downgraded bonds, but they positively impact the yield volatility of upgraded bonds in the event window. Hettenhouse and Sartoris (1976) were the first to examine the possibility that conformity of investor opinion on yields would be greater close to the rating revision. Evidence of increases in security returns volatility was also provided in Damodaran (1985), Admati and Pfleiderer (1988), and Ross (1989) and explained in terms of trades related to the arrival of private information. A more recent investigation of both volatility behaviours is carried out by DeGennaro and Shrieves (1997). They find that unscheduled policy news announcements tend to be associated with lower volatility, while scheduled news is associated with significant increase in volatility during the time interval the news is released. This result for scheduled news is consistent with results of Ederington and Lee (1993) and with the Eades (1982) signalling model that predicts that changes in "equilibrium" dividend levels are negatively correlated with changes in risk. Finally, Jayaraman and Shastri (1993) provide evidence of decreases in option prices implied volatility following the announcements of dividend increases.

We also observe asymmetric responses within various subsamples of our data. While abnormal yields of financial issues react positively to downgrade news, industrial issues show a much smaller reaction. No significant coefficient was found among the upgrades, either financial or industrial. Volatility significantly decreases during the pre-announcement, announcement and post-announcement periods both for downgraded financial and industrial issues. Volatility for the industry sub-sample follows the pattern observed for the whole sample, decreasing in the pre-announcement and post-announcement periods and rising in the announcement (event) window. Without going into a too detailed description of the results (which the interested reader can acquire from Tables A1-A8 at the end of this Chapter), we note that further investigations reveal significantly bigger reaction in the event window for longer-maturity, lower-coupon, non-UK, negative pledge, higher-liquid, AA-rated and not previously re-rated bonds respect to their counterparts that do not present any relevant response. All these findings are consistent with our expectations.

6.5. Conclusions

Using daily data this chapter estimates the effect of rating changes announcements on Eurobond abnormal yield level and volatility. We have assumed that the major rating agencies have revised ratings simultaneously and that rating changes are the only relevant factor affecting the relative yield spread of the bond over the selected time window. Ratings changes have been separated into downgrades and upgrades. While downgrades are accompanied by significant increase in the yield spreads during the announcement and post-announcement periods, we found that for upgrades, the incremental information content of bond revision is not statistically significant. The result for upgraded bonds might be due to the small sample size or to the fact that corporate news announcements are either not value-relevant or they have been fully anticipated long time before[28]. Alternatively, it could be the case that markets are inefficient, but given the results for downgrade announcements, this last hypothesis may be excluded.

The hypotheses that may help explain this asymmetric response are the following: i) companies voluntarily may release favourable information but may be reluctant to release unfavourable information; ii) rating agencies may spend more resources in detecting deterioration rather than improvement in credit quality (Ederington and Goh, 1998); or iii) bondholders (stockholders) may be more concerned with increases rather than decreases in risk.

The effects of news on volatility vary according to the news categories. Upgrades are associated with significant increases in volatility during and around the event period. For bonds being downgraded the results are reversed. Volatility is significantly depressed during and around the time the information is released. This finding may be consistent with a calming effect of such announcements, due to either a temporary reduction in information asymmetry or simply a "time-out" during which traders attempt to assess the news. One possible effect of the rating revision might be to increase the conformity of investors' opinion at the time or after the revision and this may be reflected in an adjustment of volatility downward. According to this interpretation, results for upgrades may be explained either in terms of the small size of the sample, or by considering that investors anticipate the news. DeGennaro and Shrieves (1997) find similar results for exchange rate volatility in response to scheduled news.

The persistence of volatility is also evaluated and we found that announcement shocks do not persist, and rating information takes 1-2 days to be incorporated into yields. This implies that bond yields quickly incorporate public information and that the trading process does not generate persistent volatility in response to news.

According to this asymmetric behaviour both in the mean and the volatility dynamics for downgrades and upgrades, if it is in fact known *in advance* that a rating revision is taking place in the near future, one might anticipate changes in the mean (or variance) during the period immediately preceding and following the disclosure and act consequently. According to our results there seems to be a preliminary evidence of significant cumulative abnormal returns for downgrades (78% from + 2 to +15 days and 91% from +2 to +60 days) and various subsamples of downgraded bonds (NP, financial, UK, low coupon, high maturity, AA-rated and previously revised issues). Further research could focus on the economic significance of gains deriving from the anticipation of rating change event.

Interesting would be also to relate the cause of the rating change with the likelihood that it carries significant new information to the market. Bond rating changes could be classified by

[28] See Bahattacharya et al. (2000)

cause of change. A new issue that simply refinances current debt and does not involve any change in the investment decision of the firm probably will not convey new information about the firm. Similarly mergers, leverage buyouts and share repurchases are not expected to have any impact as they are known in advance of the rating change. On the other side, a rating change due to changes in the firm's financial prospects might cause a market reaction. Future research may also investigate whether significant changes in volatility lead the way to profitable trading strategies. In other words, using options to trade on anticipated volatility effects, can we make economically significant profits once transaction costs are taken into account?

Table A1 *GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Industry Sector.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 1) type model. Observations have been classified as financial (FIN) or industrial (IND) according to the industry sector. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{i=1}^{30}\alpha_i D_i FIN + \sum_{i=31}^{98}\alpha_i D_i IND + \sum_{i=99}^{107}\alpha_i D_i FIN + \sum_{i=108}^{122}\alpha_i D_i IND + \beta_1 AY_{it-1}DOWN + \beta_2 AY_{it-2}DOWN + \beta_3 AY_{it-1}UP + \beta_4 AY_{it-2}UP + \sum_{j=2}^{5}\delta_j T_j DOWN \cdot FIN + \sum_{j=2}^{5}\kappa_j T_j DOWN \cdot IND +$$
$$+ \sum_{j=2}^{5}\phi_j T_j UP \cdot FIN + \sum_{j=2}^{5}\varpi_j T_j UP \cdot IND + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=1}^{30} a_i D_i FIN \sum_{i=31}^{98} a_i D_i IND + \sum_{i=99}^{107} a_i D_i FIN + \sum_{j=2}^{5} b_j T_j DOWN \cdot FIN + \sum_{j=2}^{5} d_j T_j DOWN \cdot IND + \sum_{j=2}^{5} g_j T_j UP \cdot FIN + \sum_{j=2}^{5} m_j T_j UP \cdot IND + \vartheta\ h_{it-1} + \xi\ \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	Mean Equation FIN Coeff.	Mean Equation FIN Cumulative	Mean Equation IND Coeff.	Mean Equation IND Cumulative	Variance Equation FIN Coeff. ($*10^2$)	Variance Equation FIN Cumulative ($*10^2$)	Variance Equation IND Coeff. ($*10^2$)	Variance Equation IND Cumulative ($*10^2$)
Downs	*(N=30)*		*(N=68)*		*(N=30)*		*(N=68)*	
-60; -16	0.0131	0.0131	0.0065	0.0065	0.0782	0.0782	0.0592	0.0592
-15; -2	-0.0029 (0.0021)	0.0103	-0.0005 (0.0018)	0.0065	-0.0272*** ($1.69 \cdot 10^{-5}$)	0.0510	-0.0122*** ($2.21 \cdot 10^{-5}$)	0.0470
-1; +1	0.0073*** (0.0026)	0.0204***	0.0045* (0.0027)	0.0110*	-0.0272*** ($1.15 \cdot 10^{-5}$)	0.0510	-0.0164*** ($3.90 \cdot 10^{-5}$)	0.0428
+2; +15	0.0073*** (0.0021)	0.0204	0.0027* (0.0015)	0.0092	-0.0218*** ($1.86 \cdot 10^{-5}$)	0.0564**	-0.0169*** ($1.46 \cdot 10^{-5}$)	0.0423
+16; +60	0.0091*** (0.0028)	0.0222	0.0035 (0.0023)	0.0100	0.0184*** ($4.55 \cdot 10^{-5}$)	0.0966***	0.0469*** ($3.84 \cdot 10^{-5}$)	0.1061***
Total Ch. (-60; +60)		0.0091 (69%)		0.0035 (54%)		$0.0184 * 10^{-2}$ (24%)		$0.047 * 10^{-2}$ (79%)
Ups	*(N=9)*		*(N=15)*		*(N=9)*		*(N=15)*	
-60; -16	-0.0293	-0.0293	-0.0268	-0.0268	0.1211	0.1211	0.1128 ($4.97 \cdot 10^{-5}$)	0.1128
-15; -2	0.0167** (0.0067)	-0.0126	0.0059 (0.0054)	-0.0209	-0.0642*** ($7.78 \cdot 10^{-5}$)	0.1047	-0.0701*** ($10.2 \cdot 10^{-5}$)	0.1437
-1; +1	0.0212 (0.0138)	-0.0081	-0.0184 (0.0126)	-0.0453*	0.0309 ($40.6 \cdot 10^{-5}$)	0.1042**	0.0234 ($39.3 \cdot 10^{-5}$)	0.0442**
+2; +15	0.0083 (0.0062)	-0.0211	-0.0014 (0.0051)	-0.0283	-0.0686*** ($5.85 \cdot 10^{-5}$)	0.1680**	-0.0823*** ($9.06 \cdot 10^{-5}$)	0.1154**
+16; +60	0.0051 (0.0074)	-0.0242	0.0015 (0.0059)	-0.0254	0.0026 ($11.4 \cdot 10^{-5}$)	0.0569***	0.0307*** ($6.01 \cdot 10^{-5}$)	0.0427***
Total Ch. (-60; +60)		0.0051 (18%)		0.0015 (-6%)		$-0.064 * 10^{-2}$ (-53%)		$-0.0701 * 10^{-2}$ (-62%)
β_1	0.6639*** (0.0135)							
β_2	0.1886*** (0.0134)				ξ	0.1001*** (0.0058)		
β_3	0.6282*** (0.0205)				ϑ	0.6963*** (0.0083)		
β_1	0.2499*** (0.0219)							

Notes: Regression statistics: Adj. R^2=0.9712, SE=0.0561, DW=1.70

Table A2 *GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Maturity.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 1) type model. Bonds have been classified as High_Mat or Low_Mat according to whether the time to maturity on the day of the rating change was above or below the median value, respectively. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it}=\sum_{i=1}^{49}\alpha_i D_i High\_Mat+\sum_{i=50}^{97}\alpha_i D_i Low\_Mat+\sum_{i=98}^{111}\alpha_i D_i High\_Mat+\sum_{i=112}^{126}\alpha_i D_i Low\_Mat+\beta_1 AY_{it-1}DOWN+\beta_2 AY_{it-2}DOWN+\beta_3 AY_{it-1}UP+\beta_4 AY_{it-2}UP+$$
$$+\sum_{j=2}^{5}\delta_j T_j DOWN\cdot High\_Mat+\sum_{j=2}^{5}\kappa_j T_j DOWN\cdot Low\_Mat+\sum_{j=2}^{5}\phi_j T_j UP\cdot High\_Mat+\sum_{j=2}^{5}\varpi_j T_j UP\cdot Low\_Mat+\varepsilon_{it}$$

$$h_{it}=c+\sum_{i=1}^{49}a_i D_i High\_Mat\sum_{i=50}^{97}a_i D_i Low\_Mat+\sum_{i=98}^{111}a_i D_i High\_Mat+\sum_{j=2}^{5}b_j T_j DOWN\cdot High\_Mat+\sum_{j=2}^{5}d_j T_j DOWN\cdot Low\_Mat+$$
$$+\sum_{j=2}^{5}g_j T_j UP\cdot High\_Mat+\sum_{j=2}^{5}m_j T_j UP\cdot Low\_Mat+\vartheta\, h_{it-1}+\xi\,\varepsilon_{it}^2+\upsilon_{it}$$

$$\varepsilon_{it}\sim N(0,h_{it})$$

	Mean Equation				Variance Equation			
Time Window	High_Mat		Low_Mat		High_Mat		Low_Mat	
	Coeff.	Cumulative	Coeff.	Cumulative	Coeff. (*10^2)	Cumulative (*10^2)	Coeff. (*10^2)	Cumulative (*10^2)
Downs	*(N=49)*		*(N=48)*		*(N=49)*		*(N=48)*	
-60; -16	0.0077	0.0077	0.0025	0.0025	0.0862	0.0862	0.0543	0.0543
-15; -2	0.0014 (0.0025)	0.0092	-0.0013 (0.0019)	0.0012	-0.0425*** ($3.92\cdot10^{-5}$)	0.0437	-0.0126*** ($2.34\cdot10^{-5}$)	0.0417
-1; +1	0.0123*** (0.0032)	0.0200***	0.0038 (0.0031)	0.0063	-0.0454*** ($4.84\cdot10^{-5}$)	0.0408	-0.0130** ($6.08\cdot10^{-5}$)	0.0413
+2; +15	0.0040* (0.0023)	0.0118***	0.0019 (0.0017)	0.0044	-0.0435*** ($3.01\cdot10^{-5}$)	0.0427	-0.0162*** ($1.81\cdot10^{-5}$)	0.0381
+16; +60	0.0073*** (0.0028)	0.0150	0.0036* (0.0019)	0.0060	0.0258*** ($4.35\cdot10^{-5}$)	0.1120***	0.0422*** ($3.91\cdot10^{-5}$)	0.0965***
Total Ch. (-60; +60)		0.0073 (95%)		0.0036 (144%)		0.0258 (30%)		0.0422 (78%)
Ups	*(N=14)*		*(N=15)*		*(N=14)*		*(N=15)*	
-60; -16	-0.0235	-0.0235	-0.0525	-0.0525	0.0886	0.0886	0.1170*** ($5.05\cdot10^{-5}$)	0.1170
-15; -2	-0.0032 (0.0037)	-0.0267	0.0189*** (0.0063)	-0.0336	-0.0201*** ($5.42\cdot10^{-5}$)	0.0685	-0.0825*** ($12.2\cdot10^{-5}$)	0.0345
-1; +1	-0.0258*** (0.0077)	-0.0493***	0.0359*** (0.0092)	-0.0166*	0.0111 ($22\cdot10^{-5}$)	0.0997	-0.0707** ($35\cdot10^{-5}$)	0.0463
+2; +15	-0.0168*** (0.0031)	-0.0403	0.0179*** (0.0053)	-0.0345**	-0.0219*** ($4.66\cdot10^{-5}$)	0.0667	-0.0972*** ($11\cdot10^{-5}$)	0.0198
+16; +60	-0.0180*** (0.0038)	-0.0415	0.0100* (0.0058)	-0.0425*	0.0123* ($6.42\cdot10^{-5}$)	0.1009***	0.0235*** ($6.93\cdot10^{-5}$)	0.1405***
Total Ch. (-60; +60)		-0.0180 (-77%)		0.0100 (+19%)		0.0123 (14%)		0.0235 (20%)
β_1	0.7201*** (0.0151)							
β_2	0.2022*** (0.0147)				ξ	0.7016*** (0.0076)		
β_3	0.5681*** (0.0207)				ϑ	0.1029*** (0.0059)		
β_1	0.2237*** (0.0226)							

Notes: Regression statistics: Adj. R^2=0.9708, SE=0.0564, DW=1.74

Table A3 *GARCH(1, 2) Pooled Estimation for Abnormal Yields (AY) broken down by Coupon Rate.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 2) type model. Bonds have been classified as having high coupon (High_C) or low coupon (Low_C) according to the median coupon rate. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{i=1}^{49}\alpha_i D_i High\_C + \sum_{i=50}^{107}\alpha_i D_i Low\_C + \sum_{i=108}^{125}\alpha_i D_i High\_C + \sum_{i=126}^{137}\alpha_i D_i Low\_C + \beta_1 AY_{it-1}DOWN + \beta_2 AY_{it-2}DOWN + \beta_3 AY_{it-1}UP + \beta_4 AY_{it-2}UP +$$
$$+ \sum_{j=2}^{5}\delta_j T_j DOWN \cdot High\_C + \sum_{j=2}^{5}\kappa_j T_j DOWN \cdot Low\_C + \sum_{j=2}^{5}\phi_j T_j UP \cdot High\_C + \sum_{j=2}^{5}\varpi_j T_j UP \cdot Low\_C + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=1}^{49} a_i D_i High\_C \sum_{i=50}^{107} a_i D_i Low\_C + \sum_{i=108}^{125} a_i D_i High\_C + \sum_{j=2}^{5} b_j T_j DOWN \cdot High\_C + \sum_{j=2}^{5} d_j T_j DOWN \cdot Low\_C +$$
$$+ \sum_{j=2}^{5} g_j T_j UP \cdot High\_C + \sum_{j=2}^{5} m_j T_j UP \cdot Low\_C + \vartheta_1 h_{it-1} + \vartheta_2 h_{it-2} + \xi\ \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	*Mean Equation*				*Variance Equation*			
	High_C		**Low_C**		**High_C**		**Low_C**	
	Coeff.	**Cumulative**	**Coeff.**	**Cumulative**	**Coeff. (*10^2)**	**Cumulative (*10^2)**	**Coeff. (*10^2)**	**Cumulative (*10^2)**
Downs	*(N=49)*		*(N=58)*		*(N=49)*		*(N=58)*	
-60; -16	0.0009	0.0009	0.0216	0.0216	0.0939	0.0939	0.1223	0.1223
-15; -2	-0.0041***	-0.0032	-0.0016	0.0200	-0.0500***	0.0439	-0.0246***	0.0977
	(0.0006)		(0.0020)		($2.70\cdot10^{-5}$)		($3.22\cdot10^{-5}$)	
-1; +1	0.0025	0.0034***	0.0085***	0.0301***	-0.0635***	0.0304***	-0.0279***	0.0944
	(0.0016)		(0.0030)		($2.40\cdot10^{-5}$)		($6.29\cdot10^{-5}$)	
+2; +15	-0.0015	-0.0005**	0.0070***	0.0286	-0.0537***	0.0402***	-0.0290***	0.0933
	(0.0018)		(0.0019)		($1.08\cdot10^{-5}$)		($1.81\cdot10^{-5}$)	
+16; +60	0.0012	0.0021	0.0076***	0.029	0.0023	0.0962***	0.0352***	0.1575***
	(0.0024)		(0.0022)		($5.58\cdot10^{-5}$)		($5.42\cdot10^{-5}$)	
Total Ch. (-60; +60)		0.0012 (124%)		0.0076 (35%)		0.0023 (2%)		0.0352 (29%)
Ups	*(N=18)*		*(N=11)*		*(N=18)*		*(N=11)*	
-60; -16	-0.0262	-0.0262	-0.0465	-0.0465	0.1856***	0.1856	0.1404	0.1404
					(0.0001)			
-15; -2	0.0116**	-0.0147	0.0009	-0.0456	-0.0537***	0.1319	-0.1300***	0.0104
	(0.0037)		(0.0062)		($4.30\cdot10^{-5}$)		($2.42\cdot10^{-4}$)	
-1; +1	0.0084***	-0.0178	-0.0095	-0.0560	-0.0658***	0.1198	0.0739	0.2143***
	(0.0002)		(0.0136)		($8.45\cdot10^{-5}$)		($5.45\cdot10^{-4}$)	
+2; +15	0.0074**	-0.0189	-0.0144**	-0.0609	-0.0545***	0.1311	-0.1297***	0.0107***
	(0.0036)		(0.0067)		($4.01\cdot10^{-5}$)		($2.35\cdot10^{-4}$)	
+16; +60	0.0062	-0.0200	-0.0196***	-0.0661	-0.0034	0.1822***	-0.0440***	0.0964***
	(0.0041)		(0.0056)		($9.64\cdot10^{-5}$)		($1.38\cdot10^{-4}$)	
Total Ch. (-60; +60)		0.0062 (24%)		-0.0196 (-42%)		-0.0034 (-2%)		-0.0440 (-31%)
β_1	0.6518***				ξ	0.1117***		
	(0.0152)					(0.0082)		
β_2	0.1834***				ϑ_1	0.4518***		
	(0.0144)					(0.0564)		
β_3	0.5648***				ϑ_2	0.1361***		
	(0.0218)					(0.0473)		
β_1	0.2293***							
	(0.0235)							

Notes: Regression statistics: Adj. R^2=0.9718, SE=0.0555, DW=1.66

Table A4 *GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Negative Pledge Guarantee.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 1) type model. Bonds have been separated in to issues with a negative pledge guarantee attached (NP) and issues with no negative pledge guarantee attached (NON_NP). The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{i=1}^{49}\alpha_i D_i NP + \sum_{i=50}^{107}\alpha_i D_i NON\_NP + \sum_{i=108}^{125}\alpha_i D_i NP + \sum_{i=126}^{137}\alpha_i D_i NON\_NP + \beta_1 AY_{it-1}DOWN + \beta_2 AY_{it-2}DOWN + \beta_3 AY_{it-1}UP + \beta_4 AY_{it-2}UP +$$
$$+ \sum_{j=2}^{5}\delta_j T_j DOWN\cdot NP + \sum_{j=2}^{5}\kappa_j T_j DOWN\cdot NON\_NP + \sum_{j=2}^{5}\phi_j T_j UP\cdot NP + \sum_{j=2}^{5}\varpi_j T_j UP\cdot NON\_NP + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=1}^{49}a_i D_i NP \sum_{i=50}^{107}a_i D_i NON\_NP + \sum_{i=108}^{125}a_i D_i NP + \sum_{j=2}^{5}b_j T_j DOWN\cdot NP + \sum_{j=2}^{5}d_j T_j DOWN\cdot NON\_NP +$$
$$+ \sum_{j=2}^{5}g_j T_j UP\cdot NP + \sum_{j=2}^{5}m_j T_j UP\cdot NON\_NP + \vartheta_1 h_{it-1} + \xi\,\varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	***Mean Equation*** NP Coeff.	NP Cumulative	NON_NP Coeff.	NON_NP Cumulative	***Variance Equation*** NP Coeff. ($*10^2$)	NP Cumulative ($*10^2$)	NON_NP Coeff. ($*10^2$)	NON_NP Cumulative ($*10^2$)
Downs	*(N=40)*		*(N=66)*		*(N=40)*		*(N=66)*	
-60; -16	0.0032	0.0032	0.0104	0.0104	0.0618	0.0618	0.0732	0.0732
-15; -2	0.0007	0.0039	-0.0055***	0.0049	-0.0206***	0.0412	-0.0247***	0.0485
	(0.0024)		(0.0018)		($2.16\cdot10^{-5}$)		($1.59\cdot10^{-5}$)	
-1; +1	0.0132***	0.0165***	-0.0017	0.0087	-0.0213***	0.0405	-0.0302***	0.0430
	(0.0032)		(0.0024)		($4.80\cdot10^{-5}$)		($2.59\cdot10^{-5}$)	
+2; +15	0.0089***	0.0121	-0.0083***	0.0021***	-0.0228***	0.0390	-0.0241***	0.0491
	(0.0022)		(0.0018)		($0.92\cdot10^{-5}$)		($1.35\cdot10^{-5}$)	
+16; +60	0.0080***	0.0112	-0.0038	0.0066*	0.0295***	0.0913***	0.0421***	0.1153***
	(0.0029)		(0.0025)		($4.05\cdot10^{-5}$)		($4.01\cdot10^{-5}$)	
Total Ch. (-60; +60)		0.0080 (247%)		-0.0038 (-37%)		0.0295 (48%)		0.0421 (57%)
Ups	*(N=14)*		*(N=15)*		*(N=14)*		*(N=15)*	
-60; -16	-0.0367	-0.0367	-0.0378	-0.0378	0.0783	0.0783	0.1172***	0.1172
							($6.00\cdot10^{-5}$)	
-15; -2	0.0073*	-0.0295	0.0106	-0.0271	-0.0119***	0.0664	-0.0835***	0.0337
	(0.0041)		(0.0056)		($4.24\cdot10^{-5}$)		($9.83\cdot10^{-5}$)	
-1; +1	-0.0114	-0.0481**	0.0105	-0.0273	0.0117	0.0900	0.0082	0.1254**
	(0.0086)		(0.0111)		($19.3\cdot10^{-5}$)		($32.9\cdot10^{-5}$)	
+2; +15	0.0011	-0.0357	0.0102*	-0.0276	-0.0184***	0.0599	-0.0761***	0.0411**
	(0.0036)		(0.0061)		($1.61\cdot10^{-5}$)		($10.4\cdot10^{-5}$)	
+16; +60	-0.0018	-0.0385	0.0042	-0.0336	0.0284***	0.1067***	0.0277***	0.1449***
	(0.0043)		(0.0059)		($7.01\cdot10^{-5}$)		($7.16\cdot10^{-5}$)	
Total Ch. (-60; +60)		-0.0018 (-5%)		0.0042 (11%)		0.0284 (36%)		0.0277 (24%)
β_1	0.7211***				ξ	0.1020***		
	(0.0156)					(0.0064)		
β_2	0.2105***				ϑ_1	0.7045***		
	(0.0151)					(0.0080)		
β_3	0.5982***							
	(0.0233)							
β_1	0.2311***							
	(0.0244)							

Notes: Regression statistics: Adj. R^2=0.9707, SE=0.0566, DW=1.76

Table A5 *GARCH(1, 2) Pooled Estimation for Abnormal Yields (AY) broken down by Amount of Bonds Outstanding.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 2) type model. Bonds have been classified as more liquid (High_AOS) or less liquid (Low_AOS) according to whether their outstanding amount was above or below the median value, respectively. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows.

$$AY_{it} = \sum_{i=1}^{26}\alpha_i D_i High\_AOS + \sum_{i=27}^{107}\alpha_i D_i Low\_AOS + \sum_{i=108}^{113}\alpha_i D_i High\_AOS + \sum_{i=114}^{136}\alpha_i D_i Low\_AOS + \beta_1 AY_{it-1}DOWN + \beta_2 AY_{it-2}DOWN + \beta_3 AY_{it-1}UP + \beta_4 AY_{it-2}UP + \sum_{j=2}^{5}\delta_j T_j DOWN\cdot High\_AOS + \sum_{j=2}^{5}\kappa_j T_j DOWN\cdot Low\_AOS + \sum_{j=2}^{5}\phi_j T_j UP\cdot High\_AOS + \sum_{j=2}^{5}\varpi_j T_j UP\cdot Low\_AOS + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=1}^{26} a_i D_i High\_AOS \sum_{i=27}^{107} a_i D_i Low\_AOS + \sum_{i=108}^{113} a_i D_i High\_AOS + \sum_{j=2}^{5} b_j T_j DOWN\cdot High\_AOS + \sum_{j=2}^{5} d_j T_j DOWN\cdot Low\_AOS + \sum_{j=2}^{5} g_j T_j UP\cdot High\_AOS + \sum_{j=2}^{5} m_j T_j UP\cdot Low\_AOS + \vartheta_1 h_{it-1} + \vartheta_2 h_{it-2} + \xi\ \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	Mean Equation				Variance Equation			
	High_AOS		Low_AOS		High_AOS		Low_AOS	
	Coeff.	Cumulative	Coeff.	Cumulative	Coeff. (*10^2)	Cumulative (*10^2)	Coeff. (*10^2)	Cumulative (*10^2)
Downs	(N=26)		(N=81)		(N=26)		(N=81)	
-60; -16	-0.0081	-0.0081	0.0161	0.0161	0.0878	0.0878	0.0958	0.0958
-15; -2	0.0027	-0.0054	-0.0042**	0.0120	-0.0254***	0.0624	-0.0324***	0.0634
	(0.0028)		(0.0017)		($3.24\cdot10^{-5}$)		($1.83\cdot10^{-5}$)	
-1; +1	0.0100**	0.0019	0.0045**	0.0206***	-0.0194	0.0684	-0.0422***	0.0536***
	(0.0048)		(0.0018)		($12\cdot10^{-5}$)		($1.81\cdot10^{-5}$)	
+2; +15	0.0125***	0.0044	0.0004	0.0165***	-0.0199***	0.0679	-0.0376***	0.0582***
	(0.0030)		(0.0016)		($5.11\cdot10^{-5}$)		($0.42\cdot10^{-5}$)	
+16; +60	0.0136***	0.0054	0.0026	0.0187	0.0389***	0.1267***	0.0190***	0.1148***
	(0.0031)		(0.0019)		($6.79\cdot10^{-5}$)		($4.15\cdot10^{-5}$)	
Total Ch. (-60; +60)		0.0136 (167%)		0.0026 (16%)		0.0389 (44%)		0.0190 (20%)
Ups	(N=6)		(N=23)		(N=6)		(N=23)	
-60; -16	-0.0341	-0.0341	-0.0371	-0.0371	0.1282	0.1282	0.1441***	0.1441
							($9.11\cdot10^{-5}$)	
-15; -2	0.0064	-0.0278	0.0030	-0.0341	-0.0596***	0.0686	-0.0889***	0.0552
	(0.0065)		(0.0043)		($8.39\cdot10^{-5}$)		($13.8\cdot10^{-5}$)	
-1; +1	0.0084	-0.0257	-0.0079	-0.0450	-0.0757***	0.0525	0.0554	0.1995***
	(0.0068)		(0.0097)		($7.88\cdot10^{-5}$)		($33.7\cdot10^{-5}$)	
+2; +15	0.0027	-0.0314	-0.0052	-0.0423	-0.0611***	0.0671	-0.0809***	0.0632***
	(0.0067)		(0.0047)		($11.5\cdot10^{-5}$)		($13.1\cdot10^{-5}$)	
+16; +60	0.0064	-0.0277	-0.0074*	-0.0445	-0.0386***	0.0896**	0.0038	0.1479***
	(0.0063)		(0.0042)		($11.3\cdot10^{-5}$)		($8.74\cdot10^{-5}$)	
Total Ch. (-60; +60)		0.0064 (19%)		-0.0074 (-20%)		-0.0386 (-30%)		0.0038 (3%)
β_1	0.6401***				ξ	0.1138***		
	(0.0144)					(0.0073)		
β_2	0.1934***				ϑ_1	0.4817***		
	(0.0137)					(0.0534)		
β_3	0.5836***				ϑ_2	0.1349***		
	(0.0206)					(0.0450)		
β_1	0.2173***							
	(0.0223)							

Notes: Regression statistics: Adj. R^2=0.9718, SE=0.0555, DW=1.66

Table A6 *GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Rating History.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 1) type model. Bonds have been classified according to their rating history into previously re-rated (PC) and not previously re-rated (NPC) bonds. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{i=1}^{30}\alpha_i D_i PC + \sum_{i=31}^{107}\alpha_i D_i NPC + \sum_{i=108}^{113}\alpha_i D_i PC + \sum_{i=114}^{136}\alpha_i D_i NPC + \beta_1 AY_{it-1}DOWN + \beta_2 AY_{it-2}DOWN + \beta_3 AY_{it-1}UP + \beta_4 AY_{it-2}UP + \sum_{j=2}^{5}\delta_j T_j DOWN\cdot PC + \sum_{j=2}^{5}\kappa_j T_j DOWN\cdot NPC + \sum_{j=2}^{5}\phi_j T_j UP\cdot PC + \sum_{j=2}^{5}\varpi_j T_j UP\cdot NPC + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=1}^{30} a_i D_i PC \sum_{i=31}^{107} a_i D_i NPC + \sum_{i=108}^{113} a_i D_i PC + \sum_{j=2}^{5} b_j T_j DOWN\cdot PC + \sum_{j=2}^{5} d_j T_j DOWN\cdot NPC + \sum_{j=2}^{5} g_j T_j UP\cdot PC + \sum_{j=2}^{5} m_j T_j UP\cdot NPC + \vartheta_1 h_{it-1} + \xi\, \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	Mean Equation				Variance Equation			
	PC		NPC		PC		NPC	
	Coeff.	Cumulative	Coeff.	Cumulative	Coeff. ($*10^2$)	Cumulative ($*10^2$)	Coeff. ($*10^2$)	Cumulative ($*10^2$)
Downs	(N=30)		(N=77)		(N=30)		(N=77)	
-60; -16	-0.0066	-0.0066	0.0048	0.0048	0.0768	0.0768	0.0694	0.0694
-15; -2	0.0058^{*}	-0.0009	0.0035^{**}	0.0082	-0.0190^{***}	0.0578	-0.0254^{***}	0.0440
	(0.0032)		(0.0016)		($3.82\cdot10^{-5}$)		($1.14\cdot10^{-5}$)	
-1; +1	0.0078	0.0012	0.0121^{***}	0.0169^{***}	-0.0133	0.0635	-0.0275^{***}	0.0419
	(0.0063)		(0.0021)		($9.38\cdot10^{-5}$)		($1.75\cdot10^{-5}$)	
+2; +15	0.0078^{***}	0.0011	0.0083^{***}	0.0130^{**}	-0.0228^{***}	0.0540	-0.0265^{***}	0.0429
	(0.0029)		(0.0016)		($1.80\cdot10^{-5}$)		($0.21\cdot10^{-5}$)	
+16; +60	0.0109^{***}	0.0043	0.0073^{***}	0.0121	0.0245^{***}	0.1013^{***}	0.0379^{***}	0.1073^{***}
	(0.0032)		(0.0021)		($5.24\cdot10^{-5}$)		($3.64\cdot10^{-5}$)	
Total Ch. (-60; +60)		0.0109 (164%)		0.0073 (154%)		0.0245 (32%)		0.0379 (55%)
Ups	(N=6)		(N=23)		(N=6)		(N=23)	
-60; -16	-0.0312	-0.0312	-0.0391	-0.0391	0.0870	0.0870	0.0985^{***}	0.0985
							($5.25\cdot10^{-5}$)	
-15; -2	0.0042	-0.0270	0.0078^{*}	-0.0313	-0.0007	0.0863	-0.0669^{***}	0.0316
	(0.0072)		(0.0043)		($16.4\cdot10^{-5}$)		($8.54\cdot10^{-5}$)	
-1; +1	-0.0094	-0.0406	-0.0035	-0.0427	-0.0181	0.0689	0.0722^{***}	0.1707^{***}
	(0.0119)		(0.0093)		($44.2\cdot10^{-5}$)		($27.3\cdot10^{-5}$)	
+2; +15	-0.0068	-0.0380	0.0043	-0.0348	-0.0084	0.0787	-0.0627^{***}	0.0358^{***}
	(0.0071)		(0.0046)		($16.9\cdot10^{-5}$)		($8.05\cdot10^{-5}$)	
+16; +60	-0.0158^{**}	-0.0470	-0.0037	-0.0428^{*}	0.0333^{**}	0.1203^{**}	0.0346^{***}	0.1331^{***}
	(0.0062)		(0.0043)		($14.6\cdot10^{-5}$)		($5.85\cdot10^{-5}$)	
Total Ch. (-60; +60)		-0.0158 (-51%)		-0.0037 (-9%)		0.0333 (38%)		0.0346 (35%)
β_1	0.6904^{***} (0.0149)				ξ	0.1043^{***} (0.0062)		
β_2	0.1981^{***} (0.0145)				ϑ_1	0.6977^{***} (0.0085)		
β_3	0.5726^{***} (0.0182)							
β_1	0.2232^{***} (0.0203)							

Notes: Regression statistics: Adj. R^2=0.9711, SE=0.05613, DW=1.70

Table A7 *GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Country of the Issuer.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 1) type model. Bonds have been classifies as UK if the country of the issuer is UK-based, or NON_UK if the origin of the issuer is any other country. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{i=1}^{72}\alpha_i D_i UK + \sum_{i=73}^{107}\alpha_i D_i Non\_UK + \sum_{i=108}^{123}\alpha_i D_i UK + \sum_{i=124}^{136}\alpha_i D_i Non\_UK + \beta_1 AY_{it-1} DOWN + \beta_2 AY_{it-2} DOWN + \beta_3 AY_{it-1} UP + \beta_4 AY_{it-2} UP + \sum_{j=2}^{5}\delta_j T_j DOWN \cdot UK +$$
$$+ \sum_{j=2}^{5}\kappa_j T_j DOWN \cdot Non\_UK + \sum_{j=2}^{5}\phi_j T_j UP \cdot UK + \sum_{j=2}^{5}\varpi_j T_j UP \cdot Non\_UK + \varepsilon_{it}$$

$$h_{it} = c + \sum_{i=1}^{72} a_i D_i UK \sum_{i=73}^{107} a_i D_i Non\_UK + \sum_{i=108}^{123} a_i D_i UK + \sum_{j=2}^{5} b_j T_j DOWN \cdot UK + \sum_{j=2}^{5} d_j T_j DOWN \cdot Non\_UK + \sum_{j=2}^{5} g_j T_j UP \cdot UK +$$
$$+ \sum_{j=2}^{5} m_j T_j UP \cdot Non\_UK + \vartheta_1 h_{it-1} + \xi\, \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	*Mean Equation* UK Coeff.	UK Cumulative	NON-UK Coeff.	NON-UK Cumulative	*Variance Equation* UK Coeff. (*10^2)	UK Cumulative (*10^2)	NON-UK Coeff. (*10^2)	NON-UK Cumulative (*10^2)
Downs	*(N=72)*		*(N=35)*		*(N=72)*		*(N=35)*	
-60; -16	0.0066	0.0066	0.0115	0.0115	0.0848	0.0848	0.0812	0.0812
-15; -2	-0.0002	0.0065	-0.0049*	0.0066	-0.0299***	0.0549	-0.0255***	0.0557
	(0.0021)		(0.0026)		($2.09\cdot10^{-5}$)		($3.38\cdot10^{-5}$)	
-1; +1	0.0054*	0.0121*	0.0117***	0.0231***	-0.0311***	0.0537	-0.0346***	0.0466
	(0.0030)		(0.0034)		($3.92\cdot10^{-5}$)		($5.88\cdot10^{-5}$)	
+2; +15	0.0030	0.0097	0.0071***	0.0186	-0.0358***	0.0490	-0.0218***	0.0594*
	(0.0018)		(0.0027)		($0.62\cdot10^{-5}$)		($3.52\cdot10^{-5}$)	
+16; +60	0.0063***	0.0130	0.0068**	0.0183	0.0283***	0.1131***	0.0214***	0.1026***
	(0.0023)		(0.0030)		($4.30\cdot10^{-5}$)		($5.39\cdot10^{-5}$)	
Total Ch. (-60; +60)		0.0063 (95%)		0.0068 (59%)		0.0283 (33%)		0.0214 (26%)
Ups	*(N=16)*		*(N=13)*		*(N=16)*		*(N=13)*	
-60; -16	-0.0370	-0.0370	-0.0373	-0.0373	0.0999	0.0999	0.1131***	0.1131
							($9.40\cdot10^{-5}$)	
-15; -2	0.0168***	-0.0202	-0.0094	-0.0467	-0.0397***	0.0602	-0.0562***	0.0569
	(0.0043)		(0.0063)		($5.28\cdot10^{-5}$)		($18.3\cdot10^{-5}$)	
-1; +1	0.0151**	-0.0219	-0.0197	-0.0570	-0.0322***	0.0677	0.0791	0.1922**
	(0.0072)		(0.0146)		($4.64\cdot10^{-5}$)		($53.8\cdot10^{-5}$)	
+2; +15	0.0055	-0.0315	-0.0097	-0.0470	-0.0496***	0.0503***	-0.0197	0.0934*
	(0.0034)		(0.0072)		($0.74\cdot10^{-5}$)		($18.2\cdot10^{-5}$)	
+16; +60	-0.0011	-0.0381*	-0.0116**	-0.0489	0.0007	0.1005***	0.0302***	0.1433***
	(0.0044)		(0.0054)		($7.78\cdot10^{-5}$)		($8.79\cdot10^{-5}$)	
Total Ch. (-60; +60)		-0.0011 (-3%)		-0.0116 (-31%)		0.0007 (1%)		0.0302 (27%)
β_1	0.6669***				ξ	0.1142***		
	(0.0157)					(0.0064)		
β_2	0.1816***				ϑ_1	0.6721***		
	(0.0153)					(0.0089)		
β_3	0.5925***							
	(0.0111)							
β_1	0.2100***							
	(0.0156)							

Notes: Regression statistics: Adj. R^2=0.9718, SE=0.0554, DW=1.70

Table A8 *GARCH(1, 1) Pooled Estimation for Abnormal Yields (AY) broken down by Rating.*

Daily data from January 1992 to December 1999 have been pooled to estimate a GARCH(1, 1) type model. The whole sample has been broken down by class of rating into AAA, AA, A, and BBB subsamples. The total panel (unbalanced) observations are 16433. Parameter estimates are obtained using the BHHH algorithm. Standard errors are in parentheses. Asterisks for the cumulative coefficients refer to the significance of the difference between the cumulative coefficient in T_j and the cumulative coefficient in T_{j-1} according to the Wald test statistic. Results are presented only for downgrades. The regression mean and variance equation are structured as follows:

$$AY_{it} = \sum_{t=1}^{15}\alpha_t D_t AAA + \sum_{t=16}^{66}\alpha_t D_t AA + \sum_{t=67}^{107}\alpha_t D_t A + \sum_{t=108}^{118}\alpha_t D_t AA + \sum_{t=119}^{130}\alpha_t D_t A + \sum_{t=131}^{136}\alpha_t D_t BBB + \beta_1 AY_{it-1}DOWN + \beta_2 AY_{it-2}DOWN + \beta_3 AY_{it-1}UP + \beta_4 AY_{it-2}UP +$$
$$+ \sum_{j=2}^{5}\delta_j T_j DOWN \cdot AAA + \sum_{j=2}^{5}\kappa_j T_j DOWN \cdot AA + \sum_{j=2}^{5}\mu_j T_j DOWN \cdot A + \sum_{j=2}^{5}\phi_j T_j UP \cdot AA + \sum_{j=2}^{5}\varpi_j T_j UP \cdot A + \sum_{j=2}^{5}\eta_j T_j UP \cdot BBB + \varepsilon_{it}$$

$$h_{it} = c + \sum_{t=1}^{15}a_t D_t AAA + \sum_{t=16}^{66}a_t D_t AA + \sum_{t=67}^{107}a_t D_t A + \sum_{t=108}^{118}a_t D_t AA + \sum_{t=119}^{130}a_t D_t A + \sum_{j=2}^{5}b_j T_j DOWN \cdot AAA + \sum_{j=2}^{5}d_j T_j DOWN \cdot AA +$$
$$+ \sum_{j=2}^{5}e_j T_j DOWN \cdot A + \sum_{j=2}^{5}g_j T_j UP \cdot AA + \sum_{j=2}^{5}m_j T_j UP \cdot A + \sum_{j=2}^{5}n_j T_j UP \cdot BBB + \vartheta_1 h_{it-1} + \xi\, \varepsilon_{it}^2 + \upsilon_{it}$$

$$\varepsilon_{it} \sim N(0, h_{it})$$

Time Window	AAA (N=15) Coefficient	AAA (N=15) Cumulative	AA (N=51) Coefficient	AA (N=51) Cumulative	A (N=41) Coefficient	A (N=41) Cumulative
Mean Equation						
-60; -16	0.0052	0.0052	0.0086	0.0086	-0.0028	-0.0028
-15; -2	0.0004 (0.0039)	0.0057	0.0015 (0.0015)	0.0101	0.0026 (0.0028)	-0.0002
-1; +1	0.0108 (0.0065)	0.0160*	0.0104*** (0.0028)	0.0190***	0.0067 (0.0046)	0.0039
+2; +15	0.0012 (0.0039)	0.0065	0.0072*** (0.0022)	0.0158	0.0044* (0.0026)	0.0016
+16; +60	0.0014 (0.0048)	0.0066	0.0085*** (0.0026)	0.0171	0.0065** (0.0030)	0.0037
Total Ch. (-60; +60)		0.0014 (26%)		0.0085 (98%)		0.0065 (232%)
Variance Equation [a]						
-60; -16	0.0808	0.0808	0.0728	0.0728	0.0855	0.0855
-15; -2	-0.0407*** ($2.25\cdot10^{-5}$)	0.0401	-0.0179*** ($3.25\cdot10^{-5}$)	0.0549	-0.0351*** ($2.99\cdot10^{-5}$)	0.0504
-1; +1	-0.0134 ($12.3\cdot10^{-5}$)	0.0674**	-0.0393*** ($3.74\cdot10^{-5}$)	0.0335***	-0.0313*** ($7.22\cdot10^{-5}$)	0.0542
+2; +15	-0.0379*** ($2.90\cdot10^{-5}$)	0.0429*	-0.0213*** ($2.14\cdot10^{-5}$)	0.0515***	-0.0411*** ($0.98\cdot10^{-5}$)	0.0444
+16; +60	0.0104 ($7.48\cdot10^{-5}$)	0.0912***	0.0437*** ($4.54\cdot10^{-5}$)	0.1165***	0.0166*** ($4.66\cdot10^{-5}$)	0.1021***
Total Ch. (-60; +60)		0.0104 (13%)		0.0437 (60%)		0.0166 (19%)

β_1	0.6992*** (0.0156)		
β_2	0.2052*** (0.0152)	ξ	0.0998*** (0.0065)
β_3	0.6002*** (0.244)	ϑ_1	0.6949*** (0.0084)
β_1	0.2174*** (0.0253)		

Notes: Regression statistics: Adj. R^2=0.9709, SE=0.0563, DW=1.73

Table A9

OLS with no AR term			
R-squared	0.851	Mean dependent var	0.084
Adjusted R-squared	0.849	S.D. dependent var	0.990
S.E. of regression	0.384	Akaike info criterion	-1.013
Sum squared resid	2343	Schwarz criterion	-0.927
Log likelihood	8302	F-statistic	505.9
Durbin-Watson stat	0.067	Prob(F-statistic)	0.000
GARCH(1,1)			
R-squared	0.978	Mean dependent var	0.084
Adjusted R-squared	0.978	S.D. dependent var	0.990
S.E. of regression	0.056	Akaike info criterion	-1.791
Sum squared resid	341	Schwarz criterion	-1.702
Log likelihood	14536	F-statistic	3901.5
Durbin-Watson stat	1.705	Prob(F-statistic)	0.000
GARCH(1,2)			
R-squared	0.979	Mean dependent var	0.084
Adjusted R-squared	0.978	S.D. dependent var	0.990
S.E. of regression	0.050	Akaike info criterion	-1.837
Sum squared resid	335	Schwarz criterion	-1.749
Log likelihood	14910	F-statistic	3961.0
Durbin-Watson stat	1.755	Prob(F-statistic)	0.000

PAGE

NUMBERING

AS ORIGINAL

Chapter VII

MODELLING EUROBOND CREDIT RATINGS AND FORECASTING THE DOWNGRADE PROBABILITY

7.1. Introduction

The objective of this chapter is to assess the role of company financial statement information in determining the risk of downgrade of firms issuing sterling-denominated Eurobonds in the period from 1992 to 1999. The contribution of long-term instability (looking at the firm's profitability, market significance, and leverage) and short-term liquidity problems (considering liquid assets and short-term liabilities of the firm) are specifically investigated. Alongside with accounting and financial variables, we will investigate the role of credit risk in affecting the probability for a firm to be downgraded, which we indicate as *Pr(D)*. A simple multivariate regression of *Pr(D)* on the rating category variable and other firm specific factors would not do a good job to help us in our objective -that is predicting *Pr(D)*. The main drawback of this procedure is an identification problem. It may indeed happen that some of the bonds' contractual characteristics and the issuing firms' operating figures affect both the rating and *Pr(D)*. As a consequence, we could not correctly identify the "clean" effect of the rating variable removing its interaction effect with the other factors.

To overcome this problem we develop a two-step estimation procedure. In the first step a conditional expectation of the default risk (rating class) is estimated as a function of bond specific and firm specific characteristics by an Ordered Probit Model (OP). The Ordered Probit seems to be a good procedure as it takes into account the ordinal nature of bond ratings and avoids any assumption about the multivariate distribution of the independent variables. In the second step, we estimate the disentangled effects of default risk, as obtained from the conditional mean estimate in step 1, and financial variables on the downgrade probability *Pr(D)*. The two-step model ends up with providing a one-year estimated downgrade probability for individual issuers.

The forecast performance of the probabilistic model for downgrades is finally evaluated. Block and full cross-validation are performed and the model is benchmarked against both a naïve constant probability model, which assumes all firms to be non-downgraded, and a more complex neural networks model.

We recall that rating agencies assign credit ratings employing both publicly available information, such as financial variables and statements, and possibly other non-public information, such as confidential reports from the firm management. However the exact set of information is generally not made public. The guidelines used in the rating process are not disclosed because such a disclosure would allow manipulation. Furthermore, the agencies state that the rating assessment requires expert subjective judgement in addition to the statistical analysis of financial data. It is thus generally believed that ratings are to a certain extent determined on the basis of subjective factors which are not easily quantifiable, and of variables not directly related to the specificity of the firm – such as the general economic situation, changes in management, currency fluctuations.

Due to these ambiguities in the bond rating process, ratings cannot be reproduced with 100 percent accuracy, and financial institutions are dependent on the rating agencies for the "official rating". However, it is useful to be able to evaluate the firm default risk independently by estimating appropriate rating models for two reasons. First, rating agencies do not rate bonds for every firm, and financial institutions might be interested in investing in a firm for which no rating is available from standard sources. Second, changes in official ratings occur infrequently, when important developments that affect a firm's default risk occur. Bond investors and corporate financial managers are concerned about rating changes, since reclassification usually affects the firm's cost of borrowing and stock price as well as the bond's price. Given the considerable value in being able to anticipate rating changes, researchers and practitioners, during the last thirty years, have built models that use firms and bonds observed characteristics to explain observed corporate bond ratings.

While the first part of this study is in line with these studies, we believe that the real contribution is provided in the second part where the downgrade probability is modelled. Modelling transitions has started only very recently and only within the framework of rating transition matrices. Reasons for the early stage of these studies may be the following: the recent release of data about rating actions by rating agencies, the traditional "default mode" way of thinking of most banks, the general consensus in viewing transitions as non-fundamental economic event.

However, it is increasingly common for banks to embrace activities with the objective to transfer credit risk. This leads banks to shift from a "default mode" approach to a transition short of default perspective. Moreover, despite default remains the ultimate outcome, it is not the only credit event.

Events such as distress and rating migration may have significant impact on the pricing of credit risk as verified in Chapter VI. For an investor holding a bond, a downgrade in the bond's rating can result in a financial loss even if the bond's issuer has continued to make all scheduled payments. Furthermore, running in parallel both a model of downgrade and a model of default may provide evidence on the possibly different causes driving the two events. Finally, while a downgrade model might serve during periods of relative stability in the economy, a failure model might be an essential tool during periods of exceptionally high failure rate.

While a large number of studies have modelled default and bankruptcy events[29], no publicly available empirical work has been devoted to model and predict directly the probability for a firm (bond) to have its rating revised downward. We attempt to fill this gap identifying the factors beneficial to predict a rating downgrade, and that may not necessarily be the same explaining the rating level or the default probability.

As well explained by Carey and Hrycay (2001), the advantages of scoring models like this lie in their mechanical nature and the possibility to match the model's time horizon with that of the portfolio credit risk model. However, scoring models rely on large and representative samples and encompass the risk of biased estimates. Despite the drawback of a limited sample size, our exercise has several practical benefits for credit risk management practices. This type of model should be useful for the following reasons. First, updating Eurobond ratings ahead of ratings agency announcements and monitoring short-term changes in the credit quality of corporate obligors. Second, identifying profitable bond strategies especially in light of the evidence of significant CAR and yield spread reaction in Chapter VI. Third, improving the pricing of credit derivative products. Finally, as a first step in the valuation of credit risk in a fixed-income portfolio, in general, and in the context of the overall value-at-risk methodology, in particular.

The remainder of the chapter is structured as follows. Section 7.2 briefly outlines the literature concerning the explanatory factors of bond ratings. The sample, the data and the methodology are described in Section 7.3. Empirical findings are presented in Section 7.4. Section 7.5 summarises and concludes the main findings of the chapter.

---

[29] See Kao (2000) for an overview and discussion of the credit risk models.

7.2. Review of the Bond Rating Related Literature

Many studies attempt to assess how the rating agencies use public information in setting quality ratings, though most are mainly US based. Although theory provides some guidance in the choice of explanatory variables, the choice of method (parametric *vesus* non-parametric, logit *vesus* probit) is not indicated by either theory or empirical evidence. There is a general consensus on the inappropriateness of least squares methods to rate bonds. There is also concern over the use of methods (such as multinomial discriminant analysis) which ignore the ordinal nature of bond rating. However, no real guidance exists as to what sort of statistical model is optimal for bond rating and no single method dominates in the empirical literature. We will try to cover the essential aspects by briefly presenting the main works on the basis of the methodology they used.

7.2.1. Linear Regression Analysis

Horrigan (1966) is the first study that estimates and predicts bond ratings based on the characteristics of bonds and issuing firms. On the basis of a sample of 200 US corporate bonds with unchanged ratings in the period 1959-1964, Horrigan uses a simple linear regression analysis to predict both the ratings of newly issued bonds and their rating changes in the period 1961-1964. The Moody's and S&P's bond rating series are coded on a nine-point scale (with 9=AAA, 8=AA, ... , 1=C) and regressed on a set of accounting data and ratios. Horrigan is able to explain 65 percent of the variation in the dependent variable through the following explanatory variables: total assets, net worth to total debt (book values), net operating profit to sales, working capital to sales, sales to net worth, and the subordination status.

West (1970) differentiates from Horrigan (1966) for the introduction of new explanatory variables and for using a regression model in logarithmic form to explain ratings assigned to outstanding US bonds. The dependent variable is constructed as in Horrigan (1966) and regressed on the variables that Fisher (1959) had previously used to explain bond risk premia –i.e. earnings variability, firm's reliability, capital structure and marketability. The logarithmic form intends to improve the fit of the model by allowing for some interaction effects among the independent variables. The impact of each independent variable is indeed a function of the levels of the other independent variables. However, West (1970) cannot improve the predictive ability of Horrigan's model.

Pogue and Soldofsky (1969) introduce a new procedure to avoid coding the ordinal bond rating onto an interval scale by comparing only two categories at the time. Moody's bond ratings are collected for industrial, utility and rail US outstanding corporate bonds (20 observations in each group) in the 1961-1966 period. A dummy variable 0-1 for all the possible pair-wise comparisons is used as dependent variable and regressed on the following variables: long term debt to total assets, coefficient of variation of earnings, and total assets. This procedure is, however, unable to make use of all the available information. Moreover, the sample size of 10 bonds in each rating class is not large enough to invoke the OLS asymptotic properties.

Ordinary least-squares analysis assumes that the underlying dependent variable (default risk in our case) has been categorised into equally spaced discrete intervals (rating categories). That is, the risk differential between an *AA*-rated bond and an *A*-rated bond is the same as between a *BBB*-rated and a *BB*-rated bond. While we can think bond ratings as conveying ordinal information, we cannot interpret ratings as equal intervals on a scale from investment-grade to speculative bonds. Treating ordinal variables as interval variables leads inevitably to misspecification. In particular the expected value of the error term does not equal zero, the variance of the error term is not constant as a function of the independent variables, and the error term is not normally distributed (McKelvey and Zavoina, 1975). Taking into account these considerations, the subsequent studies attempt to overcome these problems introducing new methodologies to classify bonds into bond-rating categories. In a chronological order the next methodology to be employed is the multiple discriminant analysis.

7.2.2. Multiple discriminant analysis (MDA)

Discriminant analysis has been one of the most popular techniques used to analyse financial data in the context of financial distress. The pioneering and still most widely used publicly available model is Altman's Z-Score model for default prediction (Altman, 1968, 1977, 1995) which uses a particular implementation of the linear discriminant analysis (LDA). The model consists of a linear function of financial ratios that produces the best classification of firms either distressed or non-distressed categories, based on a representative learning set of data. A separation line is found which maximises the separation between the two categories of firms. This linear function is then used to classify out-of-sample companies as belonging to one of the two groups. Most importantly, the magnitude of the LDA score can be interpreted as an indicator of the probability of belonging to the distressed group and not as the probability of default itself. The ratios (variables) embedded in the most recent (1995) Z"-Score model are the working capital to total assets ratio, retained earnings to total assets ratio, earnings before interest and taxes over total assets, book value of equity over book value of total debt. One of the main reasons for the popularity of Altman's methodology is that it provides a standard benchmark for comparison of companies in similar industries.

Pinches and Mingo (PM, 1973) introduce a multiple discriminant analysis (MDA) to classify bonds into rating categories. Their estimation sample includes 132 newly issued US industrial bonds rated by Moody's in the years 1967-68. After an *a priori* screening of all the financial and accounting variables, PM proceed developing the discriminant analysis. They finally identify the following factors as being important: size, leverage, return on investment, earnings stability, debt coverage, plus a subordination status variable, which results to be the most relevant "explanatory" variable. In order to make a comparison with previous empirical findings, PM (1973) apply the multiple discriminant analysis to the independent variables used in the previous studies and conclude that their own set of independent variables has higher predictive ability.

Altman and Katz (AK, 1976) apply this methodology to the bond ratings of companies in the electric public utility industry. Through a series of *ad hoc* procedures AK produce a set of variables from the large initial list and end up with the following apparently significant variables: the interest coverage ratio, earnings variability, interest coverage variability, return on investment, and maintenance and depreciation expense to operating revenues.

The use of MDA is intended to avoid the interval scale assumption required by OLS. To this aim MDA concentrates on differences between categories of variables. A series of functions is computed to maximise the ratio of between-group deviation sum of squares to within-group deviation sum of squares (Eisenbeis and Avery, 1972). However, MDA treats ratings as classifying bonds into separate categories and consequently is not able to exploit the ordinal nature of ratings. In other words, MDA treats the nine rating categories from AAA to C as nine different outcomes ignoring, however, that these nine categories can be viewed as partitions of perhaps unequal widths of a single risk dimension, the probability of default. In addition, MDA also requires strong multivariate normality distributional assumptions on the independent (classifying) variables and assumes that the group variance-covariance is equal across groups. In addition it does not provide convenient tests of significance. MDA is in fact unable to identify insignificant variables through formal significance tests on the individual coefficients. The next studies start off from these limitations and introduce ordered probit models that treat the different values of the dependent variable as an ordinal variable (but not necessarily on a linear scale) avoiding, at the same time, the restrictive statistical requirements posed by MDA. Fore detailed treatment of discriminant analysis, the reader may refer to Lachenbruch (1975).

7.2.3. Probit Models

While LDA is solved through the error squares minimisation, binory choice models (Logit and Probit) proceeds through the maximisation of the logarithm of a likelihood function (that is a logit and a normal cumulative probability in the two cases, respectively). Kaplan and Urwitz (KU, 1979) is the first study that applies ordered probit analysis to outstanding and newly issued industrial US bonds rated by Moody's in the period between 1970 and 1974. In particular, KU use an ordinal probit model that allows the use of maximum likelihood (ML) estimators, that under general conditions, are consistent, asymptotically efficient, and have a known asymptotic distribution (Theil, 1971, chap. 8). A set of financial ratios is first selected on the basis of previous studies and successively computed using a 5-year average of the annual ratios to avoid temporary anomalies. The subordination variable, size, financial leverage, and profitability are the variables found to be significant. No substantial difference in the results is revealed by the successive use of industry-adjusted ratios.

Kao and Wu (1990) estimate the default risk of new debt issued by industrial and utility Moody's rated companies for the period January 1984 - December 1985. The default risk is estimated as a function of indenture provisions and bond and issuing firm characteristics by the use of an ordered probit. The results indicate that leverage (the debt to total capitalisation ratio), profitability (ROA), size (total assets), subordination and industry dummy variables, and financing restriction provision play all an important role to determining the risk of default. Particular interest is devoted to test empirically the impact of bond indenture provisions on ratings. To this aim a sinking-fund amortisation rate variable is introduced in the model and its impact is studied separately for different categories of credit quality bonds. Results indicate that the effect of sinking funds on default risk is negative for investment-grade bonds and positive for speculative-grade bonds, suggesting that sinking funds do not reduce the default risk of speculative-grade bonds.

Blume, Lim and MacKinley (BLM, 1998) is the most recent paper on this subject. They generalise and extend the methodology of Kaplan and Urwitz (1979). BLM abandon the cross-section analysis so far utilised and introduce a panel data of S&P's bond ratings for all corporate bonds included in the Lehman Brothers Corporate Bond Index covering the period 1978-1995. The availability of data in a panel format allows them to examine whether, conditional on the included variables, rating standards have become more stringent over time and, if so, to assess the importance of this phenomenon in explaining the recent prevalence of downgrades over upgrades. The specific accounting ratios used to explain credit ratings are pre-tax interest coverage, operating income to sales, long-term debt to assets, and total debt to assets. All the ratios result to be significant, with the first two and the last two positively and negatively related to higher credit ratings, respectively. From the model BLM also obtain estimates of the intercept-dummies for each year in the estimation period. The steady downward trend over time of the intercepts is consistent with the hypothesis of more stringent standards over time in assigning ratings.

7.2.4. Neural networks

The use of a neural network approach (ANN) in accounting and financial research and to model corporate bond rating has been growing rapidly in the last ten years. In particular neural networks are recommended in Dutta and Shekhar (1988), Surkan and Ying (1991), Moody (1994), Kim et al. (1993), and Daniels, Kamp and Verkooijen (1997). ANN is a non-parametric (non-linear) modelling technique in which the data series themselves identify the relationships among the variables. The logit and probit models characterise the probability that a bond will be downgraded as a single nonlinear (sigmoid) function of the explanatory variables. Neural networks generalise this by making the downgrade probability the sum of (possibly nested) sigmoid functions. The result is that the relation between the downgrade probability and the explanatory variables may be highly nonlinear. The main justification for the use of neural networks with bond ratings prediction lies indeed in its potential to capture nonlinearities in the data which linear regression models cannot capture. Since ANN does not rely on restrictive parametric assumptions such as normality, stationarity, or sample-path continuity, it is also robust to specification errors troubling parametric models. In addition, the absence of a complete *a priori* specification of a functional form for the data-generation process of bond ratings suggests the use of a non-parametric modelling approach. In the above studies, neural network models have been proved to have the potential to achieve a higher percentage of correct risk classifications than alternative methods. The concern with this approach remains the typical limited size of the data set relative to the large number of parameters in a typical network. Since neural networks rely consistently on the quality of the data, they are likely to fail or to be trapped in overfitting if the dataset is not large enough -which is not a rare problem when working with corporate bond data.

7.3. Data and Methodology

7.3.1. Sample Selection

The sample was chosen from all bullet, that is with no sinking fund or call/put option attached, sterling Eurobonds issued from 1/1/1992 to 31/12/1999. From Datastream International. we retrieved monthly time series of Standard and Poor's ratings for each bond starting from the date it was issued. Rating data from Moody's are also provided in Datatastream International. However we decided to consider only ratings assigned by Standard & Poor's as they constitute a larger number. We preferred not to merge the data provided by the two agencies as significant differences have been observed in the credit rating assigned to the same firm (Cantor and Packer, 1995), compromising the homogeneity of the data. S&P's credit rating information was available for 473 Eurobonds.

The whole sample was split on the basis of rating migrations during the life of the issue. 312 Eurobonds were not re-rated over the sample period, while 161 issues experienced a rating change. Among the re-rated bonds, 124 were downgraded and 37 were upgraded, reflecting the generally recently observed high proportion of downgrades to upgrades. We selected the downgraded bonds[30] and we excluded bonds issued by government and supranational entities, remaining with 109 (downgraded) corporate bonds (see Figure 7.1 for the distribution over time of the Eurobond downgrades and Figure 7.2 for time, geographic, maturity and rating distribution of the data). We noticed that bonds issued by the same firm were often down-rated on the same day as a consequence of the firm's re-rating. In these cases we selected the most senior bond and we dropped the others from the sample. Successively, each Eurobond was individually matched with a couple of bonds in the non-changed sample with similar characteristics in terms of original rating, industry sector, and time to maturity on the date of the rating's change. In a second stage, bonds were also matched by coupon and by market value when feasible. We finally proceeded collecting all the available accounting information for both the changed and non-changed samples, and we ended up with a final sample of 105 bonds, of which 35 (out of 109) downgraded and 70 non-changed. For both samples financial figures and ratios were collected from Company Analysis and were all taken at the date of the last balance sheet before the event. The variables are summarily presented in Table 7.1 and more extensively described in the following section.

[30] Due to the small number of upgrades no robust analysis could have been performed on this sub-sample.

7.3.2. *Variables*

The review of previous studies suggests that a relatively small set of independent variables seems important in explaining and predicting bond ratings. These variables include size, earnings' stability, leverage, earning coverage of interest, working capital and profitability.

The size of the company is usually considered as inversely related to credit risk: the smaller the company, the higher the risk, *ceteris paribus*. The rationale is that larger firms tend to be older, with more established product lines, more varied sources of revenues and access to a wider variety of capital markets. More diversification might in turn imply less vulnerability to adverse shocks or cyclical fluctuations in one particular line of production and more stable cash flows. In other terms, larger firms have productive assets that can be sold to raise cash without disrupting core lines of business. As a consequence of all these factors, financial distress risk is likely to be lower for larger firms. Moreover, it may also be that larger firms have easier access to government aid when they fall on bad times. We therefore allow for the potential impact of firm's size on the rating classification by including the logarithm of total assets.

As an explicit measure of earnings instability we use the standard deviation of the earnings to equity ratio (*EARN_VOL*) computed over the three years before the rating change. We expect financial markets to regard a firm's volatile earnings as the results of poor management therefore demanding an extra *premium* for this risk. According to this line of argument, earnings' volatility should be positively related to the probability of being downgraded.

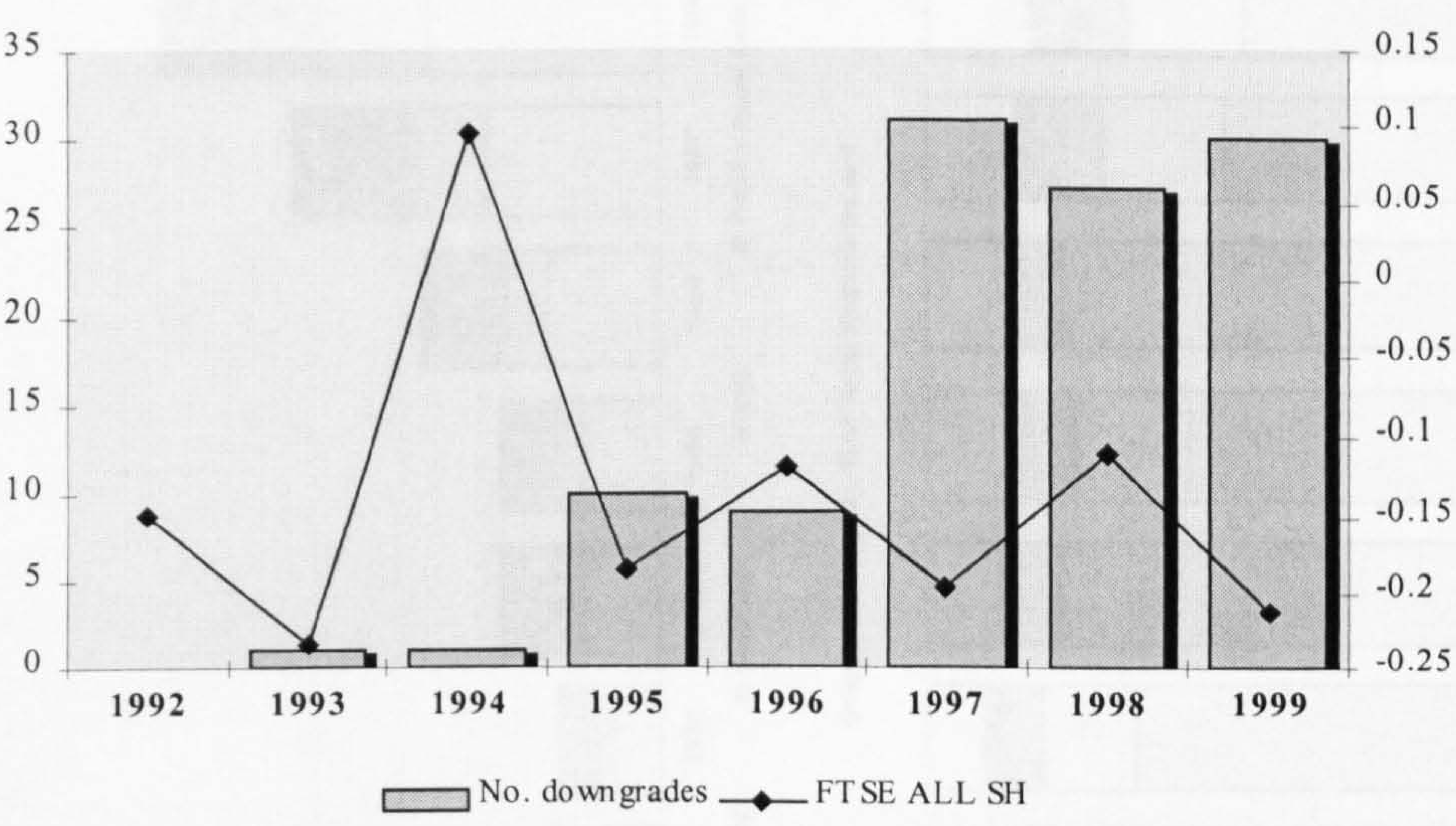


Figure 7.1 *Number of Eurobond Downgrades by Year, 1992-1999*

The total number of rating downgrades over the period 1992-1999 is 109. The figure plots both the number of downgraded bonds and the pattern of the return on the FTSE All Share Index over the same sample period. A negative relationship between the two series clearly emerges. Increases in the stock market returns are accompanied by decreases in the number of negative rating revisions

Figure 7. 2 *Eurobond Volume Distribution over time and by Country of the Issuer, Maturity and Rating*

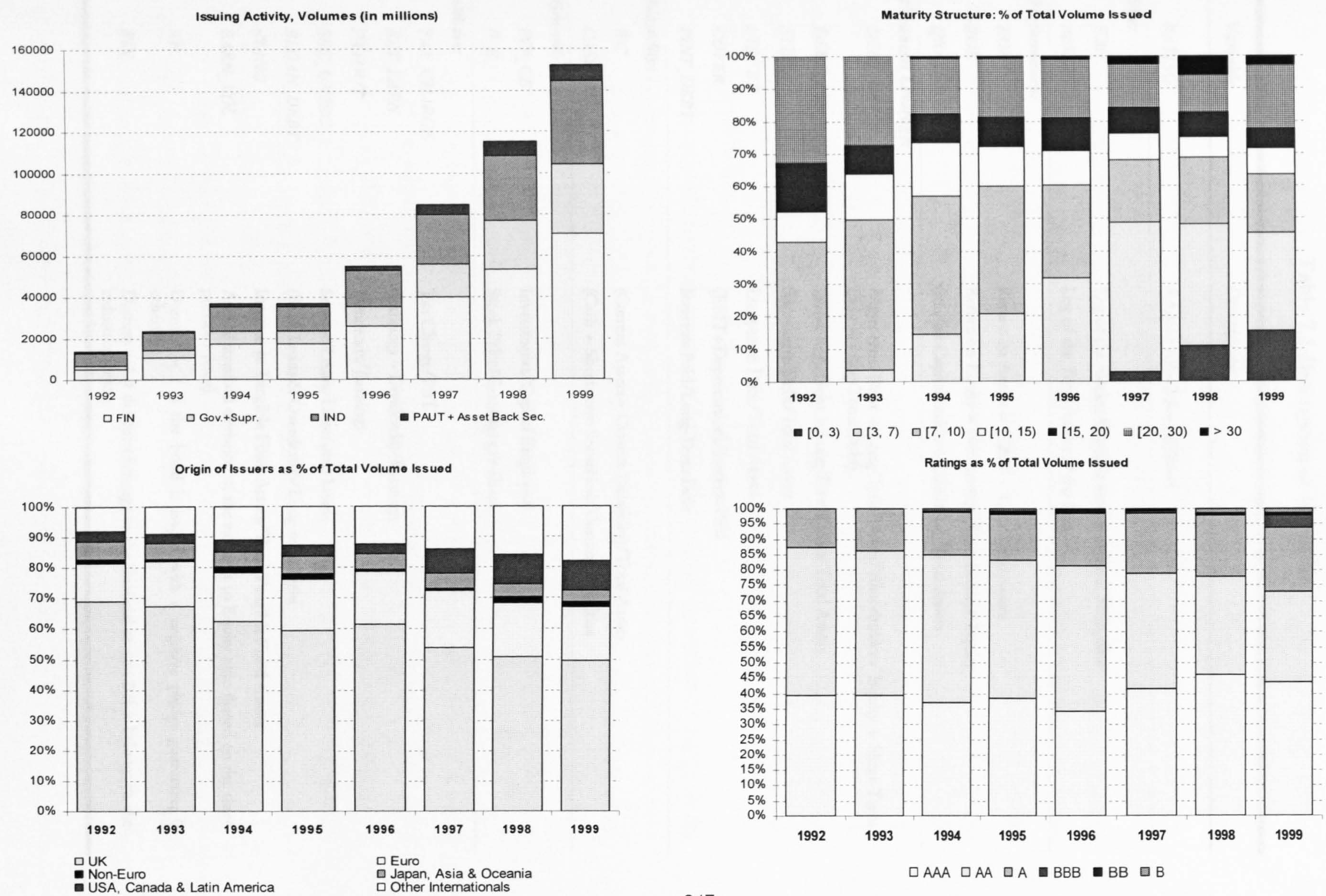


Table 7.1 *Description of Variables*

Variable	*Description*
RATING	AAA=1 AA=2 A=3 BBB=4
Size:	
CAP	Log of the Market Capitalization at Balance Sheet date
ASSETS	Log of the Total Assets of the firm
Performance:	
ROA	Return on Assets = (EBIT – Tax)/Total Assets
ROE	Return on Equity = Net Income/Shareholders' Equity
QRATIO	(Market Capitalization + Liabilities)/Total Assets
Financial Leverage:	
DEBT_CE	(Short-term Debt + Long-Term Debt)/(Shareholders' Equity + Short-Term Debt + Long-Term Debt)
DEBT_ASS	(Short-term Debt + Long-Term Debt)/Total Assets
STDEBT	Short-term Debt/Total Assets
LTDEBT	Long-term Debt/Total Assets
COVER	(EBIT+Depreciation)/Interest Paid
PINT_DEBT	Interests Paid/Long-Term Debt
Liquidity:	
WC	(Current Assets – Current Liabilities)/Total Assets
CASH_ASS	(Cash + Short-term Securities)/Current Liabilities
Growth:	
INV_CE	Investments/Capital Employed
P_E	Stock Price/Earnings per Share
Others:	
TAX_CHARGE	Tax Charge/PBT
RET_EARN	(Earnings – Dividends)/Earnings
PAYOUT	Dividends/Earnings
SEC_UNSEC	Secured Loans/Unsecured Loans
BLOAN_DEBT	(Bank Loans & Overdrafts)/Long-term Debt
dTANG	Increase in Tangible Fixed Assets/Total Tangible Fixed Assets
EARN_VOL	Annual standard deviation of the earnings to Equity ratio (based on the three previous years)
NP	Dummy = 1 if the bond is issued with a negative pledge guarantee; 0 otherwise.
FIN	Dummy =1 if the firm belongs to the financial sector; 0 if it belongs to the industrial sector.

Profitability is another key factor in affecting the firm's ability to pay its debt obligations. The ratios we used to measure firm's profitability include *ROA* (defined as the ratio of operating income to total assets), *ROE* (defined as net income to shareholders' equity), and *QRATIO* (defined as the sum of market capitalisation and liabilities over total assets). We expect profitability to be negatively related with default risk and positively related with the probability of being highly rated.

The leverage of the firm is probably generally considered to be the most important determinant of default risk and debt rating valuation. The more debt the firm employs in its capital structure, the less the firm will be likely to meet its debt service obligations in the event of even modest fluctuations in firm value. Several ratios are generally used to measure leverage, some merely variants of each other. *DEBT_CE* (defined as the book value of long-term debt plus short-term debt to the capital employed -the book value of equity plus the book value of total debt) and *DEBT_ASS* (defined as total debt to total assets) are introduced to reflect the market's perspective of current-value financial leverage relative to rating. *LTDEBT* and *STDEBT* are the ratios of long-term debt and short-term to total assets, respectively, and are introduced to capture the possible part played by the maturity of the debt.

As the debt ratios previously discussed are balance sheet ratios, they do not record changes in the values of debt and equity from the issue date. To overcome this problem we introduced also the coverage ratio (*COVER*), which is a flow ratio based on annual flows rather than on book values. The *COVER* ratio (defined as operating income to interest charges) measures the extent to which the cash flows needed to serve debt holders are covered by the firm's income, and is therefore predicted to be negatively correlated with credit risk.

To assess short-term liquidity risk we computed the working capital ratio, *WC* (defined as current assets less current liabilities over total assets) and the cash ratio, *CASH_ASS*. These ratios are useful to assess whether the firm has enough liquid sources to meet its immediate cash needs in case of a liquidity crunch. We would expect that the higher either ratio is, the more liquid is the issuing firm and the lower is the risk of default due to unavailability of sufficient funds to meet short-term cash demands.

As a proxy for the variations in the tangibility of the firm we introduce the increase in tangible fixed assets over the total tangible fixed assets (*dTANG*). We expect a negative relation between increases in tangible fixed assets and the probability of being assigned a lower rating. The rationale underlying this relation is that tangible assets are easy to collateralize and are the most widely accepted sources for bank borrowing and raising secured debt.

S&P's do not view common dividend payments as fixed obligation. Dividends can be cut or omitted without triggering debt repayment or covenant default, or increasing the risk of such default. However, many companies are extremely reluctant to cut their dividends as this may be considered as a signal of bad conditions of the firm. Following this theory we would expect higher risk to be associated with lower dividends. On the other hand, the agency theory supports the inverse relationship through the conflict of interests between shareholders and bondholders, so that the higher the dividend paid, the higher the risk of default. The relation between dividends and risk of default will be tested on two variables related to the dividend behaviour: the dividend payout ratio (*PAYOUT*) and the retained earnings ratio (*RET_EARN*).

As proxies for the growth rate of the company we computed the price to earnings ratio (*P_E*) and the investments to capital employed ratio (*INV_CE*). We expect firms with either extremely valuable or negative growth opportunities to have more severe potential financial difficulties. Moreover, we expect default risk to be negatively related both to the proportion of bank loans relatively to long-term debt (*BLOAN_DEBT*) and the proportion of secured respect to unsecured debt (*SEC_UNSEC*).

In addition to the financial and accounting ratios, we have also built two dummy variables, one for the industrial sector (*FIN*) and one for the negative pledge guarantee (*NP*). The dummy *FIN* (=1 if the firm belongs to the financial sector and =0 if the firm belongs to the industrial sector) has been introduced to test for the importance of sector differences in credit risk. A few recent reports by rating agencies and a proposed change in the bank capital regulation by the Basel Committee indicate that increasing attention has being paid to sector comparisons (Standard and Poor's, 1999; Basel Committee on Banking and Supervision, 1999). If these sector differences are in fact observed, the risk associated to firms in different industries will be weighted depending on both the credit rating and the sector. The literature on sector differences in the measurement of credit risk is fairly limited and generally does not support any strong evidence. Our study will eventually provide an additional contribution to this specific topic.

The dummy *NP* has been assigned a value one if the bond is accompanied by a negative pledge guarantee and zero otherwise. In the presence of a negative pledge clause, if the company issues new debt, the old debt must be secured as the new one. It is designed to protect the bondholder from credit deterioration as a result of the issuer's actions. The breach of the clause may accelerate the date for the repayment of the principal and put into place procedures to enforce repayment. The presence of this indenture should reduce the credit risk for bondholders, implying a negative relationship between *NP* and the probability of being transferred to a lower rating class. However the reverse relationship might occur when riskier firms issue bonds with such a guarantee attached to be able to allocate their bonds. As a result relatively risky bonds are more likely to have a NP guarantee.

So far we have described the explanatory variables of the ordered probit and the binary probit models. We now briefly present the dependent variables for the two models. Bond ratings in the sample range from *AAA* to *BBB*, but are not homogeneously distributed. Like in other studies, the + and - signs were omitted, i.e. *AA+*, *AA*, and *AA-* were all considered *AA*. For estimation purposes, the credit rating scale (*RATING*) was cardinalised and translated into numbers as follows: *AAA* = 1, *AA* = 2, *A* = 3, and *BBB* = 4 and used as dependent variable in the ordinary probit model. In the binary probit model the dependent variable is the dichotomous variable *Pr(D)*, which is equal to one if the firm is down-rated within one year and zero otherwise. As all default and rating migration studies have found an unambiguous correlation between credit quality and default remoteness -irrespectively of the time horizon-, we expect that the higher the rating, the lower is the probability of default[31].

7.3.3. *Preliminary Statistics*

Table 7.2 provides summary descriptive statistics for the variables we found to be significant in our study. In Panel A descriptive statistics are computed on individual samples, that is using all the available information (observations) for each variable. In Panel B the same statistics are based on a common sample, that is we included only the observations for which we have all the information. This is approximately the same sample our probit models will be based on.

Table 7.3 presents descriptive statistics for all the variables we collected splitting the sample into "downgraded" and "stable" bonds. The *Levene's F* test was used to test for homogeneity-of-variance. For each case (variable), the *Levene's F* test computes the absolute difference between the value of that case and its mean and performs a one-way analysis of variance on those differences. Successively, a parametric *t-test* and a non-parametric (*Mann-Whitney test*) test were performed to test for equal means and equal medians, respectively. The non-parametric test is equivalent to the *t-test* and uses the ranks of the cases to test whether two independent samples are from the same population. The parametric test was performed under the assumption of equal or different mean, according to what resulted from the *Levene's test* for each variable. The variables for which a

[31] See Nickell, Perraudin and Varotto (2000) for a recent "univariate" and "multivariate" analysis of rating transition matrices.

significant difference emerges between the two groups of bonds (downgraded and stable) are highlighted by a shaded area. Earnings' volatility and working capital present significantly higher variance and higher mean for bonds that have been down-rated than for non re-rated bonds[32]. The investment ratio and the net income to sales ratio are on average higher for the "changed" sample. Finally, downgraded bonds have lower and less volatile short-term debt ratio, more volatile dividend payout and higher secured to unsecured ratio than non re-rated bonds.

Panel A: Individual Sample	Mean	Median	Max	Min	St. Dev.	Skewness	Kurtosis	N
ASSETS	16.2165	15.6458	19.9073	13.0994	1.6265	0.7177	2.4877	105
CAP	15.6587	15.5875	17.9950	13.3770	0.9214	0.2361	2.7016	94
COVER	6.6585	5.6245	22.6613	-19.4091	4.7748	-1.2529	13.7369	81
DEBT_ASS	0.3073	0.2999	1.4084	0.0512	0.1698	2.9444	20.4562	93
DEBT_CE	0.5071	0.4685	0.9711	0.1638	0.1904	0.4757	2.6616	92
dTANG	0.0691	0.0618	0.4623	-0.1998	0.1275	0.8849	4.6653	84
EARN_VOL	0.0181	0.0105	0.1385	0.0003	0.0215	2.7794	13.7981	100
INV_CE	0.1049	0.0964	0.5287	-0.1531	0.1104	1.2293	5.9205	92
ROA	0.0852	0.0842	0.2876	-0.0430	0.0667	0.7657	3.6300	104
WC	0.1220	0.0892	0.5175	-0.1117	0.1268	0.7460	3.2375	93
Panel B: Common Sample								
ASSETS	16.1096	15.4940	19.9074	13.6163	1.5307	0.9366	2.7397	68
CAP	15.5771	15.5592	17.9951	13.3770	0.9521	0.2828	2.8442	68
COVER	7.1553	6.0753	22.6613	1.3625	3.8254	1.4145	6.0741	68
DEBT_ASS	0.2741	0.2852	0.5544	0.0512	0.1192	0.0548	2.3058	68
DEBT_CE	0.5128	0.4685	0.9711	0.1638	0.2023	0.3833	2.2678	68
dTANG	0.0575	0.0549	0.4623	-0.1998	0.1227	0.7647	4.7963	68
EARN_VOL	0.0171	0.0110	0.1385	0.0003	0.0209	3.2146	17.9750	68
INV_CE	0.0934	0.0782	0.5287	-0.1531	0.1043	1.3191	7.6620	68
ROA	0.0979	0.0893	0.2876	0.0080	0.0682	0.8668	3.6210	68
WC	0.1388	0.1129	0.5175	-0.1117	0.1293	0.6747	3.1926	68

Table 7.2 *Descriptive statistics for the estimation sample*

Descriptive statistics in Panel A are obtained using all the available observations for each individual variable. Panel B presents descriptive statistics computed using only the observations for which we have a complete set of information.

[32] The higher liquidity observed in the downgraded sample may be due to a build up in their inventories which, according to the computation of the Working Capital variable (WC) are not deducted from the current assets.

	D	N	Mean	Std. Deviation	Levene's Test (Eq. Var)	Mean Difference	t-test Eq. Means (Sig)	Mann-Whitney (Asynt.Sig)
CAP	0	62	9805861	9899278	0.0091	107677	0.0456	923
	1	32	9698184	12535325	*(0.92)*		*(0.96)*	*(0.58)*
ASSETS	0	70	42684618	67122717	2.1713	-7851786	-0.4574	1079
	1	35	50536404	108112894	*(0.14)*		*(0.65)*	*(0.32)*
EARN_VOL	0	65	0.0114	0.0123	11.00	-0.0191	-3.7809	545
	1	35	0.0305	0.0285	*(0.00)*		*(0.00)*	*(0.00)*
WC	0	63	0.0913	0.1067	3.16	-0.0953	-3.2544	566
	1	30	0.1865	0.1424	*(0.08)*		*(0.00)*	*(0.00)*
INV_CE	0	60	0.0851	0.0956	2.5240	-0.0568	-2.4134	728
	1	32	0.1419	0.1273	*(0.12)*		*(0.02)*	*(0.06)*
DEBT_CE	0	62	0.5194	0.2050	2.4045	0.0375	0.8857	850
	1	30	0.4818	0.1560	*(0.12)*		*(0.38)*	*(0.51)*
DEBT_ASS	0	63	0.3034	0.1920	0.4238	-0.0119	-0.3150	808
	1	30	0.3153	0.1121	*(0.52)*		*(0.75)*	*(0.26)*
STDEBT	0	63	0.3412	0.2515	18.48	0.0932	2.3119	799
	1	30	0.2479	0.1366	*(0.00)*		*(0.02)*	*(0.23)*
LTDEBT	0	65	0.2082	0.1850	0.2330	-0.0337	-0.9260	809
	1	31	0.2419	0.1176	*(0.63)*		*(0.36)*	*(0.12)*
dTANG	0	55	0.0682	0.1298	0.0041	-0.0027	-0.0911	788
	1	29	0.0709	0.1254	*(0.95)*		*(0.93)*	*(0.93)*
COVER	0	52	7.1014	3.4525	1.7408	1.2370	1.1196	633
	1	29	5.8644	6.5124	*(0.19)*		*(0.27)*	*(0.23)*
PAYOUT	0	68	0.5416	0.3551	26.24	-0.4165	-1.6005	1148
	1	35	0.9581	1.5183	*(0.00)*		*(0.12)*	*(0.77)*
CASH_ASS	0	64	0.0319	0.0432	0.0143	0.0033	0.3709	943
	1	33	0.0286	0.0387	*(0.91)*		*(0.71)*	*(0.39)*
ROA	0	69	0.0808	0.0656	0.0077	-0.0132	-0.9505	1051
	1	35	0.0940	0.0689	*(0.93)*		*(0.34)*	*(0.28)*
EBIT_CE	0	70	0.1439	0.3846	0.5383	0.0213	0.3211	1059
	1	35	0.1227	0.0999	*(0.46)*		*(0.75)*	*(0.26)*
ROE	0	70	0.1772	0.1967	0.5253	0.0241	0.5927	1087
	1	35	0.1531	0.1960	*(0.47)*		*(0.55)*	*(0.35)*
QRATIO	0	61	1.7937	0.6708	2.4422	-0.2194	-0.8614	934
	1	31	2.0131	1.7611	*(0.12)*		*(0.39)*	*(0.92)*
SEC_UNSEC	0	27	0.3954	0.9683	11.17	-3.6469	-1.0973	134
	1	12	4.0422	11.4951	*(0.00)*		*(0.30)*	*(0.39)*
OPI_SALES	0	45	0.2441	0.1857	0.6465	0.0570	1.4634	562
	1	29	0.1871	0.1214	*(0.42)*		*(0.15)*	*(0.32)*
NI_SALES	0	45	0.1440	0.1371	0.4833	0.0521	1.7765	531
	1	29	0.0919	0.0972	*(0.49)*		*(0.08)*	*(0.18)*
BANKL_DEBT	0	38	0.5343	0.7157	2.1406	0.2070	1.4341	416
	1	27	0.3273	0.2602	*(0.15)*		*(0.16)*	*(0.20)*
PINT_DEBT	0	51	0.0814	0.0398	2.7654	-0.0163	-1.3072	666
	1	28	0.0978	0.0716	*(0.10)*		*(0.20)*	*(0.62)*

Table 7.3 *Mean, Median and Variance Differences Tests for downgraded and stable firms*

Mean and standard deviation of variables for downgraded (D=1) and non-downgraded (D=0) firms are presented. The Levene's F test for homogeneity-of-variance is performed. The values of a parametric (t-test) and a non parametric (Mann-Whitney test) tests for equal means and equal medians, respectively, are also presented (with probability in parentheses).

7.3.4. Estimation Procedure

We first set up an *ad hoc* procedure to investigate the "true" role of credit risk and other firm specific factors in affecting the probability for a firm to be downgraded. A simple multivariate regression of *Pr(D)* on the rating category variable and other factors is likely to incur in an identification problem since it may occur that some of the bonds' contractual characteristics and the issuing firms' operating figures affect both the rating and *Pr(D)*. As a consequence, we could not correctly identify the "clean" effect of the rating variable. To overcome this problem, we represent the relationship between the probability of downgrade, *Pr(D)*, and credit risk by the following system of two equations:

$$Y_{1i} = \sum_{p=1}^{P} \beta_{1p} X_{1ip} + \sum_{s=1}^{S} \delta_{2s} W_{2is} + \gamma Y_{2i}^{*} + \varepsilon_{1i} \tag{7.1}$$

$$Y_{2i}^{*} = \sum_{s=1}^{S} \delta_{3s} W_{2is} + \varepsilon_{2i} \tag{7.2}$$

where i = 1, 2, … , N is the number of observations;
p = 1, 2, … , P is the number of explanatory variables X_1 affecting only *Pr(D)* -i.e. Y_{1i};
s = 1, 2, … , S is the number of explanatory variables W_2 affecting both *Pr(D)* and the credit risk –i.e. Y_{2i};
Y_{1i} is a dummy variable which takes value 1 if the firm has been downgraded and 0 if there was no change in the firm's rating over the sample period;
Y^{*}_{2i} is a latent random variable used to identify the rate in the S&P's rating decision process;
β_{1p}, δ_{2s} and δ_{3s} are regressions' coefficients;
ε_{1i} and ε_{2i} are disturbances terms normally distributed with mean equal to 0 and covariance matrix

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \tag{7.3}$$

In the first step we will focus on equation (7.2) and we will use an ordered probit model to estimate a conditional expectation of the default risk (rating class) as a function of bond specific and firm specific characteristics. In the second step, we will proceed estimating the pure effects of default risk

-as obtained from the conditional mean estimate in step one- and financial variables on the probability of downgrade *Pr(D)* employing a binary probit and using cross section data over downgraded and non downgraded firms.

STEP I: ORDERED PROBIT (OP) ESTIMATION

Bond ratings can be viewed as resulting from a continuous, unobserved creditworthiness index. Each credit rating corresponds to a specific range of the creditworthiness index, with higher ratings corresponding to a lower range of creditworthiness values. Since ratings are a typical example of multinomial-choice (qualitative) variables inherently ordered, the estimation of a model for such a dependent variable requires a special technique.

Our aim is to model the true credit risk -which is not observable- as a function of a few explanatory variables. To account for the ordinal nature of the dependent variable an ordered probit is used to model the observed variable for the risk of default (credit rating class) by considering a latent variable Y_{2i}^* according to the following rule:

$$Y_i = \begin{cases} 1 \;\; if \;\; Y_{2i}^* < \gamma_1 \\ 2 \;\; if \;\; \gamma_1 \le Y_{2i}^* < \gamma_2 \\ 3 \;\; if \;\; \gamma_2 \le Y_{2i}^* < \gamma_3 \\ 4 \;\; if \;\; Y_{2i}^* \ge \gamma_3 \end{cases} \tag{7.4}$$

In other terms, a bond belongs to the rating class R_j if Y_{2i}^* falls into the interval $\gamma_{j-1} \le Y_{2i}^* \le \gamma_j$. In our sample we have four rating classes, so that we will obtain three cutoff points γ which define the ranges of the creditworthiness index. As we have assigned lower values to higher credit quality classes -that is to lower default risk- ($AAA = 1, AA = 2, \dots$) we obtain negative values for the γs and we have $\gamma_1 < \gamma_2 < \gamma_3$. For example γ_1 can be interpreted as the maximum value for firms rated AAA, and γ_3 will be the lowest value for firms rated *BBB*. The widths of the intervals defining the risk categories may not be equal -that is, the interval for A-rated firms may be different from the interval for AA-rated firms.

The threshold values for the rating categories are estimated along with the β coefficients. Maximum Likelihood (*ML*) estimates of βs and γs are obtained using the generalised linear model

(*GLM*) method to exploit the asymptotic properties of *ML* estimators –i.e. consistency, normal distribution and efficiency. The estimation algorithm employed is the one proposed by Berndt, Hall, Hall, and Hausman (BHHH, 1974) and that uses first derivatives to determine both iteration updates and the covariance matrix estimates. We chose a tolerance level of 0.001 for the convergence criterion as they suggested.

From the results of the ordered probit we proceed to estimate a conditional expectation value of Y^*_{2i} for each rating class j as follows:

$$E(Y^*_{2i} \mid R_j) = \sum_{s=1}^{S} \delta_{2is} W_{2is} + m_i \qquad (7.5)$$

where m_i is the average error of the corresponding rating class from the ordered probit. The sum of the new residual series and the series of the estimated values for the rating constitutes the new default risk variable -which we indicate as *ADJ_RISK*- to insert in the following binary probit model for downgraded and non downgraded firms.

STEP II: BINARY PROBIT (BP) ESTIMATION

The dependent variable in the binary probit model may take value one in the occurrence of a downgrade and value zero in the absence of any rating change. We are then interested in modelling changes in the rating status of each firm in our sample and we aim to quantify the relationship between the firm's characteristics and the credit risk, on one side, and the probability of being downgraded, on the other side.

The unknown default risk variable Y^*_{2i} is replaced by an estimate obtained from its conditional mean (*ADJ_RISK*). The additional explanatory variables have been modified through a two-step procedure to correct for the presence of multicollinearity. In particular, each series –a part from the dummy *NP*- has been replaced with the residual series from the linear regression of the variable itself on the other independent variables included in the model and with which it showed to be correlated. As a consequence, the coefficient estimate we obtain for each variable represents the clean effect that that variable has on the downgrade probability –any interaction effect being removed.

As with the ordered probit model and for the same reasons, the binary probit model is estimated using the *GLM* method for robust standard errors and the estimation algorithm employed is the *BHHH*. The main results of the model are discussed in the following section.

7.4. Empirical Results

7.4.1. Ordered Probit Results

The results from the ordered probit are reported in Table 7.4. We will briefly list here the explanatory variables resulted to be significant and we refer the reader to Table 7.1 for an extensive description of the variables themselves. The factors found to be useful to explain (at least in part) the probability of being assigned a higher (or poorer) rating -which we indicate with *RATING* - are size, growth, leverage, profitability, tangibility, interest coverage ratio and the provision of a negative pledge guarantee. The estimated coefficients have all the expected sign. The lower part of Table 7.4 presents also the estimates of the limit points γ coefficients and the associated standard errors and probability values. A pseudo-R^2 of 0.39 is obtained, which is quite a good fit for the amount of information in the estimation.

However, the coefficients in Table 7.4 must be interpreted with care. The sign of $\hat{\beta}_i$ shows the direction of the change in the probability of falling in the endpoint rankings (Y = 1, 2, 3 or 4) when X_i changes. Pr(Y = 1) changes in the opposite direction of the sign of $\hat{\beta}_i$ and Pr(Y = 4) changes in the same direction as the sign of $\hat{\beta}_i$. However, the effects on the probability of falling in the middle ranking (Y = 2 or 3) cannot be determined *a priori* and can be either direction.

Following this logic, the probability of falling in the highest (lowest) rating class declines (increases) as the *DEBT_CE* and *INV_CE* variables increase (decrease). In other words, firms with higher growth rates and higher debt ratios are viewed as riskier than mature firms. The opposite occurs for the variables with negative estimated coefficients, namely *SIZE*, *ROA*, *dTANG*, *COVER*. Firms of bigger size, with better performance, with higher coverage ratios and which experienced an increase in tangible fixed assets have lower probability of being assigned to a lower rating class. The negative pledge guarantee (*NP*), for which we could not determine any *a priori* sign, shows to be positively correlated with credit risk.

The values of the β coefficients do not estimate the change in the probability *RATING* due to a unit change in the relevant explanatory variable. By contrast, this probability change is given by the partial derivative of the expression for Pr(Y=i) with respect to X_j, which is a function of β_j and of normal density functions at the value of X_j for which the partial derivative is calculated. To obtain the marginal effects of the continuos variables, we must calculate the standard normal density function (Φ) evaluated at $\beta'\overline{X}$ and (γ - $\beta'\overline{X}$) where $\overline{X}$ is the median value of the regressor. The predicted probabilities are $\Phi(-\beta'\overline{X})$, $\Phi(\gamma - \beta'\overline{X}) - \Phi(-\beta'\overline{X})$, and $1 - \Phi(\gamma - \beta'\overline{X})$ for Y=1, Y=2 or 3 and Y=4 respectively. Figure 7.3 shows the marginal contribution of each explanatory variable to the change in the probability of falling in each class γ of default risk.

Variable	*Exp. Sign*	*Coefficient*	*Z-Statistic*
CAP	-	-0.2321* (0.1315)	-1.7650
NP		1.6801*** (0.3262)	5.1499
INV_CE	+	3.6563** (1.6195)	2.2576
DEBT_CE	+	1.3110* (0.7825)	1.6753
ROA	-	-4.5537** (2.0010)	-2.2758
dTANG	-	-2.1031*** (0.6236)	-3.3724
COVER	-	-0.0956** (0.0453)	-2.1112
Limit Points			
LIMIT_1		-6.4488*** (1.6537)	-3.8997
LIMIT_2		-3.3897** (1.6681)	-2.0322
LIMIT_3		2.1116 (34.46)	0.0613

Table 7.4 *Ordered Probit Model Estimates for Eurobond Ratings, 1992-1999*

The estimates are for the following ordered probit model:

$$RATING = \beta_1(CAP) + \beta_2(NP) + \beta_3(INV\_CE) + \beta_4(DEBT\_CE) + \beta_5(ROA) + \beta_6(dTANG) + \beta_7(COVER) + \varepsilon$$

The estimation sample includes 105 observations from 1992 to 1999. The dependent variable (RATING) is translated into numbers as follows: AAA = 1, AA = 2, A = 3, and BBB = 4. Consequently, we will interpret higher values for RATING as higher credit risk. The expected signs for each independent variable, coefficient estimates and Z-statistics are presented. Parameter estimates and standard errors (in parentheses) are obtained using the BHHH algorithm and the generalized linear model (GLM) method, respectively. The z-statistics are asymptotically distributed as a standard normal variate under the null hypothesis that the coefficient is zero, i.e., it is the parameter estimate divided by its asymptotic standard error. The residuals of the model result to be not autocorrelated and normally distributed (with mean equal to -0.001, std. dev. equal to 0.7, skewness and kurtosis equal to 0.16 and 3.10, respectively).

NOTE: ***, **, *: Significantly different from zero at the 1%, 5% and 10% level, respectively, using a two- tailed test. The Log likelihood is equal to -33.63. The $LR_{(7\ df)}$ statistic is significantly different from zero (equal to 44.67 with a P-value of 1.58E-07). The LR index (or Pseudo-R^2) is 0.40.

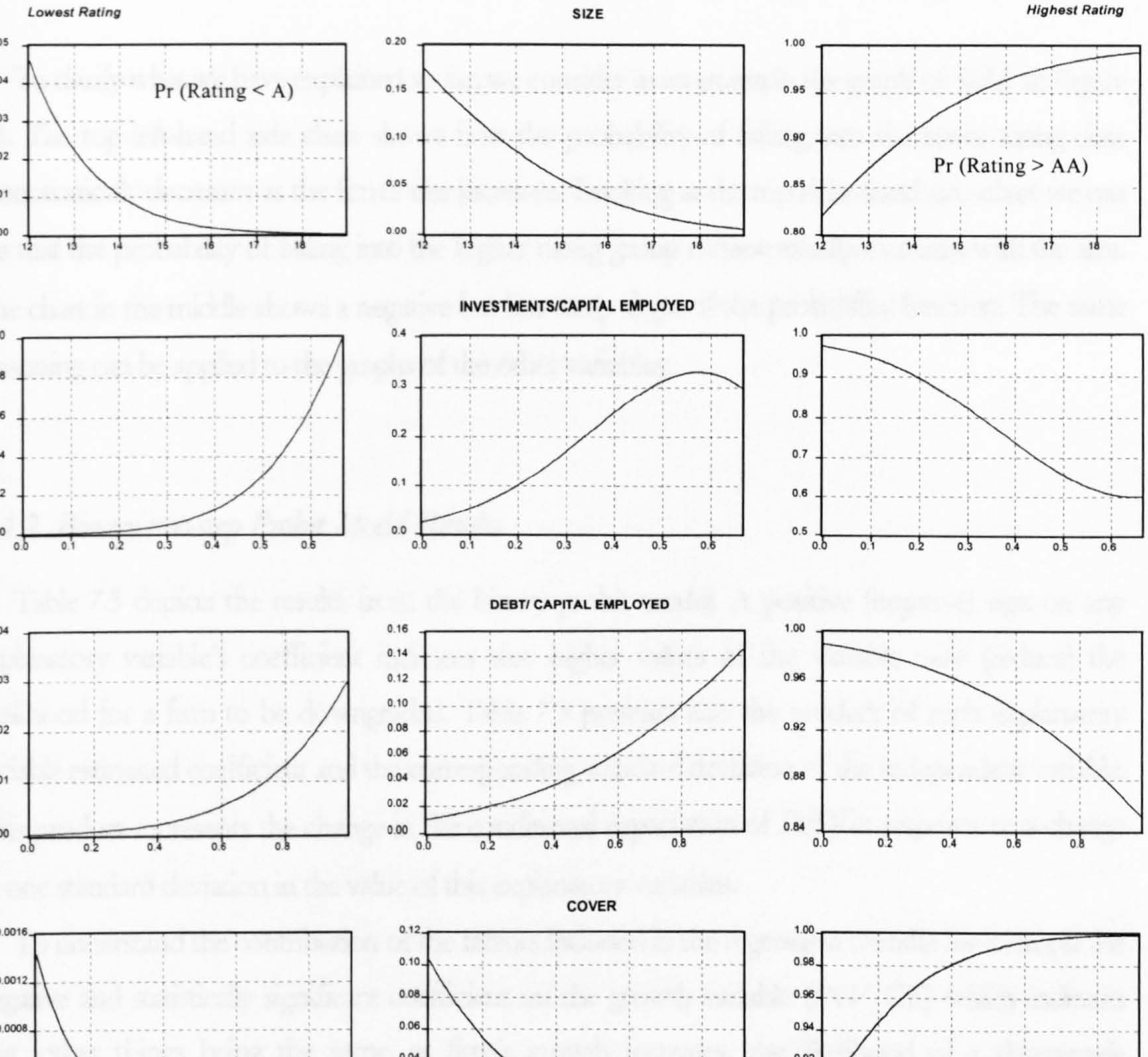


Figure 7.3 *The marginal effects of the explanatory variables*

To obtain the marginal effects of the continuous variables, we have calculated the standard normal density function evaluated at $\beta'\overline{X}$ and $(\gamma - \beta'\overline{X})$ where $\overline{X}$ and γ are the median values of the regressors and the mean of the limit points, respectively. The predicted probabilities are $\Phi(-\beta'\overline{X})$, $\Phi(\gamma - \beta'\overline{X}) - \Phi(-\beta'\overline{X})$, and $1 - \Phi(\gamma - \beta'\overline{X})$ for Y=1, Y=2 or 3 and Y=4 respectively.

To clarify what we have explained so far, we consider as an example the graph of *SIZE* in Figure 7.3. The top left-hand side chart shows how the probability of falling into the lower rating class monotonically decreases as the firm's size increases. Looking at the top right-hand side chart we can see that the probability of falling into the higher rating group monotonically increases with the size. The chart in the middle shows a negative but less steep slope of the probability function. The same reasoning can be applied to the graphs of the other variables.

7.4.2. Binary two-step Probit Model Results

Table 7.5 depicts the results from the binary probit model. A positive (negative) sign on any explanatory variable's coefficient indicates that higher values of the variable raise (reduce) the likelihood for a firm to be downgraded. Table 7.5 presents also the product of each explanatory variable estimated coefficient and the corresponding standard deviation of the independent variable. This product represents the change in the conditional expectation of *Pr(D)* in response to a change of one standard deviation in the value of this explanatory variables.

To understand the contribution of the factors included in the regression we take for example the negative and statistically significant coefficient on the growth variable (*INV_CE*) which indicates that, other things being the same, as firm's growth increases, the likelihood of a downgrade decreases. Similarly, we can say that the likelihood of a downgrade increases as earnings' instability and tangible assets increase. Firm size (*ASSETS*) does not play a significant role in determining the probability of downgrade. On the other hand, a downgrade is less likely to happen in the presence of a negative pledge guarantee (*NP*). The signs of *NP*, *INV_CE*, and d*TANG* require a brief comment. From Table 7.4 it emerges that credit risk decreases for increases in tangible assets, but this additional risk is not reflected on a greater probability of downgrade, which, instead, increases with d*TANG*. The same logic can be applied in a reverse way to the *NP* and *INV_CE* variables. The explanation of the change in the sign of some coefficient can be found in the different stories that Tables 7.4. and 7.5. tell us. While a NP guarantee may be used by weaker credits to obtain a higher rating or to lower the credit risk premium, these credits may still be weak and obtain a lower initial rating. However the NP guarantee seems to be successful in reducing the likelihood of a future downgrade -presenting a negative sign in Table 7.5.

Also company indebtedness and default risk deserve our attention and further comments. Table 7.5 and more manifestly Figure 7.4 show the presence of a non-linear relationship between leverage and downgrade probability on one side and risk of default and downgrade probability on the other side. As expected *Pr(D)* is positively related to the credit risk variable (*ADJ_RISK*), but the relation is not linear. The downgrade probability increases initially with default risk (as rating lowers) reaching a peak in correspondence of level 3 (rating A). After this point (inflection point) the relation becomes negative and the downgrade probability decreases for lower classes of credit rating. This piece of evidence confirms somehow and goes further the general finding that lower rated firms experience higher cumulative default rates (Moody's Investor Service, 1995).

From Figure 7.4 it is also apparent the quadratic response of the probability of downgrade to the company leverage (*DEBT_ASS*). *Pr(D)* decreases as leverage increases up to a critical level –i.e. when the debt ratio equals 0.28. As debt raises over this level the downgrade probability starts rising up to 1 for values of the debt ratio greater than 0.45.

Similarly to previous findings, the interest coverage variable is not significant. This ratio appears prominently in traditional writings of credit-rating analysts and has also proved to be useful in bankruptcy prediction studies. Apparently whatever the importance of this variable is, it is already captured by a linear combination of the financial leverage ratio and the profitability ratio. Finally, the insignificant coefficient of the industrial sector dummy variable (*FIN*) supports the lack of evidence of sector differences. Financial firms are not subject to higher default risk than industrial firms. This is a piece of evidence that credit ratings have been consistent and perfectly calibrated across issuer sectors.[33]

Following Flannery (1986) and Covitz and Harrison (1999) we additionally tested if long maturity debt issuance sends a negative signal of firm rating migration relative to short-term debt issuance. The intuition behind this idea is that the interest cost of issuing short-term debt and then rolling it over is lower for firms with low unobserved default probabilities than for firms with highly unobserved default probabilities. Therefore, long-term debt would signal negative information while short-term would signal positive information to the market. To this aim the total debt is split into long-term debt and short-term debt and the (*DEBT_ASS*) variable has been replaced with these two new variables. Their coefficients resulted to be not significantly different from zero rejecting any signalling hypothesis.

The probit estimate coefficients we have so far explained represent how much difference a unit change in the independent makes in terms of the cumulative normal probability of the dependent variable. This means that the effect of a unit change in the independent variables on the downgrade probability depends on the level of the independents. Therefore, to assess the effect of the probit

[33] See Ammer and Packer (2000) for a recent overview and empirical evidence on sectoral differences in the measurement of credit risk.

coefficients it is necessary to choose some reference level of the independents –i.e. their sample medians. We then introduce probability response curves to plot the fitted probabilities as a function of one of the independent variables, fixing the values of the other explanatory variables at their sample median. In Figure 7.4 *Pr(D)* represents the predicted probabilities generated using the original data and parameter estimates. If we have N explanatory variables X_1, X_2, ... X_N, the forecasted probabilities are obtained by solving the following equation:

$$\hat{p} = CumNormal(C + \beta_1 X_1 + \beta_2 \overline{X}_2 + ... + \beta_N \overline{X}_N) \tag{7.6}$$

where C and βs are the coefficients estimated from the binary probit model. In Figure 7.4 we present the charts for the variables included in the model. Let's consider the variable *ADJ_RISK* as an example. The chart on the top right-hand side is the plot of the probability of being downgraded against different values of default risk (*ADJ_RISK*). From the depicted pattern we can derive the marginal effect of a unit change in the value of *ADJ_RISK* on the conditional probability *Pr(D)*. Note that while all the regressors are involved in computing the change in the probability *Pr(D)*, the direction of the effect of a change in *ADJ_RISK* depends only on the sign of its estimated coefficient. The positive *ADJ_RISK* coefficient implies that increasing the default risk will increase the probability of the response. Negative values for β would have implied the opposite.

As the credit risk implications of a set of financial ratio values might be different for financial and non-financial firms (Carey and Hrycay, 2001), we assessed for this possibility multiplying each explanatory variable for a dummy variable taking value 1 or 0 according to the industrial sector. Wald tests on the coefficient estimates showed no statistically significant differences, excluding the need for a parallel model-building for financial and industrial firms.

In Table 7.5 we also present estimation results from a naïve probit model in which the observed S&P's credit ratings (*RATING*) replace the estimated credit risk variable (*ADJ_RISK*) from the two-step model. The *RATING* coefficient is not significant and also most of the remaining explanatory variables lose their significance. The coefficients of *NP*, *INV_CE*, and credit risk (*RATING*) change their signs becoming unexpected. The overall power of the model becomes weaker as shown by some measures of goodness of fit of the models on the bottom of the table. A detailed discussion of these measures follows in the next section.

		TWO-STEP MODEL		RATING MODEL	
	Exp.Sign	***Coefficient***	***Coeff * St.Dev.***	***Coefficient***	***Coeff * St.Dev.***
C		4.7088 (6.7983)	-	3.3651 (5.6919)	-
LOG(EARN_VOL)	+	3.4831*** (1.0702)	4.3997	1.1107*** (0.3051)	1.4030
NP	-	-5.5983*** (2.1961)	-	0.1193 (0.6909)	-
dTANG	-	14.843*** (5.2179)	1.8196	2.1659 (2.1490)	0.2655
ASSETS	-	0.2972 (0.3080)	0.4834	0.2933 (0.2672)	0.4771
ADJ_RISK	+	10.971** (4.3704)	9.7536	-	-
ADJ_RISK^2		-1.9511** (0.8333)	-	-	-
DEBT_ASS	+	-40.89** (19.902)	-4.8659	0.2691 (2.0939)	0.0320
DEBT_ASS^2		71.039** (35.805)	-	0.0469 (11.7247)	-
INV_CE	+	-19.080** (9.0058)	-1.9900	1.4119 (3.5108)	0.1473
WC	+	7.2960 (4.6024)	0.9433	4.0369 (3.2233)	0.5219
RATING	+	-	-	-1.2069 (0.9265)	-0.7124
Log Likelihood		−15.91		-26.69	
LR(df)		55.58 (10 df)		34.03 (9 df)	
(P-value)		2.45E-08		8.80E-05	
McFadden R^2		0.64		0.39	

Table 7.5 *Two Step Probit Model Estimates for Eurobond Downgrades, 1992-1999*

The two-step probit model we have developed and estimated is the following:

$$Y = \alpha + \beta_1 * Log(EARN\_VOL) + \beta_2 * NP + \beta_3 * dTANG + \beta_4 * ASSETS + \beta_5 * ADJ\_RISK + \beta_6 * (ADJ\_RISK)^2 + \\ + \beta_7 * DEBT\_ASS + \beta_8 * (DEBT\_ASS)^2 + \beta_9 * INV\_CE + \beta_{10} * WC + \varepsilon$$

The dependent variable Y is a binary variable that takes value 0 if the firm rating is stable over time (i.e. no re-rating) and value 1 if the firm has been downgraded. We included in the sample 24 observations Y=1 and 43 observations Y=0. The explanatory variables have been modified to correct for multicollinearity. In particular, each series –except for the dummy NP- has been replaced with the residual series from the linear regression of the variable itself on the independent variables with which it showed to be correlated. As a consequence, the coefficient estimate we obtain for each variable represents the pure effect that that variable has on the probability of downgrade –any interaction effect being removed. Coefficient estimates are presented both for the two-step model and for the simple RATING model, where the rating variable has replaced the ADJ_RISK variable. In both cases estimates are obtained using the GLM method for robust standard errors and the estimation algorithm employed is BHHH. An approximate estimate of the marginal effect of each explanatory variable has been computed as the product of the coefficient estimate and the standard deviation of the independent series.

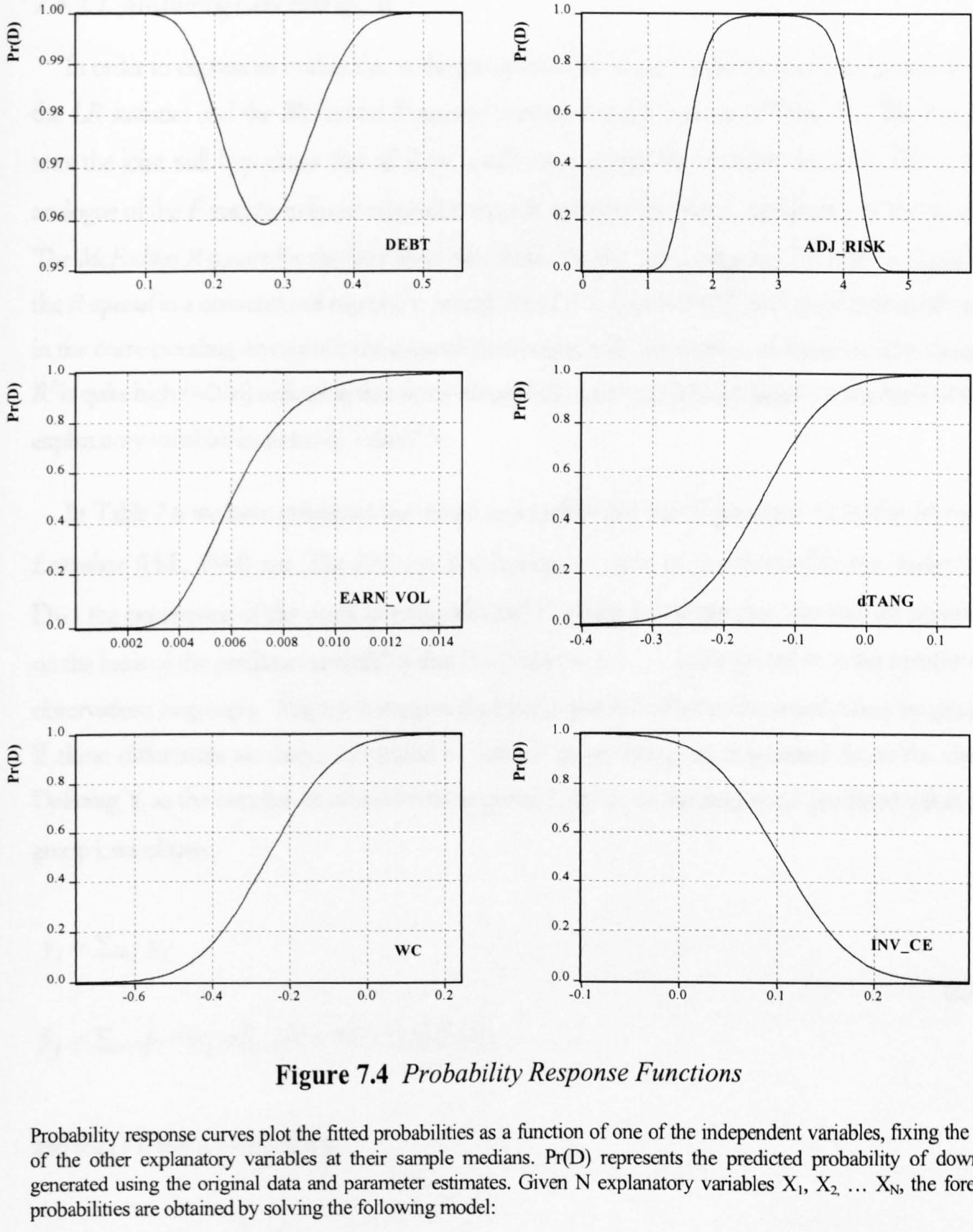


Figure 7.4 *Probability Response Functions*

Probability response curves plot the fitted probabilities as a function of one of the independent variables, fixing the values of the other explanatory variables at their sample medians. Pr(D) represents the predicted probability of downgrade generated using the original data and parameter estimates. Given N explanatory variables X_1, X_2, ... X_N, the forecasted probabilities are obtained by solving the following model:

$$\hat{p} = Cum\ Normal(C + \beta_1 X_1 + \beta_2 \overline{X}_2 + \ldots + \beta_N \overline{X}_N)$$

where C and βs are the coefficients estimated from the binary probit model.

7.4.2.1. Measuring Goodness of Fit

In order to express an evaluation on the goodness of fit of our model we focus our attention on the *LR* statistics and the *McFadden R-squared* presented at the bottom of Table 7.5. The former tests the joint null hypothesis that all slope coefficients, except the constant, are zero. This is the analogue of the *F-statistic* in linear regression models and tests the overall significance of the model. The *McFadden R-squared* is the likelihood ratio index. As the name suggests, this is an analogue to the *R-squared* in a conventional regression model. The *LR* is high (=55.58) and statistically significant in the corresponding asymptotic chi-squared distribution with ten degrees of freedom. The *pseudo-*R^2 is quite high (=0.64) indicating that firms downgrades can be predicted largely on the basis of the explanatory variables included in Table 7.5.

In Table 7.6 we have presented the results of an additional test of goodness of fit, the *Hosmer-Lemeshox* (H-L, 1984) test. The *H-L* test is a *Pearson* χ^2 –type of goodness-of-fit test. Indicating D=1 the occurrence of the event (downgrade) and D=0 the non-event case, the data are grouped on the basis of the predicted probability that D=1 into j = 1, 2, ... , J groups and m_j is the number of observations in group j. The test compares the fitted expected values to the actual values by group. If these differences are large, the model is rejected as providing an insufficient fit to the data. Defining Y_i as the number of observations in group j and $\bar{p}_j$ as the average of predicted values in group j, we obtain:

$$y_j = \sum_{i\in j} y_j$$
$$\bar{p}_j = \sum_{i\in j} \hat{p}_i / m_j = \sum_{i\in j}(1 - F(-X_i\hat{\beta}))/m_j \tag{7.7}$$

and the *H-L* test is computed as:

$$HL = \sum_{j=1}^{J} \frac{(y_j - m_j\bar{p}_j)^2}{m_j\bar{p}_j(1-\bar{p}_j)} \tag{7.8}$$

If the model is correct the distribution is well approximated by a χ^2 distribution with (J-2) degrees of freedom. Since the properties of the statistic require that the number of observations in each group is large, we select J=3. The high and low value of the predicted probability for each quantile is presented in columns *a* and *b* labelled "quantiles of risk". Columns *c-f* show the actual and expected number of observations in each group. Column *h* presents the contribution of each group to the overall *H-L* statistic. Since the *H-L* test presented at the bottom of Table 7.6 is higher than 0.05 we fail to reject the null hypothesis that there is no difference between the observed and predicted values of the dependent. This implies that the model's estimates fit the data at an acceptable level. The statistics are reported at the bottom of the table. As the *H-L* test has been criticised to depend on arbitrary cut points on predicted probabilities, we have performed the same test also for j = 4, 5, ..., 10 (Table A1) and in all the cases we could not reject the estimated model.

	Quantile of Risk		*Pr(D)=0*		*Pr(D)=1*			
	(a) *Low*	*(b)* *High*	*(c)* *Actual*	*(d)* *Expected*	*(e)* *Actual*	*(f)* *Expected*	*(g)* *N*	*(h)* *H-L Value*
1	0.0000	0.0128	22	21.9516	0	0.04841	22	0.04851
2	0.0193	0.4561	17	17.9374	5	4.06257	22	0.26530
3	0.5054	1.0000	4	3.24102	19	19.7590	23	0.20689
Total			*43*	*43.1300*	*24*	*23.8700*	*67*	*0.52071*

H-L Statistic: 0.52 *Prob[Chi-Sq(1 df)]: 0.47*

Table 7.6 *Hosmer-Lemeshow Goodness-of-Fit Test*

Data are grouped on the basis of the predicted probability into j = 1, 2, 3 groups and m_j is the number of observations in the j^{th} group. The test compares the fitted expected values to the actual values by group. If these differences are large, we reject the model as providing an insufficient fit to the data.

In evaluating the explanatory power of our downgrade probability model, it is helpful to define two types of prediction error. *Type I* error occurs when a company is downgraded (D=1) but is predicted to remain the same (Pr(D)=0); *type II* error occurs when a company maintains the same rating (D=0) but is predicted to be down-rated (Pr(D)=1). Reducing one type of error necessarily comes necessarily at the expense of increasing the other type of error. *Type I* and *type II* error rates depend on the number of companies predicted to be downgraded –which, in turn, depends on the cut off probability chosen for the model. The higher (lower) the number of companies whose rating is predicted to deteriorate, the smaller (larger) is the *type I* error rate and the larger (smaller) is the *type*

II error rate. We will use these error definitions in the next section to measure the forecast ability of our model.

7.4.2.2. In-Sample Fit

A useful presentation of the predictive ability of the model is the classification table of the hits and misses of a prediction rule. This is a contingency table of the predicted response classified against the observed dependent variable on the basis of a cut-off point. Table 7.7 displays the "correct" and "incorrect" classifications based on a) a specified prediction rule, and b) expected value calculations. The observation is classified as "correct", if the predicted probability is less than or equal to the cut off point and the observation is D=0, or when the predicted probability is greater than the cut-off point and the observation is D=1. In other words, *type I* and *type II* error rates depend on the cut-off value, which in turn, depends critically on the sample selection criterion. We set different prediction cut-off values in a range from 0.35 to 0.7, but we will look particularly at the cut-off probability of 0.35. This is indeed the appropriate or "benchmark" cut-off value obtained as the proportion of events and non-events in the sample -i.e. 24 events out of 67 observations in our study[34]. In panel A observations are classified as having predicted probabilities ($\hat{p} = 1 - F(-X'\hat{\beta})$) above or below each cut-off value. In panel B observations are classified using the predicted probabilities $\bar{p}$ given by the sample of D=1 observations. This probability is computed from estimating a model that includes only the intercept term C.

Table 7.7 shows that in correspondence of a cut-off value equal to 0.35, 38 of the 43 non-event (D=0) observations and 22 of the 24 event (D=1) observations are correctly classified by the model. In other terms, the model has a *specificity* of 88.37% and a *sensitivity* of 91.67%. Overall, the estimated model correctly predicts 89.55% of the observations. The predictive ability of the model is measured by the percentage gain (as a percentage of the incorrect classifications in the constant probability model) presented in the last row of Table 7.7. Overall, the estimated equation represents an 83.72% improvement over the correct prediction of a naïve constant probability model. We finally implemented a χ^2 *test* of independence and we obtained a value of 33.38 which rejects the null hypothesis at the 1 percent level when comparing the fitted model with a simple "chance" model.

[34] The proportion of events in the population of sterling Eurobonds is about 0.39 (= 124/312).

7.4.2.3. Out-of-Sample Forecasts

In this section we perform both block and full cross-validation of our probabilistic model. The binary probit model presented above was estimated using the data over the entire period. As this information would not have been available in real time, the technique of "hold-out" regressions was used to determine whether this probabilistic model would provide useful real time forecasts. To this aim the model's validation is carried out both out-of-sample and out-of-time. The whole sample is split into five sets of observations of approximately the same number of point forecasts and subsequent in time. The idea is to re-estimate our explanatory probabilistic model using in turn data from four sets to identify downgraded firms for the hold-out (fifth) set. In other words, the out-of-sample forecasts will yield five sets of predictions on which we will successively perform a block cross-validation analysis. The objective is also to test if classification results may depend on the date on which the exercise is done or on the historical period covered by the underlying data -i.e. the scoring model's estimation period.

As the number of observations for the estimation sample is now reduced by one fifth, we derived a more parsimonious 5-variable nested model from our previous 10-variable model. In order to identify the variables to be included in the nested model, we proceeded excluding the variables not significant at the 1 percent level. We finally obtained the following predictive model:

$$Pr(D) = \alpha + \beta_1(ADJ\_RISK) + \beta_2(ADJ\_RISK^2) + \beta_3(DEBT\_ASS^2) + \beta_4(EARN\_VOL) + \beta_5(WC) + \varepsilon \qquad (7.9)$$

where adjusted default-risk and leverage -in their quadratic form-, working capital and earnings' volatility are found to be helpful predictor variables. To evaluate the out-of-sample accuracy, the forecasting performance of this parsimonious specification of the original probabilistic model is evaluated as follows.

Table 7.8 presents *type I* and *type II* error rates for this re-estimated model during the five-holdout periods. The forecasts generated from the recursive probit regressions are probabilities, so that for a cut-off value of 0.35, we assume that if the estimated probability, *Pr(D)*, is above (below) 0.35 and the firm has (not) actually been downgraded, the forecast has been successful. By the same logic, if *Pr(D)* is found to be lower (higher) than 0.35 and the firm has (not) been downgraded, the forecast has failed. In addition to the percentage of observations correctly (hit ratio) and incorrectly (error rate) predicted by the model, we employed both a χ^2 test and a *Brier Score* (*BS*) test as measures of performance. The former tests for independence between predicted and expected frequencies, where expected frequencies were derived from a "chance" model. The latter is a measure specifically designed to evaluate probability forecasts for binary events and which assesses the overall accuracy of the model. The Brier score is equivalent to the mean square error (*MSE*) for ordinary regressions and it measures the difference between forecast probability (*r*) and observed probability (*d*) as follows:

$$BS = \frac{\sum_{n=1}^{N}(r_n - d_n)^2}{N} \tag{7.10}$$

where N is the total number of forecasts in the sample, *r* refers to the forecast vector, and *d* refers to the observation vector. The Brier score can vary between 0 and 1, and has a negative orientation; that is, smaller values of *BS* indicate more accurate forecasts, and a value of zero would indicate a perfect prediction.

		Cutoff Value							
		0.35	0.40	0.45	0.5	0.55	0.6	0.65	0.7
Panel A: Two-Step Probit Model (BP)									
Correct	*Event*	22	22	20	19	19	18	18	17
	Nonevent	38	38	39	39	40	41	42	42
Incorrect	*Event*	2	2	4	5	5	6	6	7
	Nonevent	5	5	4	4	3	2	1	1
Percentage	*Correct*	89.55	89.55	88.06	86.57	88.06	88.06	89.55	88.06
	Sensitivity	91.67	91.67	83.33	79.17	79.17	75.00	75.00	70.83
	Specificity	88.37	88.37	90.70	90.70	93.02	95.35	97.67	97.67
Panel B: Constant Probability Model (CPM)									
Correct	*Event*	0	0	0	0	0	0	0	0
	Nonevent	43	43	43	43	43	43	43	43
Incorrect	*Event*	24	24	24	24	24	24	24	24
	Nonevent	0	0	0	0	0	0	0	0
% Gain *of the PM over the CPM*		83.72	70.83	66.67	62.50	66.67	62.50	70.83	66.67

Table 7.7 *The Expectation-Prediction Table*

The predicted responses from the two-step probit model are classified against the observed dependent variable. The predicted responses are based a) on the probit model specification (Panel A), and b) on a model that includes only the intercept term C –i.e. expected value calculations (Panel B). We set different prediction cutoff values in a range from 0.35 to 0.7. Each observation is then classified as having a predicted probability that lies above or below this cutoff. The observation is classified as "correct", if the predicted probability is less than or equal to the cutoff point and the observation is a non-event (D=0), or when the predicted probability is greater than the cutoff point and the observation is an event (D=1). The predictive ability of the model is measured by the percentage Gain. This represents the percentage improvement over the correct prediction of the default (constant probability model).

Chi-square values were computed for the five sets of predictions and their values presented in Table 7.8. In all cases the null hypothesis of no dependence was rejected at a minimum significance level of 95%. Brier scores for the five sets of forecasts are also presented in Table 7.8 with their values ranging from 0.052 to 0.183. Concluding, the null hypothesis of no predictive effectiveness respect to a naïve model could be rejected in all (five) sets of out-of-sample predictions by both the tests. Moreover, the forecasting model was able to correctly identify 85% (on average) of the observations. A comparison of Tables 7.7 and 7.8 show that there is little difference between the accuracy of the model in the estimation and for the holdout samples.

In addition to the block validation, we investigated the performance of model (7.9) also by full cross-validation or "leaving-one-out" method. Unlike the previous validation method, this approach validates the model across the population of firms preserving its original distribution[35]. This method was implemented estimating the model on all-but-one-observation of the data, and successively using the estimated model to forecast the remaining observation, the holdout observation. The process is repeated leaving out and forecasting each single observation in turn. Finally all the individual point forecasts are collected and the performance of the model measured. In this case, the hit ratio and the probability score (*BS*) are 82% and 0.17, respectively.

7.4.2.4. Forecasting with Neural Networks

The in-sample and out-of-sample performance of the Binary Probit model (BP) is also benchmarked against an artificial neural networks model (ANN) in Table 7.9. Neural networks have been shown to perform well as classifiers for problems containing complex and imperfect data and relationships. For comparison purposes, inputs to the neural network consist of the same factors used in model (7.9) -that is *ADJ_RISK*, *DEBT_ASS*, *EARN_VOL* and *WC*- and the output is the downgrade probability[36]. The whole sample was used to assess the in-sample prediction ability of the ANN model, while out-of-sample results were based the same five-fold holdout sample method implemented in the regression analysis. The algorithm employed is the standard and common back propagation network described in Rumelhart et al. (1986) and that is an iterative least squares procedure applied to the connections of a multilayer network (with one or more hidden layers). The method is based on the minimisation of the total squared error of the output computed by

35 See Sobehart et al. (2000) for a clear and extensive description of the techniques for credit risk model validation and benchmarking.

36 Note that squared variables are not included in the inputs as the neural network should be able to make an approximation to the data automatically.

the network. The training algorithm involves three stages: the feed-forward of the input training set, the calculation and backpropagation of the error, and the adjustment of the weights (Chaveesuk, Srivaree-ratana, and Smith, 1997). First, inputs (*ADJ_RISK, DEBT_ASS, EARN_VOL* and *WC*) are passed forward to the hidden layers and multiplied by their respective weights to compute a weight sum. The weighted sum is successively modified by a sigmoid transfer function and then sent to the output layer. Third, the output layer recalculates the weighted sum and applies the transfer function to produce the output value. Finally an error signal is computed as the difference between the output value and the target (actual) value and "backpropagated" to the hidden layers and then to the input layers. This training process continues interactively until an acceptable mean squared error is achieved within the necessary time for convergence.

The performance measure used to compare the models was the percentage of accurate classifications (PCC) according to a cutoff value of 0.35 in order to be consistent with the previous analysis. The best classification results were obtained for three nodes in the hidden layer training with a learning rate of 1, a momentum rate of 0.1, and a sigmoid activation function in the output layer. As the optimal neural networks architecture can only be found through trial and error, thirty replications[37] were performed and evaluated varying in turn the number of hidden layers (between 2 and 4) and the learning and the momentum rates (between 0 and 1). Training was accomplished on four subsets while testing was performed on the remaining fifth subset. Training revealed that connection weights were well stabilised by 1200 epochs or learning cycles. This is therefore the ANN architecture chosen for the final network. The ANN seems to outperform probit regression analysis in terms of more correct in-sample predictions (Panel A, Table 7.9). For each data set and corresponding holdout sample the percentage of correct predictions was calculated and the results presented in Panel B. The ANN model on average results in a hit ratio of 76% *versus* a higher 85% for the Probit model. Results on the training sets provide a PCC ranging between 65% and 85%, which does not differ from the PCC obtained for the testing (holdout) samples[38].

Although BP regressions are less flexible than ANN in the form of relationship they can model, they result to be more straightforward to construct and validate, quicker to compute, more transparent and easier to interpret and replicate. Additionally, with the probit analysis we can identify the (possible) right set of predictor variables contributing most in predicting the variation in the

[37] Replications involve using the same architecture and learning parameters but with different sets of random initial weights.

dependent variable. It remains that the poorer performance of the ANN may be due to overfitting or local optima problems generally associated with a small data set. In addition, most ANN cannot guarantee neither an optimal solution to a problem nor a complete solution. Sometimes, the repeatibility itself with the same input data is not assured, making investigators nervous about interpreting the models obtained. Results however do not allow us reaching straightforward conclusions about the rejection of ANN. On the contrary, they encourage further research and suggest a combined approach for predictive corroboration.

7.4.2.5. Combining Forecasts

In order to test for the statistical significance of BP and ANN models we introduced encompassing tests. According to these tests, if a model represents more congruently the data-generating process, it must be able to account for the salient features of rival models. In more specific terms, a given model BP is considered superior to a model ANN if model BP's forecasts significantly explain model's ANN forecasting errors. Model BP would in this case in fact incorporate relevant information neglected by model ANN. The encompassing test is implemented by testing the significance of the β and δ coefficients in the following two equations:

$$\left(P_t - \hat{P}_{NNt}\right) = \beta\,\hat{P}_{BPt} + \varepsilon_t \tag{7.11}$$

$$\left(P_t - \hat{P}_{BPt}\right) = \delta\,\hat{P}_{NNt} + v_t \tag{7.12}$$

where $\hat{P}_{NNt}$ and $\hat{P}_{BPt}$ are the forecasts of models ANN and BP, respectively; while the terms in parentheses represent the forecasting errors from the two models, and ε and v are random errors. The null hypothesis is that neither model encompasses (outperforms) the other. If β (δ) is significantly different from zero but $\delta(\beta)$ is not, then we reject the null hypothesis in favour of the alternative hypothesis that model BP encompasses model ANN as information (errors) not captured by ANN is explained by BP. From the estimation of the two regressions (see Table A2) we obtain coefficient estimates both not significantly different from zero with β = -0.06 (t= -0.69)

[38] The classification accuracy achieved increasing the complexity of the network, that is increasing the number of inputs, does not improve over the simpler (4 inputs) network. With a small data set complex networks tend indeed to adopt either oscillating or non-convergent behaviour.

and δ = -0.007 (t= -0.07). We therefore fail to reject the null hypothesis and conclude that neither model encompasses the other, each of them providing different information.

This last evidence leads us to finally investigate whether combining BP forecasts with ANN forecasts we could get better results. The weight combination resulting in the best forecasts was 0.9 and 0.1 in BP and ANN, respectively, yielding a hit ratio of 87% and a Brier score of 0.12. Combined forecasts therefore perform only slightly better and provide slightly more accurate forecasts than individual methods.

7.4.2.6. Forecast stability

The forecast performance of the two-step BP (and ANN) scoring model seems to deteriorate after June 1998, during the recent turmoil in the capital markets. As it is apparent from Tables 7.8 and 7.10 the hit ratio significantly declines from a high 90 percent to a lower 77 percent raising the issue of the stability of the model. Chi-square tests still support the superiority of the model respect to a naïve one, but it is worth considering some explanations for this decline in the predictive ability. First, there has been a regime shift in the general market volatility, which may have driven a shift also in the credit risk of the firms in the Eurobond market [39]. Second, we note the remarkable increase in the number of downgrades over the last period and, the increase in the correlation between downgrades during times of highly volatility (Andersen et al. 2000). Estimating the model over a sample period where a small number of events (downgrades) have occurred may generate noisy results[40]. Whatever the explanation is, the evidence suggests that underlying macroeconomic volatility is a key factor in credit risk modelling and must therefore be taken into account in a future work.

7.4.2.7. Small and Large Firms

We finally split the sample by firm size and we indicate with *LARGE* and *SMALL* the subset of observations relative to the firms whose total assets are above and below, respectively, the median value (£6,236 millions). Table 7.10 depicts the results of the probit model ran on the two sets of

[39] Note that regime switching has been found in the conditional mean dynamics of interest rates (Hamilton, 1988; Cecchetti, Lam and Mark, 1990) and exchange rates (Engel and Hamilton, 1990), and in the conditional variance dynamics of stock returns (Hamilton and Susmel, 1994).
[40] See Carey and Hrycay (2001) for a complete explanation of this point.

observations. The objective is to test the conjecture expressed in Blume, Lim and Mackinlay (1998) that firm characteristics, accounting ratios and market-based risk measures are more informative for larger firms than for smaller firms. Default risk and earnings instability positively affect both small and large firms' probability of downgrade. Liquidity risk results to explain the downgrade probability of small firms only: as liquidity dries up small firms seem to be more likely to be downgraded. Moreover, leverage seems to have a negative impact on large firms' *Pr(D)* and a positive impact on small firms' *Pr(D)*. Firm size is generally considered positively related to leverage (Harris and Raviv, 1991) and the most effective argument is that informational asymmetries are less severe for larger firms than for smaller firms. If the public is more aware of what is going on at larger firms, the firm will find it easier to raise debt. Following these considerations, our result might be explained in terms of the *adverse selection* phenomenon in a context of asymmetric information. Small firms with higher levels of leverage are those that are willing to pay higher price (interest rate) for their loans. These firms successively result to be "not good" and will finally be downgraded. On the other hand, larger firms do not suffer from informational asymmetries between insiders and the capital markets and when they turn to banks asking for loans, banks are perfectly aware of their financial situation. As a consequence, banks will offer credit only to the ones that prove to deserve it and that are also the firms that result to be less likely to be downgraded in the future.

Comparing the variances of the standardised residuals of the two models as a measure of confidence of the prediction of the model we observe a lower value for the *LARGE* model. The importance and implications of these results for regulatory issues and for determining a firm's cost of capital require further investigation, which goes beyond the purpose of this chapter.

Table 7.8 *Type I and Type II Forecast Error and Hit Rates for 5 Sets of Forecasts*

The whole sample has been split into five sets of observations of approximately the same number of point forecasts and subsequent in time. The out-of-sample forecasts yield five sets of predictions, one for each hold-out sample. A parsimonious predicted nested 5-variable model from our previous 10-variable model was derived. In order to identify the variables to be included in the nested model, we proceeded excluding the variables not significant at the 1 percent level. The final predictive model is as follows:

$$Pr(D)= \alpha + \beta_1 (ADJ\_RISK) + \beta_2 (ADJ\_RISK)^2 + \beta_3 (DEBT\_ASS)^2 + \beta_4 (EARN\_VOL) + \beta_5 (WC) + \varepsilon$$

Type I and type II error rates for theses re-estimated models during the five-holdout periods are presented below in percentage (with frequencies in parenthesis). Type I errors represent the missclassification of downgraded bonds, while type II errors represent failures in correctly classifying stable bonds. Results from different cut-off values are presented, although they do not show substantial differences. For a cut-off value of 0.35, we assume that if the predicted probability is above (below) 0.35 and the firm has actually been downgraded (stable), the forecast has been successful. On the other hand, if the predicted probability is below (above) 0.35 and the firm has been downgraded (stable), the observation has not been correctly classified. To test for the significance of our results both a χ^2-value and a Brier Score (BS) value are presented in the last row.

	Predicted Sample																				
	Pooled Sample	***Sample 1***				***Sample 2***				***Sample 3***				***Sample 4***				***Sample 5***			
	(26 Jul 95 –30 Jun 99)	*(26 Jul 95 – 18 Dec 96)*				*(20 Dec 96 – 2 Oct 97)*				*(2 Oct 97 – 3 Jun 98)*				*(3 Jun 98 – 14 Dec 98)*				*(14 Dec 98 – 30 Jun 99)*			
	Pooled Predictions: 67	*Obs. Predicted: 14*				*Obs. Predicted: 13*				*Obs. Predicted: 13*				*Obs. Predicted: 14*				*Obs. Predicted: 13*			
	Down: 24 *Stable: 43*	*Down: 4* *Stable: 10*				*Down: 3* *Stable: 10*				*Down: 4* *Stable: 9*				*Down: 6* *Stable: 8*				*Down: 7* *Stable: 6*			
Cut off probability	***Total Hits (Average)***	***Type I***	***Type II***	***Total Missed (%)***	***Total Hits (%)***	***Type I***	***Type II***	***Total Missed (%)***	***Total Hits (%)***	***Type I***	***Type II***	***Total Missed (%)***	***Total Hits (%)***	***Type I***	***Type II***	***Total Missed (%)***	***Total Hits (%)***	***Type I***	***Type II***	***Total Missed (%)***	***Total Hits (%)***
0.35*	85.16%	7.14	7.14	14.29	85.71	0.00	7.69	7.69	92.31	0.00	7.69	7.69	92.31	21.42	0.00	21.42	78.57	7.69	15.38	23.07	76.92
	χ^2= 30.56 ***	(1)	(1)	(2)	(12)	(0)	(1)	(1)	(12)	(0)	(1)	(1)	(12)	(3)	(0)	(3)	(11)	(1)	(2)	(3)	(10)
0.40	88.24%	7.14	7.14	14.29	85.71	0.00	7.69	7.69	92.31	0.00	0.00	0.00	100.00	21.42	0.00	21.42	78.57	7.69	7.69	15.38	84.61
	χ^2= 36.40 ***	(1)	(1)	(2)	(12)	(0)	(1)	(1)	(12)	(0)	(0)	(0)	(13)	(3)	(0)	(3)	(11)	(1)	(1)	(2)	(11)
0.50	85.16%	7.14	7.14	14.29	85.71	0.00	7.69	7.69	92.31	0.00	7.69	7.69	92.31	21.42	0.00	21.42	78.57	15.38	7.69	23.07	76.92
	χ^2= 30.56 ***	(2)	(0)	(2)	(12)	(0)	(1)	(1)	(12)	(1)	(0)	(1)	(12)	(3)	(0)	(3)	(11)	(2)	(1)	(3)	(10)
Forecasts Evaluation:																					
χ^2 *test*		5.915 (0.015)				8.775 (0.003)				9.244 (0.002)				5.091 (0.024)				3.745 (0.053)			
Brier Score (BS)		0.121				0.052				0.077				0.205				0.193			

* 0.358 is the sample proportion of downgrades to non-changed bonds. 0.30 is the same proportion for the population

Panel A · In-sample Forecasts

	Hit Ratio	
Whole Sample	**PROBIT**	**ANN**
N=67	89.55%	95.52%

Panel B · Out-of-sample Forecasts

		Hit Ratio	
Holdout sample	**Predicted cases**	**PROBIT**	**ANN**
1	14	85.71%	85.71%
2	13	92.31%	76.92%
3	13	92.31%	84.61%
4	14	78.57%	71.42%
5	13	76.92%	61.53%
Total	67	85.16%	76.04%

Table 7.9 *Comparison of the Prediction Accuracy of the two-step Probit Model and a Neural Networks Model*

Forecasting results from an artificial neural networks model (ANN) are presented and compared with the Binary Probit model (BP). Inputs to the neural network consist of the same factors used in the BP model -that is ADJ_RISK, DEBT_ASS, EARN_VOL and WC- and the output is the downgrade probability Pr(D). Training was accomplished on four subsets while testing was performed on the remaining fifth subset. The number of epochs (learning cycles) was fixed at 1200. The performance measure used to compare the models is the percentage of accurate classifications (hit ratio) according to a cutoff value of 0.35. The best classification results for ANN were obtained for a backpropagation architecture with three hidden layers, a learning rate of 1, a momentum rate of 0.1, and a sigmoid activation function in the output layer. Backpropagation seems to outperform probit regression analysis in terms of more correct in-sample predictions. The ANN model on average results in a hit ratio of 76% versus a higher 85% for the BP model.

Variable	*LARGE*	*SMALL*
C	8.742** (3.643)	-0.401 (2.905)
ADJ_ RISK	1.675* (0.935)	3.422*** (1.229)
ADJ_RISK²	-	-0.854*** (0.279)
Log(EARN_VOL)	1.959** (0.773)	1.263*** (0.471)
DEBT_ASS	-14.229** (6.794)	8.526*** (3.351)
CASH_ASS	-	-0.644*** (0.215)
S.E. of regression	0.278	0.336
Log likelihood	-6.471	-11.33
LR statistic (x df)	$23.708_{(df=3)}$	$25.455_{(df=5)}$
Probability(LR stat)	2.87E-05	1.03E-04
McFadden R-squared	0.647	0.529
σ^2 (Standardised Residuals)	0.567	0.835
Obs with Dep=0	21	22
Obs with Dep=1	9	14

Table 7.10 *Downgrade Model for Small and Large Firms*

In order to test whether the probabilistic model is more informative for larger firms than for smaller firms the sample has been split on the basis of the median value of the total assets. Specifically, we classified as LARGE and SMALL firms whose total assets are above and below £6,236 millions, respectively. Two separate regressions have been run for each sub-sample. Coefficient estimates, their standard errors (in parentheses) and the regression standard errors are presented below. The Log likelihood -the maximised value of the log likelihood function- and the LR statistic test -for the joint null hypothesis that all slope coefficients except the constant are zero-, and tests of the overall significance of the model (the number in parentheses is the degrees of freedom, which is the number of restrictions under test) are presented below. Probability (LR stat) is the p-value of the LR test statistic. McFadden R-squared is the likelihood ratio index computed as $1 - l/\bar{l}$, where $\bar{l}$ is the restricted log likelihood. The variance of the standard errors of the probit models is showed as a measure of confidence of the predictive ability of the models. The total number of observations for the large and small samples is 30 and 35, respectively.

Note: ***, **, *: Significantly different from zero at the 1%, 5% and 10% level, respectively.

7.5. Conclusions

In this last work we addressed the modelling of Eurobond ratings and rating downgrades. Unlike in previous studies our key point is the transition probability and not the ultimate default. In order to assess and forecast the downgrade probability we developed a two-step estimation procedure. In the first step a conditional expectation of default risk was estimated as a function of bond specific and firm specific characteristics by an ordered probit. In the second step, we proceeded estimating the disentangled effects of default risk –as obtained from the conditional mean estimate in step I- and financial variables on the downgrade probability.

The probability of falling in the higher rating class is found to be inversely related to leverage and directly related to size, profitability and earnings coverage. In addition we find that firms with higher growth rates tend to be riskier -in terms of their "creditworthiness"- than mature firms. On the other hand, firms experiencing an increase in tangible fixed assets are associated to a lower probability to move to a lower rating class.

The results from the binary probit model show that, other things being the same, a downgrade is less likely to happen in the presence of a negative pledge guarantee and higher growth opportunities. In contrast the downgrade is triggered by positive changes in tangible assets and by earnings' instability. Firm size, interest coverage, and industrial sector do not play a significant role in determining the probability of downgrade. Additional interesting remarks may be proposed in relation to both company indebtedness and default risk. Our findings present evidence of a non-linear relationship between leverage and downgrade probability on one side and risk of default and downgrade probability on the other side.

Incorporating these two quadratic effects and replacing the rating variable with its conditional mean shows to improve both the explanatory power and the predictive accuracy of our two-step model. Passing from one step to the second, we observe that the sign of some variables changes producing apparently inconsistent results. However, this is simply explained by the fact that the two steps provide two different types of information. While the first step (ordinary probit) presents information on the initial level of the rating, the second step (binary probit) presents information on the likelihood of rating downgrade.

In order to validate our model we assessed its forecasting performance both in sample and out-of-sample. Our probabilistic model shows to outperform -in terms of correct out-of-sample classifications- both a naïve constant probability model, with the downgrade probability fixed at the sample proportion of events (cut off value) and a more complicated artificial neural network model.

Finally, our findings support the conjecture expressed in Blume, Lim and Mackinlay (1998) that firm characteristics, accounting ratios, and market-based risk measures are more informative for larger than for smaller firms. The leverage variable has been observed to have different impact on the downgrade probability according to the size of the firm. These results are important both for regulatory issues and for determining a firm's cost of capital.

We generally conclude that despite the scarce availability of rating and accounting data, the findings of this study are consistent with most of our expectations. The forecast performance of both BP and ANN models declines in the last two-fifths of the time period under observation, suggesting the necessity of a larger and longer sample. The time-varying performance of the models may also indicate that the coefficients that assign weights to the various risk factors are not stable over time, changing with different economic conditions. If some variables were major predictors of corporate performance in some years but not others, a model with frozen coefficients would not do a good job over time. This suggests the necessity to re-estimate the model from time to time. According to this, a switching-regime model in the line with Bangia, Diebold, and Schuermann (2000) may be profitably explored in future works to predict rating downgrades in both stable (expansion) and unstable (recession) periods.

Table A1

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
J = 4								
1	0 0000	0.0013	16	15.9986	0	0.00138	16	0.00138
2	0 0023	0.1245	16	16.1510	1	0.84901	17	0.02827
3	0 1335	0.7585	10	10.1132	7	6.88684	17	0.00313
4	0 7700	1 0000	1	0.86498	16	16.1350	17	0.02221
		Total	43	43.1277	24	23.8723	67	0.05498
H-L Statistic:			0 0550			Prob[Chi-Sq(2 df)]:		0.9729
J = 5								
1	0.0000	6.E-06	13	13.0000	0	1.1E-05	13	1.1E-05
2	2.E-05	0.0720	13	12.8275	0	0.17248	13	0.17480
3	0.0720	0.3197	12	11.9053	2	2.09466	14	0.00503
4	0 4230	0 8965	4	4.98832	9	8.01168	13	0.31773
5	0 9058	1.0000	1	0.40657	13	13.5934	14	0.89206
		Total	43	43 1277	24	23.8723	67	1.38963
H-L Statistic			1.3896			Prob[Chi-Sq(3 df)]:		0.7080
J = 6								
1	0 0000	2.E-06	11	11.0000	0	2.8E-06	11	2.8E-06
2	2 E-06	0 0088	11	10.9678	0	0.03216	11	0.03226
3	0.0142	0.1245	10	10.1818	1	0.81822	11	0.04363
4	0 1335	0 4654	7	7.81056	4	3.18944	11	0.29011
5	0 4727	0.9095	3	2 94570	8	8.05430	11	0.00137
6	0 9206	1.0000	1	0.22187	11	11.7781	12	2.78039
		Total	43	43.1277	24	23.8723	67	3.14776
H-L Statistic			3.1478			Prob[Chi-Sq(4 df)]:		0.5334
J = 7								
1	0.0000	6.E-08	9	9.00000	0	1.0E-07	9	1.0E-07
2	4 E-07	0.0038	10	9.98901	0	0.01099	10	0.01100
3	0 0049	0 0720	9	8 69440	0	0.30560	9	0.31634
4	0.0836	0.2212	9	8.59182	1	1.40818	10	0.13771
5	0 2227	0.6019	4	5.04487	5	3.95513	9	0.49245
6	0 6038	0 9270	2	1.73823	8	8.26177	10	0.04772
7	0 9788	1 0000	0	0.06942	10	9.93058	10	0.06990
		Total	43	43.1277	24	23.8723	67	1.07512
H-L Statistic.			1.0751			Prob[Chi-Sq(5 df)]:		0.9563
J = 8								
1	0.0000	4.E-08	8	8.00000	0	4.8E-08	8	4.8E-08
2	6 E-08	0.0013	8	7 99862	0	0.00138	8	0.00138
3	0.0023	0.0367	9	8.90094	0	0.09906	9	0.10016
4	0 0720	0 1245	7	7 25005	1	0.74995	8	0.09200
5	0 1335	0 4230	7	6.16021	1	1.83979	8	0.49781
6	0 4243	0.7585	3	3.95295	6	5.04705	9	0.40966
7	0 7700	0 9788	1	0.81671	7	7.18329	8	0.04581
8	0 9833	1.0000	0	0.04827	9	8.95173	9	0.04853
		Total	43	43.1277	24	23.8723	67	1.19536
H-L Statistic			1.1954			Prob[Chi-Sq(6 df)]:		0.9771

Table A1 Continued

J = 9								
1	0.0000	3 E-09	7	7 00000	0	6.5E-09	7	6.5E-09
2	4 E-08	2 E-05	7	6 99997	0	3.2E-05	7	3.2E-05
3	4 E-05	0 0088	8	7.96786	0	0.03214	8	0.03227
4	0 0142	0 0836	7	6.63199	0	0.36801	7	0.38843
5	0 1014	0 2024	7	6.89659	1	1.10341	8	0.01124
6	0 2212	0 4654	3	4.46376	4	2.53624	7	1.32479
7	0 4727	0 8752	3	2.65749	5	5.34251	8	0.06610
8	0 8965	0 9833	1	0.47855	6	6.52145	7	0.60989
9	0.9882	1 0000	0	0.03154	8	7.96846	8	0.03166
		Total	43	43.1277	24	23.8723	67	2.46442
H-L Statistic			2 4644			Prob[Chi-Sq(7 df)]:		0.9298
J = 10								
1	0 0000	3 E-09	6	6.00000	0	3.4E-09	6	3.4E-09
2	3 E-09	6.E-06	7	6.99999	0	1.1E-05	7	1.1E-05
3	2.E-05	0 0049	7	6.98413	0	0.01587	7	0.01590
4	0 0074	0 0720	6	5.84339	0	0.15661	6	0.16081
5	0.0720	0 1245	6	6.32210	1	0.67790	7	0.16946
6	0.1335	0.3197	6	5.58324	1	1.41676	7	0.15371
7	0 4230	0 5655	2	3.18913	4	2.81087	6	0.94644
8	0 6019	0.8965	2	1.79920	5	5.20080	7	0.03016
9	0 9058	0 9882	1	0.38685	6	6.61315	7	1.02867
10	0 9906	1 0000	0	0.01972	7	6.98028	7	0.01978
		Total	43	43.1277	24	23.8723	67	2.52495
H-L Statistic			2 5249			Prob[Chi-Sq(8 df)]:		0.9606

Table A2

	Eq. 7.11	*Eq. 7.12*
β	-0.061	-0.007
(t-stat)	(-0.690)	(-0.070)
Regression Statistics		
Multiple R	0.187	0.184
R Square	0.035	0.034
Adjusted R Square	0.020	0.019
Standard Error	0.324	0.249
Observations	69	69

CONCLUSIONS

We end this thesis by briefly reviewing our journey through the world of credit risk. We look back critically discussing what we have done and thinking, from an *ex post* perspective, of what we could have done more or differently. We finally mention new directions in which future research might evolve in this young and fascinating field.

Results, implications, and directions for future research

Credit risk has been a very active area of research over the past few years under the joint pressure of regulators and shareholders. Much progress has been made in improving the classic firm-value based model of Merton (1974). On the other hand, the empirical literature has lagged theoretical papers by a few years. In particular, little empirical research has been carried out on ratings based models. Kiesel, Perraudin, and Taylor (1999) for example have shown that most risk stems from spread changes within a credit risk class rather than from class changes, especially for highly rated bonds. Our analysis concerns with both these sources of risk within the sterling Eurobond market, typically accessible by highly regarded borrowers.

In the first part of this work, we have presented the credit risk models proposed by the largest banks. We have explained how these models are used for quantifying credit risk, estimating the probability density function of credit losses, and internally allocating capital against those risks. We have also explained how information from credit risk models may be usefully incorporated into regulatory or supervisory capital policies. Nevertheless, modelling credit risk is neither analytically or practically easy. Skewed return distributions with long and fat tails, credit correlations, and interest rate interactions represent the three biggest challenges. The evolution of better models for credit risk measurement will depend on how these challenges will be taken and will be reinforced by the development of better tools for credit risk management. In particular, the combined effect of evaluating and managing credit risks will be profound as technology becomes more widespread, the necessary data become more accessible, and credit derivatives liquidity improves.

In the second part of this work, we have presented our empirical investigations. We briefly outline here the intentions that motivated our research, the results we achieved, and their main implications.

In our first empirical study, the generating process for credit spread changes is examined. We study the dynamics of the credit spread between the ISMA sterling Eurobond index and a UK government bond index. We attempted to infer from the data what acceptable process can be used to model aggregate credit spreads for option pricing or risk management purposes. We did not attempt to describe the whole credit spread curve, which would have required the joint modelling of the risky and risk-less term structures. We focused instead on the *dynamics* of the spread index, considered an independent financial asset.

Though this index suffers from the aggregation problem typical of index data (it is an aggregate of bonds of different maturities and credit ratings), there are two reasons for studying the index series. First, reflecting the average yield spread on a well-diversified corporate bond portfolio with long maturity, they serve as an indicator of the level of credit spreads for many investors. Investors holding such a portfolio may find it convenient to protect themselves against moves in the general level of corporate spreads in a given class rather than hedge each individual issue. Second, they can be used as underlying for credit spread options whose payoff depends on the terminal value and/or the path taken by the yield spread of an instrument over the yield on a risk-free bond.

The existing literature on credit risk premia is extended through the use of high-frequency (daily) and non-US data. From the methodological point of view, GARCH models have never before been used to describe the time series behaviour of credit spreads. Searching for the underlying generating process, credit spread differences proved to possess characteristics consistent with non-linear dynamics. Using daily aggregates, we propose a GARCH mean-reverting model to fit credit spread changes and capture the observed stylised facts. The empirical results indicate that periodical rebalancing of a fixed income portfolio based on spread short-term forecasts is defensible. Results have also implications for term structure models of corporate yields, the pricing of credit derivatives, and methods for measuring credit risk.

However, (G)ARCH is not the only model recognised to produce symptoms of non-linearity. Long memory and chaos are non-linear models as well. While we have extensively studied the first type of models and we have tentatively investigated long-term dependence, we believe that the analysis could be refined by further exploring the long memory structure and a possible chaotic process for credit spreads. Identifying the source of nonlinearity is important as different generating mechanisms have totally different implications for understanding price behaviour and for trading purposes. Further analysis therefore could be conducted using Autoregressive Fractionally Integrated Moving Average (ARFIMA) models, the newest development in long-memory process studies. It could also be introduced a new non-linear model, a combination of an ARIMA mean model and a long-memory variance model. Alternatively, following Hauser and Kunster (1994) a fractionally difference model with ARCH errors, that is a combination of an AFIMA mean model and an ARCH variance model, could be beneficially developed.

Moreover, if a series proves to exhibit long-memory, persistent temporal dependence even between distant observations can be observed. In other words, distinct, but non-periodic, cyclical patterns may cause a potentially predictable component in the series dynamics. Modelling the series with a long-memory or chaotic process can be used to uncover trading opportunities. Therefore, more work on the implications of non-linear dynamics on trading practices may be needed. In this perspective, an additional contribution would concern the development of simple portfolio switching strategies for exploiting the existence of mean reversion. Moreover, exploring such trading rules allows the measurement of the economic significance of the mean reversion results, providing a further robustness check to our estimates.

Another target for further investigation is the liquidity premium included in the observed credit spreads. The spreads we computed are not only due to credit risk but they also reflect the relative liquidity of corporate and Treasury bonds. For this reason we should be careful in their interpretation. Changes in the spreads may reflect not only adjustments in the default probability but also liquidity and risk aversion variations. While changes in credit risk fluctuate with real economic variables such as the business cycle and are therefore rather long lasting, changes in liquidity premia are very volatile and depend a lot on market sentiment. It is therefore reasonable to expect that mean reversion in the liquidity component of spreads should be much higher than that of the credit component. If AAA spreads are explained in a greater proportion by liquidity they should intuitively revert more quickly to their long-term average than BBB spreads. Modelling both the credit and the liquidity components at the same time and distinguishing between investment grade and speculative bonds would provide interesting insight on the source of the observed mean reversion. Assessing the speed of mean reversion across rating classes have also implications for tactical asset allocation strategies. For example, if faster mean reversion is documented for higher rated bond yields, when expecting the end of a crisis where spreads are far above their long-term mean, it may be appropriate to invest first in AAA bonds (which recover faster) and then progressively move to more speculative securities (see Goldman, 1998).

Modelling credit spreads as GARCH and/or mean-reverting process has also implications for the pricing of credit derivatives, where the determinant variable is the evolution of the credit spread. The literature is still fairly thin on the pricing of these options and has been mainly published in practitioners' journals. An important exception is the work by Longstaff and Schwartz (1995) where the mean-reversion character of credit spreads sometimes makes European option prices less than the intrinsic value. Intuitively, in-the-money calls are less likely to remain in the money over time, because the credit spread tends to decline towards its long-run mean. An additional implication for credit spread option is that because of the mean-reversion, the dynamics of the credit spread do not satisfy the first-degree homogeneity property necessary for options to be convex functions (Merton, 1973). This implies that the delta of a GARCH credit spread call could be a decreasing function of the underlying credit spread.

The analysis would finally benefit from the implementation of a panel approach to test for non-linear effects and mean reversion. By exploiting cross-sectional variation, the power of the panel test will be enhanced, providing more accurate estimates. The hypothesis of a mixture of normal distributions and the non-linear cointegration hypothesis might also be the focus of new research in the field of credit spreads. The possible use of weekly and monthly data would allow testing GARCH models across different time frequencies. It may be also useful estimating the spread components and the speed of mean-reversion separately for various maturity bands and rating classes. For an investor thinking about purchasing a corporate bond, the size of each component for each rating class will affect the decision of whether to purchase a particular class of bonds or whether to purchase corporate bonds at all.

The second empirical study, examining bond yields reaction to rating changes, provides insight on the information value of rating agencies' revisions. The question of the impact of rating changes on bond and stock prices has been well studied in the literature. The main contribution of our study is that it employs a novel regression-GARCH approach allowing the rating change to impact volatility as well as market yields. The work also differs in examining non-US bonds and is one of the relative few using daily bond data.

Asymmetric responses for both mean and volatility of yield spreads are observed for positive and negative revisions. The incremental information content of bond revisions is statistically significant for downgrades, but not for upgrades. At the same time upgrades are associated with significant increases in volatility during and around the event period, while volatility is significantly depressed during and around the time the information is released. This finding could be related to either a temporary reduction in information asymmetry or simply a "time-out" during which traders attempt to assess the news. However, alternative explanations and interpretations of these results, especially regarding the volatility pattern, could be beneficial.

Given the mean and volatility asymmetric dynamics and the evidence of significant cumulative abnormal returns even after the rating change announcement, appropriate trading strategies could be developed accordingly. In particular, it may be investigated whether significant changes in volatility lead the way to profitable option trading on anticipated volatility effects. Further research could also focus on the economic significance of gains deriving from the anticipation and/or riding of the rating change event. Interesting would be also to relate the cause of the rating change with the likelihood that it carries significant new information to the market. Bond rating changes could be classified by cause of change and their different information value about the firm (bond) assessed.

Finally, while this study examines only the response to rating revisions by Standard and Poor's, there are other rating announcements of note occurring at around the same time. First, most S&P rating revisions are preceded by news (Creditwatch) that S&P is reconsidering the rating with negative, positive, or neutral implications. Further research could be conducted to assess whether part of the yield adjustments observed prior to the rating revision reflects the impact of this information release. On the other hand, our regression-approach provides a much better way to handle these announcements than previous studies. While previous studies examine the reaction to these announcements separately, we introduce an integrated approach by defining separate dummy variables for the various announcements.

After looking at the rating change event, we narrow our focus to the downgrade event and we model the re-grade probability itself. In particular we examine the power of the credit rating and various financial and accounting ratios to forecast Eurobond downgrades one year in advance. While there is a voluminous study on the prediction of defaults and bankruptcies, little research has been done to forecast the downgrade probability. Filling this information gap should be of interest to investors, bondholders, and to the credit community to determine maturity exposure limits and/or to measure credit risk in the context of value-at-risk models.

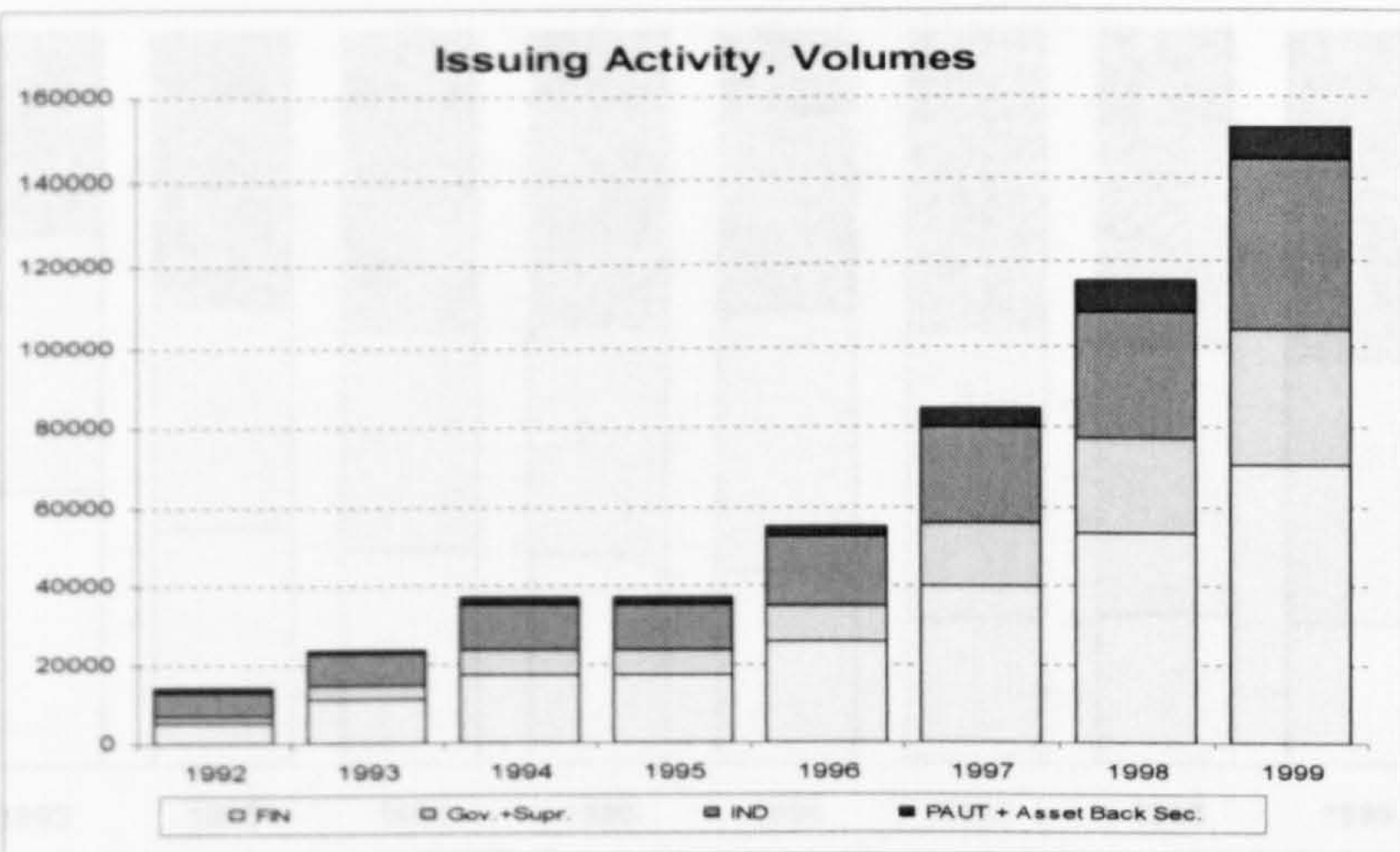
Rating agencies, like regulators, are concerned with the likelihood of firm default and aim to minimise unexpected losses to creditors. Given this similarity in objectives, we expect a strong relationship between credit ratings and financial/accounting ratios. This prevents us from simply introducing both sets of variables in the forecasting model. Therefore, we develop a two-step estimation procedure. In the first step, we find the factors explaining credit ratings. In the second step, we identify factors predicting the downgrade probability. This methodology allows us to estimate the "clean" contribution of the credit rating and the financial variables removing any interaction effect. In terms of correct out-of-sample classifications the two-step model outperforms both a naïve constant probability model and a more complicated artificial neural network model.

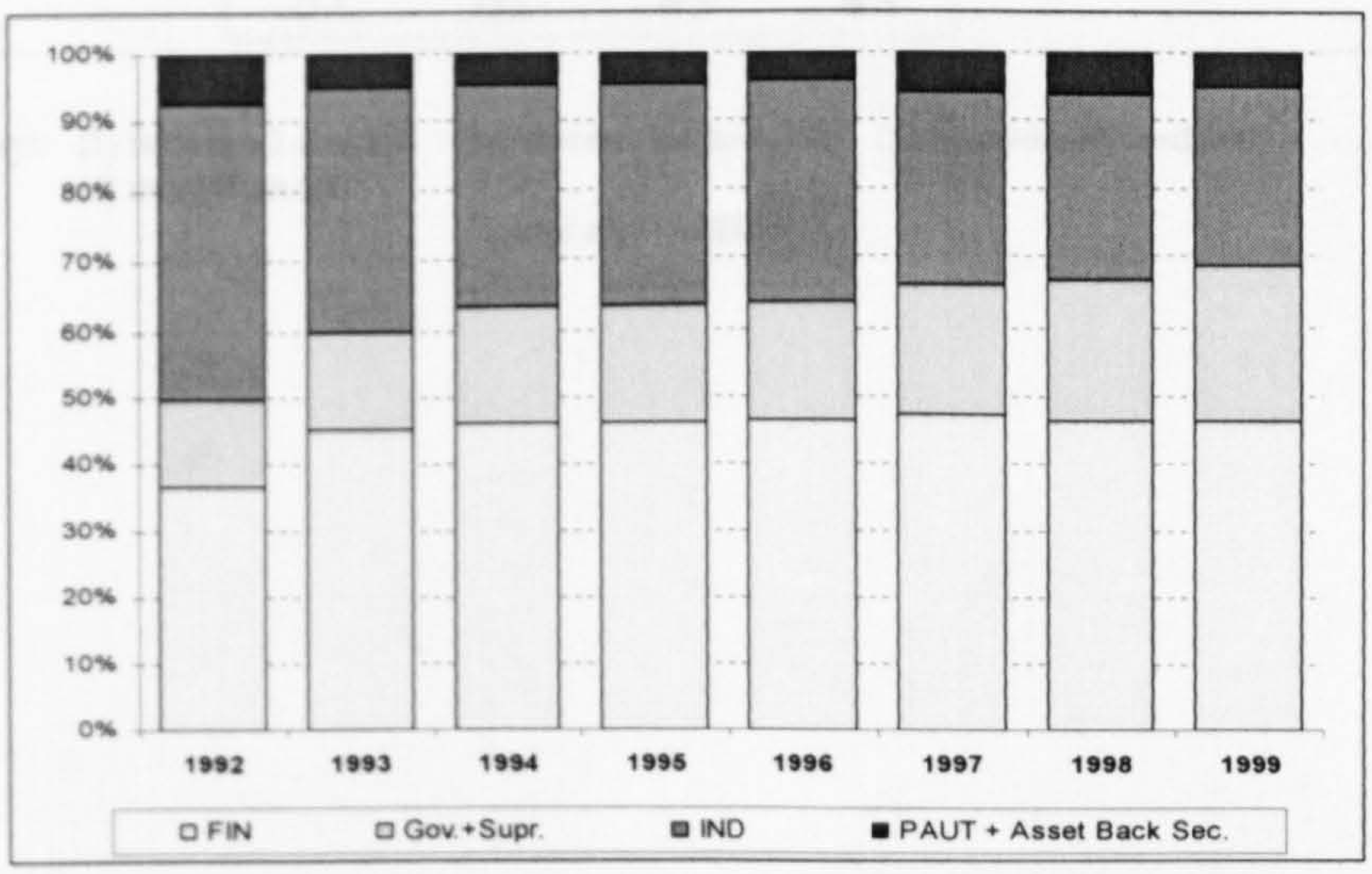
While the sign of the explanatory variables are generally consistent with our expectations, tangible assets and investment factors go in an unexpected direction regarding their contribution to the downgrade probability. Recalling that these variables were present, with the correct sign, in the first (rating) regression, we explain this result in terms of a possible over-weighting of their contribution to the assessment of the credit quality, as represented by the rating, in the first place. However, we realize that this not intuitive explanation needs further thought.

Despite the extensive validation of the model, we must recognise that our sample is rather small (105 observations). Still this work can be considered as a first effort to directly design a downgrade model. The increasing availability of data will certainly contribute to testing the robustness of the model's results and further investigate their implications. Beneficial will also be running in parallel a model of default. This would help to examine more closely the causes of downgrades, which may be different from the causes of outright failure. Moreover, a switching-regime model in line with Bangia, Diebold and Schuermann (2000) may be designed to predict rating downgrades in both stable (expansion) and unstable (recession) periods. Finally, although rating and accounting ratios can explain the downgrade outcome to some extent, it remains to evaluate the possible incremental benefit of including market data. In particular we may want to consider the relevance of the information contained in the credit spreads relatively to the bond's future re-grade.

INDUSTRIAL CLASSIFICATION

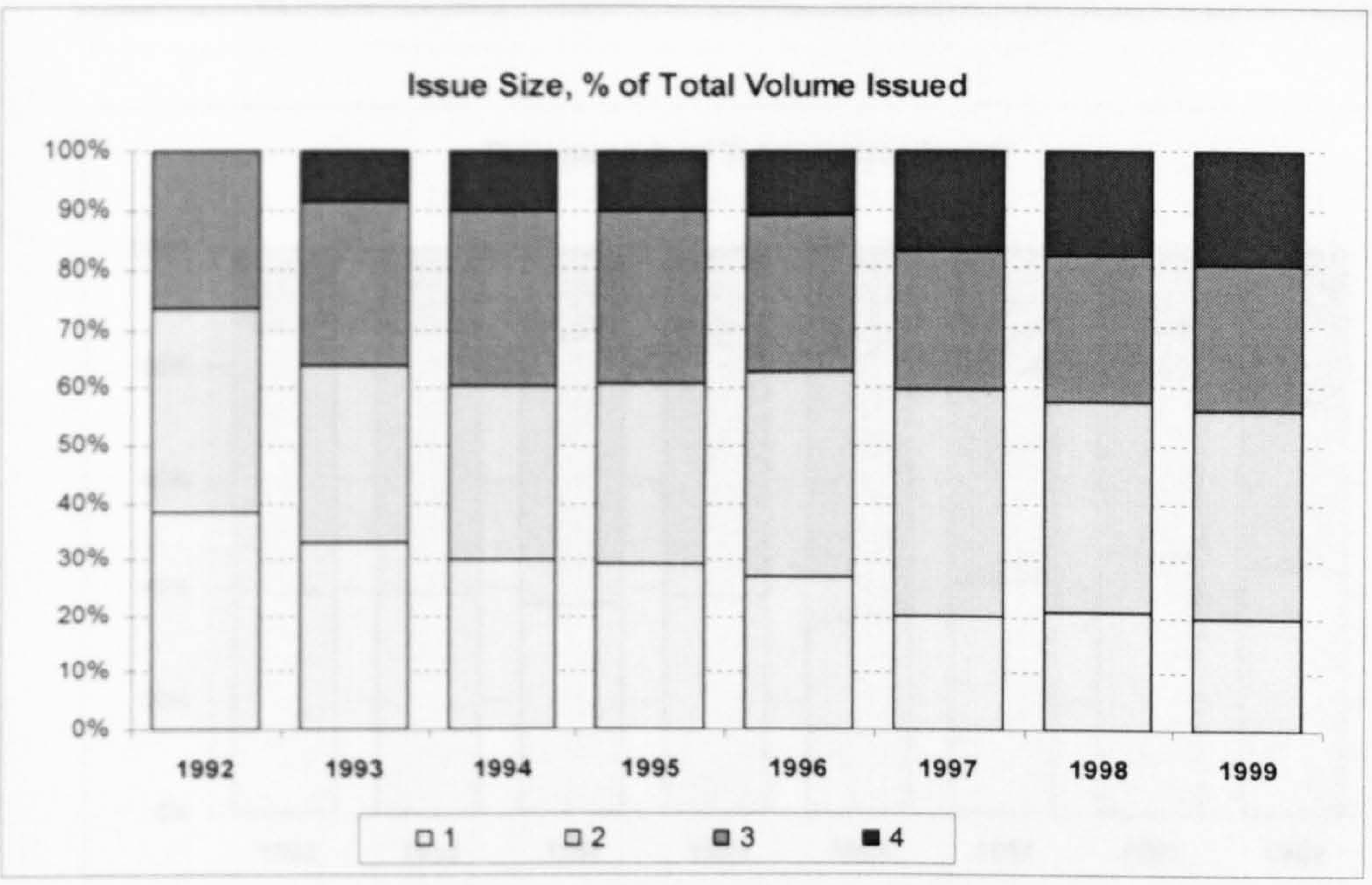
Market Value	*1992*	*1993*	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*
CVF	0	99.63	344.64	344.64	344.64	540.02	1073.43	1120.68
CVI	0	208.74	208.74	208.74	397.29	397.29	1379.2	2387.37
FIN	5070.23	10792.4	17156.08	17156.08	25594.4	40178.3	53511.6	70746.1
GOVT	686.18	1306.63	2280.7	2280.7	2972.74	4114.04	5458.72	6066.74
IND	5935.97	8366.33	11784.82	11784.82	17641.6	23910	31259.95	40273.7
MTGE	991.46	0	0	0	0	0	817.14	817.14
PAUT	0	1141.65	1783.39	1783.39	2282.07	5006.19	6346.18	6912.15
SUPR	1115.01	2148.95	4185.68	4185.68	6518.86	11619.89	17975.43	27397
Total	**13798.85**	**24064.3**	**37744.05**	**37744.05**	**55751.6**	**85765.7**	**117821.62**	**155721**





ISSUE SIZE

	1992	1993	1994	1995	1996	1997	1998	1999
1	5292.17	7925.3	11308	12845	15080.31	16649	24830	31032.4
2	4901.2	7487.98	11537	13896	19951.28	32744	42842	56431.75
3	3605.5	6589.94	11083	12623	14576.78	19157	28851	37825.87
4	0	2061.08	3813	4467	6142.3	14214	21297	30429.8

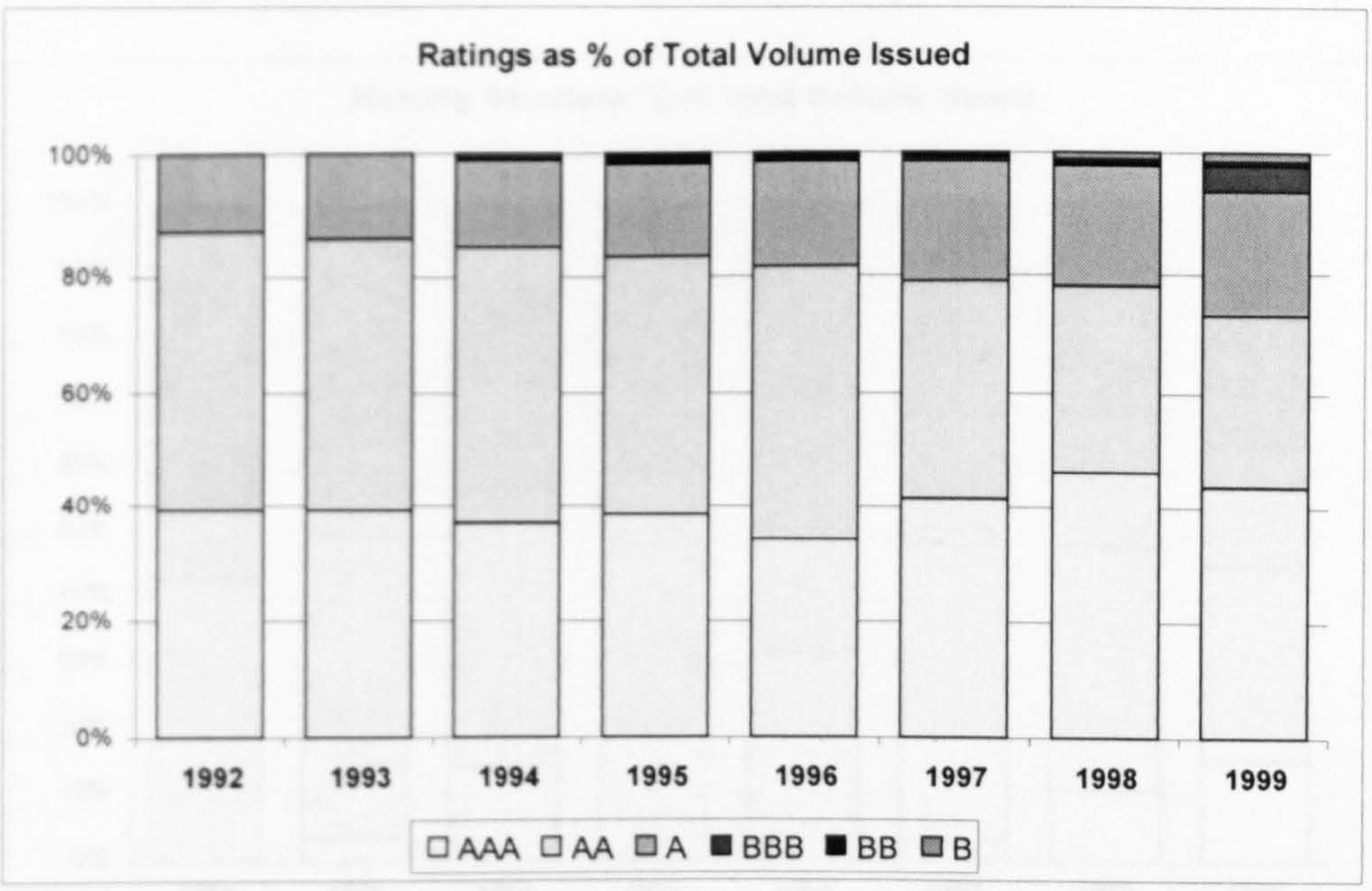


Key: (1) between 1 and 150 (2) between 150 and 300 (3) between 300 and 600
(4) more than 600

Figures are in millions

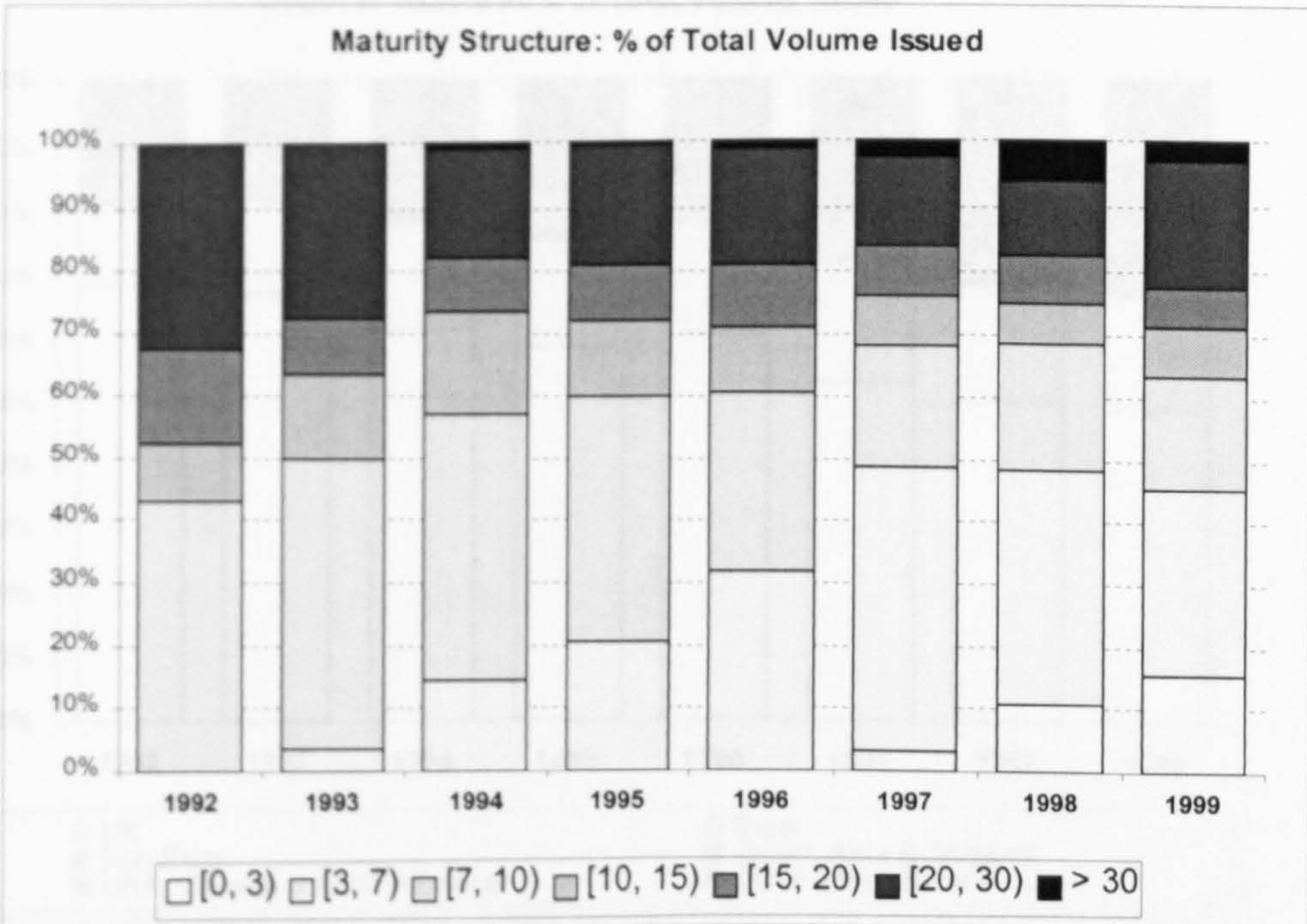
ISSUE RATING

	1992	1993	1994	1995	1996	1997	1998	1999
AAA	1832.0	3939.3	6323.1	8706.7	10867.8	20393.6	31940.4	41443.2
AA	2241.0	4683.5	8096.8	10053.1	14860.5	18278.4	21973.0	27492.4
A	581.6	1345.1	2385.7	3377.2	5425.0	9567.0	13835.6	19530.0
BBB	0.0	0.0	0.0	105.0	0.0	452.5	246.4	3972.8
BB	0.0	0.0	74.8	182.0	285.5	178.4	283.9	665.2
B	0.0	0.0	121.0	121.0	121.0	121.0	857.5	1405.2



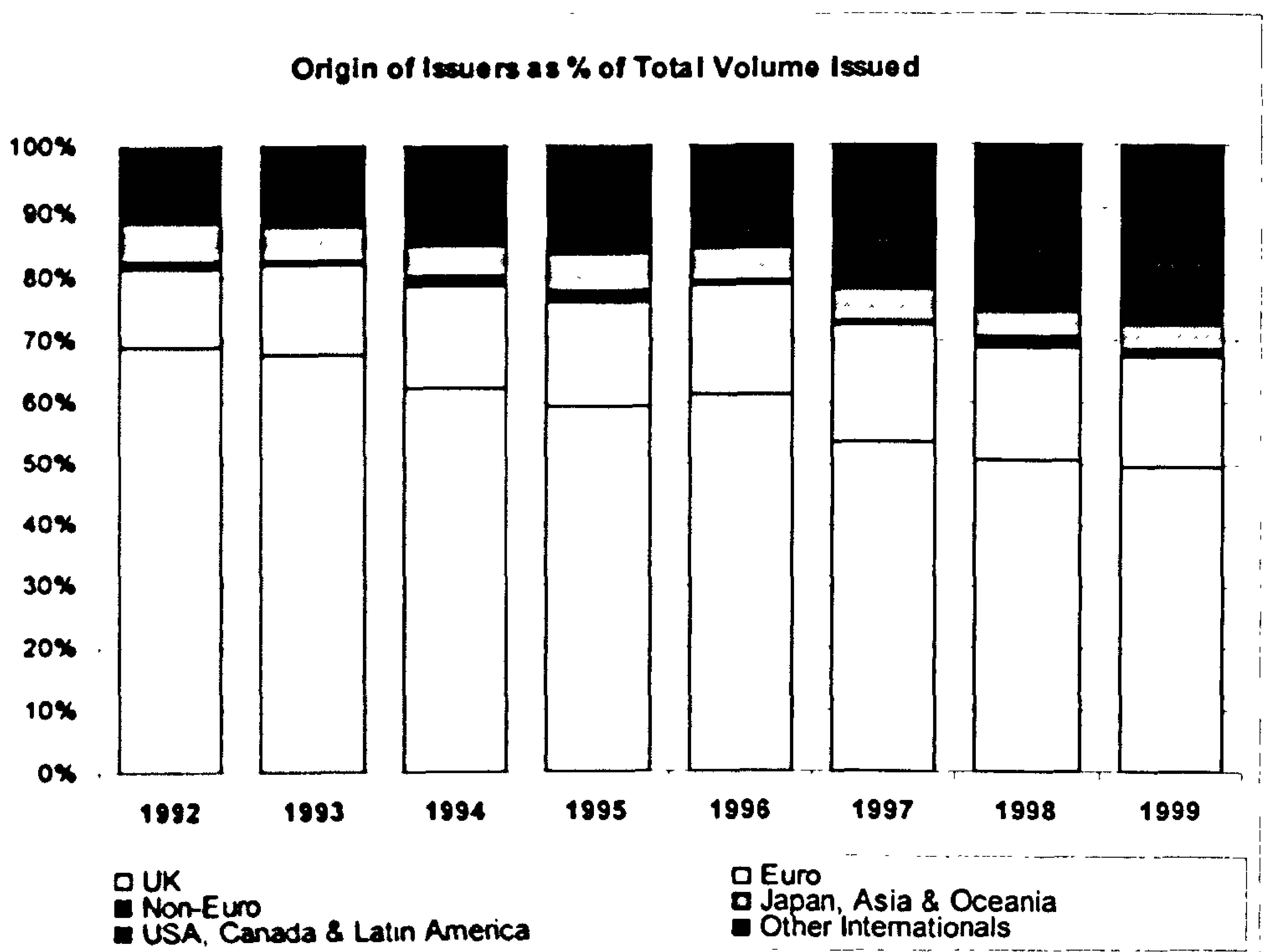
MATURITY STRUCTURE

	1992	1993	1994	1995	1996	1997	1998	1999
[0, 3)	0	0	0	0	0	2585.62	12312.11	23514.4
[3, 7)	0	857.52	5180.55	8579.69	16783.35	37342.48	42103.97	45185.13
[7, 10)	5924.93	10822.7	15253.06	16375.77	15217.94	15724.48	22984.6	27135.24
[10, 15)	1278.75	3237.4	5950.91	5107.37	5556.45	6647.72	7147.96	12028.11
[15, 20)	2103.58	2081.52	3218.62	3735.03	5404	6462.7	8629.58	9330.53
[20, 30)	4491.59	6415.41	6086.46	7564.66	9374.96	10832.35	12824.22	29260.63
> 30	0	0	223.7	223.7	546.33	2076.49	6753.06	4207.57



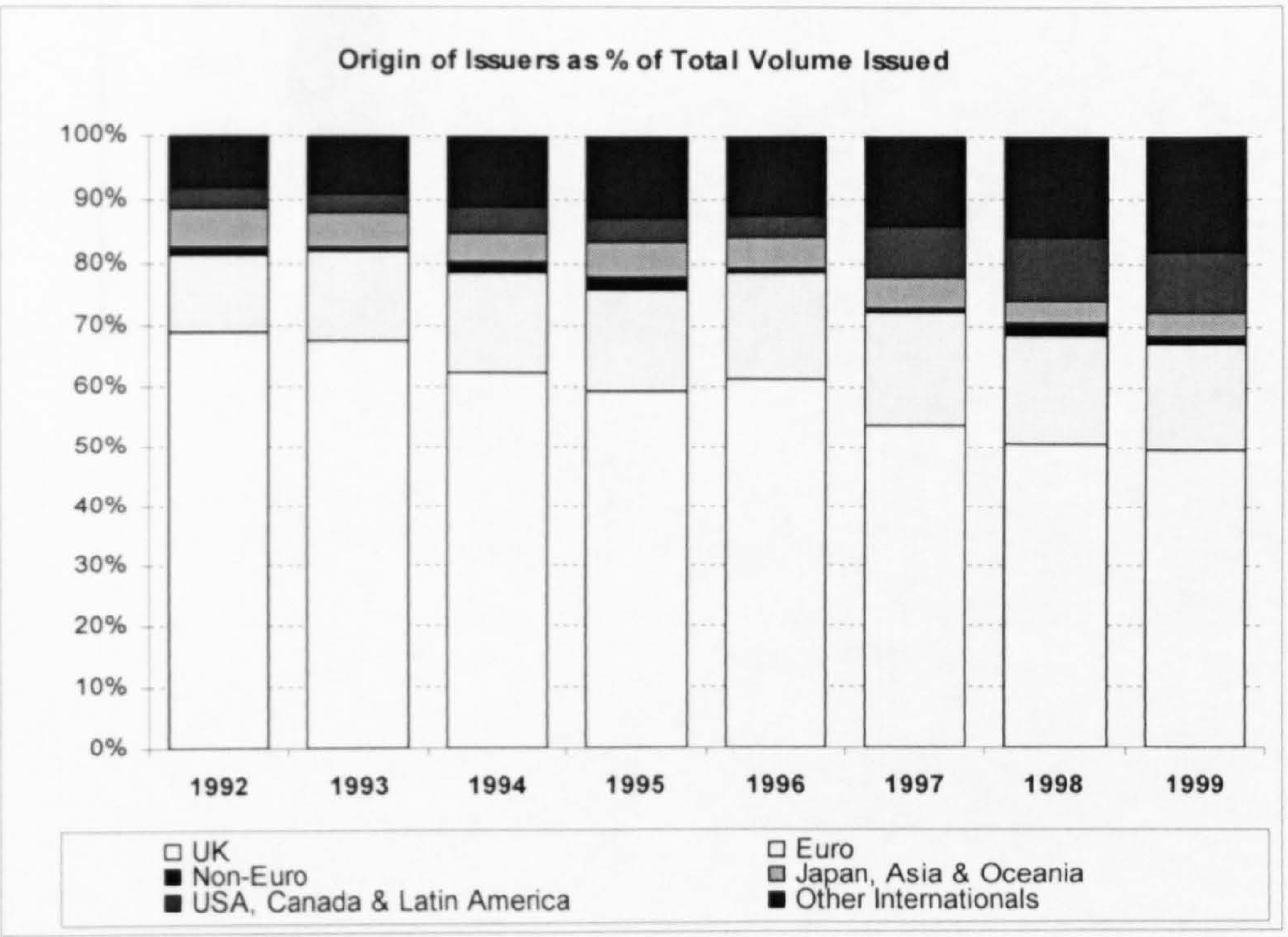
ORIGIN OF ISSUERS

	1992	1993	1994	1995	1996	1997	1998	1999
UK	9540.6	16251.9	23562.2	26049.4	34211.3	245890.0	259496.1	277123.1
Euro	1677.3	3475.0	6075.9	7265.3	9653.4	15932.2	21059.3	27366.9
Non-Euro	187.3	187.3	646.6	914.2	334.8	564.6	2320.1	2320.1
Japan, Asia & Oceania	833.9	1242.1	1782.7	2417.4	2898.3	4343.9	4699.4	5556.6
USA, Canada & Latin America	444.6	758.8	1490.7	1648.9	1850.1	6767.6	11394.0	15080.0
Other Internationals	1115.0	2148.9	4185.6	5538.5	6803.3	12067.2	18652.5	28074.0

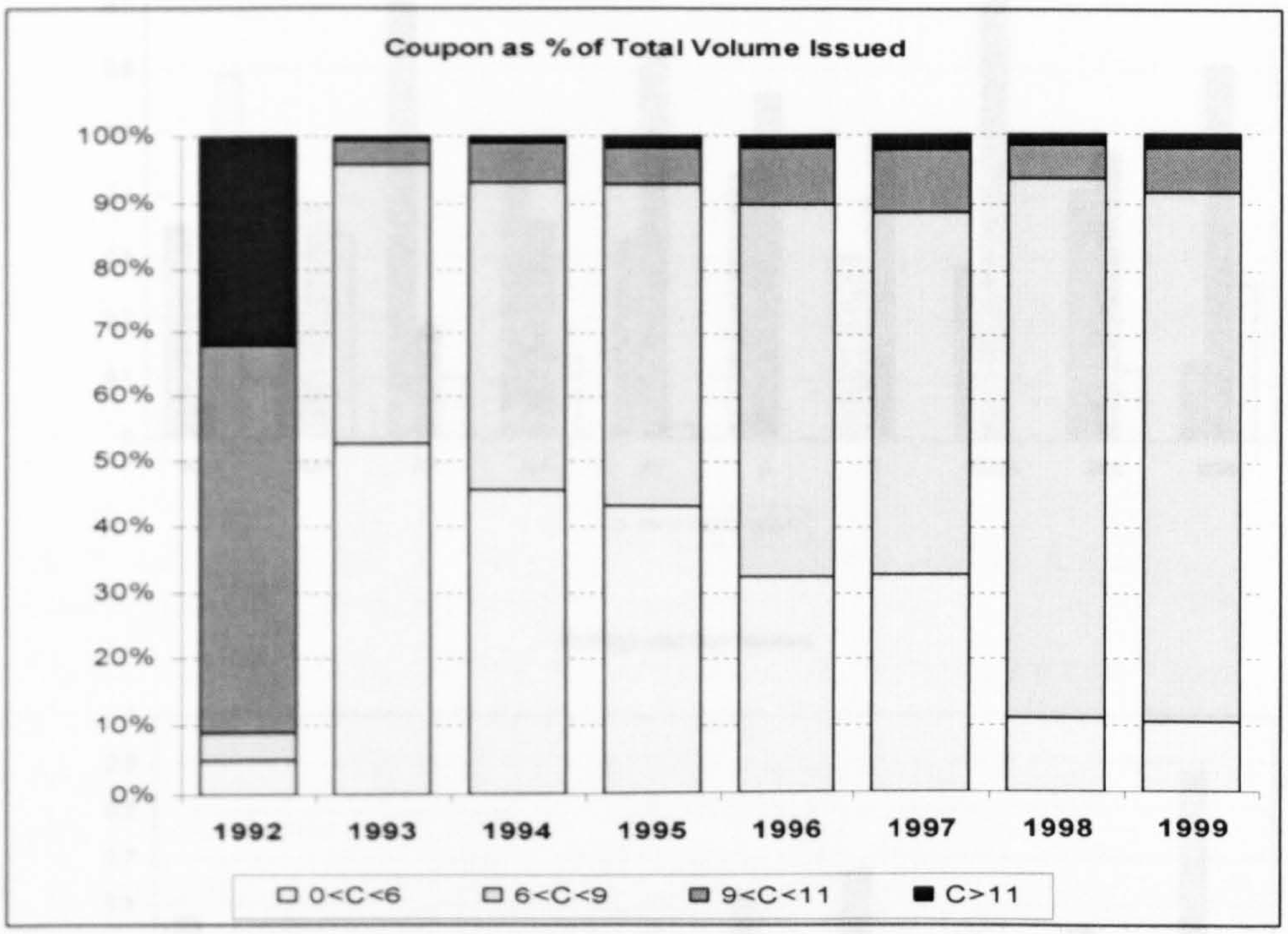


ORIGIN OF ISSUERS

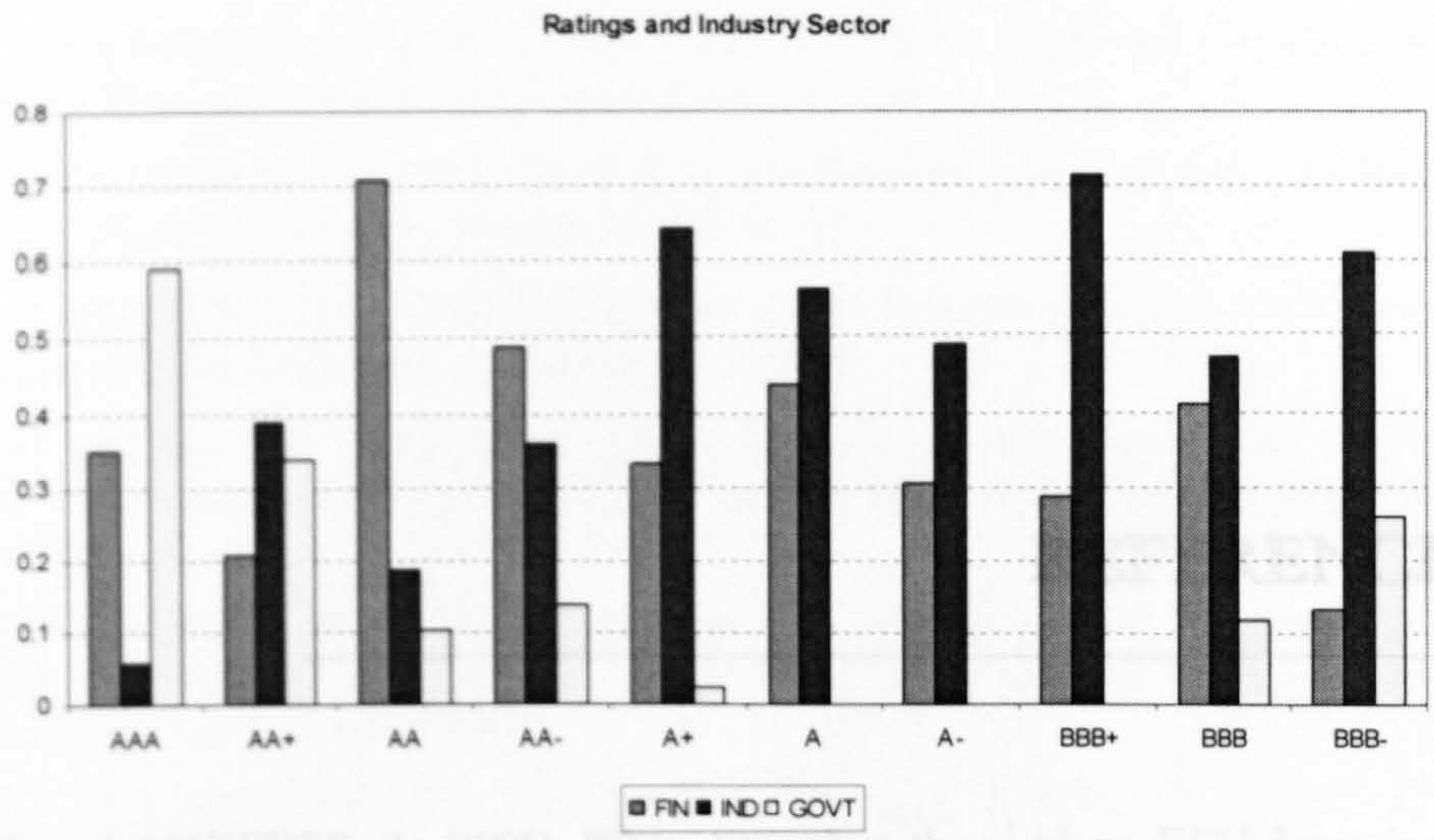
	1992	1993	1994	1995	1996	1997	1998	1999
UK	9540.6	16251.9	23562.2	26049.4	34211.3	245890.0	259496.1	277123.1
Euro	1677.3	3475.0	6075.9	7265.3	9653.4	15932.2	21059.3	27366.9
Non-Euro	187.3	187.3	646.6	914.2	334.8	564.6	2320.1	2320.1
Japan, Asia & Oceania	833.9	1242.1	1782.7	2417.4	2898.3	4343.9	4699.4	5556.6
USA, Canada & Latin America	444.6	758.8	1490.7	1648.9	1850.1	6767.6	11394.0	15080.0
Other Internationals	1115.0	2148.9	4185.6	5538.5	6803.3	12067.2	18652.5	28074.0

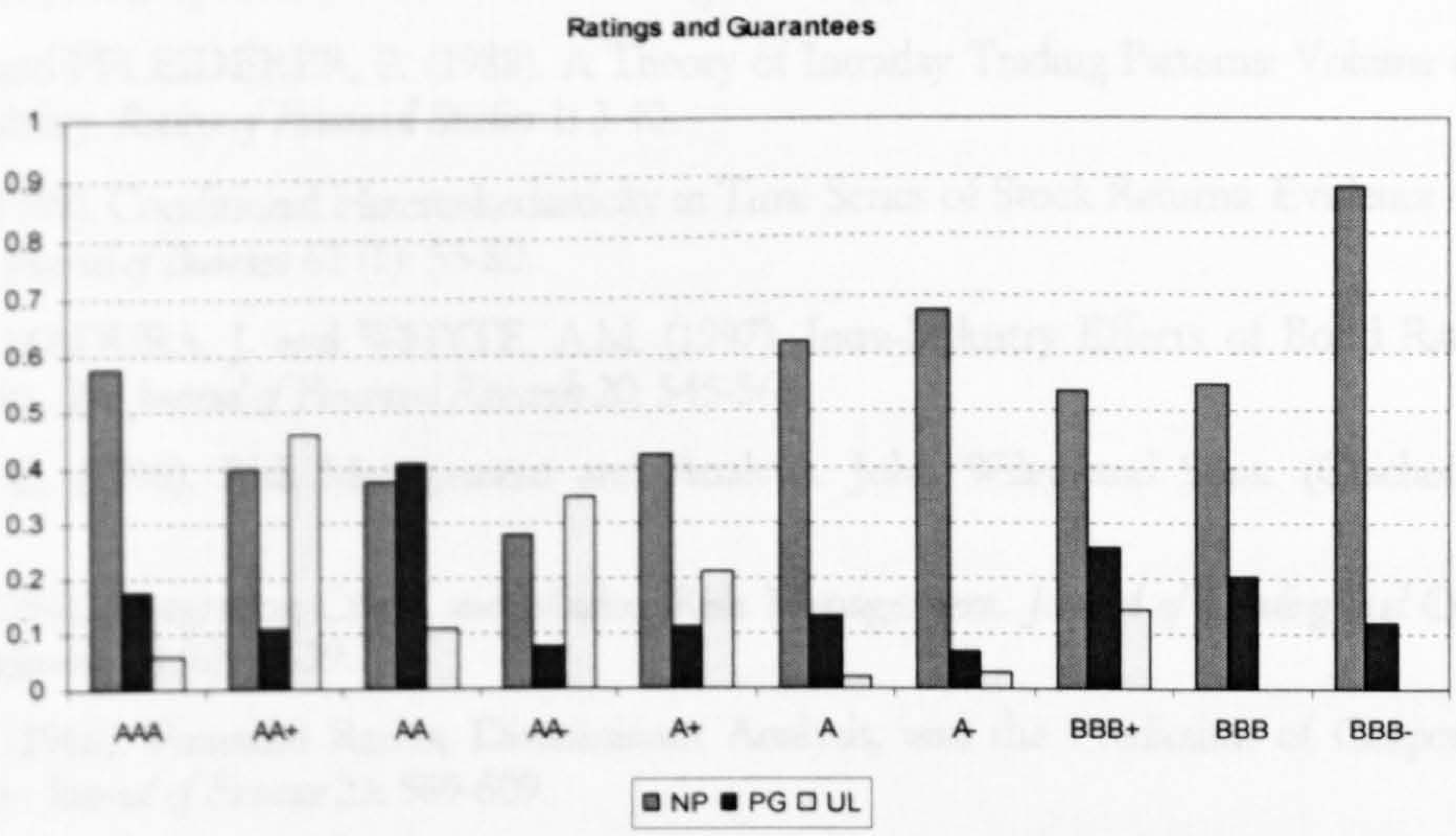


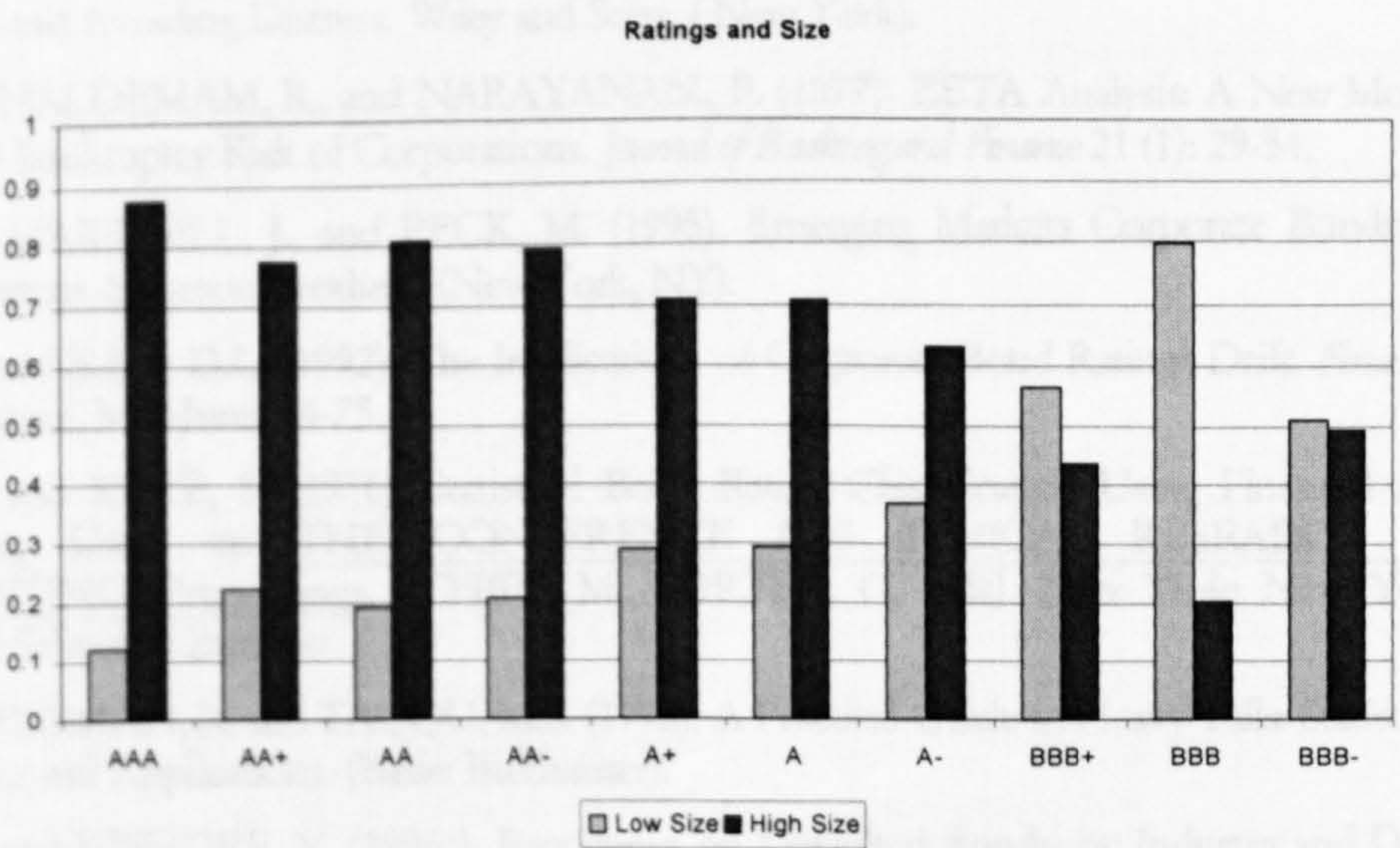
COUPON



Coupon as % of Total Volume Issued
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1992
1993
1994
1995
1996
1997
1998
1999
0<C<6
6<C<9
9<C<11
C>11


Ratings and Industry Sector
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
AAA
AA+
AA
AA-
A+
A
A-
BBB+
BBB
BBB-
FIN IND GOVT


Ratings and Guarantees
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
AAA
AA+
AA
AA-
A+
A
A-
BBB+
BBB
BBB-
NP PG UL


Ratings and Size
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
AAA
AA+
AA
AA-
A+
A
A-
BBB+
BBB
BBB-
Low Size High Size

REFERENCES

ABOU-ZEID, B. and SAVVIDES, A. (1995). What determines the yield on ECU-denominated Eurobonds? *Journal Of Multinational Financial Management* 5 (4): 29-42.

ADMATI, A.R. and PFLEIDERER, P. (1988). A Theory of Intraday Trading Patterns: Volume and Price Variability. *Review of Financial Studies* 1: 3-40.

AKGIRAY, V. (1989). Conditional Heteroskedasticity in Time Series of Stock Returns: Evidence and Forecasts. *Journal of Business* 62 (1): 55-80.

AKHIGBE, A., MADURA, J. and WHYTE, A.M. (1997). Intra-Industry Effects of Bond Rating Adjustments. *The Journal of Financial Research* 20: 545-561.

ALEXANDER, C. (1998). Risk Management and Analysis. John Wiley and Sons. (Chichester, England).

ALLEN, R.A. (1996). Integrating Credit and Market Risk Management. *Journal of Lending and Credit Risk Management* 78 (6): 14-29.

ALTMAN, E.I. (1968). Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy. *Journal of Finance* 23: 589-609.

ALTMAN, E.I. (1993). Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress. Wiley and Sons. (New York).

ALTMAN, E.I., HALDEMAM, R., and NARAYANAN., P. (1977). ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance* 21 (1): 29-54.

ALTMAN, E.I., HARTZELL, J., and PECK, M. (1995). Emerging Markets Corporate Bonds: A Scoring System, Salomon Brothers. (New York, NY).

ALTMAN, E.I. and KAO, D.L. (1992). The Implications of Corporate Bond Ratings Drift. *Financial Analysts Journal*, May-June: 64-75.

ALTMAN, E.I. and KATZ, S. (1976). Statistical Bond Rating Classification Using Financial and Accounting Data, in: THE CONFERENCE ON TOPICAL RESEARCH IN ACCOUNTING. Proceedings. SCHIFF, M., SORTER, G. (eds). New York: New York University School of Business.

ADLER, R.J., FELDMAN, R. and TAQQU, M.S. (1998). A Practical Guide to Heavy Tails: Statistical Techniques and Applications. (Basle: Birkhauser).

ALTMAN, E.I. and KISHORE, V. (1996a). Recoveries on Defaulted Bonds: by Industry and Debt Seniority. New York University, Salomon Brothers Working Paper, S/96/6:11.

ALTMAN, E.I. and KISHORE, V. (1996b). Almost Everything you Wanted to Know About Recoveries on Defaulted Bonds, *Financial Analysts Journal* 52: 57-64.

ALTMAN, E.I. and KISHORE, V. (1998). Defaults and Returns on High-Yield Bonds Analysis Through 1997. Working Paper, NYU Salomon Center, January.

ALTMAN, E.I. and SAUNDERS, A. (1997). Credit Risk Measurement: Developments over the Last Twenty Years. *Journal of Banking and Finance* 21: 1721-1742.

ALTMAN, E. I. and SUGGITT, H.J. (2000). Default rates in the syndicated bank loan market: A mortality analysis. *Journal of Banking and Finance* 24: 229-253.

ALTMAN, E.I., MARCO, G. and VARETTO, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking and Finance* 18 (3): 505-529.

AMMER, J. and PACKER, F. (2000). How Consistent are Credit Ratings? A Geographical and Sectoral Analysis of Default Risk. International Finance Discussion Paper No. 668, Board of Governors of the Federal Reserve System.

ANDERSEN, T., BOLLERSLEV, T., DIEBOLD, F.X., and LABYS, P. (2000). Great Generalizations. *Risk* 12: 105-108.

ANDREWS, D.W.K. (1988a). Chi-Square Diagnostic Tests for Econometric Models: Theory. *Econometrica* 56: 1419–1453.

ANDREWS, D.W.K. (1988b). Chi-Square Diagnostic Tests for Econometric Models: Introduction and Applications. *Journal of Econometrics* 37: 135–156.

ANGBAZO, L.A., MEI, J. and SAUDERS, A. (1998). Credit Spreads in the Market for Highly Leveraged Transaction Loans. *Journal of Banking and Finance* 22: 1249-1282.

ARAK, M. and CORCORAN, P.J. (1996). Yields on privately placed debt: examining the behavior. *Journal of Portfolio Management* (Spring): 88-96.

ARTZNER, P. and DELBAEN F. (1995). Default Risk Insurance and Incomplete Markets. *Mathematical Finance* 5: 187-195.

ARVANITIS, A., GREGORY J., and LAURENT J.P. (1999). Building Models for Credit Spreads. *The Journal of Derivatives* Spring: 27-43.

ATHANASSAKOS, G. and SCHNABEL, J. (1996). Stockholder Wealth Effects of Eurobond Financing: A Canadian Perspective. *Global Finance Journal* 7 (2): 191-208.

BAILEY, W., CHUNG, Y.P, and KANG, J.K. (1996). Investment restrictions and the pricing of Korean convertible Eurobonds. *Pacific-basin Finance Journal* 4 (1): 93-111.

BAILLIE, R.T. and DEGENNARO, R.P. (1989). The Impact of Delivery Terms on Stock Return Volatility. *Journal of Financial Services Research* 3: 55-76.

BALDAUF, B. and SANTONI, G. J. (1991). Stock Price Volatility: Some Evidence from an ARCH Model. *The Journal of Futures Markets* 11 (2): 191-200.

BANGIA, A., DIEBOLD, F.X., and SCHUERMANN, T. (2000). Ratings Migration and the Business Cycle, with Application to Credit Portfolio Stress Testing. Wharton Financial Institutions Center Working Paper.

BARNHILL, T.M., JOUTZ, F.L., and MAXWELL, W.F. (2000). Factors affecting the yields on noninvestment grade bond indices: a cointegration analysis. *Journal of Empirical Finance* 7: 57-86.

BASLE. (1988). International Convergence of Capital Measurement and Capital Standards. Basle: Basle Committee on Banking Supervision, Bank of international Settlements.

BASLE. (1995). An Internal Model-Based Approach to Market Risk Capital Requirements. Basle: Basle Committee on Banking Supervision, Bank of international Settlements.

BASLE. (1996). Amendment to the Capital Accord to Incorporate Market Risks. Basle: Basle Committee on Banking Supervision, Bank of international Settlements.

BASLE. (1999). Committee on Banking and Supervision, Capital Adequacy Framework, June.

BATTEN, J., ELLIS, C., and HOGAN, W. (1999). Scaling The Volatility of Credit Spreads: Evidence from Australian Dollar Eurobonds. CREFS Centre Working Papers, Nanyang Technological University Singapore, 99-03.

BATTEN J., HOGAN W., and PYNNÖNEN S. (2000). The dynamics of Australian dollar bonds with different credit qualities. *International Review Of Financial Analysis* 9 (4): 389-404.

BEAVER, W. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, Supplement on Empirical Research in Accounting: 71-111.

BEER, F. (1995). The Dollar Eurobond Market. *American Business Review* 13 (2): 47-53.

BERNANKE, B. and GERTLER, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *American Economic Review* 79: 14-31.

BERNDT, E., HALL, B., HALL, R., and HAUSMAN, J. (1974). Estimation and Inference in Non-linear Structural Models. *Annals of Economic and Social Measurement* 3: 653-665.

BERRY, T.D. and HOWE, K.M. (1994). Public Information Arrival. *Journal of Finance* 49: 1331-1346.

BESSIS, J. (1998). Risk Management in Banking. (Chichester, England: John Wiley & Sons).

BEVAN, A. and GARZARELLI, F. (2000). Corporate Bond Spreads and the Business Cycle: Introducing GS-SPREAD. *The Journal of Fixed Income* March: 8-18.

BHATTACHARYA, U., DAOUK, H., JORGENSOS, B. and KEHR, C.H. (2000). When an event is not an event: the curious case of an emerging market. *Journal of Financial Economics* 55: 69-101.

BIDARKOTA, P.V. (1996). On Modeling Real GNP: Non-Normality and Non-Linearity, but No Long Memory. The Ohio State University Working Paper.

BIERMAN, H. and HASS, J. (1975). An Analytical Model of Bond Risk Differentials. *Journal of Financial and Quantitative Analysis* 10: 757-773.

BLACK, F. and COX, J. (1976). Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. *Journal of Finance* 31: 351-367.

BLACK, F. and SCHOLES, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81: 637-659.

BLUME, M., LIM, E., MACKINLAY, C. (1998). The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality? *Journal of Finance* 53: 1389-1413.

BOARDMAN, C.M. and MCENALLY, R.W. (1981). Factors Affecting Seasoned Bond Prices. *Journal of Financial and Quantitative Analysis*, June: 207-226.

BOEHMER, E., MUSUMEI, J. and POULSEN, A. (1991). Event-Study Methodology under Conditions of Event-Induced Variance. *Journal of Financial Economics* 30: 253-272.

BOLLERSLEV, T. (1986). Generalised Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 31: 307-327.

BOLLERSLEV, T. and DOMOWITZ, I. (1993). Trading Patterns and Prices in the Interbank Foreign Exchange Market. *Journal of Finance* 48: 1421-1443.

BOLLERSLEV, T. and WOOLDRIDGE, J.M. (1992). Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances. *Econometric Reviews* 11: 143-172.

BOLLERSLEV, T., and MELVIN, M. (1994). Bid-ask Spreads and Volatility in the Foreign Exchange Market. *Journal of International Economics* 36: 355-372.

BOX, G.E.P. and JENKINS, G.M. (1976). Time Series Analysis: Forecasting and Control. Holden-Day Series in Time Series Analysis and Digital Processing, Holden-Day Inc.

BREEDEN, D.T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics* 7: 265-296.

BRENNAN, M. and SCHWARTZ, E. (1979). A Continuous Time Approach to the Pricing of Bonds. *Journal of Banking and Finance* 3: 133-155.

BRENNAN, M. and SCHWARTZ, E. (1980). Analysing Convertible Bonds. *Journal of Financial and Quantitative Analysis* 15: 907-929.

BROCKETT, P.L., CHEN, H. and GARVEN, J.R. (1998). A New Stochastically Flexible Event Methodology with Application to Proposition 103. Working Paper.

BROWN, S. and WARNER, J. (1985). Using Daily Stock Returns: The Case of Event Studies. *Journal of Financial Economics* 14: 3-32.

BROWN, K.C., HARLOW, W.V. and SMITH, D.J. (1994). An Empirical Analysis of Interest Rate Swap Spreads. *Journal of Fixed Income* March: 61-78.

CAD. (1993). Council Directive 93/6/EEC of 15 March 1993 on the capital adequacy of investment firms and credit institutions. Official Journal of European Communities: L141.

CAMPBELL, J. Y. and COCHRANE, J. H. (1995). By Force of Habit: A Consumption-based Explanation of Aggregate Stock Market Behavior. NBER working paper, no. 4995.

CAMPBELL, J.Y. and HENTSCHEL, L. (1992). No News is Good News: and Asymmetric Model of Changing Volatility in Stock Returns. *Journal of Financial Economics* 31: 281-318.

CANTOR, R. and PACKER, F. (1995). Sovereign Credit Ratings. Current Issues in Economics and Finance, Federal Reserve Bank of New York, June.

CANTOR, R. and PACKER, F. (1996). Determinants and Impact of Sovereign Credit Ratings. *Journal of Fixed Income* 6: 76-91.

CAREY, M. (1994). Are Bank Loans Mispriced? Unpublished Federal Reserve Board mimeo.

CAREY, M. (1998). Credit Risk in Private Debt Portfolios. *Journal of Finance* 53: 1363-1388.

CAREY, M. and HRYCAY, M. (2001). Parameterizing credit risk models with rating data, *Journal of Banking and Finance* 25 (1): 197-270.

CARTY, L.V. (1994). Moody's Rating Migration and Credit Quality Correlation, 1920-1996. In: Credit Derivatives, ed. by S. Das, 1998, (John Wiley & Sons).

CATHCART, L. and EL-JAHEL, L. (1998). Valuation of Defaultable Bonds. *Journal of Fixed Income* 2, 65-78.

CECCHETTI, S.G., LAM, P., and MARK, N.C. (1990). Mean Reversion in Equilibrium Asset Prices. *The American Economic Review* 80 (3): 398-418.

CHANCE, D.M. (1990). Default Risk and the Duration of Zero Coupon Bonds. *The Journal of Finance* 45 (1): 265-274.

CHAPLIN, G. and SAOULLIS, S. (1997). Carrying on as a normal. Risk: June.

CHAVEESUK, R., SRIVAREE-RATANA, C., and SMITH, A.E. (1997). Alternative Neural Network Approaches to Corporate Bond Rating, Dept. of Industrial Engineering, University of Pittsburgh, Working Paper.

CHEUNG, S. (1996). Provincial Credit Rating in Canada: An Ordered Probit Analysis. Financial Markets Department Working Paper, Bank of Canada.

CLARE, A.D. and THOMAS, S.H. (1994). Macroeconomic Factors, the APT and the UK Stock Market. *Journal of Business Finance and Accounting* 21: 309-330.

CLARE, A.D., OOZEER, M.C., PRIESTLEY, R. and THOMAS, S.T. (2000). Modeling the Risk Premium on Eurodollar Bonds. *The Journal of Fixed Income* 9: 61-73.

CLARE, A.D., THOMAS, S. H and WICKENS, M. R. (1994). Is the Gilt-Equity Yield Ratio Useful for Predicting UK Stock Returns?. *Economic Journal* 104: 303-315.

CLARK, C.E., DELLVA, W. and FOSTER, P. (1993). Bond Rating Changes and Beta Risk: An Analysis of the Relationship Through the Use of Influence Statistics. *Journal of Business and Economic Studies*, Winter/Spring: 23-46.

CLARK, C.E., FOSTER, P.L. and GHANI, W.I. (1997). Differential Reactions to Bond Downgrades for Small Versus Large Firms: Evidence from Analysts' Forecast Revisions. *The Journal of Fixed Income* December: 94-99.

CLINE, W.R. and BARNES, K.J.S. (1997). Spreads and Risk in Emerging Markets Lending. Institute of International Finance, IIF Research Paper No. 97-1.

COHAN, A.B. (1973). The Risk Structure of Interest Rates. (General Learning Press, Morristown, N.J.).

COLLIN-DUFRESNE, P., GOLDSTEIN, R.S. and MARTIN, J.S. (1999). The Determinants of Credit Spread Changes. Working Paper, November.

CONNOLLY, R.A. (1989). An Examination of the Robustness of the Weekend Effect. *Journal of Financial and Quantitative Analysis* 24: 133-169.

COOK, T.Q. (1981). Determinants of the Spread between Treasury Bill Rates and Private Sector Money Market Rates. *Journal of Economics and Business*, Spring/Summer: 177-187.

COOPER, I. and MARTIN, M. (1996). Default Risk and Derivative Products. *Applied Mathematical Finance* 3: 53-74.

COOPER, I. and MELLO, A. (1988). Default Spreads in the Fixed and the Floating Interest rate Markets: a Contingent Claim Approach. *Advances in Futures and Options Research* 3: 269-289.

COOPER, I. and MELLO, A. (1991). The Default Risk of Swaps. *Journal of Finance* 46: 597-620.

CORNELL, B. (1992). Liquidity and the Pricing of Low-grade Bonds. *Financial Analysts Journal* 48 (January/February): 63-68.

CORNELL, B. and SHAPIRO, A.C. (1987). Corporate Stakeholders and Corporate Finance. *Financial Management*, Spring: 5-14.

CORNELL, B., LANDSMAN, W. and SHAPIRO, A. (1989). Cross-sectional Regularities in the Response of Stock Prices to Bond Rating Changes. *Journal of Accounting, Auditing and Finance* 4: 460-479.

COVITZ, D.M., and HARRISON, P. (1999). The Timing of Debt Issuance and Rating Migration: Theory and Evidence. Board of Governors of the Federal Reserve System (U.S.). No 2000-10 in Finance and Economics Discussion Series.

COX, J. C., INGERSOLL, J.E. and ROSS. S.A. (1985). An Intertemporal General Equilibrium Model of Asset Prices. *Econometrica* 53: 363-384.

CRABBE, L.E., and TURNER, C.M. (1995), Does the Liquidity of a Debt Issue Increase with Its Size? Evidence from the Corporate Bond and Medium-Term Note Markets. *Journal of Finance* 50: 1719-1734.

CREDIT SUISSE FINANCIAL PRODUCTS. (1997). Credit Risk Plus. Technical Document. (London/New York).

CROUHY, M., GALAI, D. and MARK. R. (2000). A Comparative Analysis of Credit Risk Models. *Journal of Banking and Finance* 24: 59-117.

CUMBY, R.E. and EVANS, M. (1997). The Term Structure of Credit Risk: Estimates and Specification Tests. Georgetown University Working Paper.

DALE, R.S. and. THOMAS, S.H. (1991). The Regulatory Use of Credit Ratings in International Financial Markets. *Journal of International Securities Markets* March: 9-18.

DAMODARAN, A. (1985). Economic Events, Information Structure and the Return-generating Process. *Journal of Financial and Quantitative Analysis* 20: 423-434.

DANIELS, H., KAMP, B., and VERKOOIJEN, W. (1997). Application of Neural Networks to House Pricing and Bond Rating, Discussion Paper No. 96, Center for Economic Research, Tilburg University.

DAS, S. (1998). Credit Derivatives. (Singapore: John Wiley & Sons,)

DAS, S. (1998). Valuation and Pricing of Credit Derivatives. In: Credit Derivatives, ed. By S. Das, (Singapore: John Wiley & Sons).

DAS, S. and TUFANO, P. (1995). Pricing Credit-Sensitive Debt when Interest Rates, Credit Ratings and Credit Spreads are Stochastic. Harvard Business School Working Paper.

DEAKIN, E. (1972). A Discriminant Analysis of Predictors of Business Failure. *Journal of Accounting Research* Spring: 167-179.

DE ALMEIDA, C., DUARTES, A.M., AUGUSTO, C. and FERNANDES, C. (1998). Decomposing and simulating the movements of term structures of interest rates in emerging Eurobond markets. *The Journal of Fixed Income* 8 (1): 21-31.

DEGENNARO, R.P. and SHRIEVES, R.E. (1997). Public Information Releases, private information arrival and volatility in the foreign exchange market. *Journal of Empirical Finance* 4: 295-315.

DICHEV, I.D. and PIOTROSKI, J.D. (1998). The Long-Run Stock returns Following Bond Rating Changes. University of Michigan Working Paper.

DIEBOLD, F. (1997). Converting 1-day volatility to h-day volatility:scaling by h is worse than you think. Wharton Financial Institution Center Working Paper n. 95-11-C.

DING, Z., GRANGER C.W.J., and ENGLE R.F. (1993).A long memory property of stock market returns and a new model. *Journal of Empirical Finance* 1: 83-106.

DUFFEE, G.R. (1996). Estimating the Price of Default Risk. Federal Reserve Board, Finance and Economics Discussion Series, 1996-29.

DUFFEE, G.R. (1998). The Relation Between Treasury Yields and Corporate Bond Yield Spreads. *Journal of Finance* 53: 2225-2241.

DUFFIE, D. and LANDO, D. (1998). Term Structures of Credit Spreads with Incomplete Accounting Information. University of Stanford and University of Copenhagen Working Paper.

DUFFIE, D. and SINGLETON, K. (1999). Modelling Term Structures of Defaultable Bonds. *Review of Financial Studies* 12: 687-720.

DUFFIE, D., SCHRODER, M. and SKIADAS, C. (1995). Recursive Valuation of Defaultable Securities and the Timing Resolution of Uncertainty. Stanford University and Northwest University Working Paper.

DUFFIE, D. and LIU, J. (1997). Floating-Fixed Credit Spreads. Stanford University Working Paper.

DUFRESNE, P.C. and SOLNIK, B. (1998). On the Term Structure of Default Premia in the Swap and Libor Markets. Working Paper.

DUTTA, S., and SHEKHAR, S. (1988). Bond Rating: A non-conservative Application of Neural Networks. The IEEE Conference of San Diego. Proceedings.

EADES, K.M. (1982). Empirical Evidence on Dividends as a Signal of Firm Value. *Journal of Financial and Quantitative Analysis* 17: 471-502.

EDERINGTON, H.L., YAWITZ J.B. and ROBERTS, B.E. (1987). The Information Content of Bond Rating. *Journal of Financial Research* 10: 211-226.

EDERINGTON, L. H. and GOH, J. C. (1998). Bond Rating Agencies and Stock Analysts: Who Knows What When? *Journal of Financial and Quantitative Analysis* 33 (4): 569-585.

EDERINGTON, L.H. and LEE J.H. (1993). How markets process information: News releases and volatility. *Journal of Finance* 48: 1161-1191.

EISENBEIS, R., and AVERY, R. (1972). Discriminant Analysis and Classification Procedures. (Lexington, Mass: Heath).

EL-JAHEL, L. (1998). Defaultable Bonds and Default Correlation. Birbeck College Working Paper, London.

ELYASIANI, E. and MANSUR, I. (1998). Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: a Garch-M model. *Journal of Banking and Finance* 22: 535-563.

ENGEL, C., and HAMILTON, J.D. (1990). Long Swings in the Dollar: are they in the Data and do Markets Know it? *American Economic Review* 80: 689-713.

EMBRECHTS, P., KLUPPELBERG, C. and MIKOSCH, T. (1997). Modelling Extremal Events. (Heidelbergh: Springer-Verlag).

ENGLE, R.F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Varianve of United Kingdom Inflation. *Econometrica* 50 (4): 987-1006.

ENGLE, R.F., LILIEN, D.M. and ROBINS, R.P. (1987). Estimating Time-Varying Risk Premia in the Term Structure: the ARCH-M Model. *Econometrica* 55 (2): 391-407.

ENGLE, R.F. and NG, V.K. (1993). Measuring and Testing the Impact of News on Volatility. *Journal of Finance* 48 (5): 1749-1778.

ENGLE R.F., NG, V.K. and ROTHSCHILD, M. (1990). Asset Pricing with a Factor ARCH Covariance Structure: Empirical Estimates for Treasury Bills. *Journal of Econometrics* 45: 213-237.

ESCRIBANO, A. and GRANGER, C.W.J. (1998). Investigating the Relationship between Gold and Silver Prices. *Journal of Forecasting* 17: 81-107.

ESHO, N., LAM, Y. and SHARPE, I.G. (1999). Choice of Financing Source and International Bond and Syndicated Loan Markets. The University of New South Wales Working Paper, 1999-05.

FABOZZI, F. J. (1993). Bond Markets, Analysis and Strategies. (New Jersey : Prentice-Hall).

FADIL, M.W. (1997). Problems with Weighted-Average Risk Ratings: a Portfolio Management View. *Commercial Lending Review*, January: 23-27.

FAIR, R.C. and MALKIEL, B.G. (1971). The Determination of Yield Differentials Between Debt Instruments of the same Maturity. *Money Credit and Banking*, November: 733-749.

FAMA, E. and FRENCH K. (1989). Business Conditions and Expected Returns on Stocks and Bonds. *Journal of Financial Economics* 25: 23-49.

FANG, H.K., LAI, S. and LAI, M. (1994). Fractal Structure in Currency Futures Price Dynamics. *The Journal of Futures Markets* 14: 169-181.

FAVERO, C.A., GIAVAZZI, F. and SPAVENTA, L. (1996). High Yields: the Spread on German Interest Rates. National Bureau of Economic Research. Working Paper 5408.

FEDERAL RESERVE BOARD (1995), Request for Comment on the Precommitment Approach for Market Risk, Docket R-0886. Washington: Board of Governors of the Federal Reserve System.

FISHER, I. (1930). The Theory of Interest: As determined by impatience to spend income and opportunity to invest it. (New York: Kelley and Millman).

FISHER, L. (1959). Determinants of Risk Premiums on Corporate Bonds. *The Journal of Political Economy* 67: 217-237.

FLANNERY, M. J. (1986). Asymmetric Information and Risk Debt Maturity Choice. *Journal of Finance* 41: 19-38.

FONS, J.S. (1987). The Default Premium and Corporate Bond Experience. *The Journal of Finance* 42: 81-97.

FONS, J.S. (1994). Using Default Rates to Model the Term Structure of Credit Risk. *Financial Analyst Journal* Sept-Oct.: 25-32.

FRANKFURTER, G.M. and MCGOUN, E.G. (1993). The Event-Study: An Industrial Strenght Method. *International Review of Financial Analysis* 2: 121-141.

FRENCH, K.R. and ROLL, R. (1986). Stock Return Variances: The Arrival of Information and the Reaction of Traders. *Journal of Financial Economic* 17: 5-26.

FRIDSON, M. S. and JÓNSSON, J. G. (1995). Spread versus Treasuries and the riskiness of high-yield bonds. *Journal of Fixed Income* December: 79-88.

GESKE R. (1977). The Valuation of Corporate Liabilities as Compound Options. *Journal of Financial and Quantitative Analysis* 12: 541-552.

GLOSTEN, L., JAGANNATHAN, R., and RUNKLE, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance* 48: 1779-1801.

GOH, J.C. and EDERINGTON, L.H. (1993). Is a Bond Rating Downgrade Bas News, Good News, or No News for Stockholders? *The Journal of Finance* 48: 2001-2008.

GOLDMAN, D. (1998). Corporate Bonds: some Lessons from Past Crises and Recoveries. *Global Strategy and Asset Allocation*. Credit Suisse First Boston, October: 13-16

GONZALO, J. (1994). Five Alternative Methods of Estimating Long-run Equilibrium Relationship. *Journal of Econometrics* January: 203-233.

GOODHART, C.A.E., HALL S.G., HENRY, S.G.B. and PESARAN, B. (1993). News Effects in a High-Frequency Model of the Sterling-dollar Exchange Rate. *Journal of Applied Econometrics* 8: 1-13.

GRAHAM, B., DODD, D.L. and COTTLE, S. (1962). Security Analysis, Principles and Techniques. New York: McGraw-Hill.

GRANGER, C.W.J. and HALLMAN, J.J. (1991). Long-Memory Processes with Attractor. *Oxford Bulletin of Economics and Statistics* 53: 11-26.

GREENE, W. H. (1997). Econometric Analysis. 3rd edition. Prentice-Hall.

GRIER, P. and KATZ, S. (1976). The Differential Effects of Bond Rating Changes among Industrial Public Utility Bonds by Maturity. *Journal of Business* 49: 226-239.

GRIFFIN, P. and SANVINCENTE, A. (1982). Common Stock Returns and Rating Changes: A Methodological Comparison. *Journal of Finance* 37: 103-119.

GROSSMAN, R.J., BRENNAN, W.T., and VENTO, J. (1998). Syndicated Bank Loan Recovery Study. CreditMetrics Monitor (First Quarter): 29-36.

GUJARATI, D. (1970). Use of Dummy Variables in Testing for Equality between Sets of Coefficients in Two Linear Regressions: A Note. *American Statistician* 24: 50-52.

GUMERLOCK, R. (1996). Lacking commitment. *Risk* 9 (June): 36-39.

HAEFKE, C. and HELMENSTEIN, C. (1996). Forecasting Austrian IPO: an Application of Linear and Neural Network Error-Correction Models. *Journal of Forecasting* 15: 237-251.

HAMILTON, J.D. (1988). Rational-Expectations Econometric Analysis of Changes in Regime: an Investigation of the Term Structure of Interest Rates. *Journal of Economic Dynamics and Control* 12: 385-423.

HAMILTON, J.D., and SUSMEL, R. (1994). Autoregressive Conditional Heteroskedasticity and Changes in Regime. *Journal of Econometrics* 64: 307-333.

HAND, J., HOLTHAUSEN, R. and LEFTWICH, R. (1992). The Effect of Bond Rating Agency Announcements on Bond and Stock Prices. *Journal of Finance* 47: 733-752.

HAROLD, G. (1938). Bond Ratings as an Investment Guide. New York: The Ronald Press Co.

HARRIS, M., and RAVIV, A. (1991). The Theory of Capital Structure. *Journal of Finance* 46: 297-355.

HARVEY, A.C. (1989). Forecasting Structural Time Series Models and the Kalman Filter. Cambridge, UK: Cambridge University Press.

HAUSMAN, J.A., LO, A.W., and MACKINLAY, A. C. (1992). An Ordered Probit Analysis of Transaction Stock Prices. *Journal of Financial Economics* 31: 319-379.

HAYES, D.A. 1(956). Appraisal and Management of Securities. New York: MacMillan Co.

HAUSER, M.A. and KUNSTER, R.M. (1994). Fractionally Differenced Models with ARCH Errors. Memo. Johannes Kepler University Linz. Vienna, Austria.

HELWEGE, J. and TURNER, C. M. (1999). The Slope of the Credit Yield Curve for Speculative-Grade Issuers. *Journal of Finance* 54: 1869-1884.

HESTON, S. L. and ROUWENHORST, K. G. (1994). Does industrial structure explain the benefits of international diversification?. *Journal of Financial Economics* 36 (1): 3-27.

HETTENHOUSE, G. and SARTORIS, W. (1976). An Analysis of the Information Value of Bond Rating Changes. *Quarterly Review of Economics and Business* 16: 5-78.

HICKMAN, W.B. (1958). Corporate Bond Quality and Investor Experience. Princeton University Press.

HIGGINS, M. L. and BERA, A. K. (1992). A Class of Nonlinear ARCH Models. *International Economic Review* 33 (1): 137-158.

HITE, G. and WARGA, A. (1997). The Effect of Bond rating Changes on Bond Price Performance. *Financial Analyst Journal* May/June: 35-51.

HOLTHAUSEN, R. and LEFTWICH, R. (1986). The Effect of Bond Rating Changes on Common Stock Prices. *Journal of Financial Economics* 17: 7-89.

HOMA, K.E. and JAFFEE, D.M. (1971). The supply of Money and Common Stock Prices. *Journal of Finance* December: 1056-1066.

HORRIGAN, J.O. (1966). The Determination of Long-Term Credit Standing with Financial Ratios, Empirical Research in Accounting, *Journal of Accounting Research* 4 (suppl): 44-62.

HOSMER, D.W. Jr., and LEMESHOW, S. (1989). Applied Logistic Regression, John Wiley & Sons.

HOTCHKISS, E.S. and RONEN, T. (1999). The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis. Working Paper, November.

http://www.standardpoor.com/ratings/

HULL, J. and WHITE, A. (1995). The Impact of Default Risk on the Prices of Options and Other Derivative Securities. *Journal of Banking and Finance* 19: 299-322.

HURST, H.E. (1951). Long-Term Storage Capacity of Reservoirs. *Transactions of the American Society of Civil Engineers* 116: 770-799.

INGRAM, R., BROOKS, L. and COPELAND, R. (1983). The Information Content of Bond Rating Changes: A Note. *Journal of Finance* 38: 997-1003.

ITO, T. and ROLEY, V.V. (1987). News from the US and Japan: Which Moves the Yen/Dollar Exchange Rate? *Journal of Monetary Economics* 19: 255-277.

IZVORSKY, I. (1997). Recovery Ratios and Survival Times for Corporate Bonds. IMF Working Paper WP/97/84.

J.P. MORGAN (1997). CreditMetrics. New York. Technical Document, April.

JACKSON, P. and PERRAUDIN, W. (1999). The nature of credit risk: the effect of maturity, type of obligor, and country of domicile. The Bank of England, Financial Stability Review, November.

JAFFEE, D. (1975). Cyclical Variations in the Risk Structure of Interest rates. *Journal of Monetary Economics* 1: 309-325.

JARROW, R. and TURNBULL, S. (1995). Pricing Options on Financial Securities Subject to Credit Risk. *Journal of Finance* 50: 53-85.

JARROW, R. and TURNBULL, S. (1997). A Markow Model for the Term Structure of Credit Risk Spreads. *Review of Financial Studies* 10: 481-523.

JARROW, R. and TURNBULL, S. (2000). The Intersection of Market and Credit Risk. *Journal of Banking and Finance* 24: 271-299.

JARROW, R., LANDO, D. and TURNBULL, S.M. (1997). A Markov Model for the Term Structure of Credit Spreads. *The Review of Financial Studies* 10: 481-523.

JAYARAMAN, N. and SHASTRI, K. (1993). The Effects of the Announcements of Dividend Increases on Stock Return Volatility: The Evidence from the Option Market. *Journal of Business, Finance and Accounting* 20: 673-685.

JENSEN, F.V. (1996). An Introduction to Bayesian Networks. London: UCL press.

JENSEN, H.L. (1992). Using Neural Networks for Credit Scoring. *Managerial Finance* 18: 15-26.

JOHNSON, R.E. (1967). Term Structures of Corporate Bond Yields as a Function of Risk of Default. *Journal of Finance* May: 313-345.

JONES, E.P., MASON, S.P. and ROSENFELD, E. (1984). Contingent Claims Analysis of Corporate Capital Structures: an Empirical Investigation. *Journal of Finance* 39: 611-627.

JONES, C.M., KAUL, G. and LIPSON, M.L. (1994). Information, Trading and Volatility. *Journal of Financial Economics* 36: 127-154.

JONKHART, M.J.L. (1979). On the Term Structure of Interest Rates and the Risk of Default: an Analytical Approach. *Journal of Banking and Finance* 3: 253-261.

JUDD, J.P and SCADDING, J.L. (1981). Liability management, bank loans and deposit "market" disequilibrium. *Economic Review* Summer: 21-44.

KAMIN, S. B. and VON KLEIST, K. (1999). The Evolution and Determinants of Emerging Market Credit Spreads in the 1990s. Bank for International Settlements, Working Paper No. 68.

KAN, K. (1998). Credit Spreads on Government Bonds. *Applied Financial Economics* 8: 301-313.

KAO, D. (2000). Estimating and Pricing Credit Risk: an Overview. *Financial Analysts Journal* July/August: 50-66.

KAO, C. and WU, C. (1990). Two-step Estimation of Linear Models with Ordinal Unobserved Variables: The Case of Corporate Bonds. *Journal of Business and Economic Statistics* 8: 317-325.

KAPLAN, R. S. and URWITZ, G. (1979). Statistical Models of Bond Ratings: A Methodological Inquiry. *Journal of Business* 52: 231-261.

KARAGIANNIS, E. (1994). Credit Spreads and Fair Value in the Corporate Market. *Financial Analysts Journal* July-August: 55-62.

KATZ, S. (1974). The Price Adjustment Process of Bonds to Rating Reclassifications: A Test of Bond Market Efficiency. *Journal of Finance* 29: 551-563.

KAUFOLD, H. and SMIRLOCK, M. (1991). The Impact of Credit Risk on the Pricing and Duration of Floating-Rate Notes. *Journal of Banking and Finance* 15: 43-52.

KIESEL, R., PERRAUDIN, W., and TAYLOR, A. (1999). The structure of credit risk. Technical report: Birkbeck College.

KIM, J., RAMASWAMY, K. and SUNDARESAN, S. (1993). Does Default Risk in Coupons Affect the Valuation of Corporate Bonds? A Contingent Claims Model. *Financial Management* Autumn: 117-131.

KIM, Y.C. and STULZ, R. M. (1989). The Eurobond Market and Corporate Financial Policy: A Test of the Clientele Hypothesis. *Journal of Financial Economics* 22: 189-225.

KIM, J.W., WEISTROFFER, H.R., and REDMOND, R.T. (1993). Expert Systems for Bond Rating: A Comparative Analysis of Statistical, Rule-Based and Neural Network Systems. *Expert Systems* 10: 167-188.

KLIGER, D. and SARIG, O. (1999). The Information Value of Bond Ratings, Working Paper.

KMV (1993). Portfolio Management of Credit Risk. San Francisco: KMV Corporation.

KOUTMOS, G. (1998). The Volatility of Interest rates across maturities and frequencies. *The Journal of Fixed Income* December: 27-31.

KUBEREK, R. C. (1992). Predicting Interest Rate Volatility: A Conditional Heteroskedastic Model of Interest Rate Movements. *The Journal of Fixed Income* March: 21-27.

KUPIEC, P. and O'BRIEN, J. (1997). The Pre-commitment approach: using incentives to set market risk capital requirements. Washington: Board of Governors of the Federal System, 1997-14.

LACHENBRUCK, P. (1975). Discriminant Analysis. Hafner Press. New York.

LAMOREUX, C. and LASTRAPES, W. (1990). Heteroskedasticity in Stock Return Data: Volume versus GARCH effects. *Journal of Finance* 45: 221-229.

LANDO, D. (1995). On Cox Processes and Credit Risky Bonds. Institute of Mathematical Statistics, University of Copehangen.

LEE, C.J. (1981). The Pricing of Corporate Debt: A Note. *Journal of Finance* December: 1187-1189.

LELAND, H. (1994). Corporate Debt Value, Bond Covenants, and Optimal Capital Structure. *Journal of Finance* 49: 1213-52.

LELAND, H.E. and TOFT, K.B. (1996). Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads. *The Journal of Finance* 51 (3): 987-1019.

LEVIN, R. (1997). Challenges of Managing Credit Portfolios. J.P. Morgan Securities, Inc.

LITTERMAN, R. and IBEN, T. (1991). Corporate Bond Valuation and the Term Structure of Credit Spreads. *The Journal of Portfolio Management* 17: 52-64.

LIU, P. and THAKOR, A. (1984). Interest Yields, Credit Ratings and Economic Characteristics of State Bonds: An Empirical Analysis. *Journal of Money, Credit and Banking* 16: 344-351.

LO, A.W. (1991). Long-Term Memory in Stock Market Prices. *Econometrica* 59: 1279-1313.

LOBATO, I.N. and SAVIN, N.E. (1996). Real and Spurious Long Memory Properties of Stock Market Data. Working Paper, University of Iowa.

LONGSTAFF, F.A. and SCHWARTZ, E.S. (1995a). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *Journal of Finance* 50: 789-819.

LONGSTAFF, F.A. and SCHWARTZ, E.S. (1995b). Valuing Credit Derivatives. *Journal of Fixed Income* 51: 6-12.

LUCAS, R. (1978). Asset Prices in an Exchange Economy. *Econometrica* 46: 1429-1445.

MA, C.K., RAO, R.P. and PETERSON, R.L. (1989). The Resiliency of the High Yield BondMarket: the LTV Default. *Journal of Finance* 44: 1085-1097.

MADAN, D. and UNAL, H. (1995). Pricing the Risks of Default. Working paper, University of Maryland.

MAHAJAN, A. and FRASER, D.R. (1986). Dollar Eurobond and U.S. Bond Pricing. *Journal of International Business Studies* 17 (2): 21-36.

MALITZ, I. (1994). The modern role of bond covenants. The Research Foundation of the Institute of Chartered Financial Analysts, Virginia.

MARKELLOS, R.N. (1998). A Methodology for Nonlinear Cointegration with an Application in Forecasting Using the Gilt-Equity Ratio. Working Paper, Loughborough University, Leics.

MARCUS, A. J. (1989). An Equilibrium Theory of Excess Volatility and Mean Reversion in Stock Market Prices. National Bureau of Economic Research, Working Paper no. 3106.

MARTIN, M. (1997). Credit Risk in Derivative Products. PhD thesis: London Business School, University of London.

MASON, S.P. and BHATTACHARYA, S. (1981). Risky Debt, Jump Process, and Safety Covenants, *Journal of Financial Economics* 9 (81): 281-307.

MATOLCSY, Z. P. and LIANTO, T. (1995). The Incremental Information Content of Bond Rating Revisions. *The Australian Evidence Journal of Banking and Finance* 19: 891-902.

MCCARTHY, J. and MELICHER, R.W. (1988). An Empirical Analysis of Bond Rating Changes in a Portfolio Context. *Quarterly Journal of Business and Economics* Autumn: 69-86.

MCKELVEY, R., and ZAVOINA, W. (1975). A Statistical Model for the Analysis of Ordinal Level Dependent Variables. *Journal of Mathematical Sociology* 4: 103-120.

MCKINSEY and Co. (1997). Credit Portfolio View. New York: McKinsey and Co.

MELLA-BARRAL, P. and TYCHON, P. (1996). Default Risk in Asset Pricing, Working Paper, London School of Economics, London.

MENDELSON, M. (1972). The Eurobond and Capital Market Integration. *Journal of Finance* 27: 110-126.

MERTON, R.C. (1973). Theory of Rational Option Pricing. *Bell Journal of Economics and Management Science* 4: 141-183.

MERTON, R.C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance* 2: 449-469.

MERTON, R.C. (1980). On Estimating the Expected Return on the Market: an Explanatory Investigation, *Journal of Financial Economics* 8: 323-361.

MERRICK, J.J. (1999). Crisis Dynamics of Implied Default Recovery Ratios: Evidence from Russia and Argentina, Stern School Finance Department Working Paper Series.

MIN, H.G. (1998). Determinants of Emerging Market Bond Spreads - Do Economic Fundamentals Matter? The World Bank, Policy Research Paper No. 1899.

MITCHELL, M.L. and MULHERIN, J.H. (1994). The Impact of Public Information on the Stock Market. *Journal of Finance* 49: 923-950.

MOODY, J. (1994). Architecture Selection Strategies for Neural Networks: Application to Corporate Bond Rating Prediction. Neural Networks in the Capital Market, John Wiley, New York.

MOODY'S INVESTOR SERVICE (1995). Moody's Credit Ratings and Research, New York.

MOODY'S INVESTORS SERVICE (1996). Corporate Bond Defaults and Default Rates.

MORRIS, C., NEAL, R. and ROLPH, D. (1998). Credit Spreads and Interest Rates: A Cointegration Approach. The Federal Reserve Bank of Kansas City, Working Paper.

NELSON, D.B. (1990). Stationarity and Persistence in the GARCH (1,1) Model. In: ARCH Selected Readings, ed. by R.F. Engle, 1995, Oxford University Press.

NELSON, J. and SCHAEFER, S. (1983). The Dynamics of the Term Structure and Alternative Portfolio Immunization Strategies. In: Innovations in Bond Portfolio Management: Duration Analysis and Immunization, ed. by G.O. Bierwag, G.G. Kaufman, and A. Toevs (Greenwich, CT: JAI Press).

NICKELL, P., PERRAUDIN, W. and VAROTTO, S. (1998). Ratings-Versus Equity-Based Credit Risk Models: An Empirical Investigation. Bank of England Working Paper No. 132.

NICKELL, P., PERRAUDIN, W. and VAROTTO, S. (2000). Stability of rating transitions. *Journal of Banking and Finance* 24: 203-227.

NIELSEN, L., SAA'-REQUEJO, J. and SANTA-CLARA, P. (1993). Default Risk and Interest Risk: The Term Structure of Default Spreads. Working Paper, INSEAD.

PAGAN, A.R. and SCHWERT, G.W. (1990). Alternative Models for Conditional Stock Volatility. *Journal of Econometrics* 45: 267-290.

PAGAN, A. R., HALL, A. D. and MARTIN, V. (1996). Modeling the term structure. In Handbook of Statistics, Vol. 14, ed. by G.S. Maddala and C.R. Rao.

PAGAN, A.R. and SABAU, H. (1987). Consistency Tests for Heteroskedastic and Risk Models. Unpublished Manuscript, University of Rochester, Rochester, NY.

PAGAN, A. (1996). The Econometrics of Financial Markets. *Journal of Empirical Finance* 3: 15-102.

PATEL, J.B., EVANS, D.A. and BURNETT, J.E. (1998). Junk Bond Behaviour with Daily Returns and Business Cycles. *Journal of Financial Research* 21: 407-418.

PEDROSA, M. and ROLL, R. (1998). Systematic Risk in Corporate Bond Credit Spreads. *The Journal of Fixed Income* December: 7-26.

PERRAUDIN, W. and TAYLOR, A. (1999). On the Consistency of Bond Spreads and Ratings. Unpublished Birkbeck College mimeo.

PHILLIPS, P.C.B. and PERRON, P. (1988). Testing for a Unit Root in Time Series Regression. *Biometrika* 75: 335-346.

PHOA, W. (1999). Estimating Credit Spread Risk Using Extreme Value Theory. *The Journal of Portfolio Management* Spring: 69-73.

PINCHES, G. and SINGLETON, K. (1978). The Adjustment of Stock Prices to Bond Rating Changes. *Journal of Finance* 33: 29-44.

PINCHES, G. and MINGO, K. (1973). A Multivariate Analysis of Industrial Bond Ratings. *Journal of Finance* 28: 1-18.

PITTS, C.G. and SELBY, M.J. (1983). The Pricing of Corporate Debt: a Further Note. *Journal of Finance* 38: 1311-1313.

POGUE, T., and SOLDOFSKY, R. (1969). What's in a Bond Rating?. *Journal of Financial and Quantitative Analysis* 4: 201-228.

POTERBA, J.M. and SUMMERS, L.H. (1988). Mean Reversion in Stock Prices: Evidence and Implications. *Journal of Financial Economics* October, 22: 22-59.

PYE, G. (1974). Gauging the Default Premium. *Financial Analyst Journal* Jan-Feb: 49-52.

RAMASWAMY, K. and SUNDARESAN, S.M. (1986). Valuation of Floating Rate Instruments. *Journal of Financial Economics* 17: 251-272.

RENDLEMAN, R. (1993). How Risks are Shared in Interest Rate Swaps? *The Journal of Financial Services Research* 7: 5-34.

ROBERTS, G.S. and VISCIONE, J.A. (1984). The Impact of Seniority and Security Covenants on Bond Yields: a Note. *Journal of Finance* 39: 1597-1360.

ROBINSON, R.I. (1960). Postwar Market for State and Local Government Securities. Princeton University Press.

ROMA, A. and TOROUS, W.N. (1993). The Cyclical Behavior of Interest Rates. Unplished manuscript.

ROSS, S.A. (1989). Information and Volatility: The no-Arbitrage Martingale Approach to Trading and Resolution Irrelevancy. *Journal of Finance* 44: 1-18.

RUBENSTEIN, M. (1976). The Valuation of Uncertain Income Streams and the Pricing of Options. *Bell Journal of Economics and Management Science* 7: 407-425.

RUMELHART, D., HINTON, G., and WILLIAMS, R. (1986). Learning Representations by Backpropagation Error. *Nature* 323: 533-536.

SAID, S.E. and DICKEY, D.A. (1994). Testing for Unit Roots in Autoregressive Moving Average Models of Unknown Order. *Biometrika* 71: 599-607.

SARIG, O. and WARGA, A. (1989). Some Empirical Estimates of The Risk Structure of Interest Rates. *Journal of Finance* Dec.: 1351-1360.

SAUNDERS, A. (1999). Credit Risk Measurement. John Wiley & Sons.

SCHOLTENS, B. (1999). Bond Yield Spreads and Country Risk, University of Groningen Working Paper.

SCHONBUCHER, P. (1998). The Term Structure of Defaultable Bond Prices. *Review of Derivative Securities*. Special Issue: Credit Risk.

SHARPE, W. F. (1990). Investor Wealth Measures and Expected Return. In: QUANTIFYING THE MARKET RISK PREMIUM PHENOMENON FOR INVESTMENT DECISION MAKING. Proceedings. The Institute of Chartered Financial Analysis.

SHIMKO D., TEJIMA, N. and van DEVENTER, D. (1993). The Pricing of Risky Debt when Interest rates are Stochastic. *The Journal of Fixed Income* 3: 58-65.

SHULMAN, J.M., BAYLESS, M. and PRICE, K. (1993). Marketability and Default Influences on the Yield Premia of Speculative Grade Debt. *Financial Management* Autumn.

SILVERS, J.B. (1973). An Alternative to the Yield Spread as a Measure of Risk. *Journal of Finance* 28: 933-955.

SOBEHART, J.R., KEENAN, S.C., and STEIN, R.M. (2000). Benchmarking Quantitative Default Risk Models: a Validation Methodology. Moody's Investor Service. Global Credit Research, March.

SOLNIK, B. (1990). Swap pricing and Default Risk: a Note. *Journal of International Financial Management and Accounting* 2: 79-91.

STANDARD and POOR'S (1997). Standard and Poor's Rating Performance 1996.

STANDARD and POOR'S (1999a). Ratings Performance 1998: Stability and Transition. March.

STANDARD and POOR'S (1999b). Sovereign Versus Corporate Ratings Stability. CreditWeek, 29: 9-13 September.

STEIN, J. (1998). The Integration of Market and Credit Risk Measurement. *Financial Engineering News* 7, November.

SUNDARESAN, S.M. (2000). Continuous-Time Methods in Finance: A Review and an Assessment. *Journal of Finance* 54: 1569-1622.

SURKAN, A., and YING, X. (1991). Bond Rating Formulas Derived through Simplifying a Trained Neural Networks. In: 1991 IEEE INTERNATIONAL JOINT CONFERENCE ON NEURAL NETWORKS. Proceedings 2: 1566-1570.

SWHWERT, G.W. and SEGUIN, P.J. (1990). Heteroskedasticity in Stock Returns. *Journal of Finance* 45: 1129-1155.

THEIL, H. (1971). Principles of Econometrics. (New York: Wiley).

TURNBULL, S.M. (1979). Debt Capacity. *Journal of Finance* 34: 931-940.

VASICEK, O. (1977). An Equilibrium Characterisation of the Term Structure. *Journal of Financial Economics* 5: 177-188.

WAKEMAN, L. (1978). Bond Rating Changes and the Capital Markets, Working Paper, University of Rochester, Rochester, NY.

WAKEMAN, L. (1984). The Real Function of Bond Rating Agencies, in: The Modern Theory of Corporate Finance, ed. by M. Jensen and C. Smith (New York: McGraw-Hill).

WANSLEY, J. and CLAURETIE, J. (1985). The Impact of Credit Watch Placement on Equity Returns and Bond Prices. *Journal of Financial Research* 8: 31-42.

WANSLEY, J., GLASCOCK, J.L. and CLAURETIE, T.M. (1992). Institutional Bond Pricing and Information Arrival: the Case of Bond Rating Changes. *Journal of Business Finance and Accounting* 19: 733-750.

WEI, D.G. and GUO, D. (1997). Pricing Risky Debt: An Empirical Comparison of the Longstaff and Schwartz and Merton Models. *The Journal of Fixed Income* Sept.: 8-28.

WEINSTEIN, M. (1977). The Effect of a Rating Change Announcement on Bond Price. *Journal of Financial Economics* 5: 329-350.

WEISS, A.A. (1984). ARMA Models with ARCH Errors. *Journal of Time Series* 5: 129-143.

WEST, R. (1970). An Alternative Approach to Predicting Bond Ratings. *Journal of Accounting Research* 7: 118-127.

WEST, R. (1973). Bond Ratings, Bond Yields and Financial Regulation: Some Findings. *Journal of Law and Economics* 16: 159-168.

WHITE, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity. *Econometrica* 48: 817–838.

WHITE, H. (1982). Maximum Likelihood Estimation of Misspecified Models. *Econometrica* 50: 1-26.

WILSON, T. (1997). Portfolio Credit Risk. *Risk* 10 (9): 111-117.

YAWITZ, J.B. (1977). An Analytic Model of Interest Rate Differentials and Different Default Recoveries. *Journal of Financial and Quantitative Analysis*, September: 481-490.

ZAKOIAN, J. (1991). Threshold Heteroskedastic Model. Unpublished Manuscript, INSEE.

ZHOU, C. (1997). A Jump Diffusion Approach to Modeling Credit Risk and Valuing Defaultable Securities. Working Paper, Federal Reserve Board.