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" Credit Risk Measurement & Modelling "

by

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Research Thesis for the Fulfilment of the Requirement for the Degree of

Doctor of Philosophy

Department of Finance

Cass Business School

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Acknowledgements

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Abstract

This thesis aims to make a contribution to the understanding of the key economic and company specific components of credit spreads in the investment and non-investment grade US bond market for different maturing bond indices. It calls for the full integration of different market and firm specific variables into a unique framework, in order to predict credit spread changes. Key determinants of default risk are employed to determine credit migration risk.

Particularly, this thesis provides evidence as to the relation between different macroeconomic factors and credit spread changes in all different maturities and rating categories, it supports the use of the consumer confidence index, as the most important variable explaining changes in credit spreads in investment and high yield companies, but most importantly it provides support for the strong informational content of high yield spreads as predictors of output growth, based on Option Adjusted Spreads. It favours the inclusion of implied volatilities in explaining credit spread changes, while it criticises the incorporation of historical ones. Throughout the thesis, it becomes evident that BBB-rated bonds exhibit highly volatile patterns and are very difficult to model.

Financial ratios adjusted to reflect depreciation and amortisation expenses, which are usually very high for non-investment grade companies, prove to be very important in explaining changes of high yield spreads. However, firm specific risk, accounts only for a small fraction of the variation in the investment grade category. Ultimately, it is shown that by using solely market (equity and macro variables) and firm specific variables, i.e. some of the key determinants of default risk and the price of credit risky debt in most Merton-type models, we can accurately forecast credit spread changes at least one year ahead, particularly based on results provided from the investment grade sample. Moreover, credit spread forecasts, based on our set of OAS, tend to be overestimated rather than underestimated, as opposed to results provided by previous studies. This makes forecasts more conservative and therefore more appealing for risk management purposes.

In particular, this thesis is focused on the main drivers of credit spread movements in the US corporate bond market. There are four issues mainly considered.

The first part of the thesis examines a question that is a point of central focus in the fixed income literature, i.e. the relation between credit spread changes and the macroeconomic cycle. This chapter is inspired by the relatively little work that has been done on the empirical relationship between credit spread changes and the macroeconomy, since most of the literature on this issue focuses on macroeconomic variables and the modelling of default risk. We investigate how this relation evolves, not only with respect to short, medium and long term maturities but also for investment and non-investment rated companies, by testing the direction of causation among economic variables and credit spreads and by employing different sets of data and estimation techniques to explore the relation. We find that irrespective of the statistical method used or the time period tested that the most important variable in explaining the variation of credit spread changes is the US Consumer Confidence Index. We affirm the negative relation between the consumer confidence index, money supply and changes in credit spreads but not for the variables of GDP and industrial production. The negative relation between the term structure and credit spreads is also asserted for investment grade bonds of all maturities, consistent with the structural model's theory, while we find this relation to be positive for non-investment grade companies. Results from the OLS regressions suggest that macroeconomic variables alone, can explain at best a 17% of the variation in medium and long term maturing indices, and a 20.5% in short term indices. Findings from cross sectional regressions suggest that macroeconomic factors alone can explain 27.9% of the variation in credit spreads for investment grade bonds and a 44.4% for high yield ones. When testing the direction of causation, we find that for long and medium term maturity investment grade indices we reject the null hypothesis that macroeconomic variables don't granger cause changes in credit spreads, but not for short term maturities and the high yield sector. Indeed, results provided on that respect from the high yield category, provide evidence that non-investment grade spreads may be a good proxy for predicting/estimating overall financial conditions.

Secondly, the relation between credit spreads and equities together with their implied and historical volatilities is examined. This chapter constitutes an effort to fill the gap in the existing literature, which has focused mainly on bond returns or yield changes, while very limited work has been done in modelling credit spread changes.

Empirical evidence points out to the fact that debt markets not only in the US but also in Europe and elsewhere seem to be greatly affected by the movements in the equity markets. If that is the case we should expect changes in equity prices to affect changes in credit spreads. This assumption is tested on a cross sectional and time series basis, for quarterly and monthly frequencies and by using company specific equity prices against the respective credit spreads, but also by including equity and volatility indices. We find that there is a negative relation between credit spread and equity changes, irrespective of maturity or rating category. Results provided by univariate regressions, based on changes in equity prices alone, explain half of the variation of B-rated corporate spreads. Results affirm the positive relation between implied volatilities and their high explanatory power on credit spread changes while findings derived from historical volatilities although statistically significant don't even marginally support the hypothesis of explaining the variation in credit spreads. In particular, results from pooled regressions suggest that when implied volatilities are substituted for the historical ones, adjusted R^2s fell to 6% and 28% for the investment and non-investment grade samples respectively (from 25% and 50.3% for investment and non-investment grade companies, when implied volatilities are considered). Results from OLS regressions, suggest that equity variables explain at best a 44% for short term maturing indices, and 35% and 37% for medium and long term maturing indices as reflected by the adjusted R^2s. We also strongly reject the null hypothesis that implied volatilities don't granger cause changes in credit spreads but only with regards to short and medium term maturities.

The next chapter of the thesis focuses on how changes in a company's financials, as those are presented by ratios, actually influence changes in credit spreads. The reason for including this chapter is due to the fact that although traditional ratio analysis has been widely investigated, it has mainly been tested within the context of default risk, while very limited literature exists on the use of traditional credit risk analysis in determining credit spread changes. Cross sectional analysis is employed in this chapter to test the hypothesis that credit spread changes are influenced by changes in accounting factors, both in investment and high yield categories. On a multivariate basis, we find that 63.5% of the variation in high yield credit spreads is explained by the changes in financial ratios, as reflected by the adjusted R^2, compared to an adjusted R^2 of 19.2% for investment grade companies. Consistently, *in the randomly selected group of companies, we find that traditional ratios can explain one third of the variation in credit spreads in the high yield sector, although less than 10% in the investment grade sample. A reason for the higher explanatory power in the high yield sector entails the use of ratios adjusted, to reflect depreciation and amortisation expenses, which hasn't been considered before. The most statistically and economically significant coefficient was obtained from the current market capitalisation, which was used as a proxy for the firm's size.*

The last part of the thesis, constitutes an effort to combine all the above factors (macroeconomic, equity and financials), in order to forecast credit spread changes one and two years ahead. We show that on a multiple regression context, results provided are consistent with previous chapters and indeed highly significant in explaining credit spread variation, irrespective of the time period tested. For the total sample we get an adjusted R^2 *of 95% or 52% as part of the weighted and unweighted statistics respectively. A robust model is identified for forecasting credit spread changes one year ahead, with the employment of the dynamic solution method. The accuracy of the model doesn't fall below 85% within the first year, while we choose as the most vigorous method for estimating coefficients the GLS method adjusted for heteroscedasticity, since it consistently provides more conservative forecasts.*

1.0. Introduction
1.1. Motivation for this study

Over the past twenty years a significant number of important changes have been made in the credit risk and credit management area. The reasons for these developments are basically considered to be:

a. Rise in Credit Risk. Most bankruptcy statistics show a significant increase in the number of bankruptcies[1], some of which are attributed to the increased competition. The same forces that are driving market growth are also affecting the credit quality of issuers. Additionally, financial engineering is creating new types of securities which are often complicated. As a result, more resources should be committed to credit risk analysis, not only in order to weight the relative risk of default, *but also and most importantly to monitor and forecast changes in credit risk over time*. The role of credit analysis is increasingly becoming time sensitive, since the value of a debt security must be continuously evaluated according to the current market value, and quickly adjusted for any changes in the credit quality that may have a direct impact on secondary market prices.

b. Rating agencies responses. Following the 1998 Asian crisis and the general rise in credit spread levels, it became apparent, that credit ratings are not always consistent with the issuer's credit quality. There have been a number of defaulted issuers, whose ratings at the time were not suggesting an immediate default. This effectively poses numerous concerns about the timing and credit sensitivity to which credit agencies respond to credit quality issues.

c. More competitive margins. Interest margins and spreads tend in some periods to become very thin despite a decline in the average credit quality of loans and/or bonds. This is the result of increased competition. In terms of the competitive interest margins, this is the outcome of the increased supply of loans and the increasing number of smaller banks which are providing their services at a

[1] According to Moody's study of default rates of corporate bond issuers from 1985-2004, annual corporate default rates peaked in 2002 in Europe and in 2001 in the US while they have declined quite sharply during 2003 and 2004. In particular, in US, the number of defaulted issuers, according to Moody's definition of default, reached 155 in 2001 which represents a 42% increase from 2000 and a

discount, while on the credit spread front; this is the result of an increasing number of new issue of bonds of particular rating categories and of specific maturities.

d. Privatisation. Continuing privatisation of state-owned companies together with their need to fund their capital requirements in the public markets, effectively increases the number of potential issuers. This means that there is increased appetite for debt instruments, which in some instances have to be tailor made in order to meet the customer's needs. This increased demand for debt products in some instances is met by an increase in their supply, hence, there is credit spread equilibrium, while in other instances the increased demand may not always be accompanied by an increase in supply, and therefore we might end up with a tightening of credit spreads and vice versa.

e. Expansion of investment funds. It has been an increasing trend for ageing individuals (especially in Europe) to invest in the market through a pension fund or a life insurance company. Once an integrated market is established the investor will have a wider selection of investment opportunities from which to choose, and effectively most of the investment decision making process will pass on to the institutional investors. In other words, there is a move observed for people to move from a defined benefit scheme to defined contribution schemes.

f. Growth of off-balance sheet instruments. The increase of off balance sheet instruments came along with the increased demand for tailor made products to meet customer's specific needs and requirements. These instruments may be part of structured finance loans or structured bonds, and since part of them usually is off balance sheet, credit risk can't be properly managed or measured. This intrinsically increase credit risk and that was one of the main reasons for the introduction of risk based capital requirements by the Bank for International Settlements (BIS) 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.

638% increase from 1997. The respective statistics of European defaults show a 433% annual increase in 2001 and an 1600% increase from 1997.

g. Basel II framework. This imposes that all banks should develop more sophisticated credit risk management systems and strategies, in order to measure and efficiently manage credit risk and consequently has provided the strongest incentive for banks to develop new credit risk models. Up until 1992, all loans had been subject to the same 8% capital adequacy ratio, irrespective of the size of loan, its maturity and credit quality. This accord has been reviewed several times until it reached its present format, whose aim is to improve the way regulatory capital requirements reflect underlying risks. This framework introduces, three approaches, the standardised approach, the foundation internal ratings approach and the advanced internal ratings based approach for the calculation of risk weights. The ultimate goal is to reduce risk weights for high quality corporate credits, and to introduce a higher than 100% risk weight for lower quality exposures. Given that credit rating agencies are not always adjusting credit ratings on a timely basis, there is a stronger incentive for banks to develop internal credit risk systems to closely monitor and evaluate credit risk. For every bank, world wide the ultimate goal and objective is to follow the foundation or advanced internal ratings based approach for the calculation of credit risk weights. In that way, the chances that banks will be in position to calculate more accurate and potentially lower risk weights for their exposures, are higher. Another reason for the development of internal credit risk models, is that the Basel II framework, assigns more conservative (higher) risk weights for not rated corporates, hence there is increased appetite for banks to assign their own internal ratings which may provide them the opportunity to assume a better risk weight for their capital requirements. It should be mentioned though, that the costs to banks for developing and calibrating an internal credit risk model may be much higher than the capital reduction they will potentially incur, but those implications won't be further explored here since they are beyond the scope of this thesis.

As a result of the above mentioned developments academics and practitioners have responded by researching in depth the issue of credit risk management and by developing more sophisticated credit risk models. In particular, new models developed incorporate market and credit risk, quantify risk on a portfolio basis and are proved to help more active management of credit portfolios.[2]

1.1.1.Objectives and Contributions of this Thesis

Considering all the above developments, it is rather surprising that most of the empirical work in credit risk literature has focused on modelling default risk, while limited work has been done in estimating transitions in credit ratings as those are reflected in credit spread changes. Therefore, the main objective and idea behind this thesis, is to find the determinants of credit spread changes (only migration risk is considered throughout this thesis) as well as to explore the structural relation among credit spread changes, (which by default are used as proxy for credit ratings) together with a set of explanatory variables that incorporate both market and credit risk namely equity market information, US macroeconomic information and US firm specific company information. The aim is to construct a multi-factor credit risk model for estimating/predicting credit spread changes.

Additionally, this thesis constitutes an effort to combine variables used in the recently developed credit risk models and traditional credit risk analysis, into one model that can forecast changes in credit spreads. Models developed recently, based on the structural approach, suggest that this approach doesn't provide accurate forecasts. Also the literature on modelling credit spread changes has been rather thin, since most of the research work has focused on yield changes[3]. For example, hedge funds often take high leveraged positions in corporate bonds, while hedging the interest rate risk by shorting treasuries. Effectively, their portfolios are more sensitive to credit spread changes rather than yield changes.

This thesis is particularly relevant and motivated by credit risk analysis from the bond investment side. A corporate bond investor is particularly interested in selecting the corporate bond that will yield the better return, other things equal. However, within the context of this thesis, we are not interested at the initial price that the bond is issued, but rather in the movements – changes in spreads, realised to that particular

[2] For a detailed description of the new models and approaches developed, refer to section 2.2.1- 2.3.
[3] See Kwan (1996)

bond, once it is issued. A bond investor has two options when a bond is comes to the market:

a. Buy the bond, if he/she thinks that the issue price is fair, compared to other bonds of the same rating category and maturity, is confident about that bond's outlook and the bond's specifications meet his/her portfolio requirements, or
b. Not buy the bond.

This thesis, focuses on estimating /predicting the outlook of that bond once an investor has decided to add it to his/her portfolio of bonds and other assets. An investor's decision to buy a bond shouldn't only be driven by the price it comes to the market, but also and more importantly by the expected change in the price of that bond until maturity. Effectively, this means that the financial performance and market outlook should be carefully considered and be part of the decision making process. In other words, it is very important to consider closely internal and external factors that can influence the performance of a bond. This means that the idea and objective of this thesis is core to any investment decision.

Of course, this idea isn't first incepted here. Academic literature, has provided a number of papers dealing with credit risk and default, macroeconomic cycle and defaults or the relationship between the debt and equity markets. But here the aim is to fill the gap in the literature, by combining the theoretical background of the different default risk models developed and extend their work within the context of credit migration risk.

The main contributions of this thesis are the following:

(i) Usually credit risk models are linking different macroeconomic or firm specific variables with default. Here, we refer to less extreme movements in credit quality than default, i.e. credit migration risk is considered throughout this thesis.

(ii) Estimation of a relation incorporating market and credit risk in forecasting credit spread changes. This thesis deals with an extensive list of firm specific, market and macroeconomic variables that haven't been researched before. Significant part of this thesis is focused on how individual accounting ratios affect credit spread changes and to that extent credit ratings. Models that have been created up-to-date model credit spreads, mainly as a function of solely macroeconomic, market factors or company specific factors, but very limited work has been done in modelling simultaneously both micro and macro variables, especially within the context of credit migration risk.

(iii) Construction of an index that represents constituents of the Merrill Lynch Indices (i.e. the US High Grade Broad Market Index and the US High Yield Master II Index), which includes unique bonds per company in the dataset. Data collection and elimination process used in this thesis is of great importance for the results reported. In particular, Merrill Lynch spread indices have been eliminated to include only one bond from a particular issuer. Although this might eliminate data observations and doesn't consider the reaction of different maturity bonds to credit and market factors, on the other hand it explicitly sets the cross sections to be used and in this way it is expected that results are more representative. Due to the nature of this data, results from constituents of the Merrill Lynch indices have been based on analysis of cross sectional data, and are compared to time series results of credit spread indices from Bloomberg, where appropriate (i.e. when the relation of credit spreads to equities and macroeconomic factors was tested).

(iv) Credit spreads' data we use, is option-adjusted. In that way we avoid the problem of comparing two bonds of the same maturity which don't necessarily have the same duration (price sensitivity to interest rate changes) nor the same convexity (sensitivity to the slope of the yield curve). By using option adjusted spreads (OAS) the modified duration of bonds is calculated and option adjusted duration for bonds with an embedded option is also considered. Therefore, credit spreads correspond to the difference in the yield to maturity between bonds with the same duration, which may partially offset the coupon effect on the yield to maturity. Moreover, these spreads are clean of any coupon and index rebalancing effects.

(v) In part of the thesis, all broad seven rating categories are considered. This is very important since we can gain a better view on the overall spectrum of rating categories, compared to other studies that mainly deal with investment grade companies. Also we are testing whether different maturity credit spread indices are influenced differently by different macro or equity factors.

(vi) Frequency of the data collected. Conclusions drawn from this thesis are based on monthly (Bloomberg & Merrill Lynch Indices) and quarterly (Merrill Lynch) data. The frequency of the data collected has very important implications for the results obtained. Considering both monthly and quarterly effects is very important since in this way both short and longer term effects of the relation between credit spreads and the independent variables are captured. On the other hand, the use of daily or weekly data for modelling credit spreads or yield changes, used by other studies, although producing statistically significant results, economic wise is not as significant since credit spreads shouldn't be modelled at such frequent time intervals, but rather this is a more appropriate treatment for market risk purposes, as we expect that movements in credit quality aren't that significant on a daily or weekly basis.

(vii) Credit spreads are used as proxy for ratings. Contrary to other studies that explain credit spreads by using credit ratings as a dummy variable, or the default and recovery rates, here the pattern of credit spreads is estimated using solely macroeconomic, equity and firm specific variables as explanatory variables. I believe this is a much more accurate way for explaining movements and drivers of credit spreads rather than using credit ratings or default probabilities, since by using the latter there is a possibility of double counting, since this is information already incorporated in credit spreads. Moreover, all the reduced form models of default although proposing a simple framework for estimating credit spread changes [4], they typically deviate from the firm value process, and although they may do a good job in "fitting" the observed credit spreads, the aren't offering that good insight for estimating the

[4] See Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997) and Duffie and Singleton (1999)

determinants of credit spread changes[5]. On the other hand, structural models provide an intuitive framework for identifying the determinants of credit spread changes and offer a prediction for whether changes in these variables should be positively or negatively related to changes in credit spreads.

(viii) Existing literature focusing on the determination of a company's long term standing with the use of accounting ratios, uses credit/bond ratings as the dependent variable, and focuses on the use of those variables in predicting default or corporate collapses. In this thesis, we use changes in credit spreads as the dependent variable as we believe, in that way we can more accurately track changes in the creditworthiness of an issuer and hence predict upward or downward movements in credit spreads. Moreover, we don't only use the most "popular" financial ratios, as determined by the credit risk literature so far, but since our modelling involves high yield spreads, we are adjusting financial ratios to include depreciation and amortisation expenses, which are often very important for non-investment grade companies.

1.1.2. Hypotheses under this thesis

A number of hypotheses have been tested in the investment grade and high yield category alike, on short, medium or long term maturity indices. The concept is that the relation among credit spreads and the independent variables is looked at, initially in the investment grade sample, next in the sub investment grade sample and finally in whole sample together, including high yield and investment grade bonds and all the independent variables.

There are four broad set of hypotheses to be tested, which are common for both the investment grade and sub investment grade sample, short, medium and long term indices, which are analysed further in the respective chapters. These include:

[5] As argued in Collin-Dufrense, Goldstein and Martin's study in December 2001.

***Hypothesis 1* - Relation between changes in macroeconomic variables and credit spreads**

Changes in corporate bond spreads are not affected and/or negatively related by changes in **macroeconomic factors** (including, GDP, consumer confidence, the level of interest rates, industrial production, trade balance, money supply). Also changes in credit spreads are not positively related to changes in CPI. These hypotheses will be tested separately for investment and non-investment grade bonds, short and long term maturing indices, as different results are expected to be reached from each separate category, due to the different specifications implied. Within the context of the same chapter, we will also test the lead lag relationship among macroeconomic variables and credit spreads.

***Hypothesis 2* - Relation between changes in equities and credit spreads**

Changes in corporate bond spreads are not positively related to VIX and/or their historical volatilities. Also changes in corporate credit spreads are not negatively related to changes in individual equity prices or equity indices such as S&P 500 and the Russell 2000. These hypotheses are tested not only within the context of constituents of the Merrill Lynch indices, their respective equity prices and their historical volatilities on a cross sectional basis, but also among Bloomberg investment grade bond and equity indices on a time series basis. We also test the hypothesis that changes in equity indices or implied volatilities don't granger cause changes in different maturing bond indices.

***Hypothesis 3* - Relation between changes in accounting variables and changes in spreads**

Changes in credit spreads are affected and explained by changes in the respective company's financial information (including the company's current market capitalization, ratios such as cash flow to debt, Earnings before interest and tax to interest expense, debt to capital employed, Return on Equity, Return on Capital, Total Debt to Ebitda, etc). In particular, we will be testing the relation between the above accounting variables and groups of accounting ratios. In other words, the null hypotheses tested under this chapter, are that:

(a) Changes in corporate bond credit spreads, aren't negatively related or explained by changes in accounting ratios.

(b) Changes in corporate bond credit spreads, aren't positively related or explained by changes in leverage ratios.

(c) Changes in corporate bond credit spreads, aren't negatively related or explained by changes in liquidity ratios.

(d) Changes in corporate bond credit spreads, aren't negatively related or explained by changes in the company's current market capitalisation, which is used as proxy for the firm's size.

The above hypotheses are tested initially individually in the investment and non-investment grade category, while implicitly the hypotheses also entail testing the lead –lag relationship between the above mentioned financial variables and changes in corporate bond credit spreads.

Hypothesis 4 - Relation between spreads and equities, accounting & macroeconomic factors

Lastly, the ultimate hypothesis tested, which represents the core idea behind this thesis, is the establishment of the relationship integrating all the above variables into a unique framework in order to explain changes in corporate bond spreads. By testing all the above variables on a parallel basis we are effectively examining:

(a) whether the inclusion of all the above variables will explain changes in credit spreads better than on an individual basis,

(b) the positive or negative relations between the dependent and the independent variables can be also proven on a contemporaneous basis, and

(c) conclude with the best functioning combination statistically and financially wise, in determining/forecasting credit spreads changes one and two years ahead.

1.1.3. Summary Results of Hypotheses tested

(a)Hypothesis 1

Evidence from Bloomberg Indices – Investment Grade Bonds

We reject the null hypothesis of the negative relation between the variables of trade balance, money supply and the term structure of interest rates for all maturities, but only for the lagged values of those variables at the 95% confidence level. We also reject the null hypothesis of the negative relation between consumer confidence and changes in corporate bond credit spreads for all maturities at time t or its lagged values at the 95% confidence. However, we don't reject the null hypotheses for the variables of GDP and industrial production.

With respect to the direction of causation results obtained for long term maturing bonds, generally support confidence to reject the null hypothesis that macroeconomic variables don't granger cause changes in the credit spread indices. For medium and short term maturities the null hypotheses are rejected on a case by case scenario as analytically described in chapter 4.

Evidence from Merrill Lynch Indices – Investment & non-Investment Grade Bonds

We reject the null hypothesis about the negative relation between the variables of trade balance, money supply and the US consumer confidence for all ratings, at the 95% confidence level. The null hypothesis of the negative relation between the term structure of interest rates and changes in corporate bond credit spreads is only rejected for investment grade companies at the 95% confidence level. However, we don't reject the null hypotheses for the variables of GDP and industrial production. We also strongly reject the null hypothesis that changes in high yield credit spreads contain no marginal information for the business cycle.

(b) Hypothesis 2

Consistent with the structural approach, we reject the null hypothesis of the positive relation between changes in individual equity prices or the S&P500 index and changes in credit spreads, for all rating categories and for short and medium term maturities. We also reject the null hypothesis for the negative relation between the VIX index for all rating categories and maturities.

Although evidence to reject the hypothesis of negative relation between the dependent and changes in historical volatilities, is statistically supported, it is suggested that the inclusion of historical volatilities doesn't provide even marginal support for explaining variation in changes in credit spreads.

(c) Hypothesis 3

We reject the null hypothesis of a positive relation between changes in credit spreads and profitability, liquidity ratios and the company's current market capitalisation, although we don't reject the second part of the same hypothesis with respect to the information content of those ratios on an individual basis in explaining changes in credit spreads. The null hypothesis of the negative relation between leverage ratios and changes in credit spreads is rejected. However, on a multivariate basis, we find that part of the variation in credit spreads is explained by the changes in the aforementioned ratios, particularly for the non-investment grade category, with the most important coefficients obtained for leverage ratios and the current market capitalisation.

(d) Hypothesis 4

Testing the above hypotheses on a parallel basis, provided confidence for rejecting the null hypothesis on an aggregate basis, irrespective of the time period tested.

1.2. Structure of the thesis

The above-mentioned developments in the area of credit risk (section1.1.), together with issues in the credit risk literature that haven't been explored to a great extent (as analytically will be described in later chapters) have inspired the following thesis. The aim is to provide an in depth empirical analysis of the relation between corporate credit spreads and their key economic and company specific determinants. This implies an exploration of the relation between credit spreads and macroeconomic indicators, equity and volatility factors and firm specific information (accounting ratios). The ultimate goal will be to construct a multi-factor model that will assume the above factors and forecast credit spread changes. This model has been inspired not only by factors employed in the models produced by McKinsey and KMV but also by variables considered by the credit rating agencies when assigning a rating.

The thesis is structured in the following way:

Chapter 2, provides a critical review of the current credit risk models developed by financial institutions and corporations world-wide. The purpose of such a review is to assess their inherent strengths and weaknesses and set the foundation for this thesis. It provides the settings to the approaches of credit risk modelling (structural and reduced form) as well as a brief literature review focused on the determinants of credit spread changes.[6] It also incorporates a brief review on the credit risk (VaR) models developed by JP Morgan "Credit Metrics", by CSFB "Credit Risk +", by Moody's KMV "KMV" and "Credit Portfolio View" as created by McKinsey. These models are value-at-risk and default models, which call for the full integration of market and credit risk. The reason for their inclusion, is to enhance the fact that all recently developed credit risk models, either value at risk or default and credit scoring models, call for the incorporation of market and credit risk into their assumptions. It should be noted that credit risk literature related to the specific hypotheses tested under this thesis, is provided in the relevant chapters.

Chapter 3 sets the background to the proposed credit risk model suggested under this thesis. It outlines the main objectives and hypotheses which are tested and explored. The relations examined are based on US corporate bond market data. It provides the data and a detailed description of the statistical properties of credit spreads. The main sources of data used include spreads provided by the Merrill Lynch and Bloomberg investment grade and high-yield indices, US macroeconomic indicators, and the respective companies' equity information and accounting variables. This chapter explores the data selection criteria, data qualifying for this thesis and a descriptive statistical analysis of data by rating and years.

Chapter 4 explores the relation between credit spreads and macroeconomic factors. The main idea behind this section is the exploration of the relation between credit spreads and leading US macroeconomic indicators not only for investment and non-investment grade companies, but also for different maturity indices. Three issues have been identified and tested under this chapter. The first is the relation between macroeconomic variables and credit spreads, with the use of two sets of data, secondly the extent to which macroeconomic conditions influence different rating categories and maturities and thirdly the direction of causation between macroeconomic variables and changes in credit spreads. Overall, results provide support to the hypotheses tested more significantly though for the non-investment grade category. With respect to the direction of causation results are a bit mixed, as provided by the empirical tests in the times series data. Results from the non-investment grade category provide evidence that spreads might be a good indicator of financial conditions.

Chapter 5 provides the ideas and background for the relation between changes in equities and the respective changes in spreads. The objective is to consider how the incorporation of market conditions (i.e. equity prices) can affect changes in spreads across the rating spectrum and across different maturities. Several hypotheses have been tested including the inverse relation between changes in credit spreads and their respective equities, the relation between credit spread and implied or historical volatilities, as well as the direction of causation between credit spreads and equities. Results reported have been based on two sets of credit spread indices coming from Merrill Lynch and Bloomberg and the econometric analysis performed has been different due to the nature of data collected (i.e. cross sectional and time series analysis was employed). The strongest relation between equities and credit spreads has been provided from the non-investment grade sample, and gives confidence as to the importance of implied volatilities in explaining credit spreads rather than historical ones.

Chapter 6 tests the relation between changes in spreads and accounting information. The idea for the inclusion of this section is to check whether real accounting figures provide information to bond investors, and effectively whether they can be used as a

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[6] Literature review on credit spreads and macroeconomic variables, equity factors and accounting

tool for proactive credit risk management. It examines the extent that changes in credit spreads are affected by results reported in a company's financials reports. Specifically, accounting ratios such as the cash flow to debt, or the Ebitda cover ratio are tested in the investment and high yield category, while the results share more confidence for supporting this relation for companies rated below BBB-. The most important variable, in all rating categories is the company's current market capitalisation.

Chapter 7 considers in a multi variate context the informational content of all the above factors in determining credit spreads changes. Once the most important factors which provided the highest adjusted R^2 were determined, these were then used for back testing the credit risk model and for forecasting out-of-sample credit spread changes. Although initially it was expected that a prediction of credit spread changes would be rather hard (due to the time period tested but also due to the nature of credit spreads), it was shown that due to the fact that this model entails both company specific and market variables, credit spread forecasts have been close to traded values. The model performs well especially within the first twelve months and more accurately for investment grade companies.

Chapter 8 provides a summary of the conclusions reached under this thesis, as well as the limitations inherent and points out some issues that could be further researched, mainly related to changes in the credit risk framework, stemming from the implementation of the New Basel Accord.

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information is being provided on the relevant chapters.

2.0. Literature Review

Before proceeding with the theoretical concepts, models and issues relating to credit risk it is important to provide some background as to the nature of credit risk and its statistical properties.

2.1. Credit Risk

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 quality during the life of the instrument. In the case of a bank loan, credit risk is considered primarily the risk that the borrower may not be able to make the scheduled payments.

Credit risk is primarily focusing on default. The definition of default risk could be either a missed payment, a broken covenant or an economic default (when the value of the firm's assets falls below its liabilities). Rating agencies consider that default occurs when a contractual payment has been missed for at least three months, which coincides also with the Basel II definition of default. It should be mentioned however, that the various events of default do not necessarily mean that there are immediate losses, however, even a technical event of default would increase the probability of a bankruptcy.

However, there are three other related areas to credit risk, which are equally important. These are:

(a) <u>Credit Migration</u>: this refers to less extreme changes in credit quality than default. In the case of a corporate bond, credit risk takes the format of credit spread changes which are accompanied by rating changes and vice versa. Although it is usually the first stage of the financial distress of a firm, bondholders are very interested in this kind of credit risk than the actual event of default, since they can have an immediate impact on the value of the security. Due to the fact that bonds are relatively liquid, bondholders are usually in a position to sell them before the issuer's financial state deteriorates.

(b) <u>Exposure risk:</u> this is defined as 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 cases of committed lines of credit, the borrower can draw on these lines whenever necessary, which effectively means that the exposure is contingent upon the borrower's needs, but always subject to a limit fixed by the bank.

(c) Recovery risk: the exposure at risk is different to the loss in case of default because of potential recoveries. Those depend upon any credit mitigators, such as guarantees, collaterals and other forms of securities provided by the borrower. The recovery rate depends additionally on the industry type, seniority of debt claims and other issues. According to Moody's data source, recovery rates can vary between 70% for secured bank loans to 30% for unsecured subordinated debt.

2.1.2. Credit Risk & Market Risk

Economic theory suggests that market and credit risk are intrinsically related to each other. If the market value of a firm's assets changes, generating market risk, this will in turn affect the probability of default, generating credit risk. Market risk could be defined as the chance that an investment's value will change in price as a result of market place forces or the potential loss resulting from adverse market movements, for example, during a liquidation period. According to a paper by Allen (1996), the integration of these two functions is desirable for at least three reasons:

(a) There is a lot of transactional interactions between market and credit risk
(b) The need for comparability between market and credit risk returns
(c) The emergence of hybrid credit and market risk product structures

The close relation between market and credit risk also affects economics for banks and regulators. This is particularly important for less developed countries, that are now in the process of developing their internal credit risk system. This flows from the new Basel II capital accord, which provides to banks more incentive to use internally generated credit ratings for their exposures, in order to calculate their capital requirements based on more objective risk weights. This relation, also affects the adjusted return on capital which is used for performance related uses in different groups within a bank. Of course this correlation is not very straight forward and requires a deep understanding of the correlation between market and credit risk. This correlation between market and credit risk has been studied by Longstaff and Schwartz, (1995), Morris, (1999), Duffee, (1999). For example, Longstaff and Schwartz developed a simple approach to valuing risky debt, which incorporated both default and interest rate risk. They found that the correlation between default risk and the interest rate has a significant effect on the properties of the credit spread. Using Moody's corporate bond yield data they found that credit spreads are negatively to interest rates and that durations of risky bonds depend on the correlation with interest rates.

However, as it will be described below, these two kinds of risk are quite different in nature but also in the way of measurement. Below, some of the main differences are going to be outlined.

By credit risk we don't only mean the dimensions of risk mentioned in the previous section, but when referring to credit risk we should also mention an important component of it, market risk. Market risk refers to those cases where there is possibility of losses due to the changes in the prices of financial assets and instruments. For example shares of stocks are mainly subject to market risk since there is not an explicit scheduled payment on those. That would also be the case with a US treasury bond, treasuries which are only subject to interest rate risk. However, there are cases where this distinction is not so clear cut. For example, in the case of corporate bonds, both types of risk are assumed to be present. Although both of these types of risk are depicted by changes in bond values, they are generated from two different sources, namely market risk, resulting from adverse market movements and credit risk coming from changes in the borrower's credit quality.

There are some inherent differences in the estimation of market and credit risk. These are outlined below:

(a) Input data. While market risk data (mainly market factor returns and their respective variance/covariance matrices) is largely available in the market, credit risk data is not readily available, but rather data has to be transformed or exported for different variables in order to end up with the required values (for example estimation of default probabilities or recovery rates). Another even more important issue is that credit data is not available for a long horizon, and usually data that we get on credit risk is outdated historical data.

(b) Liquidity. Markets for credit risky debt are not that liquid, which is partly due to the size of the credit market, and partly due to the fact that credit risky debt is segmented, in that each company issues its own debt that trades at prices representing the investors' perception of that particular borrower. Moreover, changes in credit risk can cause the price of the associated instrument to exhibit large changes in price, especially in cases of multiple downgrades or default.

(c) Time horizon in liquidation status. In the case of market risk instruments, the liquidation time horizon is very short (approximately 10 days) whereas in the case of credit risk usually the time is much longer (months or years).

(d) Legal issues are very important in the case of evaluating credit risk, while they are almost not applicable in the case of market risk.

2.1.3. Statistical properties of Credit Vs Market returns

As a result of the above factors credit risk is more difficult to model than market risk. In particular, credit returns are highly skewed and fat tailed compared to equity returns which are relatively symmetric and 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 loosing a 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 reserves will be more difficult to model due to the estimation of tail risk probabilities of typical asymmetric fat tailed loss distributions. These properties of credit risk are analysed further within the context of the data used in this thesis for credit spreads, in section 3.4.

The growing complexity of credit risk has driven the development of more sophisticated methods for measuring credit risk at a portfolio level, rather than just at the level of an individual bond or loan (see section 2.2). These methods are largely statistical and build on probabilistic models of creditworthiness and asset values. As a result, nowadays there is a much larger variety of credit risk than market risk models available. The core difference between credit and market risk models, is that market risk models differ in the way they obtain the same result, the VaR of the portfolio, while credit risk models don't only differ in the way of estimating the end result, but also to the result they are trying to achieve (due to the many definitions of credit risk, as described in section 2.1.).

It is worth mentioning though, that despite the large number and variety of credit risk models that have been developed up to date(see section 2.2), there are instances that it can be hard to put these models into practice due to commercial and customer relation links. Additionally, most large banks, or investment houses tend to use models developed internally based on internal rating procedures and needs.

2.1.4.Obstacles in the successful integration of market and credit risk

The main reasons that make difficult the full integration of market and credit risk are outlined below:

(a) Relevant Time Horizons

In terms of market risk the daily horizon is an accepted industry standard time frame for risk management analysis, due to the fact that the unwinding of trading positions should be possible in 24 hours. However, regulators don't share such an optimistic view on the unwinding of trading positions and require that the market risk measures may be calculated on a 10-day period.

In terms of credit risk though, the choice of the time horizon is not as straightforward. For example, the time required to unwind a position in credit risk depends on the severity of credit crisis, the quality of the relation with the counterparty, on regulatory constraints and others. Another criterion may be the use of the time needed to appreciate a change in the counterparty credit quality. As it is obvious, choosing the right time horizon is so much harder in the case of credit risk, where the current practice followed by the large international banks is to use horizons between two weeks and one year.

(b) Scaling between time horizons

The next issue that arises is that given the different time horizons considered, the two results are not directly comparable. One way to overcome this problem is to use a common time horizon. Given that the time horizon considered for market risk is usually shorter than credit risk, there are two alternatives to consider:

i) either scale up market risk figure to the longer time horizon

ii) scale down the credit risk figure to the corresponding market risk value.

Since the "square root of time" rule exists, and allows to measure the behaviour of volatility in dependence of the time horizon on which it is measured, this effectively means that if return volatility measured on daily and monthly data is compared, then it is expected that the 1-month volatility is higher than the 1-day volatility. In other words, longer time horizons are associated with a wider dispersion of potential returns.

However, this type of time stretching is sensitive to the time periods considered as well as to the time series used, and an extreme case of time stretching might be dangerous. For example scaling 1-day volatility into yearly volatility will produce more dubious results than scaling lets say the 1-week volatility to one month.

(c) Market and credit correlations

The next issue is to formulate some hypotheses on the correlation between these two measures of risk. A simple approach would be to compute the global exposure as the sum of the two individual exposures. Another would be to assume that the market risk measure and the credit risk measure are not linearly correlated. This assumption could be justified in cases where factors affecting credit and market risk are independent. Another more quantifiable alternative would be to try and model explicitly the relation between market and credit risk measures, determining in this way the correlation coefficients.

(d) Conflicts of interest

Even if a common risk measure could be achieved for market and credit risk within a bank or an investment banking institution, there are some limitations that are very hard to overcome. These relate to the potential cultural clash between credit and market risk management staff. While market risk, as measured by VaR, is mainly dependent on quantitative assumptions, credit risk measurement and modelling is the result largely of subjective judgement. Switching therefore the subjective evaluation to objective quantitative models is very hard to achieve due to natural resistance from the credit departments.

2.2. Review of Former Credit Risk Models

Over the years a number of credit risk models have been developed ranging from systems relying solely on subjective analysis, i.e. the "4 Cs"[7] to more sophisticated objectively based credit systems. These include the:

a. univariate accounting based credit scoring systems, which essentially compare key accounting ratios of the borrower with the industry norms under consideration or group norms and
b. multivariate models, whereas the key accounting variables are combined and weighted to produce either a credit score or a probability of default measure and based on a benchmark, a loan application can be accepted or rejected accordingly.

There are different methodological methods used in multivariate credit scoring systems. These are the linear probability model, the probit model and the logit model. The most widely used models are the logit and the discriminant analysis models. For example Martin (1977) used both the discriminant analysis and the logit model, in order to predict bank failures in the 1975-1976 period, when 23 banks failed. Platt and Platt (1991) used the logit model to test whether industry relative accounting ratios rather than simple firm specific accounting ratios can better predict a corporate bankruptcy, whereas the industry relative accounting model outperformed the unadjusted model. Smith and Laurence (1995) used a logit model to find the variables that offer the best prediction of a loan moving into default. Altman et al (1977) investigated the predictive performance by using the "zeta model"[8]. Scott (1981) compares some of the discriminant analysis models and concludes that the zeta model most closely approximate his own bankruptcy model.

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[7] "4 Cs" denote the character of the borrower, capital, capacity and collateral.
[8] The zeta model, is a seven a variable discriminant analysis model which also includes the market value of equity as one variable.

However, the multivariate discriminant analysis system, although in some cases has been proved to perform quite satisfactorily, it has received some criticism from practitioners and academicians alike. These criticisms relate to the following:

- The book value of the accounting data used is not very accurate as it doesn't incorporate changes in the borrower conditions as those are reflected in the capital market values.
- The linear assumption inherent in the discriminant analysis cannot be accurate as the world is non-linear.
- Credit scoring bankruptcy prediction models usually are tenuously linked to theoretical models.

There are some other models the so called "risk of ruin" models, according to which a firm goes bankrupt when the market value of its assets falls below its debt obligations to outside creditors. Research of these models was made by Wilcox (1973), Santomero and Vinso (1977) and also Scott (1981), who actually observed that the risk of ruin model is similar in some aspects to the option pricing model – OPM – of Black and Scholes (1973), as well as Merton (1974), Hull and White (1995). In the Black-Scholes-Merton model the probability of a firm going bankrupt depends on the value of the firm's assets relative to its outside debt, as well as the volatility of the market value of the firm's assets. The ideas of the risk of ruin and OPM models, have also been used in the commercial area, where they have gained increased attention.

However, one important aspect of economic theory which has been captured, but only to some extent, is the fact that market and credit risk are intrinsically related to each other and more importantly they are not separable (i.e. if the market value of the firm's asset changes, generating market risk, which in turn affects the probability of default, consequently generating credit risk). The relation between market and credit risk is of great importance, as it affects the risk-adjusted return on capital and therefore should be treated with increased attention. This relation has been implicitly captured within the context of the models developed by CSFB, JP Morgan, KMV and McKinsey, as analytically is described in section 2.3.

2.2.1. Approaches to Credit Risk Modelling

A great deal of attention has been devoted to understanding the stochastic nature and determinants of credit spreads. This issue plays a central role in the fixed income literature, primarily due to its importance in the pricing of risky debt and credit derivatives (Duffee (1999), Duffie and Singleton (1997), Longstaff and Schwartz (1995b) and Jarrow and Turnbull (1995)). In the literature there are two main approaches used in the pricing of risky debt:

a. The first is the so called **"structural approach"(or the "firm-value")** or option pricing model approach, which started with the work of Merton in 1974, and has been extended in different ways. The essential idea behind this approach is that it uses company-specific information and treats debt as a contingent claim (option) on the firm's value.
b. The second approach is the **"reduced form approach"** developed by Jarrow and Turnbull (1995a, b) to encompass difficulties regarding the unavailability of market data, whereas market and credit risk are intrinsically related. It models default risk from what is implied in market prices, credit spreads, and in some cases rating transitions.

Before proceeding with the analysis of each of those approaches, below, it should be mentioned that the distinction between the structural 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. In other words, structural based models, could typically face problems as those encountered when extending Black-Scholes model to include american options, dividends, stochastic interest rates, whereas the reduced form models' setups resemble to the term structure modelling.

a. Structural Approach

In particular, the structural approach relates default to the underlying assets of the firm. This approach was best developed by Merton (1974, 1977), who considers a firm with a simple capital structure, and makes the following assumptions:

a. firm issues a zero coupon bond with a face value F and maturity T. Then two states are observed :

1. At maturity, if the value of the firm's assets is greater that the amount owned to debt holders, then equity holders pay off debt holders and retain the firm.
2. At maturity, if the value of the firm's assets is less than the face value, the equity holders default on their obligations.

b. No costs are associated with default and priority is given in the repayment of debt. In this case debt holders take over the firm and the value of equity is zero , assuming limited liability.

To derive a specific valuation formula, as shown directly below, Merton assumed the following:

- the term structure of interest rates is deterministic and flat,
- the probability distribution of the firm's assets is lognormal,
- the firm is assumed to pay no dividends over the life of the debt,
- capital markets are perfect

$$V_1(t, T) = F\,B(t, T) - p\,[V(t)]$$

whereby,

V_1 : the value of the risky debt

F: Face value of debt

B(t, T) : the time value of a zero coupon bond that pays one dollar for sure at time T

V(t): the time t value of the firm's assets, and

P[V(t)]: the value of a European put option on the firm's assets that matures at time T with a strike price of F.

Merton's model relates to the following:

- when a put option is deep-out-of money (V(t)> F), the probability of default is low and corporate debt trades as if it is default free, P[V(t)]~0
- if the put option is in-the money, the volatility of the corporate debt is sensitive to the volatility of the underlying asset,
- if the default free interest rate increases, the spread associated with corporate debt decreases, i.e. the rate increase keeps the firm's value constant, the mean of the assets probability increases and the probability of default declines. As the market value of corporate debt increases, the yield to maturity decreases and the spread declines. The magnitude of the change is larger, the higher the yield on debt.
- Market and credit risk are intrinsically related. A decrease in the value of the firm's assets increases the probability of default and vice versa. Croughy et al(1998) also discusses market and credit risk .
- As the maturity of the zero coupon bond tends to zero, the credit spread also tends to zero.

Generally, structural models, generate predictions about what the theoretical determinants of credit spread changes should be and their positive or negative relation to changes in credit spreads. These proposed structural determinants are basically considered to be[9]:

(i) Changes in the Spot Rate: As argued by Longstaff and Schwartz (1995) the static effect of a higher spot rate is to increase the risk neutral drift of the firm value process. A higher drift, would effectively decrease the default probability and ultimately spreads. Further evidence on this issue is provided by Duffee(1998) who uses a sample of non-callable bonds and finds a negative relationship between changes in credit spreads and interest rates.

(ii) Changes in the slope of the yield curve. Litterman and Scheinkman(1991) found that the two most important factors driving the term structure of interest rates are the level and the slope of the terms structure. It is argued that an increase in the slope of the treasury curve increases the expected future short rate and ultimately leads to a decrease in credit spreads. From another perspective though a decrease in yield curve slope might imply a weakening economy. Therefore, theory predicts that an increase in the Treasury yield curve slope will create a decrease in credit spreads.

(iii) Changes in leverage. Since default is triggered when the leverage ratio is close to one, credit spreads are expected to widen with an increase with leverage. Following the same rationale, credit spreads are expected to tighten with an increase in the firm's return on equity.

(iv) Changes in volatility. The contingent claims approach, propose that debt claim has features similar to a short position in a put option. Since when volatility increases, credit spreads increase, it follows that credit spreads would increase with volatility.

(v) Changes in the Portfolio probability of a downward jump in firm value. An increase in either the probability or the magnitude of a negative jump should increase credit spreads.

(vi) Changes in the business climate. Changes in credit spreads are dependent on recovery rates. The expected recovery rate is in turn a function of the overall economic conditions, as proposed by Altman and Kishore (1989) who find that recovery rates are time varying.

However, there are at least four practical implications in Merton's model:

a. It is difficult to find the exact market value of a firm's assets - V(t), required for the pricing formula, as usually firms have numerous complex debt contracts traded rarely.
b. Return volatility on the firm's assets is also very important to be computed, but since market prices are not available so are return probabilities.
c. The liability structure of the model is based on simultaneously pricing all different types of liabilities, senior to the corporate debt under consideration.
d. According to the model, default can only occur when a principal or a coupon repayment is made. However, in practice payments to other liabilities may also trigger default.

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[9] From the paper by Dufrense, Goldstein and Martin (2001) on the Determinants of Credit Spread

To overcome some of these practical limitations, Nielson et al(1993) and Longstaff and Schwartz (1995a, b) assume that the firm's capital structure is irrelevant. Bankruptcy can occur at any time and in default the firm pays off some fixed fractional amount. But again the volatility of the firm's assets must be computed. To facilitate this process they also assume that interest rates are normally distributed, i.e. they follow an Ornstein-Unlebeck process. Cathcart and El-Jahel (1998) also questioned this assumption while they impose an additional assumption which implies that spreads are independent of changes in the underlying default free term structure, which is in contrast to empirical observations. Kim et al (1993) assumed a square root process for the spot interest rate that is correlated with return on assets.

b. Reduced Form Approach

The earliest example of this approach was given by Jarrow and Turnbull[10] (1995 b). JT allocate firms to credit risk classes and default is modelled as a point process. Using the term structure of credit spreads for each credit class they infer the expected loss (t, t + Δ_t) which is the product of the conditional probability of default and the recovery rate under the equivalent martingale (risk-neutral) measure, i.e. they use credit spreads to infer the market's assessment of the bankruptcy process and then price the credit risk derivatives. In the JT model, stochastic changes in the credit spread only occur if default occurs. In order to model the volatility of credit spreads, a more detailed specification is required for the intensity or/and the recovery function. The specification of the recovery process is a very important component in the reduced form approach, i.e. the model assumes that if default occurs *– for example on a zero coupon bond* – then the bond holder is assumed to receive a known fraction of the bond's face value at the maturity date. This face value is determined with the default free term structure of interest rate.

Changes

[10] Jarrow and Turnbull will be denoted for the remaining of this document as JT.

Other researchers of the topic, like Das and Tufano (1996) keep the intensity function deterministic and assume that the recovery rate is correlated with the default free spot rate. They assume that the default rate depends on the state of the economy and is subject to idiosyncratic variation. Monkkonen (1997) generalises the Das and Tufano(1996) model by allowing the probability of default to depend upon the default free rate of interest, and they develop an efficient algorithm, in order to infer the martingale probabilities of default. Lando (1994/1997) assumes that the intensity function depends upon different state variables, and this is referred to as the Cox process. [11] Lando makes a simple representation for the derivation of credit derivatives. Duffie and Singleton (1998) derived a simple representation for the value of a risky bond by assuming that in default, the value of the bond is equal to some fraction of the bond's value just prior to default. Hugston (1997) showed that the same result could also be derived in the JT model. Therefore modelling the intensity function as a Cox process, and after observing the empirical observations of Duffee (1998), Das and Tufano (1996) and Shane (1994), it was derived that credit spread depends on both the default free term structure and an equity index. In addition, the work of JT (1995a, b) Duffee and Singleton (1998), Hughston (1997) and Lando (1994/1997) implies that for many credit derivatives, only the expected loss needs to be modelled, i.e. the product of the intensity and the loss function.

In the case that credit derivatives payoffs is dependent upon the rating changes, Jarrow et al(1997) described a simple model which included the credit rating of the firm as an indicator of default. There is evidence to a large extent which is consistent with changes in credit spreads and changes in default free interest rates being negatively correlated. In particular, Duffee (1998) used monthly corporate bond data from the period January 1985 to March 1995, and fit the following regression:

$$\Delta\, Spread_t = b_o + b_1\, \Delta\, Y_t + b_2\, \Delta\, Term_t + e_t$$

where:

$Spread_t$: is a spread at time t for a bond maturing at time t

[11] When the Cox process is dependent upon state variables acts as a Poisson process.

Δ Spread$_t$: is the change in spread from t to t +1, keeping maturity T fixed,

Δ Y_t : is the change in the three month Treasury yield and the 3-month treasury bill yield.

Δ Term$_t$: the change in term over a period from t to t+1

e_t :denotes a zero mean unit variance random term , and

b_1, b_2 : are the estimated coefficients which are negative and increase in absolute magnitude, as the credit quality decreases irrespective of maturity.

Das and Tufano in 1996, also reported similar results. Longstaff and Schwartz (1995a, b) using annual data from 1977 to 1992, fits the following regression:

$$\Delta \, Spread_t = b_o + b_1 \, \Delta \, Yield_t + b_2 \, \Delta \, I_t + e_t$$

where

Δ Yield$_t$: the change in the 0-year treasury

I_t : return on the appropriate equity index and

e_t : a zero mean unit variance random term

For Aaa, Aa, A and Baa industrial bonds, both the estimated coefficients are negative. This is not surprising since an increase in the treasury bill rate, increases the expected rate of return on a firm's assets, and hence lowers the probability of default. This in turn increases the price of the risky debt and thus lowers its yield. Irrespective of the bond's maturity, the coefficients b_1 and b_2 increase in absolute magnitude as the credit quality decreases. However, as argued by Duffee (1998), Longstaff and Schwartz's results must be treated cautiously as their data includes bonds with embedded options which can bias the regression results.

Shane(1994) used monthly data from 1982 to 1992 and found that returns on high yield bonds have a higher correlation with a return on equity index than low yield bonds and a lower correlation with the return on a treasury bond index rather than low yield bonds. Whether Shane filtered the data to eliminate bonds with embedded options is not known.

Wilson (1997a, b) examined the effects of macroeconomic variables, such as the GDP, unemployment, and growth rate, long term interest rates, etc, when estimating the default rates. It was argued that if an economic variable has an explanatory power then this could cause a change in the default rate, provided that the explanatory variables are not co-integrated. In order to examine this, Wilson tested the estimation using only levels whereas he should also use estimates based on changes in variables.

Altman (1983/1990) uses first order differences, and as explanatory variables the percentage change in real GNP, the percentage change in the money supply, the percentage change in S&P index and the percentage change in the new business formation. The results were that there exists a negative correlation between changes in these variables and changes in the aggregate number of business failures. The reported R-squares are substantially lower than those reported by Wilson. All the aforementioned studies have a common underlying economic inference and that is the credit spreads.

However, it should be noted that in addition to the above well-known approaches, there are some other proposals which are popular among practitioners, which could be concluded to the following:

- **Risk Factor Premium**: In this approach, as has been conceived by Fisher (1959), credit spread is considered as a compensation for various risks in a linear relation. Company specific risk factors include leverage, earnings and sector. Factors relating to debentures embody seniority, maturity and marketability. The spread estimated from this model and Treasury rates from a term-structure model are used to price bonds.

- **Credit Fundamentals:** In this approach default probabilities are estimated through a company's financial fundamentals. Recovery is based either on historical data or on comprehensive credit research of a specific deal. In order to price a bond the model applies both default and recovery estimates in a pre-specified risk-neutral relation.

- **Macroeconomic Approach:** This approach deals directly with a company's systematic risk. Systematic risk factors are mainly estimated from some forms of lagged relations with other risk factors. In this approach different scenarios of macroeconomic factors are simulated to generate a pricing distribution or weighted average scenario.

- **Direct forward Spread Pricing:** This approach doesn't rely on fundamental assumptions about the default process but it rather relates to the default of other securities. A process describing spread movements is added on a risk free interest rate process, and when is properly defined, the default free process and credit spread process can be correlated, which essentially gives us a two-factor model.

2.2.3. Determinants of Corporate Bond Spreads

The literature that has focused on credit spreads is focused on three main topics:

a. explanation of the credit risk premia
b. specification of the risk structure of credit risk premia
c. the valuation of risky debt.

However, it wasn't until 1959 that the subject gained more attention with the pioneer work of Fisher (1959). His paper constitutes the first contribution to a structured approach in the credit risk premium area. In Fishers' study the risk premiums are defined as the difference between the market yield on the bond and the corresponding interest rate. Fisher performed a cross sectional analysis in order to find what are the main factors explaining the risk premium on US domestic and industrial corporations. Transportation and public utility companies were excluded from the sample since they were subject to different kinds of regulatory control and that would make them less likely to default on their obligations compared to other industrial companies. In Fisher's model, the risk that a company will default is based on the following four variables:

i) The variability of earnings, which is measured by the coefficient of variation of the firm's net income over the last nine years. There is a negative expected relation between this variable and default, as a firm with a smaller coefficient of variation in earnings is less likely to default, compared to one with a higher coefficient.

ii) The length of time that the firm has been operating without forcing its creditors to incur losses. In other words, the longer the solvency period of the firm, the less likely 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 firm's debt. I.e. how much can a firm's asset value decrease before it becomes less than its liabilities.

iv) The total market value of all publicly traded bonds that the firm has outstanding. The smaller the amount of bonds outstanding the higher the credit risk premium is expected to be. That is because a smaller amount of bonds outstanding means that there is less trading transactions, the market is thinner and the market price of the bond more volatile.

Using cross sectional analysis, Fisher tested the logarithm of the average risk premium on the logarithms of the aforementioned four variables and found that:

(a) for each cross section the four variables account for 75% of the variance of credit risk premiums and

(b) the volatility of the risk premium with reference to those variables is stable over time.

There are a number of limitations in his work, most importantly the fact that no macroeconomic or market factors are included and the fact that the influence of term to maturity on the risk premium isn't taken into consideration either through the level and shape of the underlying basic curve or on its possible effect on the yield differential itself.

In another work by Fair and Malkiel (1971) demand and supply factors are introduced in order to explain credit risk premiums. They argue that different type of bonds of the same risk levels and maturities, may not be perfect substitutes, for the following reasons:

i) legal restrictions which affect portfolio allocations in investment houses
ii) window dressing of bonds
iii) marketability, liquidity and transaction costs considerations

Fair and Malkier (1979), employed monthly data from January 1961 until June 1969 of long term US government investment grade utility and industrial bonds. It was argued that each bond is characterised by a demand schedule which depends positively on its own rate of interest and on the stock of wealth to be distributed among the assets and negatively on the interest rates of other assets. It was also assumed that supplies of government, utility and industrial bonds are exogenous. Assuming markets are in equilibrium, (supply is equal to demand) they derived that the assets yields are a function of the relation between the supply of assets themselves. This effectively means that the yield differentials are a function of the amount of bonds outstanding and by the anticipated new financing during the future six month period.

In an effort to explain cyclical variations in spreads, Jaffee (1975) developed a supply-demand model, which achieved different results than those described above. In particular, Jaffee developed a model whereby the demand functions relates positively to its own rate and negatively to the rates of other categories and to a vector of exogenous variables. On the other hand, the supply function of the issuing firm is negatively affected by its own rate and by a vector of exogenous variables, as in the case of the demand function. Assuming equilibrium in each risk market (supply equal to demand) he obtained that the interest rate of any category is a function of the risk free rate and various exogenous demand and supply factors affecting the market. Demand and supply variables were found not to have any significant effect on the risk structure, in statistical terms.

Elton et al (2001) examined corporate bond spreads based on reduced form models and measure credit spreads as a function of local and state taxes, default risk and systematic risk factors. He concludes that similar to stock returns there are systematic risk factors in the returns of bonds.

Duffee (1998) and Morris, Neal and Rolph (1998) apply macroeconomic changes captured in the Treasury curves as a proxy for changes in default risk. However, none of these studies have shown how systematic and default risk may influence credit spreads when considered on a parallel basis and hence don't account for the potential correlation between these variables. For example, the treasury curve variables found in Duffee (1998) and Moris et al (1998) may proxy for the systematic risk measures in Elton et al(2001) or vice versa. With the exception of the study of Moris et al (where the focus is only on the long run relation), these studies focus on short-term dynamics and have not examined the long run relation between the determinants of credit spreads. Furthermore, these studies only consider investment grade bonds and leave out the most volatile segment of the market, i.e. bonds belonging to the non-investment grade.

Generally, bond pricing models, either explicitly or implicitly, include a correlation between credit spreads and the level of interest rates. However, most theoretical models reach different conclusions as to the sign of this relation. Some of the researchers document a negative correlation between changes in credit spreads and the level of interest rates (i.e. Duffee and Das & Tufano) which is consistent with Merton's model. The rationale behind this, is that the level of the Treasury rate should increase the value of the firm moving it away from the exercise price and therefore reducing the probability of default. On the other hand, as it is being argued by Leland and Toft (1996) there is the possibility of a positive relation between treasury yield and credit spreads. The idea behind this positive relation is that a change in the treasury yield doesn't only influence the discount rate but also the value of the underlying asset, which effectively implies that the value of the firm decrease and the probability of default increases.

The relation between the slope of the treasury yield curve on credit spreads is being examined, by Littermanm and Iben (1991), who provide evidence that risk premiums increase with maturity, Duffee (1998), who confirms the hypothesis that the option to call a corporate bond should rise in value when bond yields fall, at least for investment grade bonds, Joutz, Mansi and Maxwell (2000) who state that treasury yield curves are positively related to credit spreads in the long run but are negatively related in the short run.

Elton et al.(2001) and Guitteriez (2001) find that similar to stock returns there are systematic risk factors in the returns of bonds. They both find that the systematic risk factors identified by Fama and French (1993) are priced in bond returns as well. These factors include market risk premium (excess of the return on the market minus the risk free rate) and SML (size variable, i.e. small minus large portfolio returns) and HML (book to market variable, i.e. high minus low book to market portfolio returns).

Finally, Joutz, Mansi and Maxwell (2000) extend this literature by empirically examining the determinants of credit spreads and their effects on the valuation of risky debt. In particular, they proceed as follows:

1. They try to jointly model default and systematic measures compared to previous research which focuses on the determinants of either default risk (Duffee (1998)) or systematic risk (Elton, Gruber, Agrawal and Mann(2001))
2. They use cointegration analysis to examine the relation between credit spreads and the treasury term structure categorised by the level and slope
3. They confirm the findings of Elton et al (2001) that the Fama and French (1993) systematic risk factors play a role in the pricing of risky debt.
4. Finally, an analysis of investment and non-investment grade corporate bonds is included in order to better understand how these risk factors change across risk classes.

They conclude, based on a monthly data sample, that over a twelve-year period credit spreads are a non-stationary or at least close to a unit root process, but the changes in credit spreads are stationary. In order to include stationarity the usual methodology adopted is to difference the variables, which though leads to loss of information. As a result in their paper they are examining the presence of stationary cointegrating vectors between credit spreads and the treasury term structure. They use error correction models to determine the factors that influence credit spreads over the short and long run. In summary their results could be concluded to the following:

- Treasury yields are positively related to credit spreads in the long run, whereas they are positively related in the short run.
- When exploring the relation between credit spreads and the slope of the term structure, the results are somewhat mixed. In particular, for intermediate investment grade bonds, there is a positive relation in both short and long run, but for longer-term bonds this relation is negative in the long run, while there is no statistically significant relation in the short run.
- It was shown that Fama and French systematic factors do influence credit spreads over time and as a result corporate credit spreads are determined both by systematic and default risk.

One of the few papers that looks at the determinants of credit spread changes is the one by Collin-Dufrense, Goldsteing and Martin (December 2001). Using monthly observations of industrial bond prices from July 1988 through December 1997, they investigate the determinants of credit spread changes, once they have assigned each bond to a leverage group based on the firm's average leverage ratio. As explanatory variables, they use:

(i) the slope of the yield curve, i.e. the change in the 10-year minus the 2-year treasury yields,

(ii) firm leverage, i.e. the change in the firm's leverage ratio,

(iii) volatility, i.e. change in implied volatility

(iv) jump magnitudes and probabilities, i.e. change in the slope of volatility smirk

(v) S&P 500 returns

Using OLS regressions, they find that both the change in leverage and the firm equity return are statistically significant and bear the expected sign, for most groups in the multivariate analysis. However, their economic significance is rather weak. Consisten with the empirical findings of Longstaff and Schwartz(1995) and Duffee(1998), they prove that an increase in the risk free rate lowers the credit spread for all bonds. Furthermore, they argue that the sensitivity to interest rates increases monotonically across both leverage and ratings groups. The convexity and slope of the term structure of interest rates are not very significant, either statistically or economically, while the change in VIX is statistically significant. The return on the S&P 500 is extremely significant and so is the change in the steepness of the S&P 500 smirk. Although they found that most of the variables suggested by theory are significant both in economical and statistical terms, they only capture around 25% of the variation in credit spreads as measured by the adjusted R^2. To understand the remaining variation they undertake principal component analysis, but still added financial and economic variables provide only limited additional explanatory power. Their findings suggest, that contrary to the structural models of default, aggregate factors appear much more important than firm specific factors in determining credit spread changes.

In a similar fashion Huang, Zhi, Kong and Weipeng(2003), try to explain changes in credit spreads with the use of option adjusted credit spreads. Using weekly and monthly credit spread data from Merrill Lynch, they investigate the determinants of credit spread changes. As explanatory variables they use:

(i) The realised overall default rate in the US corporate bond market

(ii) Risk free interest rate dynamics

(iii) Equity market factors, such as return and volatility

(iv) Liquidity indicators from corporate bond mutual funds,

(v) The state of the US economy

They find that the Russell 2000 index historical return volatility and the Conference Board composite index have significant power in explaining credit spread changes, especially for high yield indices. Those variables together with the interest rate level, the historical interest rate volatility, the yield curve slope, the Russell 2000 index return and a high-minus-low variable explain 67.68% and 60.82% of credit spread changes for the B and BB rated indices.

2.3. Recent Developments in Credit Risk Framework

As has already been mentioned in the previous section, the ultimate framework for analysing credit risk calls for the full integration of market and credit risk. Over the past decade financial institutions have developed and implemented a variety of sophisticated models of value-at-risk for market trading portfolios. These models have gained acceptance not only among senior bank managers but also in amendments in the international bank regulatory framework. Recently advances have also been made in modelling credit risk in lending portfolios. These new models are designed to quantify credit risk on a portfolio basis, and therefore have applications in control of risk concentration, evaluation return on capital at the customer level, and are proved to help more active management of credit portfolios. These models include Credit Metrics, developed by JP Morgan, Credit Risk +, as developed by CSFB, KMV and Credit portfolio view as presented by McKinsey. Each of these models are analysed in below:

2.3.1.Credit Metrics [12]

CM represents one of the first publicly available attempts to develop a portfolio credit risk management model, which uses probability transition matrices, in order to measure the marginal impact of individual bonds on the risk and return of the portfolio. CM is based on credit migration analysis, i.e. the probability of moving from one credit quality to another, including default within a period of one year, chosen arbitrarily. Interest rates are assumed to follow a deterministic process.

CM is a Merton-based model, in that it relies on Merton's model of a firm structure, i.e. a firm defaults if the value of its assets fall below its liabilities. Effectively, a borrower's probability of default depends on two things:

a. the amount by which assets exceed liabilities and
b. the volatility of those assets.

CM is based on the estimation of the forward distribution of the changes in value of a portfolio loan and bond type products at a time horizon, usually within one year.

[12] Credit Metrics will be referred to as CM, in the remaining of this document for simplicity reasons.

Value changes are mainly related to changes in credit quality of the obligor , which include both downgrade and default. Credit VaR when compared to market VaR has the following limitations: 1st the portfolio distribution is far from being normal and 2nd measuring the portfolio effect due to credit diversification is much more complex than for market risk.

Credit returns are highly skewed by nature and fat tailed, and there is limited upside to be expected from credit quality improvements, while there is substantial downside potential when it comes downgrading and default. The level of distribution cannot be any larger, as estimated by the mean and the variance only, i.e. the calculation of VaR for credit risk requires simulating the full distribution of the changes in the portfolio value. In order to measure the portfolio diversification effect, the correlation of credit quality of all obligors should be estimated. But since these correlations cannot be directly observed, the CM model uses joint probabilities of assets returns, after making simplifying assumptions for the capital structure of the obligor and the generating process for equity returns.

CM risk measurement framework assumes the following steps:

1. The specification of the transition matrix and each borrower's default probability, which is mapped from the borrower's credit quality. The mean value of the bond, within a year horizon, is derived as the sum of each possible bond/loan value at the end of year 1 multiplied by the probability to migrate to another rating class.
2. The second step is specifying the time horizon, which within the credit risk framework, tends to be assumed on an annual basis.
3. The forward pricing model is specified. For each available 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 sum of the discounted cash flows will provide the value of the bond in one year. If an issuer defaults, a recovery rate is estimated from the rating agencies' historical information on those rates.

4. The forward distribution of the changes in portfolio value due to eventual changes in the credit quality is derived. [13]

An important element of CM is that it can derive the individual asset's impact on the overall portfolio's standard deviation, and as a result the benefits derived from portfolio diversification can be evaluated. This is of course a very important pro-active management tool and needs to be accompanied by a RAROC model which provide information on the adjusted return on capital for each transaction.

Additionally, equity prices are used as a proxy in order to calculate asset correlations. Because of the large number of bonds and loans, CM uses multi-factor analysis, according to which it allocates each obligor to the specified countries and industries, which are the most likely to determine its performance. Equity returns are then correlated to the extent that they are exposed to the same industries or countries. Then the industry and country weights are estimated for each obligor, as well as the firm's specific risk, which is idiosyncratic to each obligor and is independent of any other obligor or index.

Exposures within the CM framework mean the forward pricing model, which applies in each credit rating. Forward pricing is derived form the present values of the model using the forward yield curve for the corresponding credit quality.

a. for bonds and loans receivables, commitments, LC[14], the forward exposure relates to the future cash flows, after the one-year time frame.

b. For derivative like swaps and forwards, the exposure is conditional on future interest rates. As such, in order to estimate future cash flows some assumptions need to be made for interest rate movements. It should be noted that the process is quite complicated when it comes to swaps, whereby the risk exposure can either be positive or negative, is in or out of the money, for the bank respectively. If it is out of the money the counterparty is at risk. The

[13] An analytical description for calculating VaRs for specific loans, bonds or large portfolios as well as the calculation of capital charge is provided in Appendix 1.
[14] Letters of Credit

bank is only at risk when that exposure is positive. As interest rates are assumed deterministic, the calculation of the forward price distribution relies on an ad hoc procedure., i.e.

Value of the swap in 1 year with rating R =

Forward risk-free value in 1 year – expected loss in year 1 to maturity for the given rating R

The forward risk free value of the swap is calculated by discounting the future net cash flows of the swap , based on the forward curve and discounting them using the forward government yield curve. The data for the probability of default is either given by Moody's or S&P, or it can be derived from a transition matrix. The recovery rate comes also from statistical analysis provided by rating agencies. However, it should be noted that this ad hoc calculation of interest rate swaps, is not the most appropriate since only stochastic interest rates will allow a proper treatment of exposure calculations for swaps as well as other derivative securities.

There are however, some problems with the VaR methodology employed by Credit Metrics. In particular, the transition matrix, is assumed to follow a stable Markov process, which means that movements between rating classes are independent, according to a paper by Altman and Kao(1992). However, the empirical evidence supports the hypothesis that rating transitions are autocorrelated, so that a bond or a loan that was previously downgraded is more likely to be downgraded again in the current period, as also supported by Perraudin, Nickell and Varotto(2000).

The next thing to note, is that the transition matrix is assumed to be stable. The same matrix is used for different countries of the borrower, and for different points in time. Nickell et al(2000) show how industry and country factors, have a significant impact on rating transitions.

Moreover, as noted by Altman and Kishore(1998) there is a significant difference according to whether the transition matrix is computed on newly issued bonds or on all bonds outstanding in a rating category at a particular point in time. Using bond transition matrices to value all bonds that belong to the same rating class, ignores all other issues that make loans behave differently from bonds, such as covenants, collaterals, etc. Also the fact that interest rates and recovery rates are assumed to be deterministic leads to underestimating the VaR and the capital requirements.

To summarise, although CM is one of the first publicly available attempts using probability transition matrices to develop a framework for the calculation of Var for individual loans as well as portfolios on the other hand it faces criticism on the following points:

- Interest rates are assumed to be fixed , which effectively means that the model only considers credit events.

- There is no market risk included in the assumptions, which makes the VaR calculations of derivative transactions inaccurate, even though it is acceptable for floating and short term notes.

- Default probabilities don't depend on the state of the economy, which is inconsistent with the empirical evidence.

- The equalisation of correlation among asset and equity returns can affect the correlation coefficients , where small errors are very important. However, the accuracy of this model cannot be directly evaluated since asset returns cannot be observed.

2.3.2. Credit Risk +[15]

CR+ is a model of default risk. There are only two end of period states for the obligor, default and non-default. In the event of default the lender suffers a loss of fixed size, i.e. its exposure to the obligor. CR+ applies an actuarial approach for the derivation of the loss distribution of the loan/loss portfolio. In CR+, no assumptions are made about the causes of default, i.e. an obligor A can either be in default with a probability Pa or not in default with a probability 1-Pa. Further assumptions of the model are:

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[15] For the remaining of this document Credit Risk + will be denoted as CR+, for simplicity reasons.

- ♦ For a loan the probability of default in a given period, is the same for each other period.
- ♦ For a large number of obligors, the probability of default for a particular obligor is small, and the number of defaults that occur in any period is independent of the number of defaults occurring in any other period. The probability distribution for the number of defaults is given by the Poisson distribution.

Lets assume that there are m obligors in a portfolio, where m is a finite number and the Poisson distribution which specifies the probability of n defaults for n=1,...∞ is only an approximation. But if the number of the obligors is very large, then testing the probabilities n+1,n+2,... the number of defaults becomes negligible. Therefore, the following equation can be presented:

$$P(\text{n defaults}) = \frac{\mu^{n} * e^{-\mu}}{n\,!}$$

$$\sum_{A} P_{A}$$

where n = 0,2,...

μ: is the average number of defaults per year, and also is equal to

whereby P_A denotes the probability of default or obligor A.

n : is the annual number of defaults, which follows a stochastic process with mean μ, and standard deviation $\sqrt{\mu}$.

In order to find the frequency of the default events, the distribution of the probability of default losses for a portfolio is derived as follows:

A Poisson distribution approximates the distribution of the number of default events. Then the standard deviation should be expected to be approximately equal to $\sqrt{\mu}$, where μ is the average annual default rate. However, it is possible that the Poisson distribution will underestimate the actual probability of default. This is not surprising since the default rate variability changes over time depending of the business cycle. Therefore, the Poisson distribution can be used to represent the default process, having assumed that the mean default rate is stochastic with mean μ and a standard deviation of σ_{μ} .The assumption of stochastic default makes the distribution of default highly skewed with a fat right tail. It should also be noted that in the CR+ framework, if default occurs, then the loss incurred by a counterparty is adjusted to the recovery rate. [16]

To conclude, CreditRisk+ has closed form expressions for the probability distribution of portfolio loan losses. Thus, the methodology doesn't require simulation and is advantageous from a computational point of view. Also the methodology requires minimal data: probability of default and the loss given default for each loan. No information is required about the term structure of interest rates or probability transition matrices.

However, this model is also criticised as it assumes interest rates to be deterministic, which actually affects the credit exposure over time, i.e. the exposures are predetermined constants and disregards non-linear products such as options or even foreign currency swaps.

[16] Appendix 2 provides an analysis of how the distribution of default losses is derived for a portfolio under CR+.

2.3.3. Credit Portfolio View [17]

Another attempt which was made in order to eliminate some of the deficiencies of the above mentioned models was the one by McKinsey. This is the **Credit Portfolio view**, which was first developed by Wilson (1987, 1997). CPV is multi-factor model, which is used to simulate the joint conditional distribution of default and migration probabilities for different rating categories, belonging to different industries and countries, based on a set of macro-economic variables such as the GDP growth, the level of foreign exchange and interest rates, the aggregate savings rate and others.

CPV is based on the idea that default and migration probabilities are linked to the economy. When an economy is in recession then the rate of downgrades increase, and vice versa, i.e. when the economy grows stronger. In other words, the model assumes that credit cycles follow economic cycles. Accordingly, CPV proposes a methodology which links the macroeconomic variables to default and migration probabilities. The two most commonly used ways of dealing with cyclical movements are:

1. the sample period is divided into recession and non-recession years and then two individual transition matrices are calculated in order to produce two separate VaR calculations.
2. The relation between the macro factors and the transitional probabilities is modelled simultaneously, and then some macro shocks are generated into the model in order to simulate the evolution of transition probabilities. This is the approach which is followed by the CPV.

In order to derive such a model, the following should be considered:

Default probabilities are modelled as a logit function, where the independent variable is a country speculative grade index which depends upon current and lagged macroeconomic variables, i.e.

$$\mathbf{P}_{j,t} = \mathbf{1 / 1 + e^{-y_{j,t}}}$$

[17] Credit Portfolio View, will be denoted as CPV for the remaining of this document for simplicity

which can take values between 0 and 1, due to the logit transformation assumption and where,

$P_{j,t}$, denoted the conditional probability of default in period t

$-y_{j,t}$, is the index value derived from a multi-factor model

j: speculative grade obligors in country industry.

According to CPV, the multi-factor model which is used to determine the state of the economy is presented as follows:

$$\mathbf{Y_{j,t} = \beta_{j,o} + \beta_{j,1} X_{j,1,t} + \beta_{j,2} X_{j,2,t} + \ldots + \beta_{j,m} X_{j,m,t} + V_{j,t}}$$

Whereas,

$Y_{j,t}$ denotes the index value for the jth country /industry speculative grade, in period t

$\beta_j = (\beta_{j,o}, \beta_{j,1}, \beta_{j,2}, \ldots, \beta_{j,m})$ denote the coefficients of the jth country industry of speculative grade, at time t,

$X_{j,t} = (X_{j,1,t}\ X_{j,2,t}, \ldots, X_{j,m,t})$ are the values of the macroeconomic variables of the jth country/ industry speculative grade, at time t.

$V_{j,t}$ is the error term, which is independent of the of macroeconomic variables and is assumed to be normally distributed , whereby $V_{j,t} \sim N(0, \sigma_j)$ and $V_t \sim N(0, \Sigma_v)$, whereby the V_t stands for the vector of stacked index innovations , and $V_{j,t}$ and Σ_v is the j x j covariance matrix of those index innovations. The value of these random variables can be generated by using Monte Carlo simulations, based on historical probability data

The following step is to specify the set of the macroeconomic variables for each country and the probability of default $P_{j,t}$ and the index $Y_{j,t}$ are then defined at the country /industry level and the coefficients β_j are calculated accordingly. These macroeconomic variables are assumed to follow a univariate, auto-regressive model of order 2 (AR2), whereby:

$$\mathbf{X_{j,i,t} = \gamma_{j,i,o} + \gamma_{j,i,1} X_{j,i,t-1} + \gamma_{j,i,2} X_{j,i,t-2} + e_{j,i,t}}$$

where

$X_{j,i,t-1}$, $X_{j,i,t-2}$, are the lagged values of the macroeconomic variables $X_{j,i,t}$, $\gamma_{j,} = (\gamma_{j,i,0}, \gamma_{j,i,1}, \gamma_{j,i,2})$, which are the coefficients to be estimated

reasons.

$e_{j,i,t} \sim N(0, \sigma_{e\,j,i,t})$ and $e_t \sim N(0, \Sigma_e)$

e_t is the vector of stacked error terms $e_{j,i,t}$ of jxi AR(2) equations, and

Σ_e is the (jxi)(jxi) covariance matrix of the error terms e_t

Then the default probability model has to be calibrated and the Cholesky decomposition model is used to simulate the decomposition of the default probabilities.

The essential idea of the CPV model is represented in an unconditional matrix for a particular country, whereby each shell of the matrix shows the probability that a counterparty of a particular rating at the beginning of the period will move to another rating at the end of the period. This probability is expected to move significantly during the business cycle.

However, as shown in the model, it is possible that the unconditional transition matrix will underestimate the risk of default on low rated loans. In order to avoid this problem of underestimation all elements in the transition matrix should be adjusted for each year into the future reflecting the macroeconomic shocks on the transition probabilities. The simulated transition matrix would replace the historically unconditional matrix, and then given a particular rating, the transition probabilities could be used to calculate the VaR, which could be applied to long as well as to shorter periods.

For longer time horizons ,i.e. t, t+1, transition matrices should be multiplied to yield

$$\mathbf{M}_{t,t+1} = \mathbf{M}_t \times \mathbf{M}_{t+1}$$

Where a new matrix is produced, whose final column will give the cumulative probabilities of default for different loans during the periods t, t+1.

To summarise, the model implies that the credit cycles follow the business cycles by taking external macro economic variables into consideration in order to derive a rating. Provided that the data is available this methodology can be applied in each country, to different sector s and various classes of obligors which react differently over the business cycle.

However, the calibration of this model requires reliable default data for each country and/or industry which is not always available.

2.3.4. KMV Model

The accuracy of the Credit Metrics methodology / Credit Var has been strongly challenged by the **KMV model**. The reason for this, are the two critical assumptions on which the Credit Metrics rely, i.e. 1. All firms within the same rating class have the same default rate and 2. Actual default rate is equal to the historical average default rate. Indeed, as argued by KMV this cannot be the case, since default rates are continuous, while ratings are adjusted, simply because rating agencies take time to upgrade or downgrade companies whose default risk has changed.

The idea of applying the option pricing model to the valuation of risky bonds and loans can be dated back to Merton's model (1974). He noted that when a bank makes a loan, its compensation is isomorphic to writing a put option on the assets of the borrowing firm. In particular, as there are five variables which enter the Black-Scholes-Merton (BSM) model of put option for stock valuation, the value of default of a loan or bond will also depend on five similar variables[18].i.e.

Value of a put option on a stock $= f(\bar{s}, \bar{x}, \bar{r}, \bar{\sigma}_S, \bar{\tau},)$

Value of a default option of a risky loan $= f(A, \bar{B}, \bar{r}, \bar{\sigma}_A, \bar{\tau},)$

Where a bar above a variable denotes that it is directly observable.

r: short term interest rates,

σ_S, σ_A are the volatilities of firms equity value and the market value of its assets respectively ,

[18] The five variables included in BSM model of a put option are the original interest rate on the swap(the strike price), the current interest rate (the current underlying price), the volatility of interest rates, the sort term interest rates and the time to maturity of the swap.

τ is the maturity of a put option or for loans it is the time horizon of the loan.

As observed from the above two equations, all of the variables of the put option are directly observable, whereas the market value of a firm's assets and its volatility are not directly observable. Some researchers –Gordon and Santomero(1990) and Flannery and Sorescu (1996)- have assumed that the book value of assets is equal to the market value of assets which allows for to disregard the implied volatilites of assets. But without additional assumptions it is hard to find the values of A and σ_A based on only one equation.

Merton's ideas have been extended in many directions, such as by the KMV corporation of San Francisco, which generated default prediction models which updates default predictions for all big companies and banks whose equities are publicly traded. KMV argues that default rates are continuous, while ratings are adjusted in a discrete mode, since agencies take longer time to adjust for company downgrades or upgrades. Though a simulation exercise, it was shown that the historical average default rate and transition probabilities can differ from the actual rates. KMV doesn't use the S&P's or Moody's data in order to assign probabilities of default, which only depend on the rating of the obligor. KMV derives the Expected Default Frequency (EDF) for each obligor based on a Merton's type of model (1974) as aforementioned. Therefore, the probability of default is a function of the firm's capital structure, the volatility of asset returns and the current asset value. In particular,

KMV model, in order to solve the two unknowns A and σ_A, referred to in the equations above considers the following:

- A structural approach is used between the market value of the firm's equity and the market value of assets,
- A relation between the volatility of the firm's assets and its equity.

Once these values have been derived the EDF measure can be calculated for each borrower. KMV doesn't explicitly refer to transition al probabilities, as they are already included in the EDFs which are associated with a spread curve and an implied credit rating. [19] KMV methodology best applies to publicly traded companies where the value of equity is actually determined by the market.[20]

The conclude the main contributions of the KMV methodology is that it relies on the market value of equity to estimate the firm's volatility, and as such it includes market information of default probabilities. On the other hand, the deficiencies of the model are focused on the following:

a. The value of the firm, the volatility and the expected value of asset returns, cannot be directly observed, and therefore the accuracy of the estimates evaluated.
b. Interest rates are assumed to be deterministic, and this can be disadvantageous, when applied to loans and other interest rate sensitive instruments.
c. An implication of the KMV methodology (i.e. that as the maturity of a risky bond tends to zero, the credit spread also tends to zero) is not observed empirically.
d. Historical data are used to determine the expected default frequency rates and consequently there is the implicit assumption of stationarity, which is not accurate as it has the potential to underestimate the actual probability of default.
e. An ad hoc liability structure for a firm is used in order to apply the option theory.

[19] It should be noted that the EDF scores vary between 0 and 20.
[20] KMV's model is derived in three steps. Analytical description of the methodology involved is provided in Appendix 3.

2.3. A Comparative Anatomy of the Credit Risk Models

Having reviewed the basic and most influential credit risk models, which have been developed in the last years, it would be important to consider difference and similarities among those models as well as the advantages and disadvantages of each of those models. The following table summarises the four basic models together with their main framework of comparison :

Framework for comparisons	CM	CR+	CPV	KMV
1. Basis for Credit risk	Market Value of assets	Expected Default Rates	Macro-economic variables	Market value of assets
3. Interpretation of Risk	MTM	Default Model	MTM or Default Model	MTM or Default Model
4. Volatility of micro & macro variables	Constant	Variable	Variable	Variable
5. Correlation of dependent and independent variables	MultivariateNormal Asset Return	Expected Default Rate or Independence assumption	Factor Loadings	Multivariate Normal Asset Returns
5. Recovery Rates	Random	Constant within a band	Random	Constant or random
6. Numerical Approach	Simulation or Analytic	Analytic	Simulation	Analytic

As shown in the table above these models have some similarities and differences. In particular,

1. Basis of Credit Risk

Both CM and KMV models use the market value of assets and the volatility of assets in order to derive their credit risk, i.e. they are based on a Merton-type model. CPV's risk on the other hand is driven by a set of macro-economic variables, while in CR+ the risk is driven by the mean level of default and its volatility. However, it could be argued that all the above models could be linked to each other, since the volatility of the market value of assets as proposed by CM and KMV is linked to stock returns. In turn, stock returns are affected by macroeconomic factors – systematic – as well as non-systematic factors. CPV is also driven by a set of macro economic factors and unsystematic- shocks- in the economy; while CR+ is driven by the mean default rate in the economy, which could also be linked to the state of economy. Therefore, each of the above models can be viewed as being linked to some macro-economic variables and effectively to the state of the economy – directly or indirectly.

2. Definition of Risk

Some of the models discussed above calculate the VaR based on changes in market values, which are the mark-to-market, and allow for downgrades /upgrades as well as defaults; whereas some others concentrate only on two states of the economy the default and non-default.

3. Volatility of the variables

In CM, the probability of default is assumed to be fixed based on historical data. In CR+ the probability if default is assumed to follow a Poisson distribution around a mean default rate, which in turn is assumed to follow a gamma distribution, which results in fat tailed distributions , than those produced by CM or CPV. CPV models the probability of default as a logistic function of a set of macroeconomic factors and shocks, which follow a normal distribution and therefore as the macro economy advances, so will the probability of default and the transition matrix. KMV model is based on EDF, which changes as new information is absorbed in stock prices.

4. Correlation of credit events

The correlations, in all the four models could be seen as correlation between an individual or portfolio of loans or bonds, and the state of the economy, as aforementioned.

5. Recovery Rates

Generally speaking, the distribution of losses and the VaR calculation have proved to be rather volatile and dependent not only on the probabilities of default but also in the losses, once default has occurred. Therefore, modelling in a volatile recovery rate can increase the VaR calculation or the unexpected loss rate. The four models view recovery rates as follows:

CM allows recovery rates to be random. In the normal distribution version of the model, the estimated standard deviation of recovery is included into the VaR calculation. In the actual distribution version, recovery rates are assumed to follow a beta distribution. In CPV recovery rates are estimated through a Monte Carlo simulation, while under CR+ recovery rates are assumed to be constant, but within a specified band.

6. Numerical Approach

CM uses both the analytic and the simulation approach for calculating VaR. This happens because since the number of loans in a portfolio increases, the analytic approach becomes very complex and thus Monte Carlo simulation approach is more advantageous and produces an approximate aggregate distribution of the portfolio loan values and thus VaR.

CPV also uses a Monte Carlo simulation to generate macro shocks and the distribution of losses on a portfolio. On the other hand, CR+ based on a Poisson distribution for individual loans and a gamma distribution for the mean default rate, generates an analytic solution for the probability density function of losses. KMV also uses an analytic approach in order to generate the probability density function of losses.

2.4. Conclusions

This chapter has reviewed some of the basic ideas underlying the traditional framework of credit risk management and has given a brief review of the two most significant approaches to credit risk modelling, i.e. the structural approach and the reduced form approach. It provided some guidelines as to the theoretical determinants of credit spread changes and outlined two studies considered in the credit risk literature so far, that incorporate both market and firm specific factors, for determining credit spread changes. It considered recent developments made in the area of credit risk modelling at a portoflio level, as provided by the four mostly influential models considered in recent credit risk literature, i.e. the Moody's KMV model, the McKinsey model, Credit Metrics and the Credit Risk+. Each of the above models considered different micro and macro variables into their framework in order to model credit risk.

The idea of integrating some of those factors contemplated in the above models, into a unique framework for modelling credit risk is a topic that has received and will be receiving a great deal of attention in the credit risk literature. In essence, this is also the main driver behind this thesis, as is analytically described in the next chapters. It should be noted that this chapter provided some general thoughts to credit risk modelling and measurement. However, one can easily derive that although credit risk has been the subject of most theoretical and empirical discussions, at least during the last decade, it is rather surprising that most of the credit risk literature has focused on determining the main drivers of default. Of course, this is the most important risk faced by banks and other financial institutions world-wide, but it is also significant to model changes in credit risk before defaults occurs. More specifically, literature on credit risk migration within the context of credit spread changes is rather thin. At this point, it should also be noted that literature review related to the specific hypotheses tested under this thesis is provided in the relevant chapters.

3.0. Model Specification, Data Description & Hypotheses

3.1. Model Specification

The purpose of this thesis is to explore the impact of macro, equity, and accounting variables on credit spread changes. It constitutes an in depth analysis of the relation between the US corporate bond market, equity market and macroeconomy, while the ultimate goal is to construct a credit risk model which will provide the settings in order to forecast changes in credit spreads. The parameters used for testing the relation include not only spreads and equity information but also the respective companies' accounting information, which hasn't been included before, and a set of US leading macroeconomic indicators.

The proposed model uses some of the variables considered by MKMV and the Credit Portfolio View model, but the effort is focused on estimating credit spread changes rather than default probabilities or EDF measures. Also the idea of using transition matrices or recovery rates in order to model default or transition probabilities, is not considered under the proposed model, since the idea is to figure future changes in credit spreads. Instead the information provided by the above variables is backwards looking, but more importantly this is information already implicitly reflected in credit spreads.

3.1.2. Assumptions

The assumptions made for testing this relation are:

(1) Spreads are used as a proxy for credit ratings. When credit ratings improve, credit spreads are expected to tighten and vice versa.

(2) Companies provide reliable and efficient information to the markets on a timely basis.

(3) Financial markets are efficient in that, all information is available to investors and reflected in equity prices.

3.1.3. Proposed Credit Risk Model Format

As mentioned before, the proposed credit risk model, combines the effects of macroeconic and equity variables, as proposed by McKinsey and KMV respectively and incorporates also company specific financial information. In other words it is a multi-factor model that conforms to the structural approach to credit risk modelling but also uses variables employed in traditional credit risk analysis. Based on fundamental economic theory, we expect the relationship between changes in credit spreads and the independent variables to be of the following form:

$$\Delta \text{Spreads}_{it} = f[\alpha + (\beta_1 * (\delta X_{it})) + (\beta_2 * (\delta F_{it})) + (\beta_3 * (\delta Eit)) + \varepsilon_{it}]$$

Where:

i = 1, 2,…n and

Δ Spreads: denotes the change in spread on corporate bonds i.e. the change in the extra yield offered to compensate investors for a variety of risks such as: (1) expected default loss – the risk that in the event of default, investors will not receive the full amount of the promised cash flow (directly related to the default probability of the firm and the recovery rate in the event of default (2) credit risk premium, due to the uncertainty of defaulted losses and (3) liquidity and tax premiums which result from the difference in liquidity and tax status of corporate bonds and treasury bonds.

δX_{it}: denotes the change in a set of US macro-economic variables including GDP growth, inflation, consumer confidence, the term structure of interest rates, etc. There is assumed to be an inverse relation between spreads and macroeconomic factors, i.e. when economy improves and macroeconomic factors pick up, credit spreads tighten and vice versa. In other words, we would expect credit ratings to improve when the economy is doing better and deteriorate with a slowdown in economy.

δF_{it} : denotes the change in a set of accounting factors composing the company's financial performance, i.e. ratios such as ROA, ROE, Debt/equity, cash flow /debt, etc. Again here, there is an inverse relation between spreads and accounting factors, i.e. when a company's financials improve, spreads tighten and when financials deteriorate spreads tend to become wider. However, this is a rather complicated issue with respect to the timing of those adjustments taking place. The reason for this is that deterioration in a company's financial profile is received by the market long before the actual reporting of the companies' results. For example, a company may release information through the announcement of quarterly information, press reports or other company specific events to investors, which may proceed an actual negative change in the company's financials as those are reflected in the company's annual report.

Indeed, when considering the issue of timing within the current thesis, we should assume at least for most of the cases that the accounting information as it is provided in the company's annual report is the only information investors have.

δE_{it}: denotes the change on the company's stock price which is also inversely related to spreads, since when stock prices pick up spreads tighten and vice versa. Equity indices such as the S&P and the Russell Index are also considered and so are historical stock price volatilities as well as the implied volatilities as provided by the VIX Index.

Data on spreads for industrial bonds together with their respective equity and accounting information as well as a set of US macroeconomic indicators common for the companies mentioned above, were collected from Bloomberg and Merrill Lynch.

3.2. Data Description

Although the calculation of credit spreads between corporate and government bonds seems uncomplicated, since the most common way of figuring it, is to calculate the difference between the yield to maturity of a corporate bond and that of the government bond of the same maturity, there are other issues involved which should be carefully considered. Despite the type of the rate used or the availability of the rate, by directly comparing two bonds with the same maturity, we are effectively comparing two bonds that neither have the same duration (price sensitivity to interest rates changes) nor the same convexity (sensitivity to the slope of the yield curve). Calculating credit spreads on an aggregate basis using bond indices is subject to the same difficulties.[21] As a result in this thesis we are using two different sets of data, the first set, from Merrill Lynch which is option adjusted, and the second from Bloomberg calculated in the conventional way.[22] Therefore, the above hypotheses are tested with the use of two different sets of data.

- The **first set** includes the option adjusted credit spreads as provided by constituents of the Merrill Lynch Indices (investment and non-investment grade) on monthly and quarterly frequencies for the period from January 1997 until May 2002. An elimination procedure to Merrill Lynch Indices has been followed, whereby one bond with a medium to long term maturity profile, would be included from each company and therefore it is expected that the results would be more comprehensive and accurate, since specific company's movements in credit spreads will be matched against their respective movements in equity and financial ratios. Analytical description of the bonds and data comprising the actual and final set of the Merrill Lynch Indices is provided in section 3.4.1.

- The **second set** of data collected includes credit spread indices extracted from Bloomberg on monthly frequencies for a much longer time period than the first data set, i.e. from May 1991 until June 2005. Twelve series of credit spreads have

[21] Catherine Lubochinsky, University of Paris II, "How much credit should be given to credit spreads?", November 2002
[22] Analytical description of the calculation of ML credit spreads is provided in section 3.2.3.1. and for Bloomberg in section 3.5.1.

been gathered for short medium and long-term maturities for the AAA, AA, A and BBB rating categories. Non-investment grade indices weren't available in the second set of data. A more analytical description of the indices collected under this second set of data is provided in section 3.5.

3.2.1. Data Description –(1st set of Data –Merrill Lynch Bond Indices)

3.2.2. Rationale behind the frequency of the data collected and tested

One of the initial arguments in this thesis, was the frequency of the data to be tested. There has been no evidence, based on previous studies with regards to what should be the frequency of data collected, although in most of the studies the frequency of the data collected has usually been linked to the frequency of the independent variables included or the idea tested. In other words, papers examining the relationship between credit spreads and macroeconomic variables or financial ratios have used quarterly data, while those dealing with credit spreads and equity have mostly used monthly or weekly. Consequently, in this thesis, data has been tested on monthly and quarterly frequencies for equities and macroeconomic variables, but solely quarterly frequencies have been used when testing the relation between credit spreads and financial variables and on the combination of all the independent variables.

More specifically, data on credit spreads and equities as well some of the macroeconomic variables were available on monthly frequencies, while some of the macroeconomic and accounting variables were only available at quarterly frequencies.

For those variables that data was not available on monthly intervals, i.e. macroeconomic variables, data has been reproduced to generate monthly frequencies. For example January's GDP figure was kept the same through until the next reporting date, March, in order to generate monthly frequencies. Although this may alter to some extent the results, any effects from this extrapolation are minimised once data has been further tested on quarterly frequencies.

It should be noted from the outset, as it will be explicitly described in next chapters, that monthly and quarterly data was used to test the hypotheses on credit spreads and the macroeconomic cycle as well as equities and solely quarterly frequencies to test the relation between credit spreads and accounting information.

Another reason for focusing on monthly and quarterly frequencies is in order to implicitly induce to a longer time horizon, since in any case the concept and idea of this model is to forecast medium credit spread changes.

3.2.3. Description of Data

3.2.3.1. Data for Spreads

Data for spreads was collected from Merrill Lynch[23]. It is very important for this thesis that access to ML Indices was available, since most corporate bond databases available to academics such as the Lehman Fixed Income or Bloomberg's databases, mainly cover investment grade bonds. Also and most importantly is the fact that data collected on credit spreads takes account of the bond optionality, i.e. the modified duration[24] of bonds is calculated and the option adjusted duration for bonds with an embedded option is also considered.

ML has a number of different indices, such as the global broad market index, the global sovereign index, and others. Each of these indices have different characteristics with respect to rating, maturity, market capitalisation the currency of issuance, etc. The one chosen for the purposes of this thesis, classifies bonds according to rating category for medium term maturing bonds and is concentrated on the US investment grade and high yield market. The reason why the US market is chosen for this thesis is because there is more information both in terms of stocks quoted but also because in the US, companies are required to publish their accounts on a quarterly basis which would provide more observations for testing the relevant hypotheses.

In particular, information on credit spreads was collected from the following two indices: the US High Grade Broad Market Index and the US High Yield Master II Index:

[23] For the rest of this study, the abbreviation ML will be used to refer to Merrill Lynch

ML US HIGH GRADE BROAD MARKET INDEX – TICKER US00

The US Broad Market Index tracks the performance of the US dollar denominated investment grade government and corporate public debt issued in the US domestic bond market, including collateralised products. Qualifying bonds for the index must have at least one-year remaining term to maturity, a fixed coupon schedule and a minimum amount outstanding of US$1bn for US treasuries, US$25mn (per tranche) for asset backed securities and US$150mn for all other securities. Bonds must be investment grade based on a composite of Moody's and S&P. "Yankee" bonds (debt of foreign issuers issued in the US domestic market) are included in the Index provided the issuer is a supranational or is domiciled in a country having an investment grade foreign currency long term debt rating (based on a composite of Moody's and S&P). "Global" bonds (debt issued simultaneously in the eurobond and the US domestic bond markets) also qualify for inclusion. The index is re-balanced on the last calendar day of the month. Issues that meet the qualifying criteria are included in the index for the following month. Issues that no longer meet the criteria during the course of the month remain in the index until the next month end, re-balancing at which point they are dropped from the index. The number of bonds included in the index are 5,864. The inception date of the index is the 31/12/1996.

ML US HIGH YIELD MASTER II INDEX – TICKER H0A0

The US High Yield Mater II Index tracks the performance of below investment grade US-dollar denominated corporate bonds publicly issued in the US domestic market. "Yankee" bonds (debt of foreign issuers issued in the US domestic market) are included in the Index provided the issuer is a supranational or is domiciled in a country having an investment grade foreign currency long term debt rating. (based on a composite of Moody's and S&P). Qualifying bonds for the index must have at least one-year remaining term to maturity, a fixed coupon schedule and a minimum amount outstanding of US$100mn. Bonds must be rated below investment grade based on a composite of Moody's and S&P. The index is re-balanced on the last calendar day of the month. Issues the meet the qualifying criteria are included in the index for the

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[24] Modified Duration, i.e. the duration divided by the interest rate factor (1+R)

following month. Issues that no longer meet the criteria during the course of the month remain in the index until the next month end, re-balancing at which point they are dropped from the index. The number of bonds included in the index is 1,422. <u>The inception date of the index is 31/8/1986.</u>

Bonds qualifying for this thesis

Although the indices described above include more than one bond from the same company, the sample used in this study has been carefully eliminated (analytically described in section 3.4.1). Initially, we had to ensure that bonds were considered based solely on the creditworthiness of the issuers, and accordingly issues with asset backed and credit enhancement features (such as financials, quasi and foreign government bonds, sovereigns, securitised securities and utilities) have been excluded. The reason for the exclusion of these bonds is because ratings assigned to securitised issues don't only consider the financial standing of the issuer but also collaterals or others securities attached. Also financial and utility companies have been excluded since credit analysis applied to such companies is based on different fundamentals than those applied to industrial ones. As a result in this study we will concentrate only on corporate bonds issued by industrial companies. According to the ML classification, industrial companies include technology and electronics, services cyclical and non-cyclical, telecommunications, energy, real estate, capital goods, basic industries and media. The sample includes US dollar denominated investment and high yield grade industrial sector corporate bonds, issued in the US domestic bond market.[25] In terms of the maturity profile of the bonds chosen, there has been a careful selection to include only bonds with an average maturity profile of seven to eight years.

As a result corporate bond credit spreads were collected using option-adjusted spreads from Merrill Lynch from January 1997 through May 2002. The Merrill Lynch option adjusted credit spread indices start from December 31, 1996 and are rebalanced on the last calendar day of each month. To avoid potential bias due to index rebalancing, monthly spread is taken excluding the rebalancing day.

3.2.3.2. Data for Equities

For the sample of bonds that qualified for this thesis, we collected the respective equity prices from Bloomberg, for the period from January 1997 until May 2002. In addition to the company specific equity data, two equity indices have also been collected, the S&P500 index, which is dominated by large cap stocks and the Russell 2000 index which is related to small cap stocks. The volatility Index has also been collected (known as the VIX), which measures the implied volatility in the prices of a basket of options on the S&P 100 Index. The index is developed by taking the weighted average of implied volatility for the Standard & Poor's 100 Index (OEX) calls and puts and measures the volatility of the market. The S&P 100 itself contains the largest 100 stocks in the S&P 500 that have options traded on them. The VIX covers a relatively narrow group of stocks, but those are among the largest companies traded in the United States. The S&P 500, the Russell and the VIX indices have been collected for a much longer time period from May 1991 until May 2005.

3.2.3.3. Data on Accounting Factors

Having collected the Bloomberg tickers for the data that qualified in terms of spreads and equities, the next step was to collect the data for the respective companies' accounting information. This data was taken from Bloomberg and since most of the companies report on a quarterly basis, that was the frequency of the data collected. Data on accounting information was collected for the period from January 1997 until May 2002, since accounting variables will only been considered when testing the hypothesis of the relationship between credit spreads and accounting information and the combination of all the independent factors on a cross sectional basis. For the rest of the thesis when it comes to accounting indicators the following abbreviations are going to be used:

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[25] For a more detailed description of the ML indices by rating and industrial classification please refer to the pivot tables per rating category as shown in the Appendix 4.

Accounting Factors	Abbreviations
Cash Flow to Debt	CFD
Current Market Capitalisation	CMT
EBIT to Interest Expense	EBIT
EBIT to total interest expense	EBTI
EBITDA to total interest expense	EBITDIN
EBITDA per revenue	EBDAR
Return on capital	ROC
Return on common Equity	ROE
Return on Invested Capital	ROIC
Total Debt To EBITDA	TDEBDA
Total Debt to Total Capital	DBCP

3.2.3.4. Data on macroeconomic factors

For the purpose of testing the impact of the macroeconomic cycle on credit spreads and the implicit influence of the macro economic variables when we are proceeding with a solution for forecasting credit spreads, macroeconomic variables have been collected from Bloomberg. These variables have been collected for the period from May 1991 until June 2005, on a monthly (where available) and quarterly basis. Data collected include:

- **Interest rates**

Short term 3 months and 2 years as well as medium term 5 years and long term 10yrs and 30yrs have been collected on a monthly & quarterly basis.

- **GDP**

Bloomberg defines GPD as the value of all final goods and services produced in the country. GDP is the broadest measure of economic activity and the principal indicator of economic performance. Built as a system of interlocking sector accounts, the GDP report provides the most comprehensive reading of the nation's wealth. Also released with GDP statistics is the GDP deflator. The calculations of the GDP deflator are reported implicit deflator and a fixed weight deflator. The implicit deflator is the ratio of the current dollar GDP to constant dollar GDP. The fixed weight deflator is the sum of the deflators for individual components of GDP with each component weighted by its share of real GDP in the base period and consequently a better gauge of inflation. For the purposes of this thesis, the figure for GDP collected is the one given by GDP/GNP. Data on the GDP is collected quarterly and converted to monthly data.

- **Employment Statistics**

Data on unemployment is also collected quarterly and is retrieved from the employment report released by the Bureau of Labour Statistics, which is probably the single most important economic series for the financial markets and generally viewed as one of the best concurrent measures of business activity. There are two surveys: (1) payroll survey which measures unemployment in non agricultural industries (2) household survey which measures civilian non-institutional employment aged 16 years and older, which includes agricultural workers and self-employed.

- **US Consumer Confidence**

Consumer confidence is measured by two widely followed confidence reports (1) University of Michigan and (2) Conference Board. Over the longer term both of these surveys move together as they serve as a reflection of the national mood. Consumers are more inclined to spend when they feel confident about their financial and employment prospects. Both indices of consumer confidence, i.e. the index from the Conference Board and the one from the University of Michigan are good leading indicators of consumer spending. The University of Michigan's index of consumer expectations is one of the leading economic indicators. Business confidence is watched for early signals concerning firms' capital spending and employment plans. Here the University of Michigan's consumer confidence index is being collected on a monthly basis.

- **CPI**

CPI is one of the most widely recognised price measures for tracking the price of a market basket of goods and services purchased by individuals. The weights of the components are based on consumer spending patterns. For example an item that makes up 20% of the average household budget would have the same weight in the CPI. The food and beverage components has a relative importance of about 18% in the CPI, so a 1% rise in food prices would contribute 0.18 points to the change in the overall CPI. The CPI covers both goods and services. Here it differs from the Producer Price Index which covers just goods. The other difference between the two indices is that the CPI covers cost facing consumers while PPI covers purchases and/or wholesalers. All items in the index are seasonally adjusted. Data on the CPI is collected quarterly and converted to monthly data.

- **PPI**

PPI which is also collected quarterly, measures prices received by producers at the first commercial sale. The report published on PPI, measures prices for goods at three stages of production: finished intermediate and crude. The index for finished goods generally receives the most attention. Change in this index is the first aggregate inflation measure available for the month. Food and energy are large components of the PPI. As with the CPI, the PPI excluding food and energy is a good measure of underlying inflation. Food and energy prices are often affected by temporary and non-economic factors such as weather. The PPI for consumer goods can be a good indicator of the goods component of the CPI which represents half of the CPI. Capital goods prices measure costs facing the industry.

- **Trade balance**

The merchandise trade balance report notes the difference between the dollar volume of exports and imports. The monthly numbers are the basis for the merchandise component of the net exports in the GDP account, although other adjustments are made. This report is broken down by industry, commodity and US trade with other countries. Quarterly figures are collected on the trade balance and then converted to monthly data.

- **Industrial Production**

Industrial production, is one of the oldest statistical reports in the economy and is defined as the measure of physical output in factories, mines and utilities. Activity in manufacturing accounts for about 85% of total industrial production with the remainder of output from utilities and services. Since it is a measure of actual volume of output in "goods-producing industries" influenced by prices, industrial production is one of the more important economic indicators. The industrial production statistics is broken down by industry (e.g. mining, autos, chemicals) and market grouping (e.g. final products, intermediate products and materials). For this thesis a broad measure of industrial production index is being considered and is collected quarterly and converted to monthly.

- **Money Supply**

The H6 is published weekly providing stock and flow measures of the monetary aggregates (M1, M2, M3) of domestic non-financial debt and their components, M1, M2, M3 which are progressively more inclusive measures for money: M1 is included in M2, which is included in M3. M1 is the most narrowly defined measure, consists of the most liquid forms of money, namely currency and checkable deposits. The non-M1 components of M2 are primarily household holdings of savings deposit, time deposits, and retail money market mutual funds. The non-M2 components of M3 consists of depositories, namely large time deposits, repurchase agreements and Eurodollars. Here quarterly figures of money supply on aggregate are being selected.

For the rest of this thesis the following abbreviations are going to be used for the macroeconomic factors.

Macroeconomic Factors	Abbreviations
Interest rates	IR
GDP	GDP
Employment Statistics	UNEMP
US Consumer Confidence	CONF
CPI	CPI
PPI	PPI
Trade Balance	TRBA
Industrial Production	IP
Money Supply	MS

3.3. Data Analysis

3.3.1. Data elimination process

Spreads collected from US High Grade Broad Market Index and US High yield Master Index include investment and high yield grade corporate bonds, which only have medium to long term maturities. (i.e. 7-8 years to mature). The spreads collected were the monthly OAS* spreads as provided by ML, from the 1/1/1997 until the 31/5/2002. (*OAS: option adjusted spreads- i.e. calculating the spread over the theoretical yield curve taking into account any bond optionality). These spreads are collected for trading days only. The start and end dates that data has been collected for, are the 31/01/1997 until 31/05/2002.

The total number of issues included in the Merrill Lynch indices included 5,864 bonds from the investment grade category and 1,422 from the non-investment grade category (i.e. total number of bonds 7,286). The ultimate sample of data, which is used for the thesis, is limited to 674 bonds (corresponding to 674 companies) for the following reasons:

- The reason why the initial number of bonds is high, is due to the fact that in the ML indeces, there are different bonds for the same company, but since they have different maturities they are rated differently. Additionally, there is a restriction with regards to spread history, as the spreads of the bonds which have matured are no longer in the index. Also one company can have a number of bonds trading with different maturities and different spreads. However, one bond is selected for each company, with medium to long term maturity (seven to eight years).

- The history of some of the bonds, which are traded, doesn't go back to the starting date (i.e. 31/1/1997) and as such those bond are also deleted from the sample.

- Some of the companies which have issued debt are not quoted. As a result the data is further eliminated to include the companies which are both quoted in the stock market and also have issued bonds which means the respective companies' bonds that don't have equity traded are also deleted from the sample.

- The data has been further eliminated since not all the companies which were publicly listed on either debt or equity markets had accounting information available on a quarterly basis which means that these bonds were also excluded from the sample.

Before proceeding with the detailed description of the final number of bonds per credit rating category, the table that follows provides a picture of the final sample per credit rating category (credit spreads are presented in basis points while the last column presents the number of bonds included per credit rating category)[26].

Credit Rating	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**Number of Bonds**
AAA	106.6	109.2	112.2	119.7	113.5	85.6	6
AA	118.2	133.2	119.2	151.8	125.2	106.8	21
A	122.2	124.2	152.2	162.9	143.1	141.4	68
BBB	210.7	212.1	214.2	242.4	228.1	234.9	160
BB	342.7	344.2	346.9	356.1	392.6	388.7	143
B	510.5	522.8	521.6	553.9	591.8	530.6	191
C	1,007.2	1,098.4	1,100.2	1,105.5	1,573.1	1,419.8	85

However, as mentioned previously, the ultimate number of companies included in the sample is significantly lower than the initial one. Below is described in detail the elimination procedure of the number of bonds, during the data collection process for each of the rating categories in turn.

AAA Rated Bonds

The initial sample included 2,068 bonds. Most of the bonds in this category are quasi & foreign government bonds, securitised asset-backed and financial bonds, which from the outset have been excluded from the sample, as their rating is based on factors such as the quality of security and collateral, rather than the actual financial fundamentals of the company.[27]

As a result the number of bonds that qualify (i.e. bonds issued by an industrial company, with medium to long term maturities) under this rating category are 98. These 98 bonds correspond to 15 companies, which means that from the 98 bonds only 15 were selected. From those 15 bonds, 8 of them had been excluded since they didn't have trading history going back to 31/1/1997 and the rest didn't meet the maturity criteria set (I.e. some of them had only 1 year to maturity). For one of the companies equity trading history wasn't available and as such, the final number of

[26] This table refers to Merrill Lynch corporate bond sample

companies which met the criteria for spreads and additionally had equity issued and accounting information available were 6.

Initial Number of Bonds	Number of Industrial Bonds	Number of Companies	Spreads	Equity Information	Accounting Information	Final Data Set
2,068	**98**	**15**	**7**	**6**	**6**	**6**

AA Rated Bonds (incl. AA1, AA2 & AA3 sub-categories)

The initial sample included 583 bonds. The number of industrial bonds was 184. The number of companies which had issued the 184 bonds with the different maturities was 30.[28] The bonds that met the maturity constraints were 24 and the final number of cross sectional observations for which there were both equity and accounting information available were 21.

Initial Number of Bonds	Number of Industrial Bonds	Number of Companies	Spreads	Equity Information	Accounting Information	Final Data Set
583	**184**	**30**	**24**	**24**	**21**	**21**

A Rated Bonds(including A1, A2 & A3 sub-categories)

A lot of bonds in this category have been deleted due to the fact that the number of bonds per company issued was very high.[29] As a result for from an initial number of 633 industrial bonds which corresponded to 85 companies, 73 of them were accepted due to the maturity constraints and 68 of them were finally included, as all of their information was available.

Initial Number of Bonds	Number of Industrial Bonds	Number of Companies	Spreads	Equity Information	Accounting Information	Final Data Set
1,489	**633**	**85**	**73**	**68**	**68**	**68**

[27] For a more detailed analysis of AAA rated please refer to the Appendix 4 (Pivot_AAA)
[28] For a more detailed analysis of AA rated bonds please refer to the Appendix 4 (Pivot_AA)
[29] For a more detailed analysis of A rated bonds please refer to the Appendix 4 (Pivot_A)

BBB Rated Bonds (including BB1, BB2 & BB3 sub-categories)

A number of bonds in this category were deleted as their history didn't go as far back as 31/1/1997.[30] Following the same rationale from an initial number of 170 bonds that could be included in the analysis we ended up with 160.

Initial Number of Bonds	Number of Industrial Bonds	Number of Companies	Spreads	Equity Information	Accounting Information	Final Data Set
1,723	**1,280**	**211**	**170**	**165**	**160**	**160**

BB Rated Bonds (including BB1, BB2 & BB3 sub-categories) [31]

Using the elimination process, as being described above, the ultimate number of bonds in this band are 143.

Initial No of Bonds	No of Industrial Bonds	No of Companies	Spreads	Equity Info	Accounting Info	Final Data Set
603	**535**	**213**	**166**	**150**	**143**	**143**

B Rated Bonds (including B1, B2 & B3 sub-categories)[32]

A number of bonds were deleted in this category since there have been a number of bonds issued by the same companies.

Initial Number of Bonds	Number of Industrial Bonds	Number of Companies	Spreads	Equity Information	Accounting Information	Final Data Set
520	**484**	**228**	**215**	**203**	**191**	**191**

C Rated Bonds (including C, C2, CC1, CC2 & CC3 sub-categories)

A lot of bonds in this category have been deleted due to the fact their spread history didn't go as back as the 31/1/1997. [33]

Initial Number of Bonds	Number of Industrial Bonds	Number of Companies	Spreads	Equity Information	Accounting Information	Final Data Set
298	**279**	**176**	**124**	**86**	**85**	**85**

[30] For a more detailed analysis of BBB rated bonds please refer to the Appendix 4 (Pivot_BBB)
[31] For a more detailed analysis of BB rated bonds please refer to the Appendix 4 (Pivot_BB)
[32] For a more detailed analysis of B rated bonds please refer to the Appendix 4 (Pivot_B)
[33] For a more detailed analysis of C rated bonds please refer to the Appendix 4 (Pivot_C)

The following table shows the summary of the data, in terms of the final number of bonds collected in each rating category:

DATA SUMMARY				
ML Index Names	Rating Category	Number of Rated Bonds in the ML Index	Number of Unique Companies in the Index	Number of companies for which all of the information is available(share price, spreads, accounting information)
INVESTMENT GRADE				
C4A1	AAA	2,068	15	6
C4A2	AA	583	30	21
C4A3	A	1,489	85	68
C4A4	BBB	1,724	211	160
Total Number of Investment Grade Bonds		5,864	341	255
NON- INVESTMENT GRADE				
J0A1	BB	603	213	143
J0A2	B	521	228	191
J0A3	C	298	176	85
Total Number of Non-investment Grade Bonds		1,422	617	419
Total		**7,286**	**958**	**674**

3.4. Descriptive Statistics – Monthly Data

3.4.1. Descriptive Statistics by Rating category

Firstly the time series patterns of both credit spread level and credit spread changes are going to be examined. Descriptive statistics per rating category are provided below:

Table 3.1. Descriptive Statistics of constituents of ML Indices spread levels –Monthly Data *(In basis points)*

CREDIT SPREAD LEVELS							
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**C**
Mean	88	102	117	185	308	521	1,310
Median	79	89	111	169	283	432	841
Maximum	284	380	480	1,280	2,194	9,413	98,631
Minimum	3	2	-25	-1,000	-43	-159	63
Std. Dev.	47	62	56	103	184	373	3,311
Skewness	1	2	1	2	2	6	23
Kurtosis	6	8	4	15	14	95	588
Jarque-Bera	256	1,842	616	60,826	32,575	2,298,948	44,018,162
Probability	0	0	0	0	0	0	0
Observations	344	1,085	4,293	9,499	5,795	6,386	3,073
Cross sections	6	22	69	161	144	192	81

The above table shows descriptive statistics for credit spread levels for the seven broad rating categories. As it is obvious the mean credit spread level tends to increase as the rating deteriorates, starting from a mean of 88bps for the AAA rated bonds, and reaching 1,310 bps for C rated bonds. It is worth noting in the tables of descriptive statistics that as in Lohngstaff and Schwartz (1995b), the standard deviation of credit spreads tend to widen as credit rating deteriorates. Spread levels mainly present positive skewness, which means that the distribution has a long right tail. Credit spreads belonging to all ratings present kurtosis of more than 3, which means that they are leptokurtic (the distributions have higher peaks and thicker tails than the normal distribution does)[34]. Also the Jarque Bera statistic for the null hypothesis of normality is far beyond the critical value at the 5% level accompanied by the zero probability suggests that the credit spread series are far from being normally distributed. The unusually large values of the Jarque Bera statistic are due to the large number of observations, stemming from the nature of cross sectional data. As a result the null hypothesis for a normally distributed residuals is rejected.

Table 3.2. Descriptive Statistics of constituents of ML Indices spread percentage change – Monthly Data *(In basis points)*

	CREDIT SPREAD CHANGES						
	AAA	AA	A	BBB	BB	B	C
Mean	0.028	0.041	0.033	0.028	0.03	0.02	0.057
Median	0.000	0.000	0.000	0.00	0.00	0.00	0.015
Maximum	3.333	7.522	15.429	6.90	7.79	5.28	7.693
Minimum	-0.625	-0.889	-5.000	-2.00	-1.13	-27.50	-0.787
Std. Dev.	0.259	0.389	0.390	0.21	0.24	0.54	0.316
Skewness	6	11	8	13	14	-21	23
Kurtosis	10	15	12	27	19	45	67
Jarque-Bera	2,710	27,815	59,298	486,976	244,183	908,754	772,359
Probability	0	0	0	0	0	0	0
Observations	337	1063	4223	9335	5635	6182	2984
Cross sections	6	22	69	161	143	189	80

The above table shows descriptive statistics for credit spread changes for the seven broad rating categories. It can be noticed that mean changes in spreads are insignificantly different from zero. When we look at the standard deviation of credit

[34] If for example we use the normal distribution for risk management purposes in such kind of data, we will be underestimating the true risk and capital requirements will be insufficient.

spread changes there is not such a clear monotonical relation with a deterioration in credit quality as with credit spread levels. In particular, from AAA to A rated spreads standard deviation increases, then it tapers off for BBB and BB rated spreads and then increases for B rated bonds before it reduces again in the C rating category. This results contradicts partly to Pedrosa and Roll(1998) who find lower standard deviations for lower rating classes, while it coincides to the results found by Duffee(1998) or Longstaff and Schwartz (1995b) who indeed evidence the opposite effect. Credit spread changes mainly present positive skewness, which means that the distribution has a long right tail, except for the B rated bonds which seem to have long left tails. Credit spreads changes belonging to all ratings present kurtosis of more than 3, which means that they are leptokurtic. Also the Jarque Bera statistic for the null hypothesis of normality is far beyond the critical value at the 5% level accompanied by the zero probability suggests that the credit spread series are far from being normally distributed. As a result the null hypothesis for a normally distributed residuals, at credit spread changes is also rejected.

Descriptive statistics by year

In table 3.3. descriptive statistics of the average mean spread levels are shown. These include the average spread of all investment and non-investment rated companies, and what is very clear from the table is that there is an increase of the average spread levels from 1998 until 2002, which is also depicted in their standard deviations. Average spread levels have increased in line with the increase in annual default rates, which according to Moody's study of default rates of corporate bond issuers, have increased by 638% in the period from 1997 to 2001.

Table 3.3. Descriptive Statistics of constituents of ML Indices spread Levels per Year

DESCRIPTIVE STATS BASED ON AVERAGE MEAN SPREADS (LEVELS) BY YEAR						
	AVG 1997	*AVG 1998*	*AVG1999*	*AVG2000*	*AVG2001*	*AVG2002*
Mean	43	129	175	317	460	462
Standard Error	2.608	5.948	7.843	13.228	21.259	22.560
Median	0.000	96.250	136.000	231.750	306.750	304.000
Mode	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	65.726	149.882	197.642	333.343	535.709	568.498
Kurtosis	8.458	4.464	14.298	10.001	18.338	18.518
Skewness	2.499	1.810	2.910	2.559	3.547	3.669
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	499.000	941.000	1826.250	2877.000	5312.500	5673.000

3.4.2. Autocorrelation

The next step of the analysis is to address the question of dependence of 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 credit spread levels and credit spread changes. The pattern of autocorrelation and partial autocorrelation is important in indicating the plausible structure and nonlinear dynamics of the credit spread process. Below are presented the sample autocorrelations partial autocorrelation coefficients from lag 1 to 5 and 10, 20, and 28 for all ratings for credit spread levels.

The first lag autocorrelation in all of the rating categories is high. For example in the "AAA" rating it is 0.829, in the "BB" is 0.909 and tapers off gradually after the 10^{th} and some instances 20^{th} lag. This type of pattern together with the fact that the Q statistic exceeds the Q value from the chi-square table at the chosen level of significance, means that the null hypothesis that all ρ_k are zero, is rejected. At least some of them are non-zero. It should be noted that the results provided in the following tables are representative for each rating category. The particular results are based on the credit spread level series of one company from AAA band, one from AA band and so on. For illustrative purposes it wouldn't be that clear to show ACs for all 674 time series of bonds. However, similar kind correlograms are produced for every of the 674 companies(bonds).

Table 3.4. Autocorrelation and Partial Autocorrelation Functions per Rating Category– Spread Levels

AAA CREDIT SPREAD LEVELS					BB CREDIT SPREAD LEVELS				
Lags	AC	PAC	Q-Stat	Prob	Lags	AC	PAC	Q-Stat	Prob
1	0.829	0.829	46.797	0	1	0.909	0.909	56.197	0
2	0.715	0.088	82.168	0	2	0.794	-0.185	99.744	0
3	0.61	-0.013	108.32	0	3	0.692	0.031	133.36	0
4	0.502	-0.064	126.28	0	4	0.637	0.2	162.36	0
5	0.417	0.006	138.92	0	5	0.586	-0.087	187.27	0
10	0.136	0.144	161.01	0	10	0.435	0.007	277.32	0
20	-0.064	0.165	173.71	0	20	0.039	0.036	358.95	0
28	-0.085	-0.121	176.78	0	28	-0.134	-0.115	362.84	0
AA CREDIT SPREAD LEVELS					B CREDIT SPREAD LEVELS				
Lags	AC	PAC	Q-Stat	Prob	Lags	AC	PAC	Q-Stat	Prob
1	0.898	0.898	54.898	0	1	0.906	0.906	55.879	0
2	0.832	0.13	102.73	0	2	0.786	-0.194	98.638	0
3	0.71	-0.297	138.18	0	3	0.722	0.271	135.24	0
4	0.648	0.176	168.12	0	4	0.665	-0.103	166.8	0
5	0.587	0.117	193.16	0	5	0.594	-0.016	192.43	0
10	0.307	-0.057	264	0	10	0.458	0.063	277.78	0
20	-0.134	0.023	278.52	0	20	-0.027	0.049	331.04	0
28	-0.275	-0.001	311.25	0	28	-0.057	0.017	331.7	0

A CREDIT SPREAD LEVELS				
Lags	AC	PAC	Q-Stat	Prob
1	0.888	0.888	53.689	0
2	0.782	-0.035	95.925	0
3	0.66	-0.132	126.5	0
4	0.539	-0.07	147.28	0
5	0.395	-0.192	158.57	0
10	0.12	0.148	174.48	0
20	0.058	0.045	182.87	0
28	-0.036	-0.074	183.75	0

C CREDIT SREAD LEVELS				
Lags	AC	PAC	Q-Stat	Prob
1	0.94	0.94	60.107	0
2	0.857	-0.225	110.88	0
3	0.776	0.009	153.2	0
4	0.696	-0.058	187.74	0
5	0.645	0.225	217.91	0
10	0.556	-0.175	348.76	0
20	-0.001	-0.048	444.46	0
28	-0.291	-0.009	468.71	0

BBB CREDIT SPREAD LEVELS				
Lags	AC	PAC	Q-Stat	Prob
1	0.937	0.937	59.684	0
2	0.87	-0.06	111.98	0
3	0.797	-0.084	156.59	0
4	0.728	-0.005	194.46	0
5	0.666	0.012	226.63	0
10	0.516	-0.013	348.48	0
20	0.147	0.03	443.8	0
28	-0.145	-0.028	451.35	0

In the case of credit spread changes, we observe that autocorrelation coefficients at lag 1 are significantly lower than the respective autocorrelation coefficients of credit spread levels and much closer to zero, but we can't reject the null hypothesis at a high confidence level. Therefore, we will test for stationarity using the unit root tests as described in the next section.

Table 3.5. Autocorrelation and Partial Autocorrelation Functions per Rating Category – Spread Changes

AAA CREDIT SPREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.497	-0.497	16.321	0.00
2	0.122	-0.166	17.324	0.00
3	-0.111	-0.168	18.171	0.00
4	-0.085	-0.287	18.678	0.00
5	0.134	-0.093	19.942	0.00
10	0.013	-0.053	21.408	0.02
20	-0.049	-0.094	25.894	0.17
28	-0.037	0.047	32.629	0.25

BB CREDIT SPREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.482	-0.482	22.387	0.00
2	0.196	-0.216	24.977	0.00
3	-0.123	-0.173	26.002	0.00
4	-0.021	-0.241	26.034	0.00
5	0.007	-0.23	26.038	0.00
10	0.19	0.052	29.762	0.00
20	-0.038	-0.072	38.886	0.01
28	0.039	0.054	40.709	0.06

AA CREDIT SPREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.484	-0.484	30.883	0
2	0.434	-0.063	43.522	0
3	-0.341	-0.129	51.438	0
4	0.134	-0.262	52.676	0
5	-0.063	-0.139	52.956	0
10	-0.143	-0.037	59.973	0
20	-0.091	-0.038	74.135	0
28	0.091	0.016	80.165	0

B CREDIT SPREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.465	-0.465	14.269	0.00
2	-0.098	-0.4	14.909	0.00
3	0.072	-0.269	15.267	0.00
4	0.03	-0.157	15.331	0.00
5	-0.05	-0.148	15.506	0.01
10	-0.089	-0.135	16.757	0.08
20	0.047	0.021	19.56	0.49
28	-0.069	0.009	30.121	0.36

A CREDIT SPREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.492	-0.492	15.961	0.00
2	-0.002	-0.321	15.962	0.00
3	-0.003	-0.238	15.962	0.00
4	0.101	-0.03	16.664	0.00
5	-0.292	-0.367	22.694	0.00
10	0.133	-0.264	27.5	0.00
20	-0.097	-0.009	32.064	0.04
28	0.137	0.092	40.612	0.06

C CREDIT SREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.415	-0.415	10.872	0.00
2	-0.084	-0.31	11.327	0.00
3	0.129	-0.061	12.418	0.01
4	-0.162	-0.192	14.163	0.01
5	0.152	0.024	15.719	0.01
10	-0.001	0.028	17.445	0.07
20	-0.108	-0.067	38.136	0.01
28	-0.061	0.052	51.101	0.01

BBB CREDIT SPREAD CHANGES				
Lags	AC	PAC	Q-Stat	Prob
1	-0.487	-0.487	15.656	0.00
2	0.092	-0.19	16.224	0.00
3	-0.122	-0.219	17.235	0.00
4	0.116	-0.052	18.175	0.00
5	-0.143	-0.161	19.618	0.00
10	-0.038	-0.206	26.735	0.00
20	0.101	0.008	46.269	0.00
28	-0.074	-0.038	57.043	0.00

3.4.3. Stationarity

As a result as an alternative test for stationarity we will use unit root test. The stationarity of credit spreads is a very significant issue in the pricing of risky debt and credit derivatives as well as in the choice of the appropriate econometric method. This stationarity is being tested using the augmented Dickey Fuller test statistic.

The power of the unit root tests, is a function of the span of the data and not the number of observations (as has been shown by Shiller and Peron (1985). Since a non-stationary process implies a huge volatility structure over time it seems inconsistent that the treasury yield, the slope of the yield curve or credit spreads to be non-stationary over long periods of time. On the other hand since pricing models usually have a rather short time horizon, it is plausible that credit spreads can be non stationary over an investment horizon. In other words the investment horizon drives the data frequency and the form of the model considered.

The ADF test was first applied to credit spread levels and then their changes. Table 3.6. shows that the t-statistic is lower (in absolute terms) than the 95% MacKinnon critical value (-2.90),hence we conclude that the test fails to reject the null hypothesis of a unit root in the credit spread series at the 95% confidence level.

Table 3.6.ADF Tests per rating category – Credit Spread Levels

CREDIT SPREAD LEVELS		
AAA	ADF Test Statistic	-1.982448
AA	ADF Test Statistic	-2.230132
A	ADF Test Statistic	-1.709145
BBB	ADF Test Statistic	-1.454805
BB	ADF Test Statistic	-1.575144
B	ADF Test Statistic	-1.248110
C	ADF Test Statistic	-1.024247
**MacKinnon critical values for rejection of hypothesis of a unit root*		
. 5% Critical Value : -2.9084		

The same test was applied to credit spread changes, and table 3.7. shows that the t-statistics are larger in absolute terms than the MacKinnon critical values at the 95% significance level , which effectively means that the null hypothesis of non stationarity is rejected for all rating categories of credit spread changes.[35]

Table 3.7.ADF Tests per rating category – Credit Spread Changes

CREDIT SPREAD CHANGES		
AAA	ADF Test Statistic	-4.465751
AA	ADF Test Statistic	-4.453018
A	ADF Test Statistic	-5.009464
BBB	ADF Test Statistic	-4.878968
BB	ADF Test Statistic	-3.902930
B	ADF Test Statistic	-4.149036
C	ADF Test Statistic	-5.163401
*MacKinnon critical values for rejection of hypothesis of a unit root.		
. 5% Critical Value : -2.9084		

Phillips-Perron test, which is a method that allows for higher order serial correlation and heteroscedasticity in a series, was also implemented in parts of the sample, for comparative purposes, and it was observed that the results are totally consistent with those provided by the ADF test.

3.4.4. Correlations among the independent variables

Overall, for most of the variables the sign of the correlation coefficients provided in the correlation matrix below, seem to conform to intuition and the structural approach to credit risk modelling. As evident, there are no significant correlations amongst the macroeconomic variables. Comparatively higher correlations are exhibited within equity variables, namely, the positive correlation between the Russsell and the S&P index of 0.67, or the negative correlations between VIX and Russell and the S&P of –0.60 and –0.62 respectively. These correlations of the equity variables suggest that changes in implied volatilities should be negatively correlated to changes in equities and that changes in equity indices are positively correlated.

[35] Pedrosa and Roll (1998) examine the daily time series properties of credit spreads from October 1995 to March 1997, and cannot reject the null hypothesis that credit spreads are non-stationary. However, they conclude that it is implausible for credit spreads to have a unit root.

Table 3.8. Correlation Matrix - Macroeconomic & Equity Variables – Changes

	CONF	CPI	GDP	IP	MS	PPI	TR BL	UNEMP	RUSSELL	S&P	VIX	SLOPE
CONF	1											
CPI	-0.10	1										
GDP	0.00	-0.10	1									
IP	0.19	-0.12	0.10	1								
MS	-0.02	-0.2	-0.10	-0.2	1							
PPI	-0.06	0.21	0.03	0.10	0.07	1						
TR BL	-0.10	-0.3	0.07	-0.20	-0.0	0.20	1					
UNEMP	-0.20	-0.2	-0.00	-0.40	0.00	-0.20	0.09	1				
RUSSELL	0.21	-0.1	-0.20	-0.10	-0.20	0.21	-0.10	0.10	1			
S&P	0.12	0.18	-0.20	-0.10	-0.10	0.12	-0.30	-0.10	0.67	1		
VIX	-0.20	-0.10	0.17	0.19	0.01	-0.20	0.12	0.01	-0.60	-0.62	1	
SLOPE	0.50	0.17	-0.00	0.23	-0.10	0.26	0.09	-0.3	0.06	0.12	-0.20	1

3.5. Data Description –(2nd set of Data –Bloomberg Bond Indices)

The second set of data includes short, medium and long term maturity investment grade industrial bonds (from AAA to BBB-). Corporate spreads are constructed using data on corporate bond yield extracted from Bloomberg's Fair market value curves (FMC). These curves are constructed on a daily basis for various sectors and rating classes from a sample of Bloomberg generic bond prices at market closing. All bonds for each sector are then subject to option adjusted spreads (OAS) analysis and the option free yields are then plotted to form the FMC without any yields being distorted by embedded call, puts or sinks. This allows bonds with different structures to be compared on an equal basis. A best fit curve is then drawn from the option free yields, resulting in a specific yield curve for each bond category. Debt issues are divided into hundreds of sectors that are grouped by several variables such as ratings or industry type. Monthly time series are created using month end observations.

Data utilised here is on the curves for AAA, AA, A and BBB industrial ratings. Credit ratings are based on the Bloomberg Composite Rating, which is a blend of ratings of the major rating agencies. In particular, eight time series (namely AAA, AA, A+, A, A-, BBB+, BBB, BBB-) observations have been collected for nine maturities, i.e. for years two, three, four, five, seven, eight, nine, ten and fifteen. However, not all of the different maturity indices have been considered, but rather as proxies for short term medium and long term maturities the two year, five and ten years maturity indices were used respectively. It is worth noting that the selection of those particular maturities was made in order:

(a) to include the liquid indices (for example the 15 year index is known not to be a very liquid one) and

(b) to obtain more time series observations (for example the 8 and 9 year credit spread indices have available observations from 1996).

This data is provided on a monthly basis for the period from May 1991 until June 2005. Credit spreads have been calculated after deducting from each time series observation the US Dollar Treasury Composite bearing the corresponding maturity.

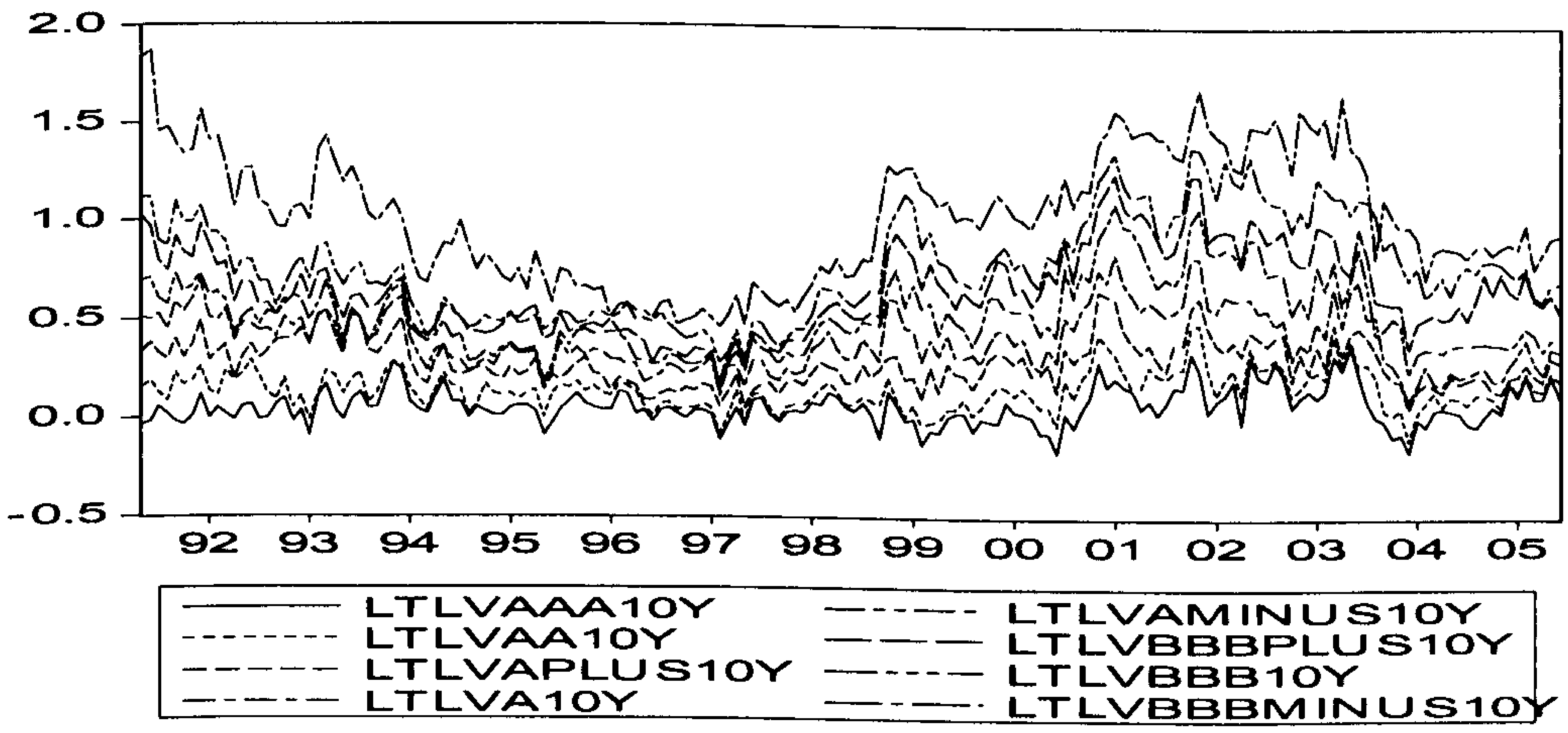
The following table presents the average credit spread of ML and Bloomberg credit spread indices per broad credit rating category, in basis points. It is worth recalling that the ML credit spreads have been averaged for the period from January 1997 until May 2002, while Bloomberg Credit Spread Indices refer to a much longer time period from May 1991 until June 2005. Also we can't infer to comparisons from the non-investment grade category, since we don't have such information from Bloomberg Credit Spread Indices.

CREDIT RATING	MERRILL LYNCH	BLOOMBERG
AAA	88	109
AA	102	119
A	117	138
BBB	185	173
BB	308	N/A
B	521	N/A
C	1,310	N/A

3.5.1. Credit Spreads

The time series patterns of both credit spread level and credit spread changes are going to be examined. Figure 3.1. shows the time series of the level of credit spreads, for short term maturing indices for the eight rating categories considered. Figures 3.2 and 3.3 show the pattern of credit spreads for medium and long term maturities respectively, for the eight rating categories. Although the level of credit spreads seems to be different for the different matutiries, it is increasing as the index maturity increases especially for AAA, AA and A+ rated indices. We can recognise a rather cyclical behaviour in the three figures over the sample period considered. There is a decreasing trend (tightening of credit spreads) observed in the period from 1994 until 1998-99 and then the series appears to trend steeply upwards and being highly volatile during the period 2000 to fall 2003. Around that time, the series seem to stabilise around the same mean level it had experienced before 1992 and in 2004 mid 2005 there seems to be a gradual tightening of credit spreads.

Figure 3.1. Long Term maturities – Credit Spread Levels



Tables 3.9, 3.11 and 3.13, show the descriptive statistics for long, medium and short term credit spread levels respectively. The mean levels of the indices are expressed in basis points. Comparing the mean levels of the Bloomberg indices to those of Merrill Lynch for the respective rating categories, it is observed that the levels of the former are higher than those of ML. However, these two indices aren't directly comparable, since different companies are considered. In the ML case we have excluded a number of companies from the index, and therefore the mean levels of spreads considered are the result of the companies we have identified to qualify for this thesis. On the other hand, data from Bloomberg, refers again to US industrial companies, but the constituents are different and hence not directly comparable. However, it should be noted that despite the differences observed, the results won't be influenced since the bottom line is that we are testing percentage changes in credit spreads and not levels.

Table 3.9. Descriptive Statistics of Long - Term Bloomberg Indices spread Levels – Monthly

Data *(In Basis Points)*

LONG TERM CREDIT SPREAD INDICES (10 years)				
	AAA	***AA***	***A***	***BBB***
Mean	113.2	121.1	141.6	178.1
Median	112.0	118.0	138.5	172.0
Mode	110.0	115.0	127.0	220.0
Standard Deviation	11.3	12.5	19.6	34.9
Kurtosis	0.3	1.1	-0.2	-1.3
Skewness	0.2	1.1	0.6	0.3
Minimum	78.0	101.0	108.4	126.0
Maximum	144.0	167.0	206.0	253.8
Count	170	170	170	170

Table 3.10. Correlation Matrix among Long Term Bloomberg Spread Indices (Levels)

	AAA	AA	A+	A	A-	BBB+	BBB	BBB-
AAA	1.00							
AA	0.83	1.00						
A+	0.67	0.88	1.00					
A	0.58	0.79	0.90	1.00				
A-	0.49	0.68	0.82	0.93	1.00			
BBB+	0.44	0.67	0.82	0.93	0.95	1.00		
BBB	0.39	0.60	0.76	0.90	0.96	0.97	1.00	
BBB-	0.40	0.62	0.76	0.90	0.94	0.97	0.97	1.00

Figure 3.2. Medium Term maturities – Credit Spread Levels

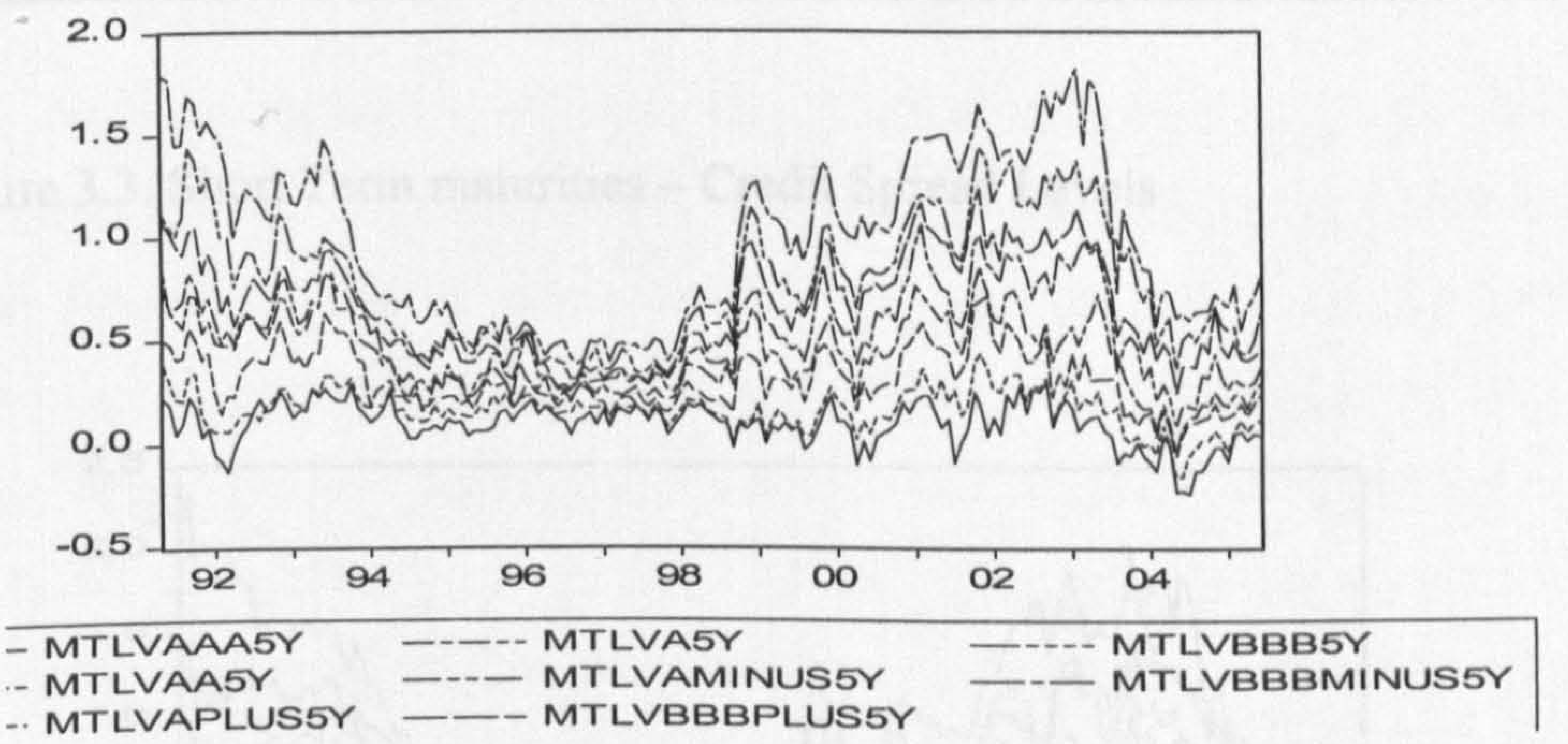


Table 3.11. Descriptive Statistics of Medium Term Bloomberg Indices spread Levels – Monthly Data *(In Basis Points)*

MEDIUM TERM CREDIT SPREAD INDICES (5 years)				
	AAA	***AA***	***A***	***BBB***
Mean	109.7	116.5	141.7	178.1
Median	110.9	117.0	139.2	176.5
Mode	115.0	117.0	133.0	139.0
Standard Deviation	10.4	9.9	18.6	31.3
Kurtosis	0.7	0.8	-0.8	-1.1
Skewness	-0.7	-0.2	0.3	0.3
Minimum	76.17	83.92	96.83	131
Maximum	129.63	143	186	244
Count	170	170	170	170

Table 3.12. Correlation Matrix among Medium Term Bloomberg Spread Indices (Levels)

	AAA	AA	A+	A	A-	BBB+	BBB	BBB-
AAA	1.00							
AA	0.83	1.00						
A+	0.65	0.82	1.00					
A	0.58	0.76	0.92	1.00				
A-	0.50	0.67	0.85	0.91	1.00			
BBB+	0.38	0.59	0.82	0.89	0.95	1.00		
BBB	0.28	0.51	0.76	0.84	0.92	0.95	1.00	
BBB-	0.27	0.48	0.73	0.83	0.91	0.95	0.96	1.00

Figure 3.3. Short Term maturities – Credit Spread Levels

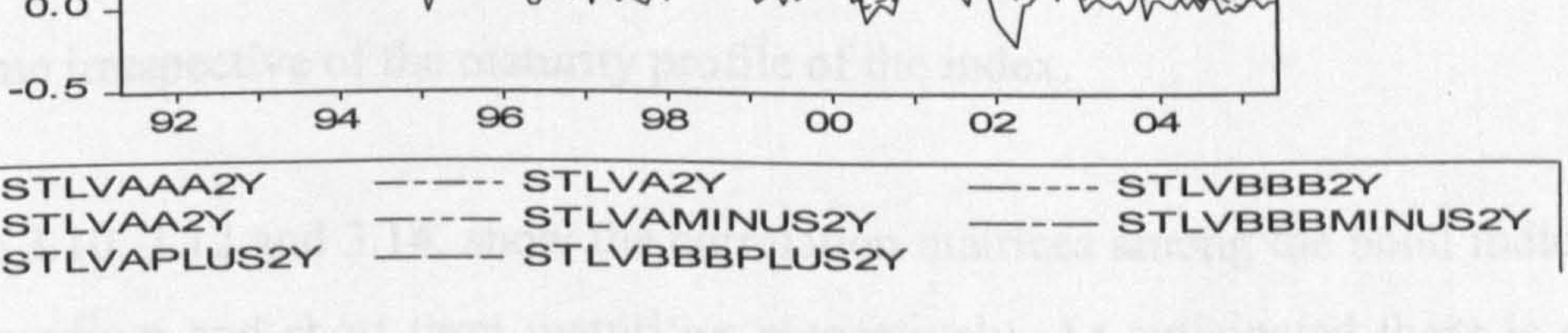


Table 3.13. Descriptive Statistics of Short Term Bloomberg Indices spread Levels – Monthly Data *(In Basis Points)*

SHORT TERM CREDIT SPREAD INDICES (2 years)				
	AAA	*AA*	*A*	*BBB*
Mean	105.9	112.1	132.3	164.3
Median	104.0	111.3	130.9	165.0
Mode	100.0	100.0	100.0	100.0
Standard Deviation	9.6	11.0	20.1	37.5
Kurtosis	1.1	0.8	-0.3	-0.6
Skewness	0.8	0.8	0.2	-0.2
Minimum	83.0	89.6	100.0	100.0
Maximum	137.5	149.0	184.0	239.0
Count	170	170	170	170

Table 3.14. Correlation Matrix among Short Term Bloomberg Spread Indices (Levels)

	AAA	AA	A+	A	A-	BBB+	BBB	BBB-
AAA	1.00							
AA	0.82	1.00						
A+	0.61	0.79	1.00					
A	0.58	0.78	0.89	1.00				
A-	0.53	0.71	0.82	0.92	1.00			
BBB+	0.47	0.68	0.75	0.85	0.93	1.00		
BBB	0.42	0.63	0.70	0.80	0.90	0.95	1.00	
BBB-	0.36	0.58	0.72	0.78	0.85	0.90	0.90	1.00

It is worth noting in the tables of descriptive statistics 3.9. 3.11. and 3.13, that the standard deviation of credit spreads tend to widen as credit rating deteriorates. Spread levels mainly present positive skewness, (except the AAA and AA medium term series that present negative skewness). Credit spreads belonging to the AAA, AA rating categories are leptokurtic, whereas the kurtosis of credit spreads of the remaining categories (broad A and BBB rating categories) are platykurtic. Also the Jarque Bera statistic for the null hypothesis of normality is far beyond the critical value at the 1% level, which suggests that the credit spread series are far from being normally distributed. The results obtained with respect toe skewness and kurtosis are the same irrespective of the maturity profile of the index.

Tables 3.10. 3.12 and 3.14, show the correlation matrices among the bond indices for long, medium and short term maturities respectively. As anticipated there is a high correlation among the broad rating categories, while as evident, all correlation coefficients are positive, suggesting that a direct relation amongst those indices exists.

3.5.2. Autocorrelation

As described in section 3.4.2. the next issue was to address the question of dependence of 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 credit spread levels and credit spread changes. The pattern of autocorrelation and partial autocorrelation is important in indicating the plausible structure and nonlinear dynamics of the credit spread process. Below are presented the sample autocorrelations from lag 1 to 5 and 10, 20, 40, 70 and 100 for all ratings long term series for credit spread levels and changes. Similar results are reported for short and medium maturities, but not reported herein.

The following table presents the autocorrelations and partial autocorrelation functions for credit spread levels. The first lag autocorrelation in all of the rating categories is high. For example in the "AAA" rating it is 0.599, in the "BBB" is 0.888 and so on, which indicates the presence of a unit root for credit spreads levels.

Table 3.15. Autocorrelation and Partial Autocorrelation Functions per Rating Category – Spread Levels

Lags	AAA CREDIT SPREAD LEVELS				Lags	A- CREDIT SPREAD LEVELS			
	AC	PAC	Q-Stat	Prob		AC	PAC	Q-Stat	Prob
1	0.599	0.599	62.088	0	1	0.866	0.866	129.85	0
2	0.436	0.12	95.141	0	2	0.795	0.177	239.73	0
3	0.318	0.026	112.85	0	3	0.745	0.103	336.84	0
4	0.219	-0.016	121.28	0	4	0.713	0.103	426.48	0
5	0.137	-0.028	124.61	0	5	0.641	-0.128	499.32	0
10	0.227	0.022	156.42	0	10	0.541	-0.028	801.18	0
20	0.063	0.026	164.94	0	20	0.205	0.062	1078.6	0
40	0.013	0.086	204.11	0	40	-0.249	-0.009	1171.9	0
70	-0.119	-0.016	232.85	0	70	-0.334	0.016	2039.5	0
100	0.008	-0.03	272.29	0	100	0.036	0.029	2288.4	0
	AA CREDIT SPREAD LEVELS					BBB+ CREDIT SPREAD LEVELS			
	AC	PAC	Q-Stat	Prob		AC	PAC	Q-Stat	Prob
1	0.650	0.65	73.121	0	1	0.888	0.888	136.5	0
2	0.498	0.131	116.33	0	2	0.814	0.121	251.92	0
3	0.412	0.08	146.04	0	3	0.779	0.173	358.23	0
4	0.323	0	164.47	0	4	0.749	0.075	457.16	0
5	0.257	0.004	176.17	0	5	0.713	0.011	547.23	0
10	0.314	0.06	248.39	0	10	0.586	-0.042	917.7	0
20	0.103	-0.053	298.86	0	20	0.346	0.098	1291.4	0
40	-0.108	0.054	361.12	0	40	-0.178	0.02	1414.2	0
70	-0.164	-0.075	524.48	0	70	-0.364	-0.003	2460.5	0
100	0.000	0.004	573.24	0	100	-0.07	0.048	2868.7	0
	A+ CREDIT SPREAD LEVELS					BBB CREDIT SPREAD LEVELS			
	AC	PAC	Q-Stat	Prob		AC	PAC	Q-Stat	Prob
1	0.743	0.743	95.55	0	1	0.928	0.928	149.11	0
2	0.646	0.21	168.28	0	2	0.876	0.102	282.62	0
3	0.559	0.054	222.95	0	3	0.836	0.083	405.04	0
4	0.52	0.101	270.62	0	4	0.79	-0.039	515.11	0
5	0.452	-0.016	306.84	0	5	0.752	0.031	615.4	0
10	0.451	0.041	468.66	0	10	0.636	-0.07	1027.1	0
20	0.114	-0.069	605.16	0	20	0.391	0.03	1525.9	0
40	-0.303	-0.052	739.74	0	40	-0.105	0.048	1703.1	0
70	-0.237	-0.074	1388.9	0	70	-0.413	-0.006	2647.9	0
100	0.177	0.001	1597.6	0	100	-0.141	-0.052	3439	0

	A CREDIT SPREAD LEVELS					BBB- CREDIT SREAD LEVELS			
	AC	PAC	Q-Stat	Prob		AC	PAC	Q-Stat	Prob
1	0.81	0.81	113.61	0	1	0.917	0.917	145.59	0
2	0.73	0.214	206.42	0	2	0.862	0.127	274.8	0
3	0.65	0.034	280.34	0	3	0.829	0.148	395.27	0
4	0.583	0.017	340.15	0	4	0.78	-0.073	502.57	0
5	0.524	0.011	388.79	0	5	0.761	0.165	605.22	0
10	0.387	-0.03	552.96	0	10	0.59	-0.075	1010.8	0
20	0.085	-0.08	672.56	0	20	0.332	0.001	1396.4	0
40	-0.292	-0.03	816.31	0	40	-0.255	0.026	1528.1	0
70	-0.249	-0.054	1448.4	0	70	-0.431	-0.004	3034.3	0
100	0.14	0.019	1597.1	0	100	0.04	0.079	3494.3	0

The table above presents coefficients for lags up to 5 and for lags 10, 20, 40, 70 and 100 for credit spread levels for all maturities. The last two columns reported are the Ljung Box Q statistic and their p-values. 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 x^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 all rating series.

Table 3.16 presents coefficients for lags up to 5 and for lags 10, 20, 40, 70 and 100 for credit spread changes for all maturities. The last two columns reported are the Ljung Box Q statistic and their p-values. When looking at the results of credit spread changes it is obvious that the sample autocorrelations at lag 1 are significantly lower than the respective autocorrelation coefficients of credit spread levels and much closer to zero. but we can't reject the null hypothesis at a high confidence level. Therefore, we will test for stationarity using the unit root tests as described in the next section.

Table 3.16. Autocorrelation and Partial Autocorrelation Functions per Rating Category – Spread Changes

	AAA CREDIT SPREAD CHANGES					A-CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob	Lags	AC	PAC	Q-Stat	Prob
1	-0.088	-0.088	1.2994	0.254	1	-0.259	-0.259	11.646	0.001
2	0.008	0	1.3108	0.519	2	-0.096	-0.176	13.266	0.001
3	-0.007	-0.006	1.318	0.725	3	0.045	-0.033	13.621	0.003
4	0.188	0.189	7.358	0.118	4	0.039	0.03	13.892	0.008
5	0.026	0.062	7.4731	0.188	5	-0.112	-0.096	16.109	0.007
10	0.038	0.022	8.8949	0.542	10	0.049	0.06	17.267	0.069
20	0.037	0.063	19.257	0.505	20	0	-0.033	31.141	0.053
40	0.003	0.047	40.186	0.462	40	0.182	0.146	74.658	0.001
70	0.052	0.011	62.63	0.722	70	-0.029	-0.128	138.66	0
100	-0.044	-0.06	74.057	0.976	100	0.042	-0.031	173.77	0

	AA CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob
1	-0.149	-0.149	3.8247	0.051
2	0.042	0.02	4.1331	0.127
3	-0.066	-0.058	4.8902	0.18
4	0.095	0.078	6.4769	0.166
5	-0.085	-0.059	7.7601	0.17
10	-0.031	-0.027	12.175	0.274
20	-0.088	-0.082	22.967	0.29
40	-0.007	-0.04	37.123	0.601
70	-0.025	-0.037	74.107	0.346
100	0.005	-0.099	100.76	0.46

	A+ CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob
1	-0.246	-0.246	20.766	0
2	0.044	-0.087	21.1	0
3	-0.042	-0.063	21.406	0
4	0.061	0.032	22.055	0
5	-0.109	-0.089	24.162	0
10	0.063	0.023	27.736	0.002
20	-0.038	-0.097	42.486	0.002
40	0.069	0.082	66.264	0.002
70	-0.064	0.02	116.53	0
100	0.007	-0.022	161.36	0

	A CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob
1	-0.173	-0.173	12.881	0
2	-0.108	-0.197	14.917	0.001
3	0.073	-0.018	15.852	0.001
4	-0.035	-0.043	16.072	0.003
5	-0.069	-0.091	16.919	0.005
10	-0.018	-0.031	19.647	0.033
20	-0.115	-0.056	42.996	0.002
40	0.169	0.066	84.776	0
70	0.019	-0.063	143.2	0
100	0.037	0.058	206.02	0

	BBB+ CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob
1	-0.346	-0.346	20.766	0
2	0.044	-0.087	21.1	0
3	-0.042	-0.063	21.406	0
4	0.061	0.032	22.055	0
5	-0.109	-0.089	24.162	0
10	0.063	0.023	27.736	0.002
20	-0.038	-0.097	42.486	0.002
40	0.069	0.082	66.264	0.006
70	-0.064	0.02	116.53	0
100	0.007	-0.022	161.36	0

	BBB CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob
1	-0.169	-0.169	4.9238	0.026
2	-0.08	-0.111	6.0298	0.049
3	0.058	0.025	6.6186	0.085
4	-0.095	-0.092	8.2021	0.084
5	-0.015	-0.042	8.2396	0.144
10	-0.023	-0.018	8.7785	0.553
20	-0.07	-0.054	16.713	0.672
40	0	-0.057	38.163	0.553
70	-0.009	-0.03	77.458	0.253
100	-0.041	-0.016	102.07	0.424

	BBB- CREDIT SPREAD CHANGES			
Lags	AC	PAC	Q-Stat	Prob
1	-0.158	-0.158	11.544	0.001
2	-0.069	-0.145	12.365	0.002
3	0.123	0.072	15.023	0.002
4	-0.158	-0.124	19.413	0.001
5	-0.02	-0.085	19.485	0.002
10	0.003	0.051	22.535	0.013
20	-0.001	0.027	29.005	0.088
40	-0.082	-0.068	50.796	0.118
70	0.028	0.005	73.183	0.374
100	-0.056	-0.022	104.17	0.368

3.5.3. Credit Spread Stationarity

As a further test to check for credit spread series correlation and in the effort to specify the best model, we test for the stationarity of the credit spread series. The Augmented Dickey Fuller test (ADF) is employed to test for the presence of a unit root. The ADF test was first applied to credit spread levels and then the changes. For credit spread levels as we move down the rating scale there have been instances as shown in the tables that follow, that the null hypothesis of unit root wasn't rejected at the levels but only at the changes. The t-statistic for this test is below the MacKinnon critical value at the 5% level at all rating categories for credit spread changes. As a result the null hypothesis of a unit root in the credit spread changes is rejected at the 5% significance level.

Table 3.17.ADF Tests per rating category – Short Term Credit Spread Levels

SHORT TERM MATURITIES - LEVELS		
AAA	ADF Test Statistic	-4.52456
AA	ADF Test Statistic	-3.27499
A+	ADF Test Statistic	-3.19178
A	ADF Test Statistic	-3.41968
A-	ADF Test Statistic	-2.23403
A-	ADF Test Statistic	-7.44246
BBB+	ADF Test Statistic	-2.61394
BBB	ADF Test Statistic	-1.88291
BBB-	ADF Test Statistic	-2.59478
BBB-	ADF Test Statistic	-10.4812
**MacKinnon critical values for rejection of hypothesis of a unit root.*		
5% Critical Value:-2.8787		

Table 3.18.ADF Tests per rating category – Medium Term Credit Spread Levels

MEDIUM TERM MATURITIES - LEVELS		
AAA	ADF Test Statistic	-3.35543
AA	ADF Test Statistic	-2.97761
A+	ADF Test Statistic	-3.38281
A	ADF Test Statistic	-2.97425
A-	ADF Test Statistic	-2.72625
A-	*ADF Test Statistic*	-9.31926
A-	*ADF Test Statistic*	*-7.44246*
BBB+	ADF Test Statistic	-2.40657
BBB+	*ADF Test Statistic*	*-9.29243*
BBB	ADF Test Statistic	-2.26357
BBB	*ADF Test Statistic*	*-9.73236*
BBB-	ADF Test Statistic	-2.33914
BBB-	*ADF Test Statistic*	*-10.4812*
**MacKinnon critical values for rejection of hypothesis of a unit root.*		
5% Critical Value:-2.8787		

Table 3.19.ADF Tests per rating category – Long Term Credit Spread Levels

LONG TERM MATURITIES - LEVELS		
AAA	ADF Test Statistic	-5.06163
AA	ADF Test Statistic	-3.61133
A+	ADF Test Statistic	-2.91557
A	ADF Test Statistic	-3.19283
A-	ADF Test Statistic	-2.78584
A-	*ADF Test Statistic*	-9.31926
A-	*ADF Test Statistic*	*-11.6636*
BBB+	ADF Test Statistic	-2.80103
BBB+	*ADF Test Statistic*	-12.0217
BBB	ADF Test Statistic	-2.30107
BBB	*ADF Test Statistic*	*-10.6048*
BBB-	ADF Test Statistic	-2.82941
BBB-	*ADF Test Statistic*	-11.4256
**MacKinnon critical values for rejection of hypothesis of a unit root.*		
5% Critical Value:-2.8787		

Table 3.20.ADF Tests per rating category – Short Term Credit Spread Changes

SHORT TERM MATURITIES - CHANGES		
AAA	ADF Test Statistic	-5.596037
AA	ADF Test Statistic	-6.388282
A+	ADF Test Statistic	-7.611434
A	ADF Test Statistic	-7.372508
A-	ADF Test Statistic	-6.730726
BBB+	ADF Test Statistic	-6.994736
BBB	ADF Test Statistic	-6.714302
BBB-	ADF Test Statistic	-5.748751
**MacKinnon critical values for rejection of hypothesis of a unit root.*		
5% Critical Value:-2.8787		

Table 3.21.ADF Tests per rating category – Medium Term Credit Spread Changes

MEDIUM TERM MATURITIES - CHANGES		
AAA	ADF Test Statistic	-4.141781
AA	ADF Test Statistic	-4.484401
A+	ADF Test Statistic	-5.763020
A	ADF Test Statistic	-5.216730
A-	ADF Test Statistic	-6.883357
BBB+	ADF Test Statistic	-6.620228
BBB	ADF Test Statistic	-6.478447
BBB-	ADF Test Statistic	-6.476230
**MacKinnon critical values for rejection of hypothesis of a unit root.*		
5% Critical Value:-2.8787		

Table 3.22.ADF Tests per rating category – Long Term Credit Spread Changes

LONG TERM MATURITIES - CHANGES		
AAA	ADF Test Statistic	-3.869530
AA	ADF Test Statistic	-5.833574
A+	ADF Test Statistic	-6.753924
A	ADF Test Statistic	-7.117285
A-	ADF Test Statistic	-6.794814
BBB+	ADF Test Statistic	-6.857824
BBB	ADF Test Statistic	-6.631109
BBB-	ADF Test Statistic	-7.224470
**MacKinnon critical values for rejection of hypothesis of a unit root.*		
5% Critical Value:-2.8787		

Credit spread stationarity has also been tested with the Phillips-Perron test, which is a semi-parametric method that allows for higher order serial correlation and heteroscedasticity in a series. The results obtained for some of the series (for comparative purposes) are consistent with those provided by the Augmented Dickey Fuller test.

3.6. Conclusions

This chapter has provided an introduction to the model we will specify, the data used and the parameters tested under this thesis. It has been described that the proposed model shares some of the assumptions and variables proposed by the KMV and McKinsey's macroportfolio view models, while incorporates other variables that seem to be important based on traditional credit risk analysis. As evident, the proposed model has several important differences compared to all other credit risk models developed so far, including the variables analysed, data sources, the elimination process used for selecting the bonds to test our hypotheses and the model specification.

The importance of using option adjusted spreads has been explained, in the sense that despite the type of the rate used or the availability of the rate, by directly comparing two bonds with the same maturity, we are effectively comparing two bonds that neither have the same duration (price sensitivity to interest rates changes) nor the same convexity (sensitivity to the slope of the yield curve). To overcome this problem, credit spread data is option adjusted, i.e. data collected on credit spreads takes account of the bond optionality, (the modified duration of bonds is calculated and the option adjusted duration for bonds with an embedded option is also considered). Therefore, credit spreads correspond to the difference in the yield to maturity between bonds with the same duration, which makes may partially offset the coupon effect on the yield to maturity.

An analytical description of the two sets of data, that will be used to test the hypotheses was provided, and the rationale for eliminating the initial set of data, in order to get the bonds that qualified for this study was also postulated. A descriptive statistical analysis of the results coincided with our anticipation that standard deviations of bonds (in level terms) tend to increase as credit rating categories deteriorate, and that the levels of credit spreads increase as an issuer's credit quality worsens. This is like assuming that an investor requires a higher return for higher risk.

Results obtained from descriptive statistics of Bloomberg indices, share some of the same properties to those reported from the ML data, although a much higher volatility is observed for long term maturing bond indices. Results obtained from the ADF tests for both sets of data, provide confidence as to the mean reverting properties of credit spread changes.

4.0. Macroeconomic Factors and Credit Spreads

This chapter of the thesis explores the relation between macroeconomic variables and credit spreads. So far, little work has been done on the empirical relationship between credit spreads and the macroeconomy, while more work has been done in examining the link between default risk and the macroeconomy[36]. Therefore, we will test this relation within two different sets of data and by using both time series and cross section analysis (due to the nature of data) for estimating coefficients. The relation is examined for investment and non-investment grade companies, and for short, medium and long term maturity indices.

This chapter of the thesis is structured in the following way:

The first Section, 4.1 provides a literature review relative to credit risk and the macroeconomic variables. Section 4.2 considers the effect of macroeconomic variables on different maturity Bloomberg investment grade indices, for the period from May 1991 until June 2005, using monthly data and time series analysis. So does section 4.3, although this time a different set of monthly and quarterly data is used, from investment and non-investment grade constituents of the Merrill Lynch indices, where the results are based on cross sectional analysis of data for a sub-period of the one mentioned above, i.e. from January 1997 until May 2002.

4.1. Credit Spreads & Macroeconomic variables – Literature Review

Finance theory has suggested that there is a relation between interest rates and default risk and hence a relation between interest rates, default risk and credit spreads. However, the theoretical models conflict as to the nature of this relation.

On the one hand the structural models based on option pricing suggest that higher interest rates may be associated with lower credit spreads. Such models view equity as a call option on the value of the firm with the strike price being equal to the face value of debt. A famous model belonging to this category is the Merton's model, which is based on options theory. In 1974, Merton showed that for a given maturity, the risk of default varies directly with the variance of the returns on the firm value. Within this framework, the business cycle and the macroeconomic factors impact both the level of the risk free rate and the variance of returns of the firm's value. These kinds of models are often used for companies that are very big in size and their stocks are traded on a stock exchange.

Reduced form models, don't attempt to model why firms default on their debt but instead assume that some bonds default on the balance of probability. There are different types of reduced form models (i.e. investors may demand compensation for default risk by grossing up the coupon paid on a default free bond by the expected probability). If interest rates rise by 1 bp the gross up effect increases the coupon by more than 1bp. Thus the differential between the coupon on the corporate bond and the coupon on the risk free bond increases in absolute terms with the size of the default free coupon and *credit spreads rise when the default free interest rate rise.*

Prior research by Forbes and Petersen (1975), Beston and Rogowski (1978) and Dialynas and Edington (1992) have shown that yield spreads are higher during recessions than during recoveries. In particular, they tested the hypothesis that economic conditions are expected to affect the size of the yield spread investors demand. The effects of economic conditions and the business cycle on yield spreads are captured with the use of three proxy variables: the annual rate of change in the consumer price index (inflation rate), the change in the shape of the term structure of interest rate and the annual rate of change in the industrial production index.

The inflation rate should be directly related to yield spreads, since during inflationary periods investors may require higher risk premia from their investments in corporate bonds.

The change in the shape of the term structure of interest rates, as presented by the quarterly change in the difference between the 20-year treasury rate and the three month T-bill rates, is also used as a proxy for the business cycle since much research in the past has linked the shape of the treasury term structure to future variations in the business cycle. A steepening term structure is usually a sign of strong economic growth and lower short-term interest rates and reflects a general belief that the

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[36] For example default probabilities depend upon macroeconomic variables in two widely appreciated risk management models, McKinsey's Credit Portfolio View and Algorithmic's Mark to Future.

economic conditions are going to be robust in the future and vice versa, i.e. a flattening term structure or one that would turn negatively sloped would be a sign of deteriorating economic conditions. Therefore this proxy should be negatively related to spreads[37].

Lastly the annual rate of change in industrial production should be negatively related to spreads since increased economic activity will bolster investor's confidence in the corporate sector and lead to a reduction in the risk premia demanded for investment grade corporate bonds.

Other research by Stock and Watson (1989), Chen (1991), Estrella and Hardouvelis (1991) and Estrella & Mishkin (1996) have linked the behaviour of the yield spreads to the shape of the term structure, as a proxy of the business cycle. In particular, they study the ability of the term structure to predict recessions in France, Germany, Italy, the United Kingdom and the United States. The authors find that the term structure predicts recessions quite well in the United States and Germany and to a lesser extent in the United Kingdom and Italy. In France however, the term structure does not seem to contain information useful for predicting recessions. The authors also demonstrate that leading indicators do not contain any information in addition to that in the term spread about the likelihood of recessions. The conclusion that the term spread is useful for predicting macroeconomic conditions suggest that it is a good monetary policy indicator.

Following Estrella and Hardouvelis (1991) and Mishkin(1996), Bernard and Gerlach (1996), study the ability of the term structure to predict recessions in eight countries. Using a probit model their results are summarised to the following:

(a) The yield curve provides information about the likelihood of recessions in all countries.
(b) Term spreads are useful for predicting recessions as much as two years ahead.
(c) While leading indicators contain information beyond what is included in the term spreads, this information is only useful for forecasting recessions in the immediate

[37] Section 4.1.2. provides a descriptive analysis of the term structure of interest rates.

future, which provides further evidence of the usefulness of term spreads as indicators for monetary policy purposes.

Studies such as those carried out by Bierman & Haas (1975) and Fons (1987) model yield spreads on the basis of differing default probabilities. Yawitz et al (1985) extent the previous work in order to take explicit account of tax effects. Rodriguez (1988) derives a general model of the relation between default risk and yield spreads in a risk neutral environment. He provides different relations for premium and discount bonds. In his model, he allows yields to depend on time to maturity. In other words, yields are evaluated on the basis of expected values. The implicit equation defining the relationship between the return on a risky bond, r, and the default free, tax free rate, i, differs for bonds sold above and below par value. For discount bonds Rodriguez finds that:

(1)

$$C\sum_{t=1}^{n}\left[y^{t}(1-T)-x^{t}\right]+F\left[y^{n}(1-G)-x^{n}\right]+BG\left[y^{n}+\left(\frac{1-P}{P}\right)\sum_{t=1}^{n}y^{t}\right]=0$$

and for premium bonds he find that:

$$\left[C(1-T)+\frac{T(B-F)}{n}+\frac{BG(1-P)}{P}\right]y^{t}+F\left[y^{n}-x^{n}\right]-Cx^{t}-\left[\frac{B-F}{n}\right]G\left[\frac{1-P}{P}\right]\sum_{t=1}^{n}(t-1)y^{t}=0$$

(2)

where:

$y = P(1+i)^{-1}$, $y = (1+r)^{-1}$ and C: coupon payments, T:tax rate on ordinary income, G:tax rate on capital gains, B:bond's purchase price, F:Par value, P:probability of default, n:years to maturity, t: Year(1,2,...n)

An important feature of equations (1) and (2) is that return depends on time until maturity which conflicts with the well known Bierman & Hass (1975) and Yawitz (1977) conclusions that argue that the default premium is invariant with respect to maturity. However, they assume that the probability that a borrower makes the full contractual payment in the stated period is constant over time and that there are no taxes (T=G=0). Under these assumptions equation (1) and (2) can be written as:

$$r = \frac{1 - P}{P} + \frac{i}{P}$$

(3)

Assuming that bonds sell at par (B=F) transforms Rodriguez's model into Yawitz, Maloney ad Ederington's (YME) model as shown in equation :

(4)

$$r = \frac{(1 - P) * (1 - G)}{P(1 - T)} + \frac{(1 - T)i}{P}$$

Although Rodriguez did not estimate his model empirically, Fons and YME (1987) have tested similar models. In both cases the probability of corporate default risk is derived rather than measured objectively.

YME's model is an alteration of equation (4) where the yield on the municipal bond depends on the government bond yield. Their data set of aggregate monthly yields on new bonds cover the period from August 1965 to March 1981. Using non-linear least squares they estimated the probability of default and the tax rate on ordinary income and concluded that the theoretical model has a high degree of explanatory power.

Fons (1987), compares a monthly index of low rated bonds to an index of high-grade bonds. He chose corporate over government bonds because they are callable. Fons alters Rodriguez's equation (4) to reflect the partial value received by investors after a bond defaults. Holding the values of I, T, G, and the in-default value of bonds constant, he estimated the probability of default (P). His estimates of (P) exceed the actual default experience of low rated bonds leading to the conclusion that a well diversified portfolio of low rated corporate bonds appears to be rewarded for bearing default risk.

Other empirical studies show that a significant relation exists between yield spreads and issue specific features, such as liquidity, callability, etc. For example, Litterman and Iben (1991) provide evidence that risk premiums increase with maturity. Ho and Singer (1984) show that the existence of a sinking fund is associated with lower bond yield spreads. Cook and Hendershott (1978) show that the time to maturity and call provisions are associated with higher bond yield spreads.

Other studies (Jaffee, 1975; Cook and Hendershottt, 1978) find evidence that risk premiums vary with the business cycle. Usually papers take the index of consumer sentiment which is based on data collected by the University of Michigan and described in detail by Fair (1971) in order to control for macroeconomic effects.

An interesting paper that incorporates macroeconomic factors in explaining credit spreads has been published by Amato and Luisi (2005). They provide new empirical evidence on the role of macroeconomic factors in an arbitrage-free model of the term structure of credit spreads. The novel feature of their approach is the inclusion of observable macroeconomic variables as explicit determinants of yields and spreads. In particular, they propose that changes in real activity and financial conditions appear to have a strong effect on BBB- and B- rated spreads at most maturities (they only investigate bonds of these rating categories). Additionally they find that changes in risk premia in treasury yields and spreads, are mainly driven by macroeconomic variables. They also find that the price of default risk in BBB-rated bonds is large and volatile and is driven to a large extent by variation in the financial conditions indicator.

Tang and Yan (2004) explore the effects of macroeconomic conditions on credit yield spread dynamics in a Lucas type economy. Unlike most other structural models, their model explicitly incorporates equilibrium macroeconomic dynamics and prices all securities consistently. Their model allows to examine how credit spreads are affected by the interaction of macroeconomic variables and firm characteristics. They find that (i)credit spread is negatively correlated with interest rates and ceteris paribus, this correlation is stronger for bonds with higher default probabilities

(ii) credit spread yield curves are upward sloping for low rated bonds,

(iii) firm characteristics, other than leverage ratios have significant effects on credit spreads and these effects also vary with economic conditions.

4.1.2. The term Structure of Interest Rates

The relationship between credit spreads and interest rates is a rather complex one. Many are the articles[38] that focus on the valuation of corporate securities and allow for both credit risk and interest rate risk. The comparative statics of these models predict that in equilibrium credit spreads are negatively related to the risk free rate. Despite strong theoretical arguments that support the relation between credit spreads and the risk free interest rate level, it is rather difficult to provide an intuitive explanation to support this negative relation.

If we rely on the Merton's (1974) model, spreads and interest rates can be negatively related. According to this approach, a corporate bond is considered as a risk free bond and a short position in a put on the firm's assets. For an investor who buys a risky bond and sells it prior to maturity, two states are observed:

a. If interest rates increase, the risk free component will decrease the investor's wealth, while the short put will increase wealth.
b. If interest rates decrease, the risk free component will increase the investor's wealth, while the short option will decrease wealth.

While it could be possible that a flight to quality could induce a short-lived negative relation between corporate and government rates, it seems more possible that higher nominal rates would be associated with high risk premiums for corporate bonds. Bernanke and Gertler (1989) imply that higher interest rates are associated with higher agency problems for borrowers. Effectively, this will increase credit spreads since it widens the gap between internal and external financing.

[38] 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 Wilner (1993), Shimko, Tejima and Deventer (1993), Genotte and Marsh (1993) Nielsen, Saa-Raquejo and Santa Clara (1993) and Longstaff and Schwartz(1995b).

In favour of a positive relationship are two arguments:

a. A fiscal argument which is based on the differing default rates applicable to corporate and Treasury bonds. Since corporate bonds, are more heavily taxed than government bonds, an increase in bond yields augments the tax gap between corporate and treasury bonds. To offset this increased tax gap, corporate yields should rise more than treasury bond yields.

b. A mathematical argument derived by Bierman and Hass (1975). Assuming that investors are risk neutral and the recovery rate given default is constant and known, he derives the following formula, at market equilibrium:

$$(1+I) = (1\text{-EDF}) * (1+\text{YTM}) + \text{EDF}\ (0)$$

where, EDF : expected default frequency, i: the default free one period rate and YTM, is the yield to maturity of the risky debt. This formula, can then be applied for the computation of credit spreads, as follows:

$$\text{Credit Spread} = \text{YTM-i} = (1+I)\ \text{EDF} / (1\text{-EDF})$$

As long as EDF is a constant probability with values between 0 and 1, a positive relationship exists between i, the default free interest rate and credit spreads. If the risk premium decreases as the risk free rate increase, this lowers the positive risk neutral effect.

4.1.3. Other Factors Pushing spreads away from equilibrium

Before empirically exploring the relation between credit spreads and the business cycle it is very important to bear in mind that there are three important factors that could push spreads away from equilibrium, which are not easily quantifiable and/or publicly available but they should be considered very carefully. These are:

(i) Liquidity Considerations: Liquidity risk refers to the ease with which an issue can be sold at a reasonable price. For an investor who plans to hold the bond until maturity liquidity risk is less important. However, for someone who is uncertain about the investment horizon, liquidity risk can play an important factor in the decision making process. The dollar amount of bonds outstanding is usually used as the proxy variable. According to a study made by Elton and Green (1997), it is suggested that the best proxy for liquidity is the trading volume. However, since trading volume isn't usually information publicly available, the amount of bonds outstanding is used instead. The amount of bonds outstanding is used as a proxy on the basis of the potential high correlation between the amount of bonds outstanding and the trading volume in the bond. Thus, the higher the dollar amount of bonds outstanding, the higher the liquidity of the issue and the lower its spread. This proxy for liquidity has been suggested by Fisher(1959) and Gardabe and Silber (1976), its advantages and disadvantages have been extensively discussed in the paper by Sarig and Warga (1989)

(ii) Temporary demand and supply fund imbalances. These imbalances may also affect yields, as examined by Dialynas (1988) who looked at the supply and demand imbalance theory and found that spreads vary as quantities at different risk classes change. As a proxy for supply and demand imbalance between corporate and treasury bonds the difference in quarterly supply between treasury and corporate bonds is used. An inverse relation between this proxy variable and yield spreads is expected, since an increased difference would suggest a greater supply of treasuries or a smaller supply of corporate bonds or both and the result would be lower yield spreads.

(iii) Tax Effects. These occur, since an investor in corporate bonds is subject to state and local taxes on interest payments, whereas government bonds are not subject to these taxes. Thus corporate bonds have to offer a higher pre-tax return to yield the same after tax return. [39] Indeed what has been found in Elton, Gruber, Agrawal and Manns' paper(2001) is that taxes account for a significant portion of the differential between corporate and treasuries. For example, for 10-year A rated bonds, taxes account for 36.1% of the difference compared to the 17.8% accounted for by expected loss. State and local taxes are important since they are paid on the entire coupon of corporate bonds, not just on the difference in coupon between corporate and treasuries.

4.2. Empirical Evidence and Hypotheses

Credit spreads are going to be tested to check their dependence on economic variables. Two sets of data are going to be employed to test this hypothesis as described in section 3.2. The first set refers to the period from May 1991 until June 2005 and is based on Bloomberg short, medium and long-term maturity credit spread indices. Time series analysis is employed for the first dataset between credit spreads and their relation to the economic variables as described in section 4.2.1. The second set of data refers to the sub-period from January 1997 until May 2002 and uses constituents of the ML indices (the extraction of these constituents is analytically described in section 3.3.1. Data Elimination Process). This section employs cross sectional analysis to test the aforementioned relation, although this time a distinction is made among investment and non-investment grade companies.

The reason for the utilisation of two different sets of data is fourfold:

1. Compare differences in the results of credit spreads from Bloomberg Indices to credit spreads given by constituents of Merrill Lynch Indices.
2. Tests and conclusions drawn from the first set of data is limited to investment grade category, whereas in the second dataset the effects on non-investment grade companies are also considered.
3. Due to the nature of the data, the first set will be based on time series analysis and results will be compared to tests coming from a cross sectional analysis.
4. Testing the hypotheses reported below, to different sets of data will allow to derive more accurate conclusions, with respect to the positive or negative relation between credit spreads and macroeconomic variables. Additionally, the robustness of results will be further explored, once the stated hypotheses will be rejected or accepted irrespective of the data used, period covered or the methodology employed.

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[39] Elton, Gruber, Agrawal and Mann, " Explaining the rate spread in corporate bonds" , The Journal of Finance, February 2001.

The hypotheses tested under this chapter include:

a. Test the relation between the different macroeconomic variables and credit spreads on a separate basis and compare the results to those presented by other studies. In other words, macroeconomic variables are expected to influence credit spreads. However, the expectation is that factors such as GDP, Consumer Confidence, the term structure, etc, although overall should drive credit spread changes, the extent of change may be different in investment and non-investment grade companies, in short or long term credit spreads. In particular, the hypotheses tested are the following:

Ho: Changes in GDP, Consumer Confidence, the term structure, money supply, industrial production and trade balance, are directly related to credit spread changes.
Ho: Changes in CPI aren't directly related to credit spread changes.

b. Test the interaction of the macroeconomic variables to credit spread changes on a multiple regression context.

c. Test the direction of causation between changes in the economic conditions and credit spreads. The specific hypotheses are stated in section 4.2.2.

One important aspect of the relation between credit spreads and the business environment that hasn't been captured explicitly within the context of the existing literature, is an examination of this relationship between investment and non-investment grade companies. Some literature that includes an examination of low rated bonds behavious is specific to their relation to the term structure of interest rates. In particular, Tang and Yan(2005) and Helwege and Turner (1999) find that credit yield curves are upward sloping for non –investment grade bonds. Intuitively, it can be argued that macroeconomic factors are expected to affect differently investment and non-investment grade companies and not only with respect to the shape of credit yield curves.

Although macroeconomic conditions such as a deteriorating, for example, economic environment will according to theory and empirical evidence lead to a widening of credit spreads, this increase in credit spreads is not expected to be the same across the rating categories. Indeed, the expectation is that non-investment grade companies will be more affected than their investment grade counterparts, i.e. high yields are expected to yield higher sensitivities to macroeconomic conditions. Considering that investment grade companies are characterised by stronger financial fundamentals compared to the high yield companies, a deteriorating macroeconomic environment should lead to a more severe deterioration in credit spreads of the high yield companies.

Similarly, a shift in macroeconomic conditions will influence credit spreads of short, medium and long term bonds, but the effect of each individual factor should be different with respect to the different maturities. The rationale behind this is that the investment in different maturity bonds is ruled by different investment objectives and therefore, probably a deteriorating figure for GDP might influence more negatively medium or long term bonds, whereas a negative change in the consumer confidence index, will probably lead to a steeper deterioration in short term rather than long term maturing credit spread indices.

4.2.1. Empirical Evidence based on Bloomberg Credit Spread Indices

The relation between macreoconomic indicators and credit-spread indices is tested initially on a monthly basis, based on 14 years of data, from 1991 to 2005. Due to the non- stationary properties of credit spread levels data, we will employ changes in credit spread indices as the dependent variable, as discussed in chapter 3[40]. For those macroeconomic variables that are reported on a quarterly basis, such as GDP, monthly frequencies have been reproduced (where the values of GDP are kept the same for three months and then change once the next figure of GDP is reported. The same procedure is followed for all quarters and variables reported on quarterly frequencies).[41]

[40] Longstaff and Schwartz (1995a and 1995b) and Duffee(1998) avoid the spurious regression problem by examining changes in credit spreads.
[41] A detailed description of the macroeconomic variables used in this thesis is provided under section 3.2.3.4.

Table 4.1. shows correlations amongst the independent variables on a monthly basis, for the period from 1991 through 2005. Apparently, there are no independent variables in this set of data that are significantly correlated, and therefore all of them can be used as independent variables on a parallel basis. As described in section 3.4.4., the signs of correlation coefficients, for most of these relations, conform to intuition and the structural approach to credit risk modelling. For example, as consumer confidence increases, we should expect CPI, unemployment or interest rates to decrease, hence the negative signs in the correlation coefficients of those variables, and so on. However, for other variables, the relationship is not that intutitive.

Table 4.1. Correlation Matrix of Macroeconomic Variables – Monthly Basis

	CONF	CPI	GDP	MS	PPI	SLOPE	TRBL	UNEMP	IP
CONF	1								
CPI	-0.016	1							
GDP	0.029	-0.154	1						
MS	-0.059	-0.099	-0.022	1					
PPI	-0.118	0.106	0.037	0.043	1				
SLOPE	-0.324	-0.174	-0.165	0.058	0.037	1			
TRBL	-0.067	-0.550	0.349	-0.048	-0.047	0.043	1		
UNEMP	-0.035	-0.109	-0.068	0.050	0.068	0.244	0.027	1	
IP	0.191	-0.032	0.105	-0.144	0.021	-0.228	-0.006	-0.311	1

In order to test the relation between macroeconomic factors and credit spreads, a number of functional relations were tested and numerous regressions were run on the different maturity credit spread changes, in order to get the most meaningful, in the statistical terms, model.

The relation between changes in credit spreads and macroeconomic variables, is expected to be of the following form:

Equation 4.1.

$\Delta Spreads_t = c + \beta_1 * (\Delta Cons\ Conf_{t,..t-n}) + \beta_2 * (\Delta CPI_{t,..t-n}) + \beta_3 * (\Delta GDP_{t,..t-n}) + \beta_4 * (\Delta PPI_{t,..t-n}) + \beta_5 * (\Delta Unemployment_{t,..t-n}) + \beta_6 * (\Delta Trade\ Balance_{t,..t-n}) + \beta_7 * (\Delta Industrial\ Production_{t,..t-n}) + \beta_8 * (\Delta Money\ Supply_{t,..t-n}) + \beta_9 * (\Delta Term\ Structure_{t,..t-n}) + \varepsilon_t$

Where ΔSpreads: changes in credit spreads at time t from (t-1), ΔCons Conf: monthly change in consumer confidence, ΔCPI: the monthly rate of change in the consumer price index, ΔGDP: the monthly change in GDP, ΔPPI: monthly change in the producer price index, ΔUnemployment: monthly change in the unemployment rate, ΔTrade Balance: monthly change in the trade balance, ΔIndustrial Production: monthly rate of change in industrial production, ΔMoney Supply: monthly rate of change in money supply, ΔTerm Structure: the change in slope, i.e. the ratio of the ratio between the 10-year to the 2-year interest rate, and e_{it} :error term. Predicted and actual signs for those variables are shown in the tables 4.2-4.5.

The adjusted R^2 criterion and the Akaike and Schwartz information criteria were considered. The White (1980) heteroscedasticity consistent method was used to estimate the coefficient covariance matrix. The main results using the OLS model by broad credit rating category and by maturity are provided in the following tables 4.2, 4.3, and 4.5. Tests reported in the tables are significant at the 90% confidence level. Results have been separately reported for the different maturities and the different broad investment grade rating categories.

Overall it should be noted that the overall explanatory power of macroeconomic variables in investment grade credit spread indices appears to be relatively low. They seem to explain at best one fifth of the variation in credit spreads, as exhibited by the adjusted R^2 of 22% of short –term BBB rated indices. This is relatively low compared to the empirical study by Athanassakos and Carayannopoulos (2001), of the relationship between bond yield spreads and macroeconomic factors, where the overall's model adjusted R^2 is 76.1%. The reason for the difference is that we are not using the lagged values of credit spreads or credit ratings as explanatory variables, but we only focus on the effect of changes in macroeconomic variables. Moreover, they are looking at changes in yield spreads, whereas here we are testing credit spread changes. The most statistically and economically significant variable in all the OLS regressions we run, is the change in US Consumer Confidence Index.

Tables 4.2, 4.3 and 4.4. present results of macroeconomic variables on long, medium and short credit spreads respectively. There are two things to bear in mind before considering the regression results. Firstly, the variables of CPI, GDP, PPI and Trade Balance have been transformed from quarterly to monthly frequencies and secondly the same variables have been regressed against all credit spread categories but for those macroeconomic variables that we didn't obtain any statistically significant results, no results have been reported in tables 4.2,4.3 and 4.4. Also it should be made clear, that lagged values of macroeconomic variables have been used where it made economic sense to do so and when the values at time t, weren't statistically significant (in most cases we obtained statistically significant results at the third lag which represents the previous quarter). Comments on the results reported in the following tables are provided below and are summarised by macroeconomic variable. In particular,

GDP: The expected sign of the relation between short, medium and long term credit spreads is expected to be negative, since a growing figure for GDP would result in a tightening of credit spreads. However, although the relation is expected to be negative, the coefficients of GDP have positive signs. Economic wise, we can't explain this positive relation. However, it can be argued that this might be a bad effect of correlation between the independent variables, which have individually negative signs and yield a positive sign. Another possible explanation for the wrong sign might be the reproduction of monthly GDP figures from quarterly data. Running univariate regressions between credit spread indices and the variable of GDP, although provided us with the correct sign, the coefficient and its accompanying t-values were insignificantly different from zero, suggesting that economic wise our results aren't that significant.

Conf (US Consumer Confidence): The relation between consumer confidence and credit spreads is also expected to be negative, since growing consumer confidence should lead to a tightening of credit spreads. The sign of the relation is proven negative in all three maturities and all the rating categories. The change in monthly consumer confidence at time t, proves to be the factor that has the greatest impact on credit spreads changes and the most significant variables economically and statistically wise. Lagged values of the consumer confidence index were also statistically and economically significant at all lags up to the fifth.

CPI: The only relation that is expected to be positive amongst the macroeconomic variables and credit spreads is the one between CPI and credit spreads. As CPI increases, credit spreads are expected to increase (widen). Results support this positive relationship, although coefficients and their accompanying t-statistics although statistically significant are not significantly different from zero, hence not significant economic-wise.

Term Structure[42]***:*** The relationship between interest rates and credit spreads is a rather composite one. As mentioned before, for some theoreticians, the interest rate effect is positive (high interest rates lead to increased vulnerability for indebted firms) and negative for others as it may result in a crowding out effect, since higher interest rates curb the supply of corporate bonds. Assuming demand remains constant, this results in a rise in prices i.e. a narrowing of spreads. There is also a negative interest rate effect in the structural approach, where higher interest rates result in an increase in the firm's forward value (beyond the strike price) which reduces the default probability and thus contributes to narrowing the credit spread.

In other words, 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 the absence of strong expectations about the direction of interest rates movements, the shape of the term structure would be determined by the importance of investors requiring liquidity versus those demanding income stability.

Term structure is defined as the change in slope, i.e. the ratio of the 10-year interest rate to the two-year interest rate. Results presented here, support the structural models' theory, whereby the relation is expected to be negative, which suggests that higher interest rates may be associated with lower credit spreads. The exception is the

[42] The term structure of interest rate is representing the change in slope

long term BBB rated indices where the sign of the coefficient is positive. This is consistent with the idea that highest risk bonds are more sensitive to long term changes in the slope of the yield curve, which is related to economic activity.[43] The slope variable is statistically significant, only in terms of its lagged values, which suggests a lag relation between the change in interest rates and the change in credit spreads. In the medium maturities the change in interest rates becomes progressively more statistically significant, as we move down the rating grades, while such a pattern doesn't exist in the short maturing indices.

MS (Money Supply): An increase in money supply stimulates increased spending. In a buoyant economy stock market prices and firms issue equity and debt. Therefore an increase in money supply should cause a tightening of credit spreads. Results prove the negative relation between changes in money supply and the respective changes in credit spreads for the third lagged value of money supply. Considering that values of money supply are reported on a quarterly basis and that monthly figures have only been produced here, in order to test them against the monthly figures of credit spreads, it makes sense to look at the third lagged value of money supply, which corresponds to the previous quarter. Consistently higher negative coefficients and accompanying t-values for money supply have been reported in short term Bloomberg indices, suggesting an immediate influence on short term spreads.

IP (Industrial Production): Industrial production should also be negatively related to credit spreads since increased economic activity should boost investors' confidence and therefore lead to lower credit spreads. The variable of industrial production, although statistically significant, doesn't bear the expected sign, suggesting that investors require higher premiums at times of increased production activity, which is contrary to theory and intuition. Running reduced form regressions between the variable of industrial production and changes in credit spreads, provides negative coefficients for this variable, which effectively means that the wrong sign we get on the aggregate regression level, might be the result of correlation. (i.e. individual

[43] Joutz, Mansi and Maxwell (2000) have reported that treasury yields are positively related to credit spreads in the long run, but negatively related in the short run. This can have implications in the contingent claims and the reduced form approaches.

variables, which are individually negative, in multivariate context may have a positive sign).

TRBL (Trade Balance): We also tested the variable of trade balance, even though no clear cut decision could be made with respect to the expected sign of the relation. This is due to the fact that simply running a trade surplus does not necessarily indicate that a nation is performing well. After all, some very poor countries have trade surpluses and some rich countries have deficits. Indeed, what was shown from the results reported here is that the variable of trade balance, is negatively related to credit spread changes, at least as far as the US economy is concerned, or in the period tested. This result does make sense, considering that during the time period covered under this section, US runs a trade deficit, which recently (September 2005) has hit new records of approximately US$ 66bn.

Unemployment : The variable of unemployment was also tested to check its impact on credit spreads. However, the inclusion of this variable on an aggregate regression level wasn't statistically significant, at all maturities. Interestingly enough, this variable wasn't even statistically significant when reduced form regressions were run.

Table 4.2. Long Term Credit Spread Regressions

LONG TERM				
			AAA (OLS)	
	Expected Sign	**Coefficient**	**t-value**	**P-value**
Constant		-0.01	-0.93	0.08
GDP (LAGS 3)	-	0.01	2.03	0.04
CONF	-	-0.02	-2.09	0.03
CPI (LAGS 3)	+	0.00	0.80	0.00
Term Structure (LAGS 3)	-	-0.03	-0.83	0.07
MS(LAGS 3)	-	-0.03	-3.06	0.00
IP(LAG 3)	-	0.02	2.28	0.02
TRBL (LAGS 3)	-	-0.13	-2.07	0.03
R^2	20.9			
Adjusted R^2	17.3			
Durbin Watson	2.3			
			AA (OLS)	
	Expected Sign	**Coefficient**	**t-value**	**P-value**
Constant		0.04	2.72	0.04
GDP(LAGS 3)	-	0.01	3.47	0.00
CONF	-	-0.02	-2.15	0.03
CPI (LAGS 3)	+	0.00	1.60	0.06
MS (LAGS 3)	-	-0.01	-2.54	0.01
TRBL(LAGS 3)	-	-0.12	-2.04	0.04
Term Structure	-	-0.02	-2.78	0.00
IP(LAG 3)	-	0.01	2.28	0.02
R^2	18.2			
Adjusted R^2	15.6			
Durbin Watson	2.1			
			A (OLS)	
	Expected Sign	**Coefficient**	**t-value**	**P-value**
Constant		-0.06	-1.08	0.08
GDP (LAGS 3)	-	0.01	2.96	0.00
CONF	-	-0.04	-3.12	0.00
Term Structure (LAGS 3)	-	-0.08	-2.62	0.01
MS (LAGS 3)	-	-0.03	-2.97	0.00
IP(LAG 3)	-	0.02	2.33	0.02
CPI (LAGS 3)	+	0.01	1.71	0.07
R^2	20.8			
Adjusted R^2	17.18			
Durbin Watson	2.2			
			BBB (OLS)	
	Expected Sign	**Coefficient**	**t-value**	**P-value**
Constant		0.07	-1.92	0.07
GDP (LAGS3)	-	0.01	1.98	0.06
CONF	-	-0.04	-3.31	0.00
Term Structure (LAGS 3)	-	0.08	1.88	0.06
MS(LAGS 3)	-	-0.02	-3.06	0.00
IP(LAG 3)	-	0.01	1.10	0.07
CPI (LAGS 3)	+	0.01	1.68	0.06
R^2	11.5			
Adjusted R^2	9			
Durbin Watson	2.2			

Table 4.3. Medium Term Credit Spread Regressions

MEDIUM TERM				
		AAA (OLS)		
	Expected Sign	Coefficient	t-value	P-value
Constant		-0.00	-1.21	0.08
GDP(LAGS 3)	-	0.01	2.16	0.03
CONF	-	-0.02	-3.00	0.00
CPI(LAGS 3)	+	0.00	0.80	0.09
Term Structure	-	-0.05	-1.70	0.08
MS(LAGS 3)	-	-0.01	-1.93	0.07
IP(LAGS 3)	-	0.02	1.96	0.06
R^2	20.2			
Adjusted R^2	16.7			
Durbin Watson	2,3			
		AA (OLS)		
	Expected Sign	Coefficient	t-value	P-value
Constant		0.05	1.96	0.00
CONF	-	-0.03	-3.14	0.00
GDP(LAGS 3)	-	0.02	2.78	0.03
CPI (LAGS 3)	+	0.01	0.88	0.08
Term Structure (LAGS3)	-	-0.07	-2.41	0.00
IP	-	0.01	1.79	0.07
MS(LAGS 3)	-	-0.03	-3.06	0.00
R^2	11.6			
Adjusted R^2	9.3			
Durbin Watson	2.3			
		A (OLS)		
	Expected Sign	Coefficient	t-value	P-value
Constant		-0.01	-1.17	0.08
CONF	-	-0.04	-3.86	0.00
Term Structure (LAGS 3)	-	-0.06	-2.88	0.00
MS (LAGS 3)	-	-0.01	-1.84	0.06
IP (LAGS 3)	-	0.02	1.71	0.08
GDP(LAGS 3)	-	0.01	2.09	0.03
CPI (LAGS 3)	+	0.00	1.01	0.07
R^2	14.1			
Adjusted R^2	11.9			
Durbin Watson	2.05			
		BBB (OLS)		
	Expected Sign	Coefficient	t-value	P-value
Constant		0.03	1.44	0.06
CONF	-	-0.04	-3.38	0.00
MS(LAGS 3)	-	-0.02	-2.37	0.01
Term Structure(LAGS 3)	-	-0.01	-1.56	0.00
GDP(LAGS 3)	-	0.00	1.04	0.03
CPI (LAGS 3)	+	0.00	0.79	0.09
IP (LAGS 3)	-	0.03	1.65	0.08
R^2	11.3			
Adjusted R^2	9			
Durbin Watson	2.05			

Table 4.4. Short Term Credit Spread Regressions

SHORT TERM				
			AAA (OLS)	
	Expected Sign	Coefficient	t-value	P-value
Constant		0.001	1.25	0.09
GDP(LAGS 3)	-	0.01	2.04	0.04
CONF	-	-0.15	-3.31	0.00
Term Structure (LAGS 3)	-	-0.12	-3.19	0.00
TRBL (LAGS 3)	-	-0.09	-2.37	0.01
MS(LAGS 3)	-	-0.04	-3.06	0.00
CPI (LAGS 3)	+	0.00	0.56	0.09
R^2	14.2			
Adjusted R^2	12.1			
Durbin Watson	2.5			
			AA (OLS)	
	Expected Sign	Coefficient	t-value	P-value
Constant		0.05	0.09	0.09
GDP(LAGS 3)	-	0.01	1.84	0.07
CONF	-	-0.02	-2.83	0.00
Term Structure (LAGS 3)	-	-0.12	-3.63	0.00
TRBL(LAGS 3)	-	-0.09	-2.47	0.01
MS(LAGS 3)	-	-0.04	-3.66	0.00
IP(LAG 3)	-	0.01	1.11	0.08
CPI (LAGS 3)	+	0.01	0.80	0.09
R^2	14			
Adjusted R^2	12			
Durbin Watson	2.3			
			A (OLS)	
	Expected Sign	Coefficient	t-value	P-value
Constant		0.08	1.25	0.09
GDP(LAGS 3)	-	0.01	2.57	0.01
CONF	-	-0.03	-3.83	0.00
Term Structure (LAGS 3)	-	-0.02	-2.7	0.00
MS (LAGS 3)	-	-0.03	-3.64	0.05
IP (LAGS3)	-	0.02	1.66	0.09
TRBL (LAGS 3)	-	-0.01	-2.9	0.00
CPI (LAGS 3)	+	0.01	0.84	0.09
R^2	23.9			
Adjusted R^2	20.5			
Durbin Watson	2.13			
			BBB (OLS)	
	Expected Sign	Coefficient	t-value	P-value
Constant		-0.01	-0.17	0.09
CONF	-	-0.02	-1.88	0.08
GDP(LAGS 3)	-	0.02	2.57	0.01
Term Structure(LAGS 3)	-	-0.07	-1.69	0.09
MS(LAGS 3)	-	-0.03	-3.30	0.01
IP(LAGS 3)	-	0.02	1.99	0.04
TRBL (LAGS 3)	-	-0.01	-2.50	0.01
PPI (LAG 3)	+	0.03	1.70	0.09
CPI (LAGS 3)	+	0.01	0.72	0.09
R^2	26.8			
Adjusted R^2	22.3			
Durbin Watson	2.02			

Overall, as provided from the results of the OLS regressions the most important relation and driver of credit spread changes in all maturities and rating categories is the US Consumer Confidence Index. This means that there is much more information contained in than index, than any other macroeconomic measure. Also this variable has been significant at time t, rather than at previous periods, and bears the expected negative sign. In essence, this means that a close look on the movement of this variable can prove to be a very significant management tool for predicting changes in credit spreads.

4.2.2. Direction of Causation between spread movements & the business cycle *(based on times series analysis & Bloomberg Indices)*

Studies made on the direction of causation between macroeconomic variables and credit spreads suggests that there is a direct link between aggregate economic activity and default rates and/or credit spreads widening. When the economy is in an expansion, corporate earnings and profitability are on the rise so it seems logical that the default rate should go down. Conversely, during an economic contraction, slack demand may result in lower operating margins and cash flow, prompting an increase in the default rate. The direction of causation is assumed to flow from measures of economic growth, such as GDP or industrial production to default rates.

In the case of the emerging markets, defaults in the period 1997-1998, the direction of causation seemed pretty clear cut: the dramatic slowdown and freezing up of debt capital markets resulted directly in a high number of corporate defaults. Moody's research has found that the relation between the macroeconomic factors and default rates is more complex than simple, intuitive explanation suggests. From 1920 to 1965 significant increases in the default rate were typically preceded by weakness in the economy (as presented by industrial production). Since 1965, it has been noticed that increases in the default rate occur in advance of a weakening in industrial production. This shift in the lead lag relation demonstrates that the statistical relation between default rates and macroeconomic variables is tenuous.

Moody's default forecasting model includes changes in real (inflation adjusted) US Industrial production to measure the effect of the fluctuations in the macroeconomy. The industrial production variable actually adds very little to the forecasting power of Moody's default forecast model and is in fact only barely statistically significant.

Fears that a dramatic increase in defaults would cause the broader economy to falter fail to recognise the distinction between correlation and causality. A rise in default rate can precede an economic downturn in time, but not be the cause of it. The possibility exists that stirrings of problems in the macroeconomy affect firstly the most highly levered, cash dependent firms before manifesting themselves in macroeconomic variables such as GDP or industrial production.

The predictive power of the term spread for future output has been studied by Harvey(1988, 1989), Chen(1991) Estrella and Hardouvelis(1991), Estrella and Mishkin(1998) and Stock and Watson(1989) among others. The term spread contains information on inflation expectations as well as monetary policy. Because the underlying assets are default risk free, the term spread does not capture information about credit risk.

Other literature, that relates output forecasts to credit risk is focused on the paper –bill spread (Bernanke and Blinder, 1992, Stock and Watson, 1989, and Friedman and Kuttner 1992, 1993a, b, 1998, among others). As a leading indicator, the paper bill spread faces at least two problems.

(1) the underlying assets (commercial paper and Treasury bills) are short term debts that are not affected by long term credit risks. Therefore, they cannot reflect investors' expectations regarding business cycles in the future.
(2) According to Friedman and Kuttner (1998), commercial paper and Treasury bills could be nearly perfect substitutes because of the low default rate in the commercial paper market. The empirical failure of the paper bill spread to anticipate the 1990-91 recession calls into question its extra predictive power beyond the federal funds rate.

Within the context of this thesis using the same set of data as has been described above, the goal is to test the following hypothesis:

Changes in macroeconomic variables don't cause changes in spreads. Effectively this would mean that the causation of change in spreads is not driven by changes in economic activity. In other words, the hypothesis tested is that changes in credit spreads precede changes in economic activity.

In order to find the direction of causation between macroeconomic factors and changes in credit spreads, Granger causality tests have been performed and the null hypothesis for each pair of credit rating category and macroeconomic variables are shown in tables 4.5, 4.6, 4.7, and 4.8. In particular, the four tables show the granger causality tests for AAA, AA, A and BBB rated indices respectively and according to maturity (short, medium and long term). Granger causality, measures precedence and information content, but does not by itself indicate causality in the more common use of the term.

The Granger (1969) approach to the question of whether x causes y is to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. Y is said to be Granger-caused by x if x helps in the prediction of y, or equivalently if the coefficients on the lagged x's are statistically significant. Note that two-way causation is frequently the case; x Granger causes y and y Granger causes x.

In particular, the hypotheses tested, for AAA rated indices (for example) are of the following form:

Ho: Consumer Confidence doesn't granger cause changes in AAA credit spread indices

Ho: CPI doesn't granger cause changes in AAA credit spread indices

Ho: GDP doesn't granger cause changes in AAA credit spread indices

Ho: MS doesn't granger cause changes in AAA credit spread indices

Ho: MS doesn't granger cause changes in AAA credit spread indices

Ho: PPI doesn't granger cause changes in AAA credit spread indices

Ho: Slope doesn't granger cause changes in AAA credit spread indices

Ho: Trade Balance doesn't granger cause changes in AAA credit spread indices

Ho: Unemployment doesn't granger cause changes in AAA credit spread indices

The same hypotheses are tested for the remaining rating categories at the 5% and 10% level of significance. Results presented below are a bit mixed in terms of statistical significance.

In particular, granger causality tests performed for long term maturity indices provide evidence that changes in macroeconomic variables precede changes in credit spreads, i.e. the null hypotheses that macroeconomic variables don't granger cause changes in the credit spread indices is rejected. However, results obtained for unemployment in all rating categories aren't statistically sufficient to reject neither the null or the alternative hypothesis. This result is contrary to the Zhang's (2002) conclusion, who looks at the predictive power of corporate spreads to predict business cycles and finds that high yield bond spread and investment grade spread can explain 68% and 42% of unemployment variation one year ahead.

With respect to medium term maturities, the null hypothesis is rejected for the macroeconomic variables of consumer confidence, CPI, GDP, money supply and the slope of the interest rates. This effectively means that changes in the US consumer confidence index, in CPI, etc, cause credit spreads to change. For the rest of the variables, i.e. for PPI, trade balance and unemployment, results don't provide confidence to reject neither hypotheses.

Particularly interesting results are provided from the short term maturing indices. When CPI , PPI and money supply were tested against spreads, results lead to the rejection of the inverse of the null hypotheses previously reported, i.e. we reject the hypothesis that credit spreads don't granger cause changes in CPI, PPI or money supply. This implies that changes in short-term credit spreads can proceed CPI, PPI, unemployment or money supply changes. Of course this doesn't mean that changes in credit spreads cause macroeoconomic variables to change, but rather that credit markets may incorporate and or reflect this information in credit spreads quicker than this information is reported in the monthly or quarterly macroeconomic reports. This could suggest that short term spread indices could help investors to improve forecasts with respect to the above variables. For the rest of the variables in short term maturing indices, we can reject the null hypothesis that macroeconomic variables don't granger cause changes in credit indices.

Table 4.5. Granger Causality Tests **AAA** Rating - Long, Medium & Short Term Credit Spreads

		LONG TERM		MEDIUM TERM		SHORT TERM	
		AAA					
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CONF does not Granger Cause AAA	168	0.565	0.069	1.030	0.035	1.986	0.099
AAA does not Granger Cause CONF		0.123	0.885	1.799	0.169	1.414	0.232
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CPI does not Granger Cause AAA	168	0.054	0.094	2.720	0.069	0.377	0.864
AAA does not Granger Cause CPI		1.419	0.245	2.301	0.103	2.423	0.038
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
GDP does not Granger Cause AAA	168	0.599	0.075	1.676	0.090	0.810	0.059
AAA does not Granger Cause GDP		0.407	0.667	0.075	0.928	1.011	0.431
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
MS does not Granger Cause AAA	168	1.596	0.020	2.954	0.014	4.499	0.113
AAA does not Granger Cause MS		0.419	0.658	1.491	0.196	2.740	0.068
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
PPI does not Granger Cause AAA	168	0.478	0.062	0.054	0.947	2.665	0.173
AAA does not Granger Cause PPI		0.771	0.464	2.096	0.126	2.437	0.091
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
SLOPE does not Granger Cause AAA	168	1.032	0.035	0.733	0.082	3.192	0.025
AAA does not Granger Cause SLOPE		0.903	0.408	0.173	0.841	1.520	0.211
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
TRBL does not Granger Cause AAA	168	1.314	0.027	1.392	0.251	3.143	0.046
AAA does not Granger Cause TRBL		1.716	0.183	0.844	0.432	1.430	0.242
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
UNEMP does not Granger Cause AAA	168	0.538	0.158	0.106	0.900	1.086	0.374
AAA does not Granger Cause UNEMP		0.422	0.657	1.706	0.185	0.835	0.544

Table 4.6. Granger Casuality Tests **AA** Rating - Long, Medium & Short Term Credit Spreads

		LONG TERM		MEDIUM TERM		SHORT TERM	
		AA					
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CONF does not Granger Cause AA	168	1.737	0.017	0.080	0.077	2.455	0.089
AA does not Granger Cause CONF		0.478	0.621	1.294	0.257	0.022	0.978
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CPI does not Granger Cause AA	168	0.581	0.056	1.603	0.017	0.442	0.723
AA does not Granger Cause CPI		1.430	0.242	2.879	0.025	2.520	0.060
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
GDP does not Granger Cause AA	168	3.049	0.050	1.171	0.031	3.051	0.083
AA does not Granger Cause GDP		0.789	0.456	2.182	0.116	0.032	0.858
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
MS does not Granger Cause AA	168	1.092	0.033	0.368	0.093	1.098	0.367
AA does not Granger Cause MS		1.429	0.243	1.729	0.181	1.391	0.213
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
PPI does not Granger Cause AA	168	0.794	0.095	2.348	0.099	1.253	0.288
AA does not Granger Cause PPI		1.203	0.303	2.106	0.125	2.454	0.089
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
SLOPE does not Granger Cause AA	168	0.447	0.064	1.314	0.072	2.751	0.067
AA does not Granger Cause SLOPE		0.135	0.874	1.417	0.245	0.245	0.783
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CHTRBL does not Granger Cause AA	168	1.349	0.026	0.041	0.196	2.961	0.055
AA does not Granger Cause CHTRBL		1.118	0.329	3.474	0.033	0.131	0.877
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
UNEMP does not Granger Cause AA	168	1.480	0.223	0.710	0.193	2.789	0.197
AA does not Granger Cause UNEMP		0.048	0.953	0.520	0.595	0.369	0.544

Table 4.7. Granger Casuality Tests **A** Rating - Long, Medium & Short Term Credit Spreads

		LONG TERM		MEDIUM TERM		SHORT TERM	
		A					
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CONF does not Granger Cause A	168	1.589	0.020	2.083	0.086	0.467	0.062
A does not Granger Cause CONF		0.430	0.651	0.606	0.659	0.607	0.546
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
CPI does not Granger Cause A	168	0.537	0.058	2.793	0.064	0.212	0.957
A does not Granger Cause CPI		0.573	0.565	0.664	0.516	2.140	0.064
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
GDP does not Granger Cause A	167	2.671	0.049	0.979	0.378	0.455	0.063
A does not Granger Cause GDP		0.356	0.785	0.701	0.498	0.554	0.576
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
MS does not Granger Cause A	163	0.971	0.094	0.746	0.076	1.158	0.283
A does not Granger Cause MS		0.690	0.680	1.908	0.152	4.624	0.033
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
PPI does not Granger Cause A	168	0.074	0.092	0.205	0.815	1.849	0.176
A does not Granger Cause PPI		0.557	0.574	1.682	0.189	5.148	0.025
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
SLOPE does not Granger Cause A	168	0.107	0.089	0.040	0.061	2.513	0.084
A does not Granger Cause SLOPE		1.040	0.356	0.691	0.503	1.160	0.316
Null Hypothesis:	**Obs**	**F-Stat**	**Prob**	**F-Stat**	**Prob**	**F-Stat**	**Prob**
UNEMP does not Granger Cause A	168	0.073	0.192	1.439	0.203	0.063	0.193
A does not Granger Cause UNEMP		1.001	0.370	0.893	0.502	0.960	0.385

Table 4.8. Granger Causality Tests **BBB** Rating - Long, Medium & Short Term Credit Spreads

		LONG TERM		MEDIUM TERM		SHORT TERM	
		BBB					
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
CONF does not Granger Cause BBB	168	1.572	0.021	1.268	0.028	3.422	0.066
BBB does not Granger Cause CONF		0.213	0.808	0.674	0.511	0.090	0.764
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
CPI does not Granger Cause BBB	168	0.216	0.080	1.913	0.095	0.774	0.463
BBB does not Granger Cause CPI		0.486	0.616	0.904	0.480	0.187	0.083
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
GDP does not Granger Cause BBB	168	1.613	0.020	0.673	0.012	3.697	0.027
BBB does not Granger Cause GDP		1.387	0.253	1.397	0.250	1.492	0.228
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
MS does not Granger Cause BBB	168	0.425	0.054	0.083	0.092	1.247	0.290
BBB does not Granger Cause MS		3.649	0.028	1.417	0.245	2.944	0.055
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
PPI does not Granger Cause BBB	168	0.326	0.072	0.770	0.546	1.801	0.168
BBB does not Granger Cause PPI		0.073	0.929	2.566	0.140	2.683	0.071
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
SLOPE does not Granger Cause BBB	168	0.386	0.068	0.206	0.014	3.551	0.031
BBB does not Granger Cause SLOPE		0.101	0.904	0.764	0.468	0.365	0.695
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
TRBL does not Granger Cause BBB	168	0.199	0.082	0.929	0.448	3.514	0.063
BBB does not Granger Cause TRBL		0.257	0.774	1.764	0.139	0.070	0.792
Null Hypothesis:	**Obs**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**	**F-Stat**	**Prob.**
UNEMP does not Granger Cause BBB	168	0.022	0.097	0.446	0.064	1.006	0.368
BBB does not Granger Cause UNEMP		0.288	0.750	2.533	0.183	2.899	0.058

4.3. Evidence based on Merrill Lynch Indices & Cross Sectional Analysis

In this section, the relation between credit spread changes and macroeconomic indicators is examined. The difference compared to the previous section focuses on the following three points:

(1) A different set of credit spreads will be used. Instead of looking on how macroeconomic variables influence spread indices, we focus on how changes in financial conditions affect constituents (analytically described in section 3.3.1.) of Merrill Lynch credit spread indices. Contrary to other studies that use the so called refreshed indices which are constructed by bonds that have the same characteristics (but not necessarily the same bonds comprise the index in the previous period), in this section of the thesis, only bonds that have the same characteristics and have the same remaining years to maturity that would cover for the remaining life of the index are going to be included and tested. Additionally here, we are looking at option adjusted spreads. In that way we avoid the problem of comparing two bonds of the same maturity which don't necessarily have the same duration (price sensitivity to interest rate changes) nor the same convexity (sensitivity to the slope of the yield curve).

(2) Both investment and non-investment grade companies making the constituents will be tested and analysed. Jaffee (1975) was first to introduce the idea that risk spreads between low and high quality bonds move differently with the business cycle. In particular he suggests that top quality bonds might be risk-free regardless of the business cycle, while low rated bonds are expected to deteriorate significantly during recessions. Hence, in recessions, spreads of low quality bonds widen more than top quality bonds.

(3) Due to the new set of data and since we have information on credit spreads of particular companies, over time, cross sectional analysis of data will be employed. Due to problems usually arising with intercorrelated error terms in cross sectional regressions, two different methods of cross sectional analysis will be used, the cross section weights method and the Seemingly Unrelated Regressions. Results will be tested on a fraction of the period mentioned above, i.e. from January 1997

to May 2002. Quarterly data was used at an initial stage in order to mitigate any effects from autocorrelation. Even if the period under this section is much tighter than the previously analysed, it covers both high and low interest rate regimes.

Since we are testing quarterly data in this section, macroeconomic variables have been tested to check whether there were any signs of correlation on a quarterly basis. As shown in table 4.8. presenting the correlation matrix amongst the macroeconomic variables on a quarterly basis, the following variables exhibit correlations of above or below 0.70 and hence can't be used as regressors on a parallel basis. These are interest rates with unemployment and industrial production (correlation: 0.78 and -0.78 respectively), industrial production with unemployment (correlation –0.75) and PPI with CPI (correlation 0.87). Comparing correlation coefficients of macroeconomic variables on a quarterly basis, to those based on a monthly data (table 4.1.), we observe that the former exhibit much higher correlations than the latter. This can either be due to the fact that since some of these macroeconomic variables report on a quarterly basis, they change at the same point in time, hence provide higher correlation or it may be due to the fact that during this short time period tested (January 1997 through May 2002) macroeconomic variables have indeed exhibited higher correlations.

Table 4.9. Correlation Matrix amongst Macroeconomic Variables (quarterly basis)

	Slope	*GDP*	*UNEMP*	*CONF*	*CPI*	*PPI*	*TRBL*	*IP*	*MS*
Slope	**1.00**								
GDP	-0.49	**1.00**							
UNEMP	**0.78**	-0.62	**1.00**						
CONF	-0.36	0.28	-0.05	**1.00**					
CPI	-0.40	**0.58**	0.23	-0.17	**1.00**				
PPI	-0.48	0.65	0.43	-0.30	**0.87**	**1.00**			
TRBL	0.26	-0.40	0.01	**-0.58**	-0.04	-0.11	**1.00**		
IP	**-0.78**	0.38	**-0.75**	0.28	0.06	0.17	-0.23	**1.00**	
MS	0.46	-0.27	0.17	-0.55	0.01	0.15	-0.52	-0.21	**1.00**

After running numerous regressions we end up with a regression equation of the following form:

Equation 4.2.

ΔSpreads$_{it}$ = c + β_1* (ΔCons Conf $_{it,..it-n}$) +β_2* (ΔCPI $_{it,..it-n}$) + β_3* (ΔGDP $_{it,..it-n}$) + β_4* (ΔPPI $_{it,..it-n}$) + β_5* (ΔUnemployment $_{it,..it-n}$) + β_6* (ΔTrade Balance $_{it,..it-n}$) + β_7* (ΔIndustrial Production $_{it,..it-n}$) + β_8* (ΔMoney Supply $_{it,..it-n}$) + β_9* (ΔTerm Structure $_{it,..it-n}$) + ε_{it}

Where Δspreads: changes in OAS at time t from (t-1),

ΔCons Conf: quarterly change in consumer confidence,

ΔCPI: the quarterly rate of change in the consumer price index,

ΔGDP: the quarterly change in GDP,

ΔPPI: change in the producer price index

ΔUnemployment: quarterly change in the unemployment rate,

ΔTrade Balance: quarterly change in the trade balance,

ΔIndustrial Production: quarterly rate of change in industrial production,

ΔMoney Supply: quarterly rate of change in money supply,

ΔTerm structure: the quarterly change in the slope, i.e. difference between the 10-year and the 2-year interest rates, and

e_{it} :error term.

Predicted and actual signs for those variables are shown in the table 4.10.

Despite the correlation of some of the independent variables, at an initial stage, all of the parameters are regressed against spreads, on a univariate context. However, only those not correlated amongst them and those, which are statistically significant, are reported in tables 4.10 – 4.12. Regressions on quarterly data have been estimated with the use of cross section weights and the White test for heteroscedasticity and autocorrelation consistent covariance matrix to calculated t-statistics.

Table 4.10: Pooled Cross-section, time series regression, **Total Sample**

Variables	Expected Sign	Coefficient	t-value	P-value
GPD	-	0.07	4.17	0.00
US Confidence	-	-2.58	-19.23	0.00
CPI	+	3.12	8.19	0.00
Industrial Production		4.13	13.3	0.00
Interest rates (Term Structure)	-	-1.64	-7.5	0.00
Money Supply	-	-4.04	-13.6	0.00

The estimation of the above coefficients is achieved using pooled cross-section and time series data.

The expected coefficient of GDP is negative, since it is expected that at times of GDP growth, investors would demand lower premiums. In terms of the US consumer confidence index the expected sign is also negative, since when consumer confidence is high spreads are expected to tighten. The expected sign of CPI is positive and displays the direct relation between the size of yield spreads, which means that at inflationary times investors require higher premia. Lastly, the negative sign of the term structure of interest rates suggests that a steepening curve has a mitigating effect on the yield spread investors demand from corporate bonds, while a flattening in the slope of the structure (which is associated with a slowdown in economic activity) decreases investors' tolerance towards risk and as a result a higher yield spread is required.

As shown above, most coefficients are highly significant with high accompanying t-values. The most significant coefficient is obtained for the variable of US consumer confidence, with a high t-statistic of -19.23 and the variable of money supply. Significant results are obtained for the rest of the variables with the exception of the coefficient of GDP and industrial production where we don't get the correct sign for which is in contrast to our initial expectation. This finding coincides with results obtained from the OLS regressions. However, this doesn't make good intuitive sense for two reasons.

- First, when the economy is doing well, the chances of default tend to diminish. Rating agencies try to rate through the economic cycle, but the probability of a default varies substantially through time.
- Second, when the economy is doing well, the improvement in sentiment means that investors are prepared to settle for lower spreads on a credit with a given rating. Conversely, when the economy is in trouble, spreads widen as sentiment becomes more bearish and investors tend to shift in safer assets, in an attempt to avoid defaults and to a lesser extent downgrades.

Thus, the positive sign of the coefficients of industrial production and GDP, are not correct, mistakenly implying that increased GDP or increased production mean that investors need to be compensated by higher spreads. However, one possible explanation, might be a bad effect of correlation that still exists between the independent variables which are individually negative, in a multivariate context may have a positive sign. Another explanation might be that the wrong signs are the effect of testing on a parallel basis investment and non-investment grade companies, the latter of which seem to be ruled by some inconsistencies caused by extreme movements in credit spreads in the high yield category.

The overall model has an adjusted R^2 of 40%, while the Durbin Watson statistic is 2.23, which indicates that there is no serial autocorrelation in the residuals.

The next step of the analysis focuses on testing the above hypotheses separately on investment and non-investment grades categories. To examine the differences in the rating categories, the equation to be estimated, is run separately for corporate bonds in the investment grade and high yield categories.

In particular, a set of time series regressions stacked cross sectionally are run for investment grade bonds (i.e. AAA, AA, A & BBB), whose estimated parameters are shown in table 4.11.

Table 4.11: Pooled Cross section, time series regression, **Investment Grade Sample**

Variables	Expected Sign	Coefficient	t-value	P-value
GPD	-	0.00	1.42	0.00
US Confidence	-	-2.14	-14.4	0.00
CPI	+	7.57	6.25	0.00
Industrial Production	-	4.82	14.3	0.00
Interest rates (Term Structure)	-	-0.72	-8.71	0.00
MS	-	-4.89	-14.3	0.00

Overall, the investment grade model has an adjusted R^2 of 27.9%, while the Durbin Watson statistic is 2.25. Particularly significant t-statistics are reported for the variables of US consumer confidence (14.4), money supply (14.3), and the term structure of interest rates (8.71). Still though, we are left with the variables of GDP and Industrial production not bearing the expected sign.

Considering though, that investment grade companies include by definition BBB rated bonds, which are highly volatile in nature compared to their investment grade counterparties, it will be interesting to see how the results look if we exclude that rating category from the sample.

Indeed once we remove bonds belonging to this rating band from the investment grade sample, we find that even if the coefficient of GDP bears the expected sign, the coefficient of industrial production is still positive and the overall adjusted R^2 is lower than before, i.e.21.3%. Testing the lagged values of GDP and industrial production, although provides a slightly higher R^2 of 31.5%, still the expected negative relation between GDP and Industrial production isn't empirically proven.

Next the high yield category (i.e. BB, B, C) is being tested. The estimated parameters are shown in table 4.12.

Table 4.12: Pooled Cross section, time series regression, **High Yield Sample**

Variables	Expected Sign	Coefficient	t-value	P-value
GPD	-	0.01	5.05	0.00
US Confidence	-	-3.09	-18.6	0.00
CPI	+	4.04	2.52	0.00
Industrial Production	-	5.19	12.1	0.01
Interest rates (Term Structure)	-	0.58	7.00	0.00
Money Supply	-	-3.45	-12.9	0.00

The non-investment grade model, as defined by the above variables has an adjusted R^2 of 44.4%[44] while the Durbin Watson statistic is 2.21, which indicates that there is no serial correlation in the residuals. The very strong relation between the changes in sentiment and credit spreads, is also depicted here, with a t-statistic of -18.6. The variables of GDP and industrial production, still don't have the expected sign, while

[44] It should also be noted that when the lagged value of CPI and money supply are used as independent variables in the regression, the explanatory power of the non-investment grade model is significantly increased to an adjusted R^2 of 60%.

we also find here that the term structure of interest rates is positively related to credit spreads.

Econometric studies carried out on this issue (Litterman and Iben 1991, Fons 1994 and Duffee 1999) converge to the same result, i.e. for investment grade issues the structure is upward sloping, while this slope becomes steeper for lower rated bonds. Authors such as Sarig and Warga (1989) and Fons (1994) find that for lower rated issues the term structure of credit spreads is inverted, consistent with the structural approach, while others such as Helwege and Turner (1999) argue that in the tests carried out there is a selection bias in the choice of maturities, among firms with the same rating the least risky tend to issue the longest bond. Effectively, the spread narrows as the maturity lengthens, while for a given firm the spread widens along with maturity. [45] In particular, they examine sets of bond issued by the same firm with equal priority in the liability structure, but with different maturities, thus holding credit quality constant. They find, counter to prior research that risky bonds typically have upward sloping credit yield curves. Moreover, when they combine their matched sets of bonds(no longer controlling for quality) the estimated slope is negative, indicating a sample selection bias problem associated with maturity. Contrary to the above studies, Tang and Yan (2004) found that credit spread is negatively correlated with interest rate, and ceteris paribus, this correlation is stronger for bonds with higher default probability, i.e. non-investment grade bonds.

The relation between macroeconomic variables and credit spreads was also tested on two more levels:

a. On a monthly basis, for the total investment and non investment grade sample respectively, under the GLS method and the White test for hetersocedasticity[46] and consistent covariance.
b. On a monthly basis for the individual credit rating categories, using the SUR method[47].

[45] For more comments on this issue, refer to the Lubochinsky's paper "How much credit should be given to credit spreads"(2002)

[46] Analytically, results are reported in Appendix 5(a)

Results reported with respect to the first set of tests, are complying with the evidence provided by inferences drawn from the quarterly data not only with respect to the individual structure of the relations but also support the hypothesis that changes in macroeconomic conditions affect mostly the high yield sector, as evident from the adjusted R^2 statistic, as part of the weighted statistics, which is almost doubled for non-investment grade companies. (adjusted R^2 : 7% in the investment grade to adjusted R^2 :14% in the non-investment grade)

As far as the second set of tests is concerned, based on the SUR method of estimating weighted versions of the required specification, results show that the relations between the independent macroeconomic variables and credit spreads become progressively more significant as we move down the rating bands. Highly statistically significant t-values are being reported from A category and towards the C-rated bonds and the adjusted R^2s also progressively increase the lower the credit rating (from an adjusted R^2 of 2% for AAA-rated bonds to an adjusted R^2 of 14% for C-rated bonds).

Very important results are reported for the variables of consumer confidence, CPI and industrial production. It is worth noting that when those "reduced" form regressions were run on the individual rating categories, it was shown that the third lagged value of GDP (corresponding to the previous quarter) had the expected sign, although only in the investment grade categories. It is also important to note that the term structure of interest rate was negatively related for investment grade companies, while the coefficient was positive for the most of the non-investment grade categories, and indeed highly significant. Rather interesting is also the finding that under the SUR method, the relationship between credit spreads and the term structure is positive from the BBB rating category and for all rating categories until C. This provides further support to the argument put forwards in previous chapter of this thesis, i.e. that bonds in this category tend to be very volatile and share properties of their non-investment grade counterparties.

It should also be noted that results provided from quarterly data, propose higher coefficients for the variables under question and also are accompanied by higher t-

[47] Analytically, results are reported in Appendix 5(b)

statistics and R^2s. There most possible explanations for this, as has been previously explained, is that for some of the macroeconomic variables that are only reported on a quarterly basis, had to be reproduced to monthly figures (by keeping observations constant from the one reporting period to the next). Hence, on a monthly basis, the change in those variables might not be immediately or accurately reflected in credit spreads.

4.3.1. Direction of Causation between spread movements & the business cycle *(based on time series stacked cross sectionally & Merrill Lynch Indices)*

The literature on the relationship between corporate bond spreads and business cycle is limited. Chan –Lau and Ivaschenko (2000, 2002) illustrate the predictive power of the investment grade spread for the business cycle. Only two papers explore this relationship between the context of the high yield category, i.e. the one by Gertler and Lown (1999) and that by Zhang (2002), which are analysed further together with our results.

When using time series data stacked cross sectionally, Granger causality tests can't be performed, since those are considering the causality effects between two groups, whereas in this set of data we have company specific credit spreads.

As a result, as a way to test the hypothesis of the precedence effect between macroeconomic factors and credit spreads, we employed cross sectional regressions for lagged values of the dependent and the independent variables. This is not to say that by running the cross sectional regressions on the lagged values we'll get similar information to that measured by the granger causality tests, but the purpose is to find whether we can gain some more insight with reference to investment or non-investment rated companies.

The first set of regressions performed tests the null hypothesis that changes in investment and high yield credit spreads don't influence (contain no marginal information) for the business cycle (results of which are shown in table 4.13.). In other words, the direction of causation is assumed to flow from changes in credit spreads to macroeconomic factors, i.e. macroeconomic variables are the dependent variable (y) and changes in credit spreads are the independent variable (x). This hypothesis is tested initially for all companies and then separately for investment and non-investment grade ones.

After performing regressions of spreads at time t, (t-4) and (t-8) against the six macroeconomic variables, which are not correlated, it was shown that previous months' spreads have explanatory power on macroeconomic fundamentals especially when it regards the non- investment grade category. This effectively means that ratings as those are reflected into spreads incorporate useful financial information at least for the non- investment grade category. It can also mean as explained above, that a slowdown in economic activity is firstly becoming apparent to companies that tend to be in financial difficulties and then be reflected in the macroeconomic variables. A virtue of the high yield spread is that because it is extremely sensitive to default risk, it may detect a greater variety of factors that influence the macroeconomy than do other indicators. It is found that all of the parameters of the variables were statistically significant. For non-investment grade companies the null hypothesis is strongly rejected at the 95% level, whereas for the investment grade companies it is rejected at the 90% level but not for all variables. For simplicity reasons herein only the adjusted R^2 are depicted.

Table 4.13 Direction of Causation (Dependent Variable: Macroeconomics, Independent: Credit Spreads)

Macroeconomic Variables	Investment Grade	High Yield
GDP	1%	2.2%
GDP (t-4)	45.4%	91.2%
GDP (t-8)	55.4%	95.9%
US Confidence	4.2%	19.6%
US Confidence (t-4)	52.3%	59.7%
US Confidence (t-8)	64.9%	83.6%
CPI	0%*	10.1%
CPI (t-4)	35.2%*	63.2%
CPI (t-8)	37.6%*	47.3%
Industrial Production	2.7%	1.1%
Industrial Production (t-4)	25.4%	35.1%
Industrial Production (t-8)	54.3%	86.7%
Term Structure	0%	2.1%
Term Structure (t-4)	55.3%	63.7%
Term Structure (t-8)	60.5%	88.6%
Money Supply	0%*	3.1%
Money Supply (t-4)	54.8%*	75.8%
Money Supply (t-8)	55.3%*	85.6%

**Not statistically significant at the 95% or the 90% confidence level.*

Our result coincides with a paper published by Zhang (2002), of Bank of Canada[48], despite the fact that he uses credit spreads in level terms. His paper focuses on forecasting solely the employment growth rate one year ahead, based on credit spreads. He finds that the high yield bond spread and investment grade spread can explain 68% and 42% of output variations (employment growth) one year ahead, while the term spread based on government debts can explain only 12% of them. Results also point to the fact that for one year ahead output forecasts, the corporate bond spreads outperform popular indicators such as the paper-bill spread, federal funds rates, consumer sentiment index, Conference Board leading indicator, and the S&P's index.

Results are also similar to Gertler and Lown (2000)[49], who using quarterly data look at the information in the high yield bond spread for the business cycle. Their results also support that the high yield bond spread contains statistically significant and quantitatively important information for aggregate economic activity since the time of the development of the market for below investment grade debt. They find that since the middle 1985, the high yield spread outperforms the other leading financial indicators of real economic activity, including the paper –bill spread, the term spread and the Federal Funds rate. They argue that the high yield spread may be a good proxy for overall financial conditions. However, Duca (1999) points out that the conclusion of their experiment largely relies on the collapse of the high –yield bond market in the late 1980s and early 1990s, which could be coincidental.

Our results show, the information content of high yield credit spreads, is not only important for explaining/predicting variations in the unemployment rate but also and most importantly in other macroeconomic variables, such as the term structure or even money supply.

It is worth mentioning that this area is of great interest and hasn't been researched extensively. These findings can have important implications both empirically and theoretically. The strong explanatory ability of credit spreads, especially in the high

[48] Z. Zhang, Corporate Bond Spreads and the Business Cycle, Working Paper, Bank of Canada, 2002

yield sector, can help central bankers or other investors to improve different output forecasts. More importantly, credit spreads, compared to other market indicators, such as equities are much less volatile. Additionally, credit spreads contain information on the expected long term credit risks, which is not available in indicators from other financial markets. The unique information content of credit spreads justifies their superior /complementary value to the conventional leading indicators used in the prediction of output indicators, such as the term spread and federal fund rates.

In the second set of tests (results of which are shown in Table 4.14.) the direction of causation is assumed to flow from macroeconomic factors into spreads. After performing regressions of the different macroeconomic factors at time t, (t-4) and (t-8) against spreads, it was shown that the macroeconomy affects changes in spreads more significantly when it comes to the non- investment grade category.

Table 4.14. Direction of Causation (Dependent Variable: Changes in Credit spreads, Independent: Macroeconomic Variables)

Spreads	Total Sample	Investment Grade (including BBB ratings)	Investment Grade (including BBB ratings)	High Yield
Spreads	40.3%	27.9%	21.3%	44.4%
Spreads (t-4)	18.9%	20.1%	20.1%	20.2%
Spreads (t-8)	25.4%	20.2%	24.4%	35.9%

Even though the tests performed under this section are not equivalent to proper causality tests, they do provide support as to the informational content provided by changes and movements of credit spreads in the high yield sector.

[49] M. Gertler & C.S.Lown, The Information Content in the High Yield Bond Spread for the Business Cycle: Evidence and some implications, National Bureau of Economic Research, Working Paper, February 2000.

4.4.Concluding Remarks & Comments

Three issues have been identified and tested under this chapter. The first was the relation between macroeconomic variables and credit spreads, with the use of two sets of data. The second dealt with differences arising from the effect of macroeconomic variables to the different rating categories and maturities and thirdly the direction of causation between macroeconomic variables and changes in credit spreads.

With respect to the first set of tests, results provided by the OLS model, based on time series analysis of data, it was shown that the negative relation between changes in credit spreads and consumer confidence, trade balance, money supply and the term structure of interest rates is strongly supported for all maturities, but only for their lagged values. (except the US confidence index which is also statistically and economically significant at time t). The expected negative relation wasn't though supported for the variables of GDP and industrial production. Results from the OLS regressions of investment grade indices, suggest that macroeconomic variables explain at best a 17% of the variation in the medium and long term maturities and a 20.5% of the variation in short term maturing indices, as reflected by their adjusted R^2s.

Evidence provided by the constituents of ML indices, supports strongly the consumer confidence variable, money supply and trade balance, while again we get the wrong sing for the variables of GDP and industrial production. It should be noted that relation between the term structure and changes in credit spreads is negative for investment grade companies (although mixed results are produced for BBB-rated bonds), while is positive for the non-investment grade ones. This result is supported irrespective of the frequency of the data used or the methodology employed. This finding can have important implications in the contingent claims approach and the reduced form approach for valuing risky debt. It is also worth mentioning that more of the variation in credit spreads is explained by macroeconomic variables in the high yield sector rather the investment grade one, as reflected by the 27.9% and 44.4% of adjusted R^2s respectively (it should be noted that the adjusted R^2 increases to 60% for high yield companies when we use the lagged values of CPI and money supply).

Overall, in both samples, the variables of US consumer confidence, plays by far the most important role in explaining the variation in credit spreads, on a consistent basis. If we consider that this variable can be explained as a function of other economic variables, its intuitive appeal is quite clear.

With respect to the direction of causation results are a bit mixed, as provided by the empirical tests of the times series data. Results obtained from the granger causality tests for long term maturity indices generally reject the null hypotheses that macroeconomic variables don't granger cause changes in the credit spread indices. In other words, results coincide with intuition in the sense that changes in macroeconomic variables proceed changes in credit spreads. However, results obtained for unemployment in all rating categories aren't statistically sufficient to reject the null nor the alternative hypothesis.

With reference to medium term maturities, the null hypothesis is rejected for the macroeconomic variables of consumer confidence, CPI, GDP, money supply and the term structure of interest rates. For the rest of the variables, results don't provide confidence to reject the null hypotheses. Results reported from bonds of a short term maturity profile suggest that for the variables of CPI, PPI, unemployment and money supply we should reject the hypothesis that changes in credit indices don't granger cause the aforementioned macroeconomic variables. This doesn't mean that changes in credit spreads cause inflation or changes in the money supply but rather that credit markets perceive and reflect those changes in a more timely fashion than compared to the timing of reporting of the macroeconomic variables. For the rest of the variables in short term maturing indices, we can reject the null hypothesis that macroeconomic variables don't granger cause changes in credit indices.

Results provided by the constituents of the ML indices lend support to the higher and more significant informational content existing in companies of the high yield sector. Most importantly, results of the latter set of data, provided evidence about the predictive power of credit spreads to leading output indicators, and not only for the estimation of unemployment growth, which is a point that should be further researched. Again it is worth mentioning that these results don't mean that changes in credit spreads cause changes in macroconomic variables or indices. However, since debt market and especially the high yield segment moves and changes on a much more frequent basis than the reporting of the macroeconomic variables, investors' sentiment and general macroeconomic perceptions are incorporated in credit spreads on a timely basis. Hence, changes in credit spreads can be seen as an active forecasting tool for investors to improve their macroeconomic forecasts.

5.0. Credit Spreads and Equity Market Variables

Numerous studies[50] have focused on the relationship between stock and bonds returns. Some of those have tested the relationship both at the individual firm level and at the portfolio level. However, most of the studies, focus on corporate bond returns or yield changes. The distinction between changes in credit spreads and yield changes is very important. According to a study by Dufrense, Goldstein and Martin(2001), who are looking at the determinants of credit spread changes in a regression context, find that while an R^2 of 60% is obtained when regressing high grade bond yield changes on Treasury yield changes and stock returns, while the R^2 falls to 5% when the dependent variable is credit spread changes.

Inspired by the limited credit risk literature on the issue, the purpose of this chapter is to examine the relation between changes in credit spreads and equity changes. As both intuition and literature suggests, equities should be considered as an explanatory variable, since they are expected to add significantly to the analysis of credit spreads. The rationale behind this is, that since equity markets seem to incorporate more quickly financial and other information into their prices, they can provide useful insight for credit spread movements. All information going into a credit rating should be captured in the equity price. Equity markets are thought of as reflecting more up-to-date information whereas credit ratings may be revised infrequently and with a time lag.

Section 5.1. provides a literature review relative to credit spreads and equities. Section 5.2. sets the hypotheses to be tested and provides the rationale behind it, section 5.3. explores the relation based on time series data stacked cross-sectionally from Merrill Lynch. Section 5.4 tests the same relation but this time based on a different set of investment grade data extracted from Bloomberg indices for short, medium and long term maturities and is limited to the investment grade category.

5.1. Literature Review on the relation between equities and credit spreads

The relation between credit and equity risk has initially been set in Merton's model (1974). According to his theory, the holders of risky bonds can be thought of as owners of riskless bonds who have issued put options to the holders of the firm's equity. When volatility increases, the value of put options increases, thus benefiting equityholders at the expense of bondholders. The volatility that is appropriate for corporate debt is total firm volatility, i.e. the one that includes both idiosyncratic and systematic (market) volatility.

Merton's model supports that the market value of a risky bond and effectively the value of spread depends on two fundamental factors:

a. Leverage (i.e. the ratio between the present value (price of debt) and the firm's capital (equity)). An increase in the price of equity - except in the case of a speculative bubble – or a capital increase (share issuance) results, in ceteris paribus, a reduction in leverage and hence a decline in default risk, leading to a narrowing of spreads. Conversely a decline in the share price, or a company share buyback results in an increase in leverage and hence an increase in default risk leading in turn to a widening in spread. The above assumes that changes in the value of the firm measured by changes in its share price actually reflect changes in its fundamental value. If this was not the case, this linkage between share prices and default risk reflected by the credit spread would cease to be relevant. Therefore, in the case of a speculative bubble the narrowing of spreads shouldn't be interpreted as a sign of structural decline on the companies' default risk.

For example, over a period it is common to see a continuous rise in spreads while the prices of share rise and then fall. The explanation could be that over the period the leverage effect increases regularly firstly due to growing corporate debt (increase in the numerator, debt) and secondly to the fall in stock prices (decrease in the denominator, the value of equity).

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[50] Fama and French (1989, 1993), Campbell and Ammer (1993)Keim and Stambaugh(1986) and others.

However, there are a number of reasons why the prices of corporate bonds might be different from prices of equities.[51] These include the following:

1. Stock prices will increase if investors are more optimistic about a company's future profits. In turn this optimism favours more stocks than bonds, since equity holders receive all residual profits, whereas bondholders receive no more than the predetermined payments of interest and principal.
2. The difference may be due to the fact that corporate bonds may be issued by other companies than those that dominate the value–weighted equity indices and as a result equity prices may seem more volatile than the respective movements in credit spreads.
3. An increase in the liquidity premium on corporate bonds relative to treasury bonds, which might drive down corporate prices while not influence equity prices.
4. Volatility can have opposite effects on the stock and bond prices. An increase in volatility given that it increases the risk of default can drive down bond prices while have a positive effect on equity prices.

b. <u>Volatility of the asset value of a firm</u>: If we assume that default occurs at maturity, the higher the volatility of the asset value, the greater the likelihood at this date, that this value will be lower than that of the firm's debt. Logically the spread, which corresponds to the additional yield, increases along with the risk measured here by volatility. The problem is that the value of the firm's assets and its volatility cannot be directly measured. The solution adopted for testing this type of model consists of replacing this volatility by that of the firm's share price which is undeniably easier to measure.

However, this Merton's type model (structural approach) has the following limitations:

- The assumption of a log normal distribution of assets prices doesn't make it possible to take account for the asymmetry and the thickness of distribution tails (kurtosis)

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[51] "Equity Volatility and Corporate Bond Yields" J.Y. Campbell and G.B. Taksler, NBER Working Paper Series

- The assumption that default can occur only at maturity is very restrictive, as it doesn't allow for a sudden fall in the firm's value and thus estimated default probability in the short term becomes negligible.

Consequently, using this modelling technique short-term credit spreads for investment grade securities are likely to be almost zero which is contrary to empirical evidence. Using jump diffusion approach, yields more realistic results, but the modelling technique becomes much more complex.

Indeed, in the so-called "Reduced form approach" model which doesn't relate the default to the firm's value (i.e. doesn't state the exact cause of default and hence it is not necessary to estimate the parameters of the value of the firm in order to solve these models). Studies tend to favour this type of model because company default (bankruptcy) is a complex event for which the exact causes are often inaccurately specified, i.e. are either too restrictive or too vague.

Another major difference is the degree of default predictability. The date of default is a random variable and is therefore unpredictable, which is not the case in structural models. Lastly, if we assume that the default probability varies over time and depends on the level of interest rates, these reduced form models reflect two essential characteristics of defaults, i.e. the probability of default occurring and the recovery rate.

The advantage of this type of approach is that it provides a priori fairly simple valuation model for a risky bond and hence for the yield spread, derived from the following data: the price of a risk free bond of the same maturity, the default probability and the recovery rate. The price of the risk free bond is observed on the market, or interpolated from the term structure of the price of zero coupon bonds and the recovery rate can be estimated using historical data for similar bonds, such as those provided by the international credit rating agencies.

The difficulty is focused in estimating the default probability which is not the historical default probability but the risk neutral default probability, i.e. the default probability adjusted so that the expected yields on all bonds, risky and risk free alike are the same and equal to the risk free interest rate. This probability may be interpreted as a probability adjusted for the default risk premium paid to the investor. This premium corresponds to the price differential between a risk free bond and a risky bond divided by the expected loss. The adjusted probability can then be estimated by multiplying the historical probability by this risk premium (Jarrow and Turnbull, 1997).

Reduced form model nevertheless have two main limitations:

- For bonds with specific clauses relating to rating, such as bonds with embedded triggers, changes in the rating comes fundamental in valuing their prices as these clauses result in changes in the cash flows from these bonds. A more complex rating technique is then required.
- These models do not take into account the systematic risk of bond portfolios i.e. that the defaults of different firms are correlated and coincide with fluctuations in the business cycle.

Those two approaches provide the framework research in order to further explore the relation between spreads and equity.

A very interesting paper that has been recently published is the one by Campbell and Taksler (2002) who explore the relation between corporate bond yields and equity volatility. Usually research on the issue, has explored drivers of the variation in corporate bond yield spreads but not much focus has been given on the effect of equity volatility on the cross sectional variation and long term time series behaviour. Campbell & Taksler's paper constitutes an effort to fill in this gap in the academic literature.

Data used in Campbell & Taksler's thesis, came from Fixed Investment Securities Database (FISD) and National Association of Insurance Commissioners (NAIC) transactions data. The sample was restricted to fixed rate US dollar bonds in the industrial, financial and utility sectors that are non- callable, non-puttable, non-convertible. Additionally, only bonds belonging to the AA, A and BBB rated categories were being considered. AAA rated bonds were being excluded since NAIC data for these issues appeared problematic. Also non-investment grade bonds were being excluded since insurance companies often limit or prohibit the purchase of these issues.

After running cross sectional regressions on their sample data they concluded with the following results:

- Including equity volatility as an independent variable, increases the explanatory power of credit spreads and as such it is proven that volatility is an important determinant of corporate bond yields.
- Equity volatility matters at least as much as credit ratings. A regression of yield spreads on equity volatility results in higher adjusted R-squared (nearly 2 percentage points higher) than a regression of spreads on credit ratings (36% and 34% respectively in percentage figures).
- Equity volatility and credit ratings may be considered on a parallel basis to better explain bond spreads. Including both variables in the regression results in R-squared of 40.8%, i.e. 5 percentage points higher than volatility alone and 7 percentage points higher than credit ratings alone. This result implies that credit ratings may capture information that is not contained in volatility.
- Credit ratings explain more of the yield spread than accounting data
- Adding accounting variables on top of credit ratings does not meaningfully raise the R-squared over credit ratings alone.

Furthermore they concluded to the following:

1. After comparing the average yield spreads reported by S&P and Moody's with a panel dataset on corporate bond transactions between 1995 and 1999, they found that credit spreads widened in the late 1990s although less in the panel dataset than in the spread indices reported by the rating agencies.
2. It was proven that idiosyncratic equity volatility is directly related to the cost of borrowing for corporate issuers. It was suggested that in their sample, volatility could explain as much cross sectional variation in yields as could credit ratings and that volatility contributes to the explanatory power even in the presence of

credit ratings. These findings were robust even after the inclusion of monthly time dummies, the time window used to measure volatility and the estimation of a zero coupon term structure to control for maturity effects.

3. Using S&P and Moody's corporate bond yield indices for the period 1963 until 1999, it was shown that aggregate corporate yield spreads widen during periods of higher idiosyncratic risk.

In another paper by Cremers, Driessen, Maenhout and Weinbaum[52] (2004) the relation between individual stock option prices and credit spreads is considered. In their paper, implied volatilities of individual options are shown to contain important information on credit spreads and improve on both implied volatilities of index options and on historical volatilities when explaining the cross sectional and time series variation in corporate bond spreads.

In their study they are attempting to explain credit spreads over time and across issuing firms based on implied volatilities skews of the individual options on the issuers' equity. The implied volatility of at the money options is a natural proxy for the volatility of the issuing firm. They argue that implied volatitily is a better measure than historical volatility as used by Campbell and Taksler (2002) since this measure is forward looking rather than historical; and implied volatility skew is also considered as a second explanatory variable.

Their analysis is based on individual option prices and US corporate bond prices for 69 firms for the period 1996-2002. In their benchmark analysis a panel regression of the level of credit spreads and a number of explanatory variables is performed. As it becomes apparent from their analysis, implied volatilities alone can explain about one third of the total variation in credit spreads. The coefficients of at the money implied volatility are highly significant both statistically and economically. The implied volatility skew also proves to be a significant explanatory variable, although with somewhat less economic impact.

[52] Cremers, Driessen, Maenhout and Weinbaum will be referred as CDMW, for the rest of this chapter.

Option prices explain to a much greater extent credit spreads than do credit ratings. The explanatory power in a pooled regression of credit spreads is 5-15 percentage points higher (depending on bonds maturities) when regressing option based information than when using credit ratings as an explanatory variable. Consistently with the structural firm value model, it was found that the sensitivity of credit spreads to volatility is much larger for non-investment rated debt (BBB+ or worse) than for bonds belonging to the investment grade category.

Additionally, short-term credit spreads are significantly affected by measures of firm-specific option market liquidity, whereas longer-term maturity bonds remain unaffected. This is quite sensible and consistent with previous studies which have shown that the liquidity spread is largest for short maturity bonds (Janosi, Jarrow and Yildirim (2002) and Driessen (2003)). The fact that there is some evidence of a liquidity spillover effect for short term maturity bonds, but not for longer maturing ones is also apparent from the 1 percentage higher R-squared evident when regressing only short term maturity bonds.

Furthermore it was shown that implied volatilities anticipate downward credit rating migrations in a striking way, especially for issuers that already have a low credit rating. It was shown that downgrades tend to occur during volatile times, while upgrades tend to happen in periods with lower implied volatilities. Issuers that are downgraded have higher volatilities than their non-downgraded counterparts. Also the fact that the volatility of a firm peaks 2 to 3 weeks before the rating announcement (in this case of a downgrade) suggests that option markets anticipate to a large extent that downgrade or that most of the information that triggers the downgrade is already reflected in the option prices. After the downgrade the volatility of the firm tend to decrease but very gradually.

Lastly it was shown that traded individual options can be used as a hedge against credit risk in corporate bonds.

In a similar fashion, Demchuk and Gibson (2003), have studied the stock market performance on the term structure of credit spreads. They built a structural two-factor model where the stock market index is one of the stochastic factors. However, they find a weak impact of the volatility of the stock market index returns on credit spreads. In particular, it was observed that credit spreads slightly increase with the volatility of the stock index. But as explained this weak effect results from the modelling assumptions. In particular, the variable introduced, refers to the recent performance of the stock market index, whereby high values of that variable would imply economic improvements and low values would imply economic slowdowns. In other words, it is the volatility of the stock index performance rather than the volatility of the index which matters for bond pricing.[53]

Ederington, Yawitz and Roberts(1987) argue that investors fully anticipate rating changes and rating changes almost never affect bond returns. From that point of view, somebody may view equity as junior debt, where a dividend is paid only when the firm doesn't default, equity investors should take into account default probabilities, recovery rates and relevant accounting ratios.

5.2.Hypotheses tested and rationale

In this section we will proceed with estimating the relation between changes in credit spreads and equities and their implied and historical volatilities. This chapter extends previous work of Campbell and Taksler's and CDMW, in the following ways:

a. In our analysis, we are using option adjusted spreads. In that way we avoid the problem of comparing two bonds of the same maturity which don't necessarily have the same duration (price sensitivity to interest rate changes) nor the same convexity (sensitivity to the slope of the yield curve). By using option adjusted spreads (OAS) the modified duration of bonds is calculated and option adjusted duration for bonds with an embedded option is also considered.

b. All individual rating categories (investment and non-investment grade) are tested at least in the pooled regressions, where data was available.

c. In the pooled regressions we are using heteroscedasticity corrected standard errors but more importantly we have only one bond per issuer in our sample, compared to CDMW's sample that includes multiple bonds per issuer, where potential cross

[53] For a more detailed analysis of this result please refer to their paper "Stock Market Performance and the Term Structure of Credit Spreads, pg.18, whereby they provide the formulas behind this result.

correlations might be ignored. Moreover, the same coefficients are imposed over time and on different bonds, compared to Campbell and Taksler's study, who are using a fixed effects model.

d. Equally important is the fact, that in our pooled regressions we are testing the relationship between equities and credit spreads on an one - to-one basis. In other words, for a specific bond we have attached its respective equity price. In that way, we avoid problems usually faced in other studies, caused by the different constituents of bond and equity indices.
e. We are testing monthly and quarterly data in our sample as opposed to weekly data, used in CDMW's study, as this data frequency is more preferable for credit risk purposes, as credit quality of an issuer rarely changes within very short time intervals (except for non-investment grade companies, where changes are likely to occur in short time breaks).

We will proceed the analysis, by using market based proxies to determine another market based proxy. By default, therefore, we should expect to find statistically and economically significant results of this relation. Equities are expected to be the variable with the most added value in explaining credit spread changes, since it is assumed that the stock market provides the most important information for predicting a company's financial status.

The relation between spreads and equity will be examined with the use of two different sets of data. The first set includes OAS spreads provided by ML. Analytical description of the data collected has been described in chapter 3. This relation will be first explored on a quarterly and monthly basis with the use of seemingly unrelated regressions (in section 5.3). The second set of data includes monthly Bloomberg credit spread indices for a longer time period, from May 1991 until June 2005 (section 5.4).

The hypotheses to be tested under this section are the following:

H1: The inverse relation between credit spreads changes and equity changes. As equities increase we shall expect credit spreads to tighten and vice versa. Effectively, we are testing the null hypothesis that a change in equity doesn't lead to a corresponding but opposite in sign change in credit spreads.

H2: The relation between credit spread changes and their implied volatitilies. As implied volatilities increase credit spreads are expected to widen. In other words, we are testing whether we can reject the null hypothesis, stating that a change in implied equity volatility isn't directly related to a change in credit spreads.

H3: The relation between credit spread changes and their historical volatilities. As historical volatilities increase, credit spreads are expected to widen. The respective null hypothesis state that that a change in historical equity volatility isn't directly related to a change in credit spreads.

H4: Changes in equities (and equity markets) proceed or cause changes in spreads (bond markets). Consequently, the null hypothesis tested is that changes in equities don't proceed or cause changes in spreads in the different rating categories and maturities tested.

Within the context of testing the above hypotheses data will also be tested, in order to find whether changes in equities of previous months or quarters affect monthly spreads. In other words, whether there is a particular time, i.e. t, (t-1), (t-2), (t-3), etc, where equities seem to explain mostly changes in spreads.

5.3. Empirical Evidence based on cross sectional analysis of quarterly and monthly Merrill Lynch data

5.3.1. Data used

Credit Spreads

Data for spreads was collected from Merrill Lynch (ML). The two indices chosen for the purposes of this thesis were the US High Grade Broad Market Index and the US High Yield Master II Index. Data has been collected from January 1997 until May 2002. Constituents of these indices have been used as analytically described in section 3.3.1.

Equity Market Variables

a. Company specific equity prices

For those bonds (constituents of the Merrill Lynch Indices) that qualified for this thesis, their respective equities were collected from Bloomberg. Data on equities was collected on monthly and quarterly frequencies.

b. VIX Index

The volatility Index (known as the VIX) measures the implied volatility in the prices of a basket of options on the S&P 100 Index. (OEX). The index is developed by taking the weighted average of implied volatility for the Standard & Poor's 100 Index (OEX) calls and puts and measures the volatility of the market. The S&P 100 itself contains the largest 100 stocks in the S&P 500 that have options traded on them. The VIX covers a relatively narrow group of stocks, but those are among the largest companies traded in the United States. This index can be used as a tool for measuring investor fear. High readings, mark periods of maximum fear and have marked important market bottoms. Low readings, while not as accurate and timely as high readings illustrate investor comfort and usually point to market tops. Data on this index has also been collected on a monthly and quarterly basis. Indeed, the VIX pinpointed tradable market bottoms during the height of the late 1990s super bull market and also on other such occasions.

It should be noted that in the period considered under this section, i.e. from January 1997 until May 2002 there were three times where equity and consequently bond markets faced a crisis. These were:

- The October 1998 market bottom (the long term capital management crisis)
- The September 2001 market bottom (September 11 Terrorist attacks)
- July 2002 market bottom (insider trading and accounting scandals)

For the purpose of testing the four hypotheses reported in the previous section, the sample data was tested using monthly and quarterly data on spreads, equities and their implied volatilities with the use of seemingly unrelated regressions which take into account heteroskedasticity and contemporaneous correlation in the errors across equations. Due to the stationarity exhibited in the credit spread and equity levels (as has been described in chapter 3) changes in credit spreads and equities were calculated.

Time series regressions stacked cross sectionally, were run separately for investment and non-investment grade bonds, as this would allow for a better understanding of the responsiveness of credit spread to stock price changes.

Intuition would suggest that at least for bonds in the investment grade category and assuming that the company is financial healthy, a decrease in the stock price shouldn't affect the respective company's spread significantly. The default probability wouldn't be expected to increase significantly and as such we shouldn't expect to find economically significant results for bonds in the investment grade sample.

However, when non-investment grade bonds are considered, we should expect to find a more significant relation to exist between spreads and equities, since it is expected that high yield companies are often in not that good financial shape.

All the above should hold, once we assume that rating agencies rate companies on a consistent and timely basis. This of course could be a whole different subject for discussion, since over the past few years the performance of rating agencies has been widely debated. Numerous concerns on the timeliness and the predictive accuracy of ratings have been expressed world-wide particularly after high profile collapses, such as the cases of Enron and WorldCom in the United States. Similar scenarios have arisen in Australia too, with HIH Insurance, which had an investment grade rating only a few weeks before it became insolvent.

These concerns have prompted observers to question the value of rating agencies and suggest that their opinions do not contain information beyond what is already available to debt and equity market participants. However, according to a recent paper by Adam Creighton(2004), it is suggested that rating agencies still perform a useful function in financial markets, since as tested at least in the Australian market, credit rating changes result in noticeable price movements for both equities and bonds.

The analysis beyond, is based on the following assumptions:

- Rating agencies respond on a timely basis to changes in a company's financial structure
- Debt and equity markets are efficient, so that changes in ratings and the company's financial position is directly incorporated into companies' share prices.

In an effort to achieve more accurate and hopefully more reliable results, data was tested both on a monthly and a quarterly basis as aforementioned. More importantly, monthly observations were considered, in order to test which is the turning point at which, changes in equities have the strongest explanatory –forecasting power over explaining changes in credit spreads.

5.3.2. Empirical Results based on Monthly Frequencies

The relation between spreads and equities will be initially tested with the use of monthly data for the period from January 1997 until May 2002. As discussed in the previous chapter 3 of this study, the time series properties of credit spreads (levels) provided strong evidence for non linearities which means that any tests performed on credit spread levels would produce not statistically significant results. Therefore we will focus on the modelling of credit spread changes.

The first hypothesis to be tested, is that the change in stock price over the period t to (t-1) will be correlated to a corresponding change in spreads but opposite in sign.

First the results analysed, are based on a cross sectional analysis of monthly data. The seemingly unrelated regression (SUR) method, is used, also known as the multivariate regression, or Zellner's method, which estimates the parameters of the system, accounting for heteroskedasticity and contemporaneous correlation in the errors across equations.

The equation being tested is of the following form:

Equation 5.1.

$$\Delta Spreads_{it} = c + \beta_1 * (\Delta Equity_{i,t,\ldots t-n}) + \beta_2 * (\Delta VIX_{it}) + \beta_3 * (\Delta Hist.Vol_{it}) + \varepsilon_{it}$$

When all data (investment and non-investment grade) is examined, it was found that changes in equity prices alone, nor their lagged values, provided not significant results, but when the VIX was introduced in the equation, a highly statistically and economically significant coefficient was obtained for the latter variable, but the overall adjusted R^2 was rather low, as shown in table 5.1. The sample size used includes all investment and high yield bonds (i.e. 674 bonds for 65 time series observations). However, by default, Eviews uses the largest sample possible in each cross-section. An observation will be excluded if any of the explanatory or dependent variables for that cross section are unavailable in that period. The total panel observations of the following table is 26,072 while the F-stat is 1, 863.427(0.00):

Table 5.1.Cross Sectional Regressions based on ML Constituents, Monthly Frequencies

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019	0.00	4.51	0.00
Equity	-0.001	0.00	-1.69	0.07
VIX	0.262	0.02	10.94	0.00
R-squared	0.036			
Adjusted R-squared	0.035			

However, in order to properly test the effects of changes in equities to changes in spreads, data should be tested separately for investment and non-investment grade bonds. But even for the separate rating categories, regressions run using equity solely, as the independent variable although statistically significant in terms of supporting the negative relation between credit spreads and equity movements at the 5% level of significance, they provided not economically significant results in terms of explaining credit spread movements.

Once the VIX variable was introduced, results were somewhat more significant. The results provide strong evidence for the negative relation between equity and credit spread performance with highly significant t statistics as shown in the summary table 5.2. Including equity volatility raises the adjusted R^2 by 7% in the investment grade companies and by 12% in the high yield sector. This is the same on average as the results reported by Campbell and Taksler (2002), who find that the inclusion of historical volatilities raises the adjusted R^2 by 6 to 10 percentage points, in explaining corporate bond yield spreads.

Table 5.2. Cross Sectional Regressions based on ML Constituents, Monthly Frequencies

	Equity					VIX					R^2
	Exp. Sign	Coefficient	t-value	p-value	Stand. Error	Exp. Sign	Coefficient	t-value	p-value	Stand. Error	
All Ratings	-	-0.12	-14.4	0.00	0.00	+	0.18	17.5	0.00	0.00	**13.50%**
Investment Grade - including BBBs	-	-0.08	-8.87	0.00	0.09	+	0.16	16.5	0.00	0.00	**10.60%**
Invesment Grade - excluding BBBs	-	-0.02	-1.96	0.09	0.01	+	0.15	15.8	0.00	0.01	**9. 0%**
Non-investment Grade	-	-0.19	-23.8	0.00	0.00	+	0.24	21.5	0.00	0.00	**15.00%**

As it can be observed from the table 5.2., results although statistically significant, it seems that the overall explanatory power of equities and the volatility index provides an adjusted R^2 at best of 15% in the non-investment grade categories. Indeed, up to this point, results have shown that we can reject the null hypotheses of H1 and H2 at the 95% confidence level. However, there was no evidence to support that there is indeed a defined time lag between equity changes and spread reaction. This was being tested by including lagged values of the independent variable (equities) at time t, (t-1), (t-2), (t-10), to see whether they could explain spread movement.

5.3.3. Empirical Results based on Quarterly Frequencies

The next step was to check the same data but on a quarterly basis. Once quarterly observations were examined, results were somewhat different. In particular, when the whole sample was tested (using seemingly unrelated regressions) it was observed that an R^2 of 24% was obtained only at time t, whereas changes of previous quarters' equity prices were not found to explain the credit spread changes pattern.

Testing the rating categories in groupings of investment, non–investment grade (excluding and including BBBs) yielded the following results as shown in table 5.3.The sample size used refers to all 674 bonds included in the sample for 21 time series observations. However, the total panel observations as mentioned above, refer to the actual sample used in Eviews by default, i.e. an observation will be excluded if any of the explanatory or dependent variables for that cross section are unavailable in the period.

Table 5.3. Cross Sectional Regressions based on ML Constituents, Quarterly Basis

	Equity					VIX					R^2	f-statistic	Total Panel Obs.
	Exp. Sign	Coef	t-value	p-value	S.E	Exp Sign	Coef	t-value	p-value	S.E.			
All Ratings	-	-0.09	-19.4	0.00	0.0	+	0.34	30.4	0.00	0.00	35.5 %	2,552.33 (0.00)	8,507
Investment Grade (incl. BBBs)	-	-0.05	-6.23	0.00	0.0	+	0.24	18.8	0.00	0.00	23.6 %	1,173.13 (0.00)	4,456
Invesment Grade (excl.BBBs)	-	-0.06	-3.54	0.09	0.0	+	0.36	12.7	0.00	0.01	25.0 %	250.65 (0.00)	1,594
Non-investment Grade(excl. BBBs)	-	-0.20	-19.8	0.00	0.0	+	0.49	28.9	0.00	0.01	50.3 %	1,897.07 (0.00)	4,051
Non-investment Grade (incl. BBBs)	-	-0.25	-25.3	0.00	0.0	+	0.40	27.3	0.00	0.00	37.3 %	2,156.92 (0.00)	6,813

As shown above, the inclusion of the volatility index on quarterly OAS spreads data, raises significantly the adjusted R^2. Quarterly analysis provided more significant results particularly in the non-investment grade category and especially when BBB bonds are excluded from the sample. It is important to note that all coefficients bring the expected sign and are highly statistical and economically significant. The values of adjusted R^2s show that in conjunction to our initial expectation changes in equities explain more changes in spreads of companies belonging to the high yield sector. When the more volatile BBB category was included in the non-investment grade category the R^2 obtained was at 37.30%.

As a further step in the analysis, investment and non-investment grade categories have been broken down to their respective distinct rating categories, i.e. rating categories were tested separately. Working from the AAA rated bonds towards C rated bonds, results were still statistically significant in terms of coefficients but in terms of the overall explanatory power the most significant relation was found in the B rating category bonds, when equities were the only explanatory variable considered.

Once we include implied volatilities in the different rating categories, results prove that since we move progressively down the rating scale, equities and their implied volatilities add gradually to the explanation of changes in spreads.(as shown in Table 5.4.)

This kind of relation coincides with our initial intuition since the additional explanatory power of equities seems to become more visible once we move down the rating scale reaching its peak for companies belonging to the B rating category with an R^2 of 52% and falls to 35% for C-rated bonds. The relation between spreads and equities belonging to the B rating category is significant even if implied volatilities aren't taken into consideration, as apparent from the highly significant t-statistic obtained in this category.

Table 5.4. Cross Section Regressions based on ML Constituents, Individual Rating Categories on a Quarterly Basis

	Equity					VIX					R^2
	Exp. Sign	Coef.	Stand. Error	t-value	p-value	Exp.Sign	Coef.	Stand. Error	t-value	p-value	
AAA	-	-0.04	0.09	-0.01	0.01	+	0.03	0.04	0.01	0.00	**1%**
AA	-	-0.10	0.09	-1.04	0.02	+	0.18	0.04	6.01	0.00	**15.6%**
A	-	-0.03	0.01	-2.06	0.03	+	0.37	0.01	20.80	0.00	**27.2%**
BBB	-	-0.15	0.02	-7.27	0.00	+	0.32	0.01	27.10	0.00	**26.8%**
BB	-	-0.24	0.02	-10.90	0.00	+	0.40	0.01	25.40	0.00	**43.8%**
B	-	-0.25	0.01	-14.30	0.00	+	0.44	0.01	29.60	0.00	**51.9%**
C	-	-0.31	0.02	-14.00	0.00	+	0.36	0.01	12.90	0.00	**35.0%**

It is worth noting from table 3.2 of statistical properties of credit spread changes (chapter 3), that B rated bonds is the only rating bucket that exhibits negative skewness, i.e. a small probability of a large loss is offset by a large probability of a small gain. It would interesting to test bonds belonging to the B rating category in greater depth. But given that there is a strong relation in companies belonging to this bucket, it would be interesting to test whether any more hindsight could be gained at this point with respect to the lag relation between changes in equity returns and the respective changes in credit spreads.

Running some more regressions of lagged values of equities on credit spreads, it was observed, that changes in equities of 9 months before the change in spreads occur have the most explanatory power on spreads at time t. If this is true then, that would mean that there is a very big time lag between perceived changes in the company's financial position, i.e. between equity and bonds holders.

Testing at the same time this exact time difference in other rating categories yielded the same results, i.e. that changes in equities at time (t-3), i.e. 9 months before explain mostly spreads at time t. However, if these results are to have any meaningful sense for investors, properties of the equities of the companies at time (t-3) should be explored further.

5.3.4. Inclusion of Historical Volatilities in Cross Sectional Regressions

The next step of the analysis would be to incorporate historical volatilities in the equation to be estimated[54]. As a result standard deviations for the respective equities' were estimated. Standard deviation is considered a good indication of volatility. Although implied volatilities are considered to be more responsive to current market conditions (have already been incorporated in the regressions through the inclusion of VIX index), the idea is to test whether more hindsight could be added by using historical volatilities.

However, before proceeding with the effect of historical volatilities of equities into spreads we should bear in mind that there are two key aspects of standard deviations:

a) standard deviation scales (increases) in proportion to the square root of time and
b) since returns are expressed in percentages – key assumption of the random walk idea – returns might be eroded.

As a result historical volatilities were calculated both for monthly and quarterly intervals to compare differences in the results. Those historical volatilities were not annualised, since here volatilities are used as an explanatory variable to spreads (and

[54] Campbell and Taksler(2003) report a very strong relationship between the historical volatility of equity returns and bond yields.

therefore the effect on spreads, would be the same irrespective of whether historical volatilities are annualised or not). After calculating standard deviations for equity belonging to the different rating categories, a historical volatility index for the companies belonging to the different rating buckets was generated.

5.3.4.(a) Inclusion of Monthly Historical Volatitilies

Table 5.5 shows the descriptive statistics of these historical volatility indices per rating category and table 5.6 the respective correlations, based on monthly data. The mean levels of historical volatilities increase with a deterioration in credit quality, consistent with the structurals' model theory.

Table 5.5. Descriptive Statistics of Historical Volatilities, calculated monthly

	VEAAA*	VEAA	VEA	VEBBB	VEBB	VEB	VEC
Mean	0.06	0.07	0.10	0.10	0.13	0.16	0.20
Median	0.06	0.07	0.09	0.10	0.13	0.16	0.19
Maximum	0.14	0.13	0.84	0.17	0.19	0.30	0.44
Minimum	0.02	0.04	0.05	0.06	0.08	0.10	0.10
Std. Dev.	0.03	0.02	0.10	0.03	0.03	0.04	0.07
Skewness	0.79	0.73	7.21	0.57	0.12	1.02	1.14
Kurtosis	3.26	3.11	55.88	2.83	2.23	4.48	4.69
Jarque-Bera	6.82	5.75	8012.49	3.60	1.72	16.86	21.40
Probability	0.03	0.06	0.00	0.17	0.42	0.00	0.00
Observations	64	64	64	64	64	64	64

**VEAAA: represents the historical volatility index for the AAA rating category, etc*

Table 5.6. Correlation Matrix of Monthly Historical Volatilities

	VEA	VEAA	VEAAA	VEB	VEBB	VEBBB	VEC
VEA	1.00						
VEAA	0.44	1.00					
VEAAA	-0.06	0.15	1.00				
VEB	0.44	0.37	0.11	1.00			
VEBB	0.15	0.28	0.18	0.77	1.00		
VEBBB	0.22	0.50	0.24	0.74	0.76	1.00	
VEC	0.01	0.03	0.10	0.65	0.49	0.48	1.00

Once data including the new independent variable, i.e. the historical volatility was tested, SUR regressions were run, firstly for all rating categories and then separately for investment and non-investment grade buckets and by excluding BBB rated companies respectively. However, the results (as shown in table 5.7), don't provide any proof that the inclusion of the historical volatilities as an index figure compared to the implied volatilities presented by the VIX index, add to the explanatory power of changes in spreads, but rather the opposite. It should be noted that the t and p-values are still significant and the coefficients have the expected sign, but since the scope was to check whether they add to explaining credit spread changes only R^2s are reported here.

Table 5.7. Cross Sectional Regressions based on Equities and Historical Volatilities

MONTHLY DATA							
Rating Buckets	f-stat	Total Panel Obs.	R^2 [55] per Pool	Rating Buckets	f-stat	Total Panel Obs.	R^2 [56] per Rating
All Ratings	387.89 (0.00)	26,072	5%	AAA	1.85 (0.15)	155	2%
Investment Grade (including BBB)	107.22 (0.00)	13,822	2%	AA	2.31 (0.09)	937	0%
Investment Grade (excluding BBB)	13.84 (0.00)	4,926	1%	A	25.57 (0.00)	4,132	1%
Non Investment Grade (including BBB)	299.36 (0.00)	22,287	8%	BBB	127.23 (0.00)	8,832	2%
Non Investment Grade (excluding BBB)	253.05 (0.00)	12,250	7%	BB	143.25 (0.00)	5,588	4%
				B	144.97 (0.00)	4,84	5%
				C	205.22 (0.00)	2,787	12%

Comparing tables 5.2 to 5.7, it is clear that reported R^2s are significantly lower when historical volatilities are compared to the implied ones. Even when rating categories are tested individually, the explanatory power of the relation isn't significant.

5.3.4.(b) Inclusion of Quarterly Historical Volatitilies

For comparative purposes, the same rationale has been applied when testing quarterly data. Table 5.8. shows the descriptive statistics of the quarterly historical volatilities per rating bucket in the sample and table 5.9. the respective correlations.

[55] (Independent Variables: Equities and Respective Historical Volatilities)

[56] (Independent Variables: Equities and Respective Historical Volatilities)

Table 5.8. Descriptive Statistics of Historical Volatilities, calculated quarterly

	VEAAA	VEAA	VEA	VEBBB	VEBB	VEB	VEC
Mean	0.11	0.16	0.20	0.17	0.23	0.31	0.37
Median	0.09	0.14	0.16	0.16	0.23	0.31	0.35
Maximum	0.39	0.28	1.12	0.29	0.32	0.48	0.62
Minimum	0.06	0.09	0.08	0.09	0.12	0.14	0.18
Std. Dev.	0.07	0.06	0.21	0.05	0.05	0.08	0.13
Skewness	2.76	4.11	4.04	0.72	-0.24	-0.02	0.44
Kurtosis	11.08	18.28	17.92	3.04	3.51	2.77	2.19
Jarque-Bera	83.81	263.49	251.87	1.79	0.44	0.05	1.27
Probability	0.00	0.00	0.00	0.41	0.80	0.98	0.53
Observations	21	21	21	21	21	21	21

Table 5.9. Correlation Matrix of Quarterly Historical Volatilities

	VEA	VEAA	VEAAA	VEB	VEBB	VEBBB	VEC
VEA	1.00						
VEAA	-0.04	1.00					
VEAAA	0.16	-0.14	1.00				
VEB	0.07	0.21	-0.04	1.00			
VEBB	0.35	0.10	0.15	0.71	1.00		
VEBBB	0.25	0.02	0.12	0.66	0.84	1.00	
VEC	0.03	-0.15	0.06	0.71	0.48	0.45	1.00

Once again, when tables 5.3 and 5.4. are compared to table 5.10., it becomes evident that historical volatilities don't add to the explanatory power of the model. The only rating bucket that seems to provide a bit more support than the rest on the relation between changes in spreads, equities and their historical volatilities is once again companies belonging to the B and C rating bucket, as it has also been previously shown, with the use of the VIX Index.

Table 5.10. Cross Sectional Regressions based on Equities and Historical Volatilities

QUARTERLY DATA							
Rating Buckets	Total Panel Obs.	F-Stat (Prob. F-Stat)	R^2s Per Pool[57]	Rating Buckets	Total Panel Obs.	F-Stat (Prob. F-Stat)	R^2s per Rating[58]
All Ratings	8,507	468.33 (0.00)	22%	AAA	78	0.04 (0.95)	0% -
Investment Grade (including BBB)	4,456	77.83 (0.00)	6%	AA	341	16.5 (0.00)	6%
Investment Grade (excluding BBB)	1,594	21.44 (0.00)	5%	A	1,257	48.26 (0.00)	2%
Non Investment Grade(including BBB)	6,913	621.57 (0.00)	31%	BBB	2,398	98.50 (0.00)	6%
Non Investment Grade(excluding BBB)	4,051	495.79 (0.00)	37%	BB	1,679	173.34 (0.00)	17%
				B	1,658	447.93 (0.00)	34%
				C	714	221.57 (0.00)	39%

Overall, in our pooled regressions we found that the VIX index is the most important determinant of credit spread changes, irrespective of the data frequency tested, while historical volatilities don't add to the explanation of credit spreads, although they are statistically significant. The strong explanatory power of historical volatilities documented by Campbell and Taksler, isn't supported by our results. Indeed, we can argue that volatility index is a superior proxy for the volatility of the issuer, since it is forward looking rather than historical in nature. Additionally, to the extent that risk volatility matters and is prices, this would be captured by implied volatilities, but not by a historical measure.

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57 (Independent Variables: Equities and Respective Historical Volatilities)

58 (Independent Variables: Equities and Respective Historical Volatilities)

5.4. Evidence based Bloomberg Credit Spread Indices and Time Series Analysis

The results presented above, are based on a set of monthly and quarterly cross sectional data and explore the relation between individual bonds of the Merrill Lynch indices together with their accompanying equities and their implied and historical volatilities. Due to the limited time period available when running the cross sectional regressions, the same relationship was tested on monthly credit spread data, where observations were available for a much longer time period, from May 1991 until June 2005.

5.4.1. Data Used

Credit Spread Data: The new set of data includes short, medium and long term maturity investment grade industrial bonds (from AAA to BBB-). In particular, eight time series (namely AAA, AA, A+, A, A-, BBB+, BBB, BBB-) observations have been collected for nine maturities, i.e. for years two, three, four, five, seven, eight, nine, ten and fifteen. However, not all of the different maturity indices have been considered, but rather as proxies for short term medium and long term maturities the two year, five and ten years maturity indices were used respectively. It is worth noting that the selection of those particular maturities was made in order:

(a) to include the liquid indices (for example the 15 year index is known not to be a very liquid one) and
(b) to obtain more time series observations (for example the 8 and 9 year credit spread indices have available observations from 1996).

Credit spreads have been calculated after deducting from each time series observation the US Dollar Treasury Composite bearing the corresponding maturity.

Equity Market variables: The equity indices are the S&P 500 index, which is dominated by the large cap stocks, the Russell 2000 index which is related mostly to small-cap stocks and an index measure of market volatility, the VIX index. These equity market variables are also collected on monthly frequencies for the same period.

The time series properties of the new set of credit spreads have been discussed in chapter 3. In this chapter, we will focus on the relation between the credit spread changes and changes in equity indices. Before proceeding with the empirical work, it would be interesting to see some of the patterns and descriptive statistics exhibited on those indices in the time period under consideration.

5.4.2. Descriptive Statistics of Equity Variables

Figures 5.1. and 5.2. provide the price levels of the two equity indices (Russell and the S&P) and the next provides the implied market volatility during that period, as measured by VIX.

Figure 5.1.

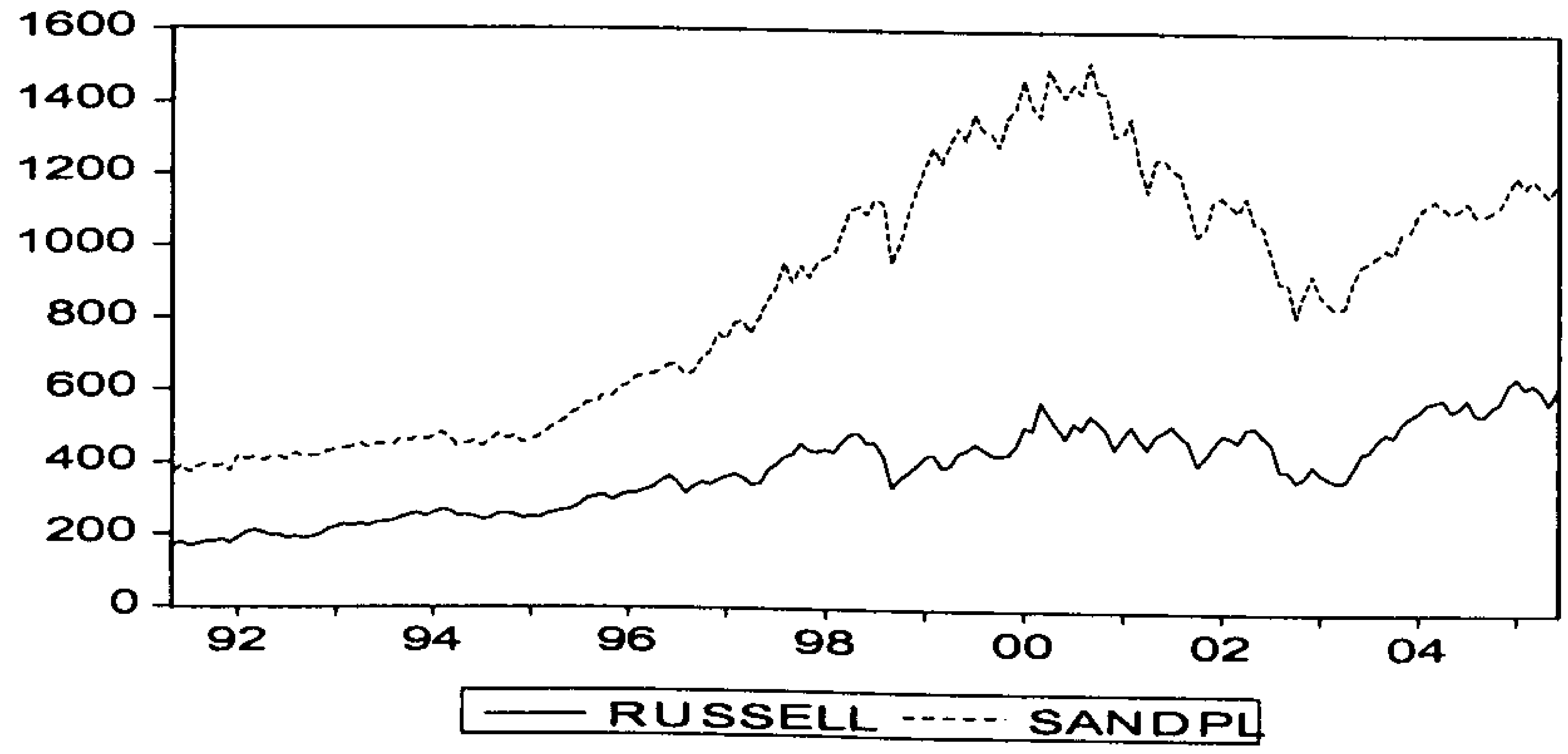
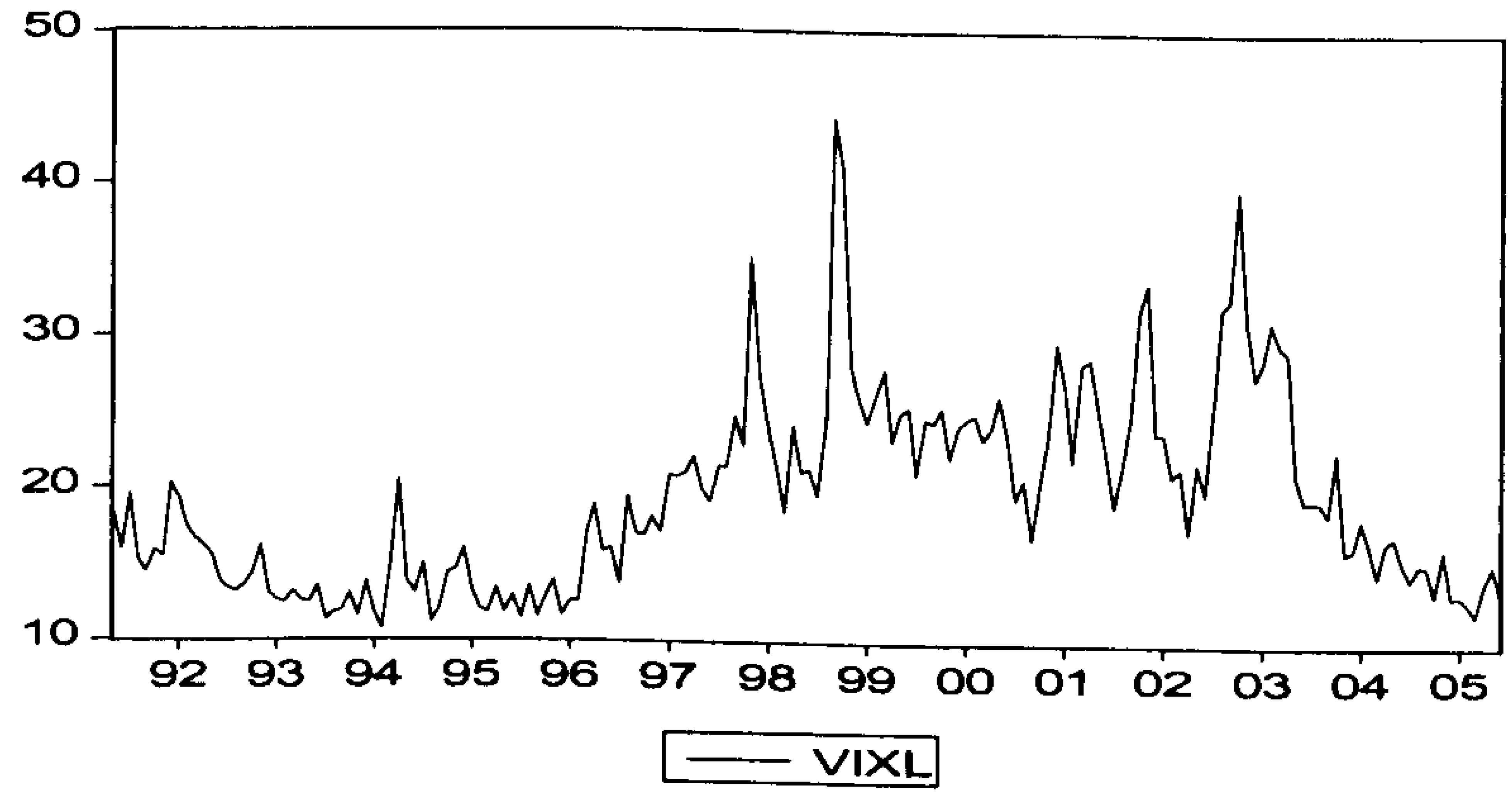


Figure 5.2.



There seems to be a rising trend in equity prices from 1992 until 1998, after which there is a slowdown, mainly attributed to the Russian crisis. Volatilities also exhibit an increasing trend from 1995 to 1999, at which point the index reaches its peak.

Equity levels seem to reach their peak in 2001(as especially depicted by the S&P Index) and then there is two-year slowdown before they start picking up again from 2003 until June 2005.

For comparative purposes the figures 5.3, 5.4 and 5.5. show the patterns of short, medium and long term maturity credit spread indices for the corresponding period.

Figure 5.3. Long Term Credit Spread Indices

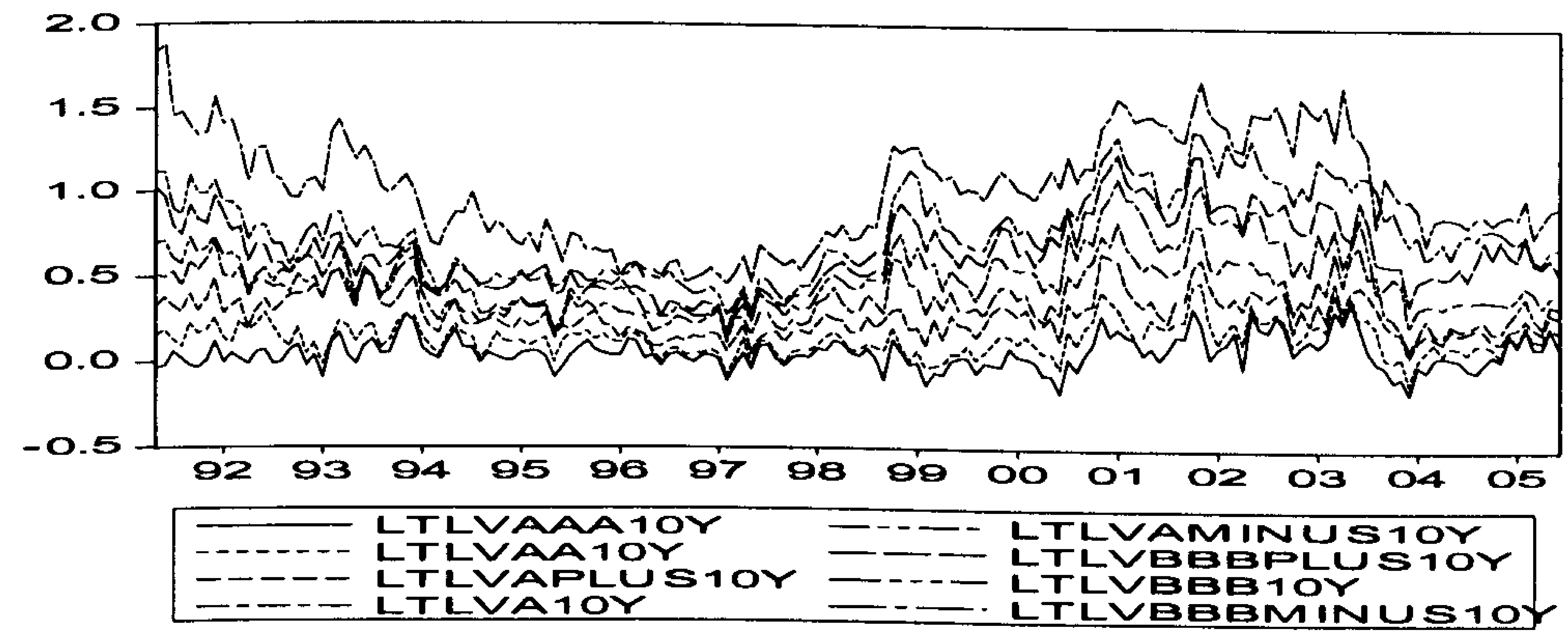


Figure 5.4. Medium Term Credit Spread Indices

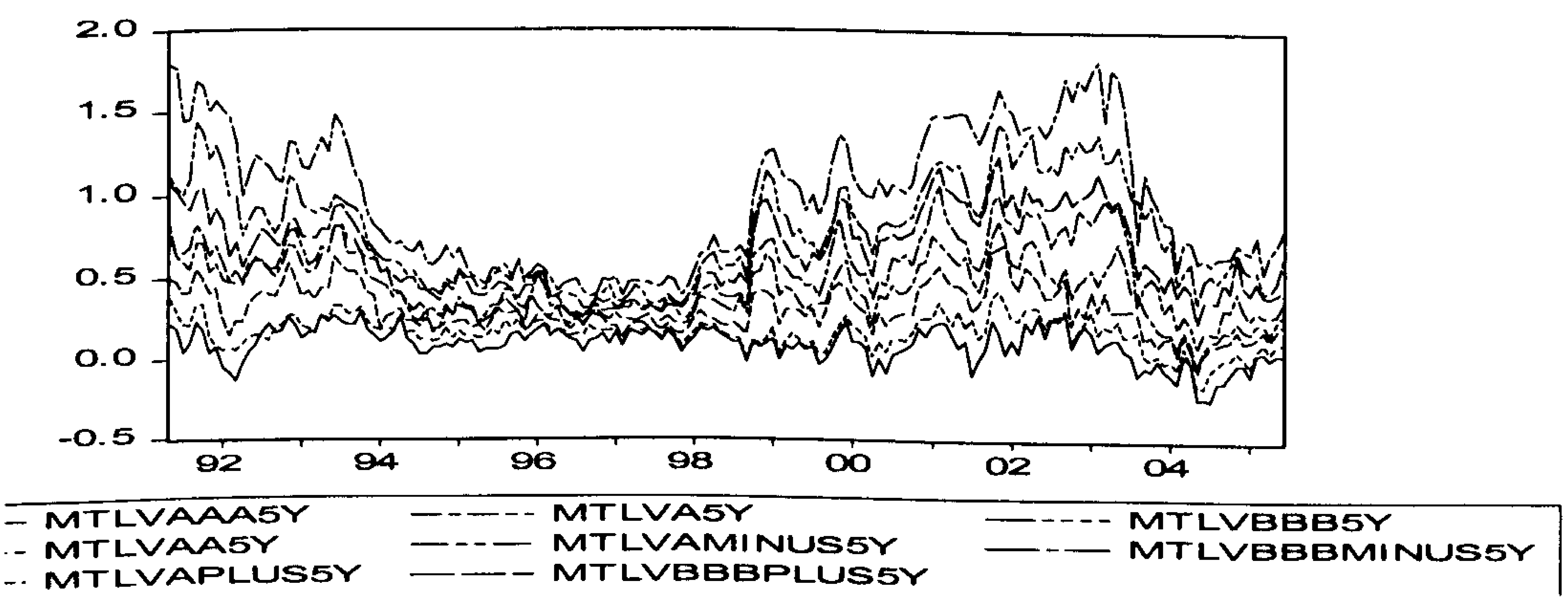
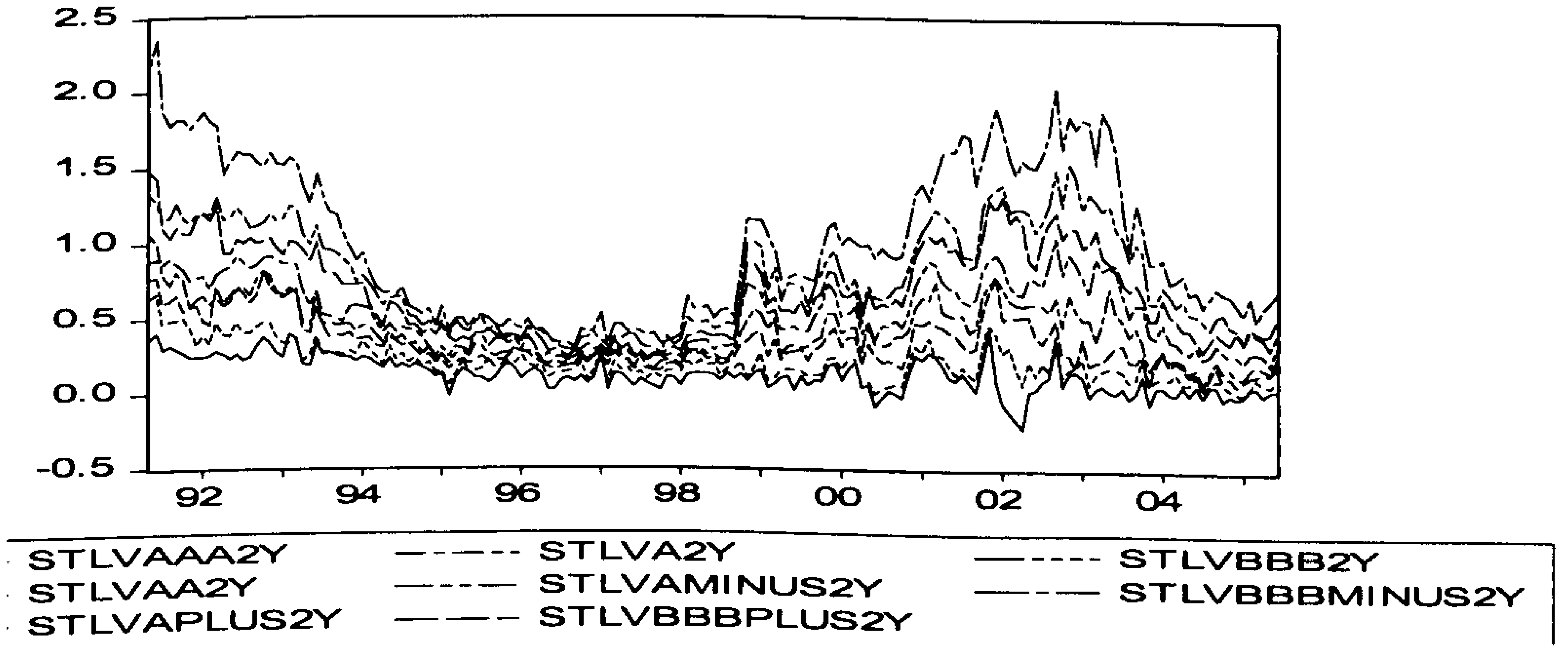


Figure 5.5. Short term Credit Spread Indices



There seems to be a corresponding pattern both in terms of how the credit spread indices moved in the period under consideration but also within the different maturity indices. In particular, credit spreads tend to widen in times of increased volatility and they tend to tighten as equity prices increase and vice versa.

The following tables present descriptive statistics for these three variables, both for levels and their computed changes.

Table 5.11.Descriptive Statistics for Equity Indices, Levels

DESCRIPTIVE STATISTICS FOR LEVELS			
	S&P	RUSSELL	VIX
Mean	870.1	382.8	19.4
Median	916.5	392.3	18.6
Maximum	1517.7	651.6	44.3
Minimum	371.2	167.6	10.6
Std. Dev.	348.2	127.5	6.4
Skewness	0.0	0.0	1.0
Kurtosis	1.6	2.0	4.1
Jarque-Bera	13.6	7.8	36.9
Probability	0.0	0.0	0.0
Observations	170	170	170

Table 5.12.Descriptive Statistics for Equity Indices, Changes

DESCRIPTIVE STATISTICS FOR CHANGES			
	S&P	RUSSELL	VIX
Mean	0.01	0.01	0.01
Median	0.01	0.02	0.00
Maximum	0.11	0.16	0.79
Minimum	-0.15	-0.19	-0.33
Std. Dev.	0.04	0.05	0.16
Skewness	-0.47	-0.48	1.02
Kurtosis	3.76	4.09	5.50
Jarque-Bera	10.28	14.92	73.68
Probability	0.01	0.00	0.00
Observations	170	168	170

As it becomes obvious from the skewness of the equity variables (in level terms) the S&P and Russell index seem to be normally distributed, but if we consider their kurtosis, it is evident that they are platykurtic. The VIX index is leptokurtic, while it presents positive skewness, which means that the distribution has a long right tail. With respect to changes in equity variables, it is evident that all three variables are leptokurtic, while the S&P and Russell present negative skewness (but close to zero), whereas the VIX has a long right tail.

In terms of correlations, it was shown that there is no presence of multicollinearity as shown by the very small correlation coefficients, between the independent variables and the short, medium and long term maturing indices. Correlation matrices for equity indices, and correlations among the dependent and independent variables for long, medium and short term maturing indices, are provided in tables 5.14-5.16, which are shown in Appendix 6.

5.4.3. Empirical Results based on OLS method

In this section we will employ an OLS model to estimate the relation between changes in credit spreads and equity variables. The regression specification is of the following format:

$$\Delta Spreads_t = c + \beta_1 * (\Delta \mathrm{Russell}_{t,\ldots t-n}) + \beta_2 * (\Delta \mathrm{S\&P}_{t,\ldots t-n}) + \beta_3 * (\Delta \mathrm{VIX}_{t,\ldots t-n}) + \varepsilon_t$$

This model will be employed for testing the parameters across the rating spectrum and the short, medium and long-term maturities.

Numerous regressions were run on credit spread changes, and their lagged values and the following general conclusions were drawn:

(1) The most important equity factor that explains changes credit spread indices is the VIX index. In particular, the VIX index was statistically significant at the 10% level in all rating categories of short and medium term maturities, although higher t-statistics were obtained for medium term maturities. In long-term bond indices, the VIX index was statistically significant only for A, BBB and BBB- rated indices, at the 5% level of significance. This means that the hypothesis that credit spreads tighten as implied volatilities increase, can be rejected at the 10% level of significance for short and medium term maturities, while the same hypothesis, although statistically significant at the 5% level, in part of the long term rating categories, can't be rejected for AAA and AA rated indices. Indeed the sign of the coefficient is positive suggesting that an increase in volatility is associated with decreasing credit spreads, which is contrary to all Merton-type models.

(2) In terms of the S&P index, results vary according to maturity and the rating categories, although results provide evidence to reject the positive relationship between changes in equities and changes in credit spreads at the 10% level.

(3) The Russell index wasn't statistically significant at the 5% nor at the 10% level at none of the rating categories or the different maturities, hence hasn't been reported in the following tables. Lagged values of the Russell Index were also considered, but not statistically significant results were obtained either. This finding is contrary to results obtained by Huang, Jing-Zhi, Kong and Weipeng (2003), who find that the Russell 2000, can explain a significant portion of credit spread changes for both investment and non-investment grade series, over the period from January 1997 through May 2002. The adjusted R^2s ranges from 9.27% for the AAA-AA 10-15 years series to 38.25% for the BBB-A 15+ year series. Adjusted R^2s are 41.12%, 47.09% and 39.66% for the BB-, B- and C-rated portfolios.

(4) Short-term and medium credit spread indices are affected more from movement in equities than their longer-term counter parties. This result is contrary to CDMW's study, who although use volatility and skew as independent variables they get a larger R^2 for long term maturities of almost 28% and approximately half for short term maturities. However, it is worth noting that CDMW define short maturity bonds (between 1 and 5 years) and long term maturity bonds (at least five years to mature). Effectively, their results are more comparable and coincide with our medium term maturing indices.

(5) Overall, the explanatory power of the OLS model progressively increases as we move down the rating scale towards the BBB- rated indices, but we can't infer to results from the non-investment grade category at this section, since there is no data available for non-investment grade indices.

The results for short, medium and long-term maturities are reported in tables 5.16, 5.17, 5.18.

5.16. OLS Regressions for Short Term Maturity Credit Spreads, All Rating Categories

Short Term Maturity					
		Coefficient	t – value	P-value	Adjusted R^2
AAA					
	Constant	-0.05	-0.23	0.08	1%
	VIX	1.12	0.69	0.14	
	S&P	-0.01	-0.17	0.06	
AA					
	Constant	-0.11	-0.72	0.07	7%
	VIX	1.31	1.28	0.12	
	S&P	-0.00	-0.04	0.08	
A					
	Constant	-0.05	-1.01	0.03	16%
	VIX	0.82	2.32	0.02	
	S&P	-0.02	-1.08	0.21	
BBB					
	Constant	-0.06	-1.88	0.16	33%
	VIX	0.73	3.51	0.00	
	S&P	-0.00	-0.62	0.09	
BBB-					
	Constant	-0.10	-3.34	0.00	44%
	VIX	0.91	4.42	0.00	
	S&P	-0.01	-0.92	0.09	

5.17. OLS Regressions for Medium Term Maturity Credit Spreads, All Rating Categories

Medium Term Maturity					
		Coefficient	t – value	P-value	Adjusted R^2
AAA					
	Constant	0.00	0.04	0.25	18%
	VIX	0.53	0.36	0.17	
	S&P	-0.13	-2.02	0.05	
AA					
	Constant	-0.27	-1.96	0.05	35%
	VIX	2.99	3.51	0.00	
	S&P	-0.03	-0.72	0.17	
A					
	Constant	-0.05	-0.85	0.03	15%
	VIX	0.86	2.01	0.05	
	S&P	-0.00	-0.17	0.16	
BBB					
	Constant	-0.06	-1.42	0.09	20%
	VIX	0.79	2.63	0.01	
	S&P	-0.01	-0.95	0.14	
BBB-					
	Constant	-0.09	-2.84	0.00	33%
	VIX	0.81	3.78	0.00	
	S&P	-0.03	-2.48	0.01	

5.18. OLS Regressions for Long Term Maturity Credit Spreads, All Rating Categories

Long Term Maturity					
		Coefficient	t – value	P-value	Adjusted R^2
AAA					
	Constant	-0.04	-0.12	0.19	0%
	VIX	-0.44	-0.16	0.13	
	S&P	-0.00	-0.08	0.22	
AA					
	Constant	-0.11	-0.66	0.10	8%
	VIX	-1.37	-1.34	0.09	
	S&P	-0.00	-0.12	0.19	
A					
	Constant	-0.08	-1.91	0.08	18%
	VIX	0.70	2.52	0.01	
	S&P	-0.01	-0.99	0.17	
BBB					
	Constant	-0.09	-2.76	0.00	37%
	VIX	0.90	4.06	0.00	
	S&P	-0.03	-2.91	0.00	
BBB-					
	Constant	-0.07	-2.76	0.00	26%
	VIX	0.55	3.22	0.00	
	S&P	-0.01	-1.69	0.10	

Results provided from the new set of indices are not as statistically significant as those obtained from the ML indices. The main reasons for that are:

(1) the first sample involves analysis of cross sectional data while the second time series analysis

(2) there is an immediate relation among the credit spread and equities used in the first sample, since equity prices were collected for the respective bonds. On the other hand, here, only indices are considered and since not the same bonds that comprise the bond indices are included in the equity indices, the difference arises.

However, results are still statistically and economically significant and the coefficients bear the expected sign. In terms of how maturity levels affect this relation there doesn't seem to be a distinct pattern except that short term maturity bonds belonging to the BBB- category are more significant than those povided from the same category in the medium or long term maturity levels. This is contrary to empirical results found by Cremers, Driessen, Maenhout and Weinbaum (2004) and the structural model approach by Huang and Huang (2003) who propose that short maturity bonds are typically harder to explain and empirically provide less significant results compared to those provided from the longer maturity profiles.

5.4.4. Causality Tests

In order to test the fourth hypothesis of whether equity variables cause changes in spreads, causality tests were performed, in the different rating categories for the volatility and S&P index. The Russell index was not considered, since no statistically significant relation was established in the OLS regressions.

The Granger (1969) approach to the question of whether x causes y is to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. Y is said to be Granger-caused by x if x helps in the prediction of y, or equivalently if the coefficients on the lagged x's are statistically significant. Note that two-way causation is frequently the case; x Granger causes y and y Granger causes x.

It is important to note that the statement "x Granger causes y" does not imply that y is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term.

The statistical results observed from the Granger tests for causality, are somewhat mixed. In particular, the hypothesis tested for the S&P Index, can't be rejected with a great degree of confidence. More specifically, the hypothesis that S&P doesn't granger cause credit spreads can only be rejected for long term AA and for short term A indices. Indeed results obtained from the long term BBB index suggest that the alternative hypothesis should be rejected. For the rest of rating categories and maturities no statistically significant results were attained. In conjunction to the regression results obtained in section 5.4.3., it seems that there is not a significant case for rejecting the hypothesis that S&P doesn't granger cause changes in credit spreads.

On the other hand, the hypothesis that the VIX index doesn't granger cause credit spreads can be rejected at the 10% level of significance, for all rating categories, for short and medium maturities, while not statistically significant were obtained for long term maturing bonds. This effectively means, that the VIX index can be used as an adequate measure to draw conclusions on expectations of short and medium term indices, (corresponding to two and five years maturities) while for long term maturities, (bonds maturing in ten years) not significant conclusions can be drawn. Analytical description of those results is provided in tables 5.19, 5.20 and 5.21.

Table 5.19. Granger Causality Tests for Long Term Maturities

LONG TERM MATURITIES			
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause AAA	168	1.11617	0.3300
AAA does not Granger Cause S&P		0.06188	0.9400
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause AA	168	2.82994	0.0619
AA does not Granger Cause S&P		0.88242	0.4157
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause A	168	0.65941	0.5185
A does not Granger Cause S&P		1.97884	0.1415
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause BBB	168	0.02189	0.9783
BBB does not Granger Cause S&P		2.6058	0.0769
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause AAA	168	0.81705	0.4435
AAA does not Granger Cause VIX		0.14962	0.8611
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause AA	168	2.70148	0.1101
AA does not Granger Cause VIX		0.30704	0.7360
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause A	168	1.76283	0.1748
A does not Granger Cause VIX		1.1946	0.3054
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause BBB	168	1.00603	0.3679
BBB does not Granger Cause VIX		1.17573	0.3112

**** Rejected at the 1% significance level, ** Rejected at the 5% significance level, * Rejected at the 10% significance levelNot statistically significant*

Table 5.20. Granger Causality Tests for Medium Term Maturities

MEDIUM TERM MATURITIES			
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause AAA	168	0.16177	0.8507
AAA does not Granger Cause S&P		0.51407	0.5990
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause AA	164	1.4067	0.2155
AA does not Granger Cause S&P		0.94821	0.4625
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause A	168	0.67971	0.5081
A does not Granger Cause S&P		2.48102	0.1168
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause BBB	166	3.33891	0.1178
BBB does not Granger Cause S&P		1.60384	0.1759
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause AAA	168	0.30183	0.0987*
AAA does not Granger Cause VIX		0.48364	0.6174
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause AA	168	0.39266	0.0758*
AA does not Granger Cause VIX		0.15251	0.8586
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause A	168	6.01594	0.0030***
A does not Granger Cause VIX		0.76248	0.4681
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause BBB	168	4.47335	0.0128***
BBB does not Granger Cause VIX		0.63688	0.5302

**** Rejected at the 1% significance level, ** Rejected at the 5% significance level, * Rejected at the 10% significance level, Not statistically significant*

Table 5.21. Granger Causality Tests for Short Term Maturities

SHORT TERM MATURITIES			
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause AAA	168	0.47021	0.6257
AAA does not Granger Cause S&P		0.86898	0.4213
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause AA	168	0.53225	0.5880
AA does not Granger Cause S&P		0.69604	0.5000
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause A	165	4.11083	0.00156***
A does not Granger Cause S&P		0.7175	0.61121
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
S&P does not Granger Cause BBB	168	0.21924	0.80337
BBB does not Granger Cause S&P		3.17492	0.4439
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause AAA	166	0.51217	0.0726*
AAA does not Granger Cause VIX		2.14048	0.7831
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause AA	168	8.10146	0.0085***
AA does not Granger Cause VIX		0.56935	0.5670
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause A	169	11.0317	0.0011***
A does not Granger Cause VIX		0.11658	0.7332
Null Hypothesis:	**Obs**	**F-Statistic**	**Probability**
VIX does not Granger Cause BBB	168	9.44023	0.00013***
BBB does not Granger Cause VIX		0.97056	0.38105

****** Rejected at the 1% significance level, ** Rejected at the 5% significance level, * Rejected at the 10% significance level, Not statistically significant*

5.6. Conclusions

The purpose of this section was to test the relation between changes in credit spreads and their respective changes in equities. The main hypothesis tested was that changes in equities should prove significant for changes in spreads. Intuition would suggest that this relation should be more strongly supported by data of companies belonging to the non-investment grade categories[59]. Indeed, what has been shown from the regressions tested, was that this relation holds mainly for companies belonging to the B rating bucket and once implied volatilities were included as depicted by the VIX index. Historical volatilities didn't provide any further support for the hypothesis tested although statistically significant. In particular, adjusted R^2s we get from our pooled regression sample when we use as independent variables equity and the implied volatility index are 25% and 50.3% for investment and high yield companies respectively. When implied volatilities are substituted for the historical ones, adjusted R^2s fell to 6% and 28% for the investment and non-investment grade samples respectively.

In terms of the relation between different maturity credit spread indices and equity variables, results strongly support the negative relation amongst them for short and medium term maturing indices, while the null hypothesis couldn't be rejected for long term maturities. Results we get from the OLS regressions, suggest that equity variables explain at best a 44% for short term maturing indices, and 35% and 37% for medium and long term maturing indices as reflected by the adjusted R^2s.

Furthermore, the hypothesis that the VIX index doesn't granger cause credit spreads can be rejected at the 10% level of significance, for all rating categories, for short and medium maturities, while not statistically significant were obtained for long term maturing bonds.

Part of the results reported under this chapter support both theoretical and empirical evidence as to the importance for including on the one hand implied volatilities while

[59] The fact that low-grade bonds are more sensitive to stock returns is documented by Kwan (1996), Blume, Keim and Patel(1991), Cornell and Green (1991), who investigated the relation among equities and yield changes or corporate bond returns.

excluding historical ones, as well as to the fact that the inclusion of equities add significant explanatory power to the modelling of non-investment grade companies. There are three points that should be further tested or considered:

a. It would be interesting to elaborate further on bonds belonging to the B rating class as results provided, irrespective of time attributions (data frequencies checked) have been mostly significant.
b. With respect to the time lag between changes in equities and the respective changes in credit spreads, results provided only by option adjusted spreads support the nine month time lag. Further evidence should therefore be tested and evaluated accordingly.
c. Lastly, with respect to the index maturities, it should be noted that based on the current set, short term maturity bonds seemed to be better modelled by changes in equities than their longer term counterparts. Although this argument verifies that bond market aren't that far behind from equity markets, we should expect this relation to hold also for longer term maturities and therefore should be further explored.

6.0. Credit Spreads and Accounting variables

Past studies that have dealt with the relation between accounting ratios and credit ratings, have used ratios as independent variables in an effort to estimate a default prediction model. Only limited literature has focused on accounting variables and spreads changes within the context of credit spread changes as opposed to yield changes.. The purpose of this section is to establish a relation between accounting ratios and credit spread changes (which are used as a proxy for ratings) and is not limited to a default and non-default status of the firm. Within the context of this thesis, accounting ratios are used as independent variables, in order to estimate changes in the rating or intra-rating categories and the assumed direction of the financial position of a company (as those are reflected in their respective credit spreads). Of course, there is the implicit assumption that companies whose financial ratios deteriorate significantly will ultimately be led to default.

Additionally, as it is going to be described below after careful consideration of financial ratios that have been used in other studies, this thesis will not include the most popular financial ratios academic wise, but those ratios that tend to influence mostly credit spreads, based on empirical evidence. Additionally, since the dependent variable considered here are the medium to long term credit spreads, the independent variables should also point to the same time frame and as such the data used are financial ratios determining the long term financial standing of a company (i.e. longer term liquidity and leverage ratios are mostly considered, etc).

However, it is worth noting that during the last years, the way companies report their financials has come under increased scrutiny due to different accounting scandals related to big company names such as Enron, Tyco to name a few. In the first case of Enron, investors could have been warned of the deteriorating profile of the company by closely looking at ratios such as its debt to capital employed ratio which rose from 46% to 50% in 2000 and by its interest cover ratio which in the three years leading to 2001, has fallen below the magic level of 1.0x. This would imply an inability of the company to cover interest expense from operating profits and could lead to limited or no access to working capital. On the other hand in the case of Tyco, the reasons for its severe downgrades was mainly due to accounting transparency issues. In that case, it wasn't that easy for investors to be alerted of the company's deteriorating profile, by solely looking at their fundamentals.

Bearing these two examples in mind, the following analysis, between ratios and credit spreads can only provide accurate results assuming that there is reasonable accounting transparency in a company's annual reports. Otherwise, incomplete accounting information can lead to serious concerns for investors and effectively a deteriorating confidence on a company's credit profile, which although may be reflected in its credit spreads it won't be supported by a ratio analysis.

6.1. Literature Review – Credit Spreads & Accounting Ratios

There has been a series of research and literature that deals with the use of financial ratios in the determination of a company's long term credit standing. Generally speaking, the main reason of financial ratios is to serve as measures of the financial position of business and other entities. In particular, the main uses of financial ratios are:

a. The estimation of a functional relation for the purpose of prediction. For example an investment analyst seeking to predict a company's profits or to predict a company's financial distress, etc.
b. To serve as size deflators, since regular accounting data suffer a size effect, (absolute values).

The basic assumption of ratio analysis is that of proportionality[60], i.e. that a proportionate relation should exist between the two variables whose ratio is being calculated. However, in an empirical relation between a pair of accounting variables, two of the conditions necessary for proportionality are likely to be violated. <u>Firstly</u>, there may be a constant term in the relation, i.e. an element of the firm's profit may be unrelated to a sales element, so that the profit /sales ratio isn't an adequate description of the relation between profit and sales. <u>Secondly</u>, the functional form of the relation may be non-linear, i.e. a firm which is in a saturated market might not be expected to

[60] Some basic properties of Accounting Ratios, Geoffrey Whittington, Journal of Business Finance & Accounting 7, 2 (1980)

yield a constant increment to profit for each unit of revenue added to sales. In the case that these two conditions are violated, regression analysis provides a much more powerful and flexible tool in estimating a functional relation between the two pairs of variables.

Most of academic work and research that has been published up to date, refers to the use of financial ratios as estimators of a functional relation between accounting variables and default. Default prediction models as those developed by Beaver (1967, 1968) and Altman (1968) have set the background for further work. Altman used discriminant analysis to rank firms on the basis of a weighted combination of five ratios. His results were 95% effective in selecting future bankruptcy companies in the year prior to bankruptcy. The firms examined in Altman's study went bankrupt on average seven and a half months after the close of the last fiscal year for which reports were prepared. However, the model's predictive ability fell rapidly, once previous years were considered. For example in the years two to five prior to default the discriminant model led to more misclassifications than Beaver's dichotomous model.

Beaver has studied liquid versus non-liquid assets, in order to determine default. The non-liquid ratios examined were the cash flow to debt, net income to total assets and total debt to total assets. Those ratios are regarded as measures of long term solvency whereas the liquid ratios are regarded as shorter-term predictors. According to Beaver's interpretation, liquid asset ratios are expected to predict failure better than non liquid ratios, one and two years prior to default, while non-liquid ones are expected to be better predictors four and five years before failure. However, liquid assets and in particular current assets have received quite some criticism in the following respects:

1. The inclusion of inventory impairs the measure's usefulness. Inventory is not considered to be liquid asset since it must be sold before it can be converted into cash or receivables. Even though this criticism could be overcome with the use of the quick asset ratio, still another issue arises in the form of
2. Window dressing, which involves the temporary repayment of current debt just prior to the financial statement date, which results in spurious improvement in the current ratio.

After analysing and testing the data with the dichotomous classification test, Beaver's study concluded the following:

- non liquid assets measures predict failure better than the liquid asset measures even in the years immediately before failure
- failed firms tend to have lower rather than higher inventory balances
- less frequently advocated liquid asset measures outperform the more frequently used ones.

As a result, Beaver's research showed that none of his findings were previously anticipated by the priori arguments in the literature. Deakin[61] (1976) has replicated Beaver's (1967-68) study, using the same set of ratios and concluded that the use of statistical techniques, particularly discriminant analysis, can be used to predict business failure from accounting data almost three years before bankruptcy actually occurs, with a high degree of accuracy. However, it must be clarified that the model was derived from a rather small population and while the results are encouraging, it should only be used as a tool for providing probability of failure rather than an absolute proof of failure.

Studies which document the relation between yield spreads and default risk include Fisher (1959) who uses a set of financial ratios and finds a positive relation between default risk and yield spreads. West (1973), Ederington et al (1987) and Reiter and Ziebart (1991) conclude that both bond ratings and financial ratios play an important role in the determination of yield spreads.

Another group of research has focused on the distributional properties of financial ratios (Bird and McHugh 1977, Bougen and Drury 1980, Deakin 1976, Horrigan 1965, Mecimore 1968, O'Connor 1973, Pinches et al 1973). The findings are that, in general financial ratios are not normally distributed and that skewness exists. In Paul Barnes' paper[62], it was shown that where financial ratios are non-normally distributed, the comparison of a financial ratio with some industry norm, is likely to misinform.

[61] A discriminant analysis of predictors of business failure, Edward, D. Deakin – Research Report

However, since financial ratios in the context of the aforementioned studies and also in the present thesis, are used as inputs to certain statistical models (regression analysis and multiple discriminant analysis) normality is irrelevant. According to Barnes' paper, a financial ratio is composed of two variables and it is the behaviour of these and their relation with one another, that governs the behaviour of the financial ratio which they make up. The critical assumption when using financial ratios is proportionality, i.e. the relation between two variables is linear and the constant is zero (Whittington 1980). In Barnes' paper it was shown that violation of this assumption accounts for non-normal distributions. Also it was argued that heteroscedasticity in the residuals in the original data is to be expected if they are cross sectional. But given the likely form of heteroscedasticity, this will tend to be cancelled out by the ratio transformation. In other words, as argued by Barnes, residuals in the cross sectional data are likely to be heteroscedastic tending to make the residuals in the ratios homoscedastic.

Some other issues concerning financial ratios are the following:

1. Financial ratios tend to be highly correlated with each other. This collinearity means that careful selection must be carried out when determining which financial ratios should be used in the analysis.
2. Distributions of financial ratios tend to be significantly correlated over time. This means that ratios are not likely to be efficient predictors of dependent variables which shift in a random pattern over time, such as stock market prices.

Generally, the use of financial ratios as predictors of corporate bankruptcy has been researched quite substantially in the past (in approximately 53 studies)[63]. However, only recently a paper[64] has been published which provides a formal ranking of the popularity of financial ratios in modelling corporate collapse. According to the

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[62] Methodological Implications of non-normally distributed financial ratios

[63] Key papers used are: "Altman, E.I.(1983b), Why business fail, Journal of Business Strategy, Vol.4,p36" , "Poston, K.M. and Harmon, W.K.(1994) A test of financial ratios as predictors of turnaround versus failure among financially distressed firms, Journal of Applied Business Research, Vol.10, p41", "Ohlson J.A.(1980), Financial Ratios and the Probabilistic Prediction of Bankruptcy, Journal of Accounting Research, Vol 18.p109", "Frecka, T.J. and Lee, C.F. (1983), Generalised Financial Ratio Adjustment Processes and their Implications, Journal of Accounting Research, Vol.21, p308", "Gentry, J.A., Newbold P. and Whitford, D.T.(1987), Funds Flow Components, Financial Ratios and Bankruptcy, Journal of Business Finance & Accounting , Vol.14, p.595".

[64] "A comprehensive formal ranking of the popularity of financial ratios in multivariate modeling of corporate collapse", Hossari & Rahman, The Journal of American Academy of Business, Cambridge, March 2005

following table, whereby financial ratios are broadly defined, the most popular financial ratios used in past studies are exhibited in table 6.1.

Table 6.1. Popularity of Financial Ratios

The popularity of 48 financial ratios across 53 studies					
Ratio	**Rank**	**Ratio**	**Rank**	**Ratio**	**Rank**
NI/TA	43%	NI/TE	13%	AR/INV	4%
CA/CL	42%	EBIT/I	11%	C+MS/CL	4%
TL/TA	40%	TE/TA	9%	C+MS/TA	4%
WC/TA	34%	INV/S	9%	CF/CL	4%
EBIT/TA	30%	QA/S	9%	CF/S	4%
CF/TL	23%	WC/S	9%	CL/TA	4%
TL/TE	23%	QA/TA	8%	CL/TE	4%
RE/TA	21%	S/FA	8%	DIV/NI	4%
S/TA	21%	TE/TL	8%	EBT/TA	4%
C/TA	19%	C/CL	6%	EXP/S	4%
CA/S	17%	C/S	6%	INV/WC	4%
CA/TA	17%	EBIT/S	6%	LTL/TE	4%
MVE/TL	15%	EBIT/TE	6%	OpEx/TA	4%
QA/TL	15%	FA/TA	6%	S/INV	4%
CF/TA	13%	FA/TE	6%	S/TE	4%
NI/S	13%	LTL/TA	6%	TE/LTL	4%

***Source**: A comprehensive formal ranking of the popularity of Financial Ratios in Multivariate Modelling of Corporate Collapse, The Journal of American Academy of Business, Cambridge, March 2005*

It should be noted however, that the calculation for the derivation of those ratios might not be common across the 53 studies, but potentially there are some adjustments. But even if these adjustments are made, this can't alter significantly the results. As it becomes obvious only 5 out of the 48 financial ratios depicted have been useful to more than 25% of the studies that have been identified. Those are the Net Income to Total Assets, Current Assets to Current Liabilities, Total Liabilities to Total Assets, Working Capital to Total Assets and Ebit to Total Assets, with rankings of 43%, 42%, 40%, 34% and 30% respectively. From the table it becomes obvious that many ratios have the same ranking and only about 5 of them were popular amongst more than one quarter of the relevant literature.

Within the context of the literature which involves the exploration of the relation between accounting ratios and credit ratings or credit spreads, an important issue, is the quality of raw information that is provided by companies. In particular, a topic that has gained a lot of attention lately, particularly after collapses of big company names, is the quality of financial disclosures provided to the market and investors alike.

This last topic, i.e. the importance of accounting transparency and corporate disclosures on credit spreads, has received quite a lot of attention from academics. As a result, even if it is beyond the scope of the current section, I would believe it would be useful to mention briefly some of the most important findings of some of this research work.

A particularly interesting paper was that of Fan Yu[65], who investigated the relation and the effects of a firm's informational disclosure on the term structure of its corporate bond yield spreads. To the extent that the lack of transparency may signal hidden bad news about a company, the quality of accounting information may have an impact on its costs of debt offering yields. Using AIMR (Association for Investment and Management Research) rankings and cross sectional regressions, it was shown that firms with higher AIMR disclosure rankings tend to have lower credit spreads, a relation that is particularly strong for short term bonds. These findings are consistent with the theory of discretionary disclosure as well as the incomplete accounting information model of Duffie and Lando(2001).

The empirical evidence on the relation between firm performance and disclosure, has been mixed. Some research on management earnings forecasts (Patel, 1976, Penman, 1980, and Lev and Penman, 1990) suggests that firms tend to disclose more frequently when they are experiencing good earnings results and their earnings forecasts are associated with positive returns[66]. Research focused on later time periods (Ajinkya and Gift, 1984, and McNichols, 1989), indicates that firms are as likely to issue good news forecasts as bad news forecasts. In another paper, by McNichols, 1988, who incorporates other measures of voluntary disclosure, concludes that based on the negative skewness of returns of earnings announcements dates, that good news is disclosed prior to earnings announcements while bad news is disclosed through announced earnings.

[65] "Accounting Transparency and the Term Structure of Credit Spreads", Draft Doc, University of California, Irvine

[66] " Cross-sectional determinants of Analyst Ratings of Corporate Disclosures", Mark Lang & Russell Lundholm, Journal of Accounting Research, Vol 31, No 2, Autumn 1993

The reason for the incorporation of some conclusions reached by research focusing on corporate disclosure and accounting transparency, is that although intuition would suggest that accounting factors are expected to be mostly significant in the determination of a company's spread, there are a number of difficulties caused by informational asymmetries and other issues, which may not lead to the expected results. A clear illustration of the implications of imperfect accounting data is provided by Leland (1994). He assumed that outside investors cannot observe the issuer's credit quality directly and receive only periodic and imperfect accounting reports. 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. However, with imperfect accounting information, the model implies that credit spreads remain bounded away from zero as maturity goes to zero.

Moreover, Leland, plots the term structure 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 the term structure may provide some indication of the quality of information assumed by investors.

6.2. Evidence based on current data and Rationale

In this section the relation between spreads and accounting variables is going to be investigated. Typical ratios (such as profitability, leverage, liquidity, etc.) which are used to predict the financial status of a company are going to be explored. The rationale behind this is based on the assumption that a company's financials account for more than 45% of the weight given to the overall rating of a company (as per research provided by the largest and most recognised rating agencies internationally, such as Moody's, S&P, Fitch, to name the most important). The remaining 55% is usually a function of macroeconomic and market factors, the nature of the firm's industry, its competitive position, as well as subjective factors relative to the company's management and its risk tolerance, its ownership influence etc, which are rather difficult to model. Effectively it could be argued that by default, financial ratios are expected to explain at a maximum half of the variation in credit spreads (which in turn are largely based on the ratings assigned by the rating agencies)

Assuming that rating agencies take into consideration changes in a company's financial position on a timely basis, then any changes should be reflected in the company's spreads. Furthermore, assuming that markets price correctly bonds, any change in the company's financial position should be reflected in the respective's company's spreads on or sometimes before a rating announcement (upgrade, downgrade, or no change). In this thesis since we don't have information on the timing of rating announcements, it is going to be assumed that spreads are adjusted according to rating announcements provided by the rating agencies.

Consequently, option adjusted spreads provided by Merrill Lynch are going to be the dependent variable and accounting variables are going to be the independent variables in the equation estimated. The analysis based solely on quarterly data, since most of US companies publish updates of their financial position on a quarterly basis. There is a concern, however, with respect to the data tested since credit spreads reflect a continuous variables, while, by default, accounting ratios are considered to be more static or discrete.

The overall hypothesis tested under this chapter is that changes in credit spreads at time t, are affected and explained by changes in the respective company's financial information at time t, (t-1), (including the company's current market capitalisation and ratios such as cash flow to debt, earnings before interest and tax to interest expense, debt to capital employed, etc)

In particular, the null hypotheses tested under this chapter are the following:

Ho: Profitability ratios don't explain changes in credit spreads and aren't negatively related to them.

Ho: Leverage ratios don't explain changes in credit spreads and aren't positively related to them.

Ho: Liquidity ratios don't explain changes in credit spreads and aren't negatively related to them.

Ho: Current Market Capitalisation doesn't explain changes in credit spreads and isn't negatively related to them.

6.2.1. Data and Methodology
6.2.2. Data Collected

Data on Spreads

Under this chapter, data collected on credit spreads include the constituents of the ML US High Grade Broad Market Index and the US High Yield Master II Index. The period covered is from January 1997 until May 2002. Analytical description of the qualifying data and the elimination process used is provided in Chapter 3, section 3.3.1.

Data on Accounting Factors

For those companies that made up the constituents of the ML Index, the respective Bloomberg tickers were collected and the respective companies' accounting information was gathered. This data was taken from Bloomberg and since most of the companies report on a quarterly basis, that was the frequency of the data collected. For the rest of the thesis when it comes to accounting indicators the following abbreviations are going to be used:

Accounting Factors	Abbreviations
Cash Flow to Debt	CFD
Current Market Capitalisation	CMT
EBIT to Interest Expense	EBIT
EBIT to total interest expense	EBTI
EBITDA to total interest expense	EBITDIN
EBITDA per revenue	EBDAR
Return on capital	ROC
Return on common Equity	ROE
Return on Invested Capital	ROIC
Total Debt to EBITDA	TDEBDA
Total Debt to Total Capital	DBCP

The definitions for the ratios used are provide below:

(a) Cash Flow to Debt, where:

$$\frac{\text{(Net Income)} + \text{(Depreciation \& Amortisation)} + \text{(Change in working capital)} + \text{(non cash adjustments)}}{\text{(Long Term debt)} + \text{(Current portion of LT debt)} + \text{(Newly issued Debt)}}$$

(b) Current Market capitalisation

(c) EBIT to Interest expense, where:

$$\frac{\text{Earnings before interest \& taxes}}{\text{Interest Expense}}$$

(d) EBITDA to Interest Expense, where:

$$\frac{\text{Earnings before interest, taxes, depreciation and amortisation}}{\text{Interest expense}}$$

(e) EBITDA per revenue, where:

$$\frac{\text{Earnings before interest, taxes, depreciation and amortisation}}{\text{Sales}}$$

(f) Return on Capital, where:

$$\frac{\text{Net Income}}{\text{(Total Assets)} - \text{(Liabilities)}}$$

(g) Return on Equity, where:

(Net profit margin) * (asset turnover) * (asset /equity) =

i.e. (net income/sales) * (sales/assets) * (assets/equity)

(h) Return on Invested Capital

$$\frac{\text{Net Income}}{\text{Total Capital (Minority Interest + Share Capital \& Premium+Reserves)}}$$

(i) Total Debt to EBITDA, where:

$$\frac{\text{(Long Term debt) + (Current portion of LT debt) + (Newly issued Debt)}}{\text{Earnings before interest, taxes, depreciation \& amortisation}}$$

(j) Total Debt to Capital Employed, where:

$$\frac{\text{(Long Term debt)} + \text{(Current portion of LT debt)} + \text{(Newly issued Debt)}}{\text{Total Capital (Minority Interest + Share Capital \& Premium+Reserves)}}$$

Given the academic literature on financial ratios, the intuition would lead to different selection of ratios than the one that has been chosen for the purpose of this thesis. The rationale behind choosing the above financial ratios instead, has been based on the following four points:

1. The purpose of this thesis is not the use of financial ratios to predict a company's failure, but to estimate a functional relation between long-term credit spreads and accounting information.
2. Given recent collapses of big company names (2001 –2003) it became apparent that the most important reasons behind those companies' collapse were the high leverage and to another extent, issues relating to their accounting transparency.
3. This sample contains a number of firms belonging to the non-investment sector. Usually companies that are categorised as "high-yield" tend to be smaller companies, that are in a growth stage and that tend to have higher capital expenditures than their investment grade counterparts. As a result their depreciation & amortisation expenses should be taken into consideration seriously when trying to estimate this relation, as it hasn't been considered by past studies, since none of them has used financial ratios adjusted for depreciation and amortisation expenses.
4. A very important accounting and market variable, that of the company's current market capitalisation, has been included in this thesis, as it hasn't been done previously. Hopefully, the inclusion of this variable, will be able to capture more subtle and fast moving changes in a borrower's conditions.

6.2.3. Descriptive Statistics of Accounting Variables

Before proceeding with the required estimation of the relation between credit spreads and accounting variables, descriptive statistics of the accounting variables are provided. First descriptive statistics of the ratios used for the analysis are presented for the seven rating categories on an individual basis. Tables 6.2 to 6.8. provide descriptive statistics for all accounting variables used and for each credit rating category.

As evident, financial ratios are far from being normally distributed as evident from their kurtosis, the skewness of distribution and the Jarque bera statistic. In terms of volatility of the accounting variables, it is worth noting the following:

a. The large values of standard deviation associated to the variable of current market capitalisation compared to the rest of the accounting variables, is because CMT is expressed in actual figures, while we are using ratios for all the other variables.
b. Another thing worth mentioning is that the volatility of profitability ratios is higher, overall in the investment grade categories than the leverage ratios while liquidity depicted here by the ratio of CFD tends to be the less volatile of all.
c. An unanticipated result is that although we should expect the volatility of the majority of ratios to increase with a deterioration in the credit quality, the standard deviations don't support this. Instead, we see higher volatiliy in most of the variables in the investment grade categories, which tends to decrease in the non-investment grade sector, while in some instances there is a significant rise in the c-rating category.

However, the mean values of the respective ratios follow the anticipated pattern per rating category. In particular, the mean values of liquidity, profitability ratios and the company's current market capitalisation tend to decrease as the credit rating category deteriorates. Huge declines in mean values are depicted for the "C" rating category. In contrast the mean values for leverage ratios tend to increase as the ratings move from investment to non-investment grade, as presented by their total debt to ebitda and debt to capital employed ratios. It is worth noting that the mean value of the total debt to ebitda ratio instead of increasing in the "C" rating category, it declines, which is possibly attributed to the fact that companies assigned a credit rating of "C" face difficulties in raising financing from the debt markets, hence the decrease.

Table 6.2.Descriptive Statistics of Accounting Variables – AAA Rating, levels

AAA-Rating											
	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	1.20	223,339	39.49	20.42	41.32	53.02	41.32	18.84	32.27	8.97	2.29
Median	1.03	180,141	27.23	21.06	38.69	51.36	38.69	22.33	27.40	9.94	0.69
Maximum	3.19	572,273	79.72	34.59	152.14	200.47	152.14	30.99	51.78	12.81	8.64
Minimum	0.10	18,570	10.30	6.64	3.11	4.98	3.11	5.15	17.21	4.16	0.29
Std. Dev.	0.94	139,297	28.35	7.68	31.04	40.50	31.04	8.81	9.86	2.73	2.91
Skewness	0.43	0.43	0.47	-0.26	1.42	1.48	1.42	-0.35	0.98	-0.37	1.31
Kurtosis	2.05	2.58	1.39	2.35	5.99	6.32	5.99	1.77	2.50	1.71	2.97
Jarque-Bera	7	4	14	3	69	81	69	8	17	9	28
Probability	0	0	0	0	0	0	0	0	0	0	0
Observations	98	98	98	98	98	98	98	98	98	98	98
Cross sections	5	5	5	5	5	5	5	5	5	5	5

Table 6.3. Descriptive Statistics of Accounting Variables – AA Rating, levels

AA-Rating											
	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	0.89	96,294	40.43	24.59	26.45	33.87	26.22	16.20	25.98	11.11	1.65
Median	0.56	72,953	37.71	22.98	11.33	15.64	11.25	14.93	25.99	8.90	1.34
Maximum	4.75	572,273	84.21	50.02	892.74	1112.18	892.74	41.98	208.06	48.87	56.64
Minimum	0.00	3,240	6.49	-7.82	-3.37	-1.13	-3.13	-12.06	-35.02	-1.81	-60.07
Std. Dev.	0.93	105,272	18.43	11.87	80.30	99.10	80.33	8.74	16.12	9.87	7.22
Skewness	2.42	2.51	0.31	0.13	9.31	9.50	9.30	0.16	2.96	3.03	-1.27
Kurtosis	8.55	9.61	2.63	2.72	98.32	101.52	98.23	3.96	42.37	11.87	62.84
Jarque-Bera	946	1,201	9	3	164,660	75,741	164,367	18	27,669	2,014	62,631
Probability	0	0	0	0	0	0	0	0	0	0	0
Observations	419	419	419	419	419	419	419	419	419	419	419
Cross sections	22	22	22	22	22	22	22	22	22	22	22

Table 6.4.Descriptive Statistics of Accounting Variables – A Rating, levels

A-Rating											
	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	0.50	31,164	41.86	21.54	8.68	12.90	8.41	10.91	6.60	16.64	2.15
Median	0.36	13,710	42.85	19.06	5.58	8.25	5.35	11.07	6.35	16.79	1.80
Maximum	2.83	208,371	81.29	83.88	115.00	188.00	115.00	113.95	16.96	46.50	37.68
Minimum	-0.02	0	0.25	-8.00	-19.87	-1.99	-19.87	-18.19	-2.48	-24.74	0.21
Std. Dev.	0.42	40,713	14.48	13.63	12.24	17.01	11.96	9.11	3.18	12.10	2.25
Skewness	2.72	2.17	-0.30	1.71	3.93	5.78	4.07	3.40	0.42	-0.07	10.85
Kurtosis	12.61	7.35	3.51	7.92	26.11	49.70	28.11	44.79	3.27	3.44	164.79
Jarque-Bera (in '000s)	5.8	1.8	0.029	1.7	28.7	111.6	33.6	86.4	0.037	0.010	1,285
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158
Cross sections	54	54	54	54	54	54	54	54	54	54	54

Table 6.5.Descriptive Statistics of Accounting Variables – BBB Rating, levels

BBB-Rating											
	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	0.38	13,149	47.63	20.31	5.31	8.15	4.84	8.18	5.62	12.04	3.16
Median	0.25	6,278	45.88	15.17	3.49	5.69	3.39	7.82	4.88	11.63	2.52
Maximum	3.20	120,147	95.19	79.99	133.93	162.13	90.50	42.18	23.63	69.16	68.64
Minimum	-0.44	354	0.07	-29.09	-18.34	-8.12	-18.34	-17.50	-7.21	-62.86	-89.16
Std. Dev.	0.40	19,486	16.11	16.34	8.62	10.15	6.96	7.08	3.54	14.81	5.18
Skewness	2.51	3.04	0.55	1.45	6.86	7.62	5.26	0.28	1.11	-0.37	-2.95
Kurtosis	12.25	13.29	3.54	5.32	82.01	91.74	52.36	4.55	5.76	6.89	161.71
Jarque-Bera (in '000s)	11.4	14.8	0. 155	1.430	667.2	841.1	264.2	0.281	1.3	1.7	2,616
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	2490	2490	2490	2490	2490	2490	2490	2490	2490	2490	2490
Cross sections	118	118	118	118	118	118	118	118	118	118	118

Table 6.6.Descriptive Statistics of Accounting Variables – BB Rating, levels

BB-Rating											
	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	0.24	4,288	53.62	18.22	4.42	4.83	2.73	5.34	4.45	6.85	3.91
Median	0.17	1,725	53.40	13.50	2.24	3.48	2.13	6.20	4.02	7.00	3.44
Maximum	2.95	198,462	99.35	80.66	98.84	46.15	36.72	51.24	26.70	607.27	150.24
Minimum	-0.44	118	6.08	-68.57	-84.00	-79.20	-84.00	-142.80	-21.63	-262.50	-60.07
Std. Dev.	0.33	9,663	16.62	17.23	11.49	7.20	6.62	10.83	3.61	39.81	8.18
Skewness	3.61	10	-0.40	1.35	2.97	-1.04	-3.66	-3.85	0.77	6.89	9.89
Kurtosis	22.99	173	3.42	6.51	33.37	44.35	68.65	49.03	11.53	115.73	196.46
Jarque-Bera (in '000s)	31.3	2,040	0.057	1.3	66.3	118.7	302.3	150.9	5.2	893.7	2,620
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	1663	1663	1663	1663	1663	1663	1663	1663	1663	1663	1663
Cross sections	112	112	112	112	112	112	112	112	112	112	112

Table 6.7.Descriptive Statistics of Accounting Variables – B Rating, levels

B-Rating											
	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	0.21	1,587	61.39	20.97	2.39	3.34	1.77	5.02	4.06	2.04	7.89
Median	0.13	587	61.82	15.99	1.52	2.71	1.49	5.06	3.90	3.44	4.09
Maximum	3.37	189,888	99.13	88.25	161.47	48.88	34.65	70.21	29.48	137.20	500.98
Minimum	-0.89	5	13.08	-195.10	-26.27	-22.81	-25.34	-72.18	-88.22	- 186.47	-30.88
Std. Dev.	0.36	7,953	15.63	24.02	9.04	4.67	3.75	11.53	4.88	33.47	35.90
Skewness	5.22	20	-0.25	-0.91	11.50	3.98	1.39	-0.68	-9.44	-0.64	-26.24
Kurtosis	40.37	459	3.05	14.96	175.07	36.15	26.22	12.14	187.95	8.49	689.33
Jarque-Bera('000s)	130.1	18.1	0.021	12.6	2.6	100.4	47.2	7.3	2.9	2.7	40.9
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	2074	2074	2074	2074	2074	2074	2074	2074	2074	2074	2074
Cross sections	127	127	127	127	127	127	127	127	127	127	127

Table 6.8.Descriptive Statistics of Accounting Variables – C Rating, levels

C-Rating	CFD	CMT	DBCP	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	TDEBDA
Mean	0.06	1,706	65.28	-10.7	-0.23	1.18	-0.22	-3.12	-1.45	-29.45	4.48
Median	0.06	199	65.68	9.61	0.05	1.21	0.05	-1.08	1.51	-14.34	5.63
Maximum	0.93	36,837	98.68	86.28	9.00	9.71	7.09	99.05	12.49	148.15	180.07
Minimum	-0.66	11	24.66	-450	-7.03	-5.22	-6.95	-65.58	-125.48	-264.44	-174.21
Std. Dev.	0.17	5,948	17.11	7240.07	1.88	1.79	1.80	13.09	18.00	49.87	31.99
Skewness	0.75	5	-0.25	-15.02	-0.45	0.26	-0.63	0.89	-5.76	-0.93	0.18
Kurtosis	7.87	24	2.56	226.98	6.91	6.02	5.64	21.06	36.80	6.48	17.32
Jarque-Bera	745	15090	13	1466154	461	270	245	9451	36609	448	5889
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	689.00	689.00	689.00	689.00	689.00	689.00	689.00	689.00	689.00	689.00	689.00
Cross sections	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00	45.00

6.2.4. Methodology

Once analytical description of data has been provided, the next step was to test the variables for correlations. Firstly we tested which of the independent variables tend to be more correlated with credit spreads (dependent) in order to get an initial idea of which are the variables expected to explain mostly changes in credit spreads.

Table 6.8. presents Pearson correlation coefficients for all variables considered. As evident, current market capitalisation is the most highly correlated variable with credit spreads with a strong negative relation. Then follows the return on capital employed and the EBIT coverage ratios, which are both negatively related to credit spreads. Leverage ratios on the other hand are positively correlated to changes in credit spreads, consistent with the structural approach.

Table 6.8. Correlation among Changes in Credit Spreads & Accounting Variables

	SPREADS
SPREADS	1
CFD	-0.004
CMT	-0.171
DBCP	0.003
EBDAR	-0.004
EBIT	-0.005
TDEBDA	0.004
EBITDIN	-0.005
EBTI	-0.004
ROC	-0.012
ROE	-0.004
ROIC	-0.013

The next level of correlation tested was between independent variables. Financial ratios tend to be highly intercorrelated with each other. This means of course that careful selection must be carried out when determining which financial ratios should be used in the analysis. Table 6.9. shows the correlations between the independent variables.

Table 6.9. Correlation among the Independent – Changes in Accounting Variables

	EBDAR	EBIT	EBITDIN	EBTI	ROC	ROE	ROIC	CFD	CMT	TDEBDA	DBCP
EBDAR	1.00										
EBIT	0.00	1.00									
EBITDIN	**0.73**	0.00	1.00								
EBTI	0.01	**1.00**	0.01	1.00							
ROC	0.00	0.00	0.00	0.00	1.00						
ROE	**0.96**	0.00	**0.73**	0.01	0.00	1.00					
ROIC	0.01	0.00	0.00	0.00	-0.02	0.00	1.00				
CFD	-0.01	0.00	-0.01	0.00	0.01	-0.01	0.00	1.00			
CMT	0.00	0.01	-0.01	0.01	0.01	0.00	0.01	0.00	1.00		
TDEBDA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	
DBCP	0.02	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	1.00

When testing for correlations amongst the independent (accounting) variables, it was observed that the variables of EBITDIN & EBDAR , ROE & EBDAR , ROE & EBITDIN, EBTI & EBIT should not be regressed on a parallel basis against changes in credit spreads since they exhibit correlations of 0.73, 0.96 , 0.73 and 1.00 respectively.

In the cases of multicollinearity being present, (in this instance the above accounting variables have values of above +0.70) the usual remedy is to drop one of the independent variables that are strongly correlated and recompute the regression equation. In this instance it means that when running the regressions the combination of the above variables will provide spurious results and therefore regressions including the above variables should only be run on an individual basis.

It should be noted that the size of the firm was being introduced in this study by including the variable of the company's current market capitalisation.

Once changes in spreads and accounting ratios have been computed, the effort is focused in estimating the coefficients of the following regression:

Equation 6.1.

$$\Delta Spreads_{it} = c + \beta_1 * (\Delta Profitability_{it \ldots t-n}) + \beta_2 * (\Delta Liquidity_{it, \ldots, t-n}) + \beta_3 * (\Delta CMT_{it, \ldots t-n}) + \beta_4 * (\Delta Leverage_{it, \ldots t-n}) + \varepsilon_{it}$$

Where Δspreads is the changes in credit spreads from time (t-1) to time t, ΔProfitability represent the change in profitability ratios from time (t-1) to t, ΔLiquidity represent the change in liquidity ratios from time (t-1) to t, ΔCMT Represnet the change in the current market capitalisation from time (t-1) to time t and ΔLeverage is the change in the leverage ratios from time (t-1) to t. A constant term in the relation is being introduced, since there are factors not included in the independent variables that possible influence the dependent variables. This intercept is assumed to be constant for all pool members, $c_{it} = c$

Data has been arranged in the following way. Firstly, pool objects have been created, with each pool including as cross sectional identifiers the respective rating category's companies. Next ratios have been classified in three classes, namely profitability (including Ebitda ratios, ROE, ROIC, etc), leverage ratios (including debt to capital employed and total debt to Ebitda), long term liquidity ratios (cash flow to debt) and the current market capitalisation which was used as a proxy for the company's size.

A number of cross sectional regressions have been performed in order to estimate the coefficients of the equation 6.1. Firstly, cross sectional regressions of the different ratio categories (profitability, liquidity, leverage, size) were run both for investment and non-investment grade categories, and then changes of the most influential ratios against changes in spreads were tested.

Firstly the different ratio categories were examined against the different rating categories, i.e. separate groups including profitability, liquidity, leverage ratios and the current market capitalisation were being created in Eviews and each category was being regressed against pool groups which contained credit spreads of the different rating categories.

Before proceeding with the regression results it should be noted that the classical regression model can't be used, due to the cross sectional nature of data. Therefore, we will proceed by estimating the coefficients using two different methods for estimating the weights of the coefficients, since we have heteroscedasticity of unknown form, i.e. the GLS and the SUR method and then compare the results. (Analytical description of the calculation of the weighted versions of our pooled regressions is provided in Appendix 4A)

Before proceeding, it should also be made clear, that when estimating the coefficients for the relations with the use of Seemingly Unrelated Regressions, subsets of the initial data were tested, since a prerequisite for using the SUR methodology, is that the number of time series is equal to the number of cross sections used. Eviews may be unable to compute estimates for the model when there is a large number of cross sections or a small number of time periods. The average number of periods used in estimation must be at least as large as the number of cross section units. Even if there is a sufficient number of observations, the estimated residual correlation matrix must also be non-singular. If either condition is violated then we get an error message[67].

Clearly, this condition is violated since in our data sample we have a limited number of time series observations and a large number of cross sections identifiers per pool. Consequently, data has been tested on two levels.

a. based on the total sample of data, using a common constant for all pool members and the cross section weights methodology whites correction for hetersocedasticity and
b. based on a sub group of the initial data estimated with the use of both GLS and SUR methodologies.

[67] Please refer to "Help Topics in Eviews 4,1" and the accompanying Technical Discussion

6.2.5. Empirical results based on different group of ratios and univariate analysis

In this section, ratios have been categorised under three groups and cross sectional regressions are run on the those different groups. The hypothesis tested is that there is a negative relation between profitability ratios and credit spread changes. More specifically,

(a) Group A includes profitability ratios. More specifically the ratios included and hypotheses tested are:

Ebitda per Revenue: when the ratio increases (usually costs decrease and therefore earnings at the ebitda level increase) spreads are expected to tighten hence the negative expected sign.

Ebit to Interest Expense : when the ratio increases (either earnings increase or the cost of debt decreases) spreads are also expected to narrow. In other words, when interest payments are better covered by the level of profits, creditworthiness improves, and credit spreads tighten.

Ebit to Total Interest Expense: this ratio is slightly differentiated than the previous one in that it also considers interest revenue (i.e. total interest expense = interest income – interest expense). Once again the overall effect to credit spread is the same, when the ratio increases spreads are expected to come in.

Ebitda to total Interest Expense: the only differentiation of this ratio compared to the previous one, is that it contemplates depreciation and amortisation expense to ebit, expenses which are particularly important once non-investment grade companies are looked at. Once again, its influence on credit spreads is the same, i.e. when this ratio increases, which means that the company's profitability improve, spreads are expected to tighten.

Return on Capital: i.e. the ratio of a company's profit as a percentage of the capital employed. It is usually one of the most frequently used ratios for assessing the performance of organisations. An increase in this ratio signifies an improvement in the company's profitability and consequently credit spreads are expected to tighten.

Return on invested Capital: a company's income as a percentage of its invested capital. The expected sign of this ratio coefficient relative to credit spreads is also expected to be negative.

Return on Equity: i.e. the ratio of a company's net income as a percentage of its equity capital. Again there is an inverse relation between this ratio and credit spreads, which explains the negative sign of the coefficient.

Due to multicollineriry problems, as described in section 6.2.4., when looking at profitability ratios on a parallel basis only EBDAR, EBIT and ROC will be considered for the different rating categories:

Table 6.10 presents regression results based on cross sectional regressions using a common intercept and the GLS method. Results reported in the following table are based on the total sample of 674 companies, where the dependent variable are the changes in credit spreads.

Table 6.10. Profitability Ratios

Profitability Ratios	**All Rating Categories**							
	Exp. Sign	Coef	t-value	p-value	Stand Error	F-Stat	Total Panel Obs.	R^2
EBITDA per Revenue (EBDAR)		0.03	-1.02	0.09	0.00	5.89 (0.09)	7,456	0.01
EBIT to Interest Expense (EBIT)	-	- 0.00	-0.15	0.17	0.00			
Return on Capital (ROC)	-	- 2.33	-1.06	0.15	0.00			
Profitability Ratios	**Investment Grade Including BBB**							
	Exp. Sign	Coef	t-value	p-value	Stand. Error	F-Stat	Total Panel Obs.	R^2
EBITDA per Revenue (EBDAR)	-	- 0.00	-0.45	0.08	0.00	1.65 (0.17)	2,981	0.01
EBIT to Interest Expense (EBIT)	-	- 0.01	-2.35	0.01	0.00			
Return on Capital (ROC)	-	- 0.00	-0.37	0.09	0.00			
Profitability Ratios	**Investment Grade Excluding BBB**							
	Exp Sign	Coef	t-value	p-value	Stand. Error	F-Stat	Total Panel Obs	R^2
EBITDA per Revenue (EBDAR)		0.00	-0.45	0.08	0.00	1.58 (0.18)	1,179	0.02
EBIT to Interest Expense (EBIT)	-	- 0.01	-2.35	0.01	0.00			
Return on Capital (ROC)	-	- 0.00	-0.37	0.08	0.00			

Profitability Ratios	**Non - Investment Grade Including BBB**							
	Exp Sign	Coef	t-value	p-value	Stand. Error	F-Stat	Total Panel Obs	R^2
EBITDA per Revenue (EBDAR)	-	-0.00	-0.47	0.11	0.00	3.29 (0.07)	4,776	0.01
EBIT to Interest Expense (EBIT)	-	0.00	1.34	0.09	0.00			
Return on Capital (ROC)	-	-0.00	-0.24	0.12	0.00			
Profitability Ratios	**Non – Investment Grade Excluding BBB**							
	Exp Sign	Coef	t-value	p-value	StandError	F-Stat	Total Panel Obs	R^2
EBITDA per Revenue (EBDAR)	-	-0.00	-0.48	0.06	0.00	1.25 (0.05)	2,980	0.01
EBIT to Interest Expense (EBIT)	-	0.02	1.98	0.04	0.01			
Return on Capital (ROC)	-	-6.23	-0.17	0.06	0.00			

When all data was tested, the negative relation between accounting ratios and credit spreads is supported at the 90% confidence level, with the most significant coefficients presented for the Ebit to interest expense ratio, supported by the relatively higher t-statistics for the investment grade sample. The negative relation of EBIT to interest expense ratio to credit spreads was not supported given the result presented from non-investment grade companies. This is either due to the fact that credit spreads for non-investment grade companies aren't driven by the particular ratio or that non-investment grade companies' financials present peculiarities which can't be depicted with the use of that ratio.

Due to problems that arose with the sign of the EBIT ratio and credit spreads and the zero R^2 obtained from the regressions between profitability ratios and credit spread changes, the same hypotheses have been tested on a fraction of the original set of data. Tables 6.11 – 6.13, present results based on a much smaller number of randomly selected companies, based on the cross section weights and the SUR methodology. In these tests lagged values of the profitability ratios are also considered, whose results are provided in the following tables. It should be noted though, that values of the same ratios have been regressed at time t, but since the lagged values of the profitability ratios provided most statistically significant results, we only report the latter ones. It should also be made clear that when we are referring to (minus 1 lag) we effectively mean one quarter before, and so on. For accounting variables, it makes sense to use previous quarter's information, since credit spreads may not adjust promptly to the new information provided by a company's financial accounts.

Table 6.11. Profitability Ratios (sub-group of initial data)

Ratios	**All Rating Categories**											
	Cross Section Weights						**SUR**					
	Exp Sign	Coef.	t-value	p-value	f-stat	R^2	Exp Sign	Coef.	t-value	p-value	f-stat	R^2
Constant		0.071	5.52	0.00	1.22 (0.00)	0.01%		0.066	3.38	0.00	1.18 (0.00)	0.00%
EBDAR (-1)	-	-0.004	-2.45	0.01			-	-0.003	-1.76	0.09		
EBIT(-2)	-	-0.002	-2.29	0.02			-	-0.004	-1.35	0.06		
ROC(-1)	-	-0.004	-3.14	0.001			-	-0.003	-2.02	0.05		

Table 6.12. Profitability Ratios (sub-group of initial data)

Ratios	**Investment Grade**											
	Cross Section Weights						**SUR**					
	Exp .Sign	Coef.	t-value	p-value	f-stat	R^2	Exp . Sign	Coef.	t-value	p-value	f-stat	R^2
Constant		0.076	6.35	0.0	2.85 (0.00)	0.02%		0.07	4.57	0.0	1.63 (0.00)	0.01%
EBDAR(-1)	-	-0.005	-7.64	0.0			-	-0.00	-3.94	0.0		
EBIT(-2)	-	-0.017	-2.71	0.0			-	-0.011	-2.76	0.0		
ROC(-1)	-	0.001	3.73	0.0			-	0.001	2.08	0.03		

Table 6.13. Profitability Ratios (sub-group of initial data)

Ratios	**Non-Investment Grade**											
	Cross Section Weights						**SUR**					
	Exp. Sign	Coef.	t-value	p-value	f-stat	R^2	Exp. Sign	Coef.	t-value	p-value	f-stat	R^2
		0.069	2.66	0.00	165.4 (0.00)	3%		0.072	2.266	0.02	2.87 (0.00)	0.00%
EBDAR (-1)	-	-0.020	-1.45	0.08			-	-0.013	-1.096	0.033		
EBIT(-2)	-	-0.006	-8.70	0.00			-	-0.000	-1.411	0.068		
ROC(-1)	-	-0.001	-3.18	0.00			-	-0.000	-1.075	0.093		

The results provided from the subset of data, support the negative relation between profitability ratios and credit spreads both in investment and non-investment grade bands. However, not all of the results are significant at the 95% confidence level. Coefficients estimated by the cross section weights method are significant at the 95% confidence level compared to those estimated by the SUR method, which are significant at the 90% level. In particular, there is a negative relation between credit spreads and the profit margin ratio, as defined by the Ebdar ratio. The ratio of Ebit to interest expense, which is one of the most important ratios for determining a company's credit profile is negatively related to changes in credit spreads. So is the Return on Capital ratio. Statistical results provided though, don't give any more insight on whether changes in profitability ratios affect mostly non-investment grade companies, nor do they have any power as explanatory variables. (R^2s are almost 0). The fact that similar results are reported from both methods of cross sectional analysis, provides more confidence as to the fact that the low R^2s are likely due to a systematic effect rather than noisy data.

From one point of view, the low explanatory power of profitability variables on credit spread changes make sense, since bond holders are not that interested in the profitability of a company as they are in its leverage. On the other hand it can also be argued that increased profitability increases the interest coverage ability of a company, and therefore should make bond investors more confident. However, results don't affirm this second argument.

(b) Next Group B, was tested, which included long term leverage ratios. A positive relation is expected to exist among leverage ratios and changes in credit spreads, as depicted by the positive expected sign. Consistent with the structural framework, default is triggered when the leverage ratio approaches unity. Hence, it is clear that credit spreads are expected to increase with leverage. In particular, the hypotheses tested are:

<u>Debt to capital employed</u>: as this ratio increases (the respective's company debt increases or capital decreases) spreads are expected to widen.

<u>Total Debt to Ebitda</u>: as this ratio increase (or the company's debt increases or EBITDA decreases), credit spreads are expected to widen.

Table 6.14. Leverage Ratios based on GLS

Leverage	**All Rating Categories**							
	Exp Sign	Coef	t-value	p-value	S.E.	R^2	f-stat	No of Obs
Constant		0.05	19.29	0.00	0.00	1%	9.88 (0.00)	5,485
Debt to Capital Employed	+	0.02	1.55	0.11	0.01			
Total Debt to EBITDA	+	1.51	18.96	0.00	0.00			
Leverage	**Investment Grade Including BBB**							
	Exp Sign	Coef	t-value	p-value	S.E.	R^2	f-stat	No of Obs
Constant		0.05	9.7	0.00	0.00	0%	0.16 (0.02)	2,956
Debt to Capital Employed	+	0.01	1.39	0.09	0.00			
Total Debt to EBITDA	+	0.03	2.67	0.00	0.01			
Leverage	**Investment Grade Excluding BBB**							
	Exp Sign	Coef	t-value	p-value	Stand. Error	R^2	f-stat	No of Obs
Constant		0.05	7.98	0.00	0.00	0%	0.21 (0.25)	1,863
Debt to Capital Employed	+	0.00	0.59	0.09	0.00			
Total Debt to Ebitda	+	0.00	0.38	0.13	0.01			
Leverage	**Non – Investment Grade Excluding BBB**							
	Exp Sign	Coef	t-value	p-value	S.E.	R^2	f-stat	No of Obs
Constant		0.05	11.6	0.00	0.00	0%	0.13 (0.04)	2,960
Debt to Capital Employed	+	0.02	0.95	0.33	0.01			
Total Debt to EBITDA	+	1.55	11.3	0.00	0.00			
Leverage	**Non – Investment Grade Including BBB**							
	Exp Sign	Coef	t-value	p-value	S.E.	R^2	f-stat	No of Obs
Constant		0.05	13.4	0.00	0.00	0%	0.28 (0.00)	4,237
Debt to Capital Employed	+	0.03	1.19	0.20	0.01			
Total Debt to EBITDA	+	1.56	11.5	0.00	0.00			

As presented in table 6.14., when all companies from the broad rating categories are examined, the positive relation between leverage ratios and credit spreads is confirmed for both debt to capital employed and total debt to ebitda. The most significant coefficients are those estimated for the non-investment grade category for the total debt to ebitda ratio with highly significant t- values, while the debt to capital employed ratio is not statistically significant in the non-investment grade category with p-value of 0.33 and 0.20 for high yield companies excluding and including BBB respectively . It is worth noting that the fact that depreciation and amortisation was also considered for the calculation of the total debt to ebitda ratio explains the fact that more significant coefficients were obtained for the non-investment grade category compared to the investment grade one. As mentioned at the beginning of this section, depreciation and amortisation expenses tend to be highly significant for companies which are in a growth stage (usually companies rated below BBB).

Due to the significantly high t-statistics obtained when regressions are assessed with the GLS method using estimated cross sectional residual variances, regression coefficients have been re-estimated with the SUR method (i.e. using estimated cross-section residual covariance matrix), in order to compare results and draw more accurate conclusions on the relation we are estimating.

Using a subset of the original data, more regressions were run, whose results are presented in tables 6.15-6.17. Although the positive relation between the leverage ratio and credit spreads is consistent with the findings based on the cross section weights method, it seems that the coefficient of debt to capital employed is more significant. This is not to say that the coefficient of the total debt to ebitda ratio isn't important as supported by the following results. It is worth noting though, that the t-value of the debt to capital employed ratio is very significant for the investment grade category, compared to the second leverage ratio that considers depreciation and amortisation expenses.

Table 6.15. Leverage Ratios (sub group of data)

Ratios	**All Rating Categories**						
	SUR						
	Exp Sign	Coef	t-value	p-value	R^2	f-stat	Total Panel Obs
Constant		0.051	2.995	0.002	1%	15.54 (0.00)	869
Debt to Capital Employed	+	0.327	6.560	0.000			
Total Debt to EBITDA	+	0.045	3.856	0.000			

Table 6.16. Leverage Ratios(sub group of data)

Ratios	Investment Grade						
	SUR						
	Expected Sign	Coefficient	t-value	p-value	R^2	f-stat	Total Panel Obs
Constant		0.088	6.721	0.000	2%	1.76 (0.00)	574
Debt to Capital Employed	+	0.812	17.15	0.000			
Total Debt to EBITDA	+	0.096	4.245	0.000			

Table 6.17. Leverage Ratios(sub group of data)

Ratios	Non Investment Grade						
	SUR						
	Exp Sign	Coefficient	t-value	p-value	R^2	f-stat	Total Panel Obs
Constant		0.077	3.770	0.000	6%	89.5 (0.00)	994
Debt to Capital Employed	+	0.089	6.523	0.000			
Total Debt to EBITDA	+	0.075	3.989	0.000			

(c) Group C, involves looking at how the liquidity position of the company, as this is reflected in its cash flow to debt ratio affects credit spreads. The company's liquidity position here, is reflected by the <u>Cash Flow to Debt</u> ratio. As this ratio increases (either the company's cash flow increases or debt decreases) spreads are expected to tighten.

Table 6.18. Liquidity Ratio

LT Liquidity	All Rating Categories							
	Exp Sign	Coef	t-value	p-value	StandError	f-stat	No of Obs	R^2
Cash Flow to Debt	-	-0.03	-0.32	0.09	0.00	89.70 (0.00)	6,260	0.01
LT Liquidity	**Investment Grade Including BBB**							
	Exp Sign	Coefficient	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
Cash Flow to Debt	-	0.00	-0.53	0.08	0.00	0.45 (0.00)	3.753	0.00
LT Liquidity	**Investment Grade Excluding BBB**							
	Exp Sign	Coef	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
Cash Flow to Debt	-	-0.08	-0.58	0.106	0.00	0.31 (0.00)	1.424	0.00

LT Liquidity	Non – Investment Grade Excluding BBB							
	Exp Sign	Coef	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
Cash Flow to Debt	-	-0.03	-0.08	0.09	0.00	0.87 (0.00)	3.441	0.00
LT Liquidity	**Non – Investment Grade Including BBB**							
	Exp Sign	Coef	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
Cash Flow to Debt	-	-0.05	-0.35	0.08	0.00	0.92 (0.00)	5.987	0.00

Results provided in table 6.18, are based on the total number of data and the cross section weight method, confirm the negative relation between credit spreads and the cash flow to debt ratio. Coefficients of cash flow to debt are not significantly different from zero, although statistically significant at the 90% level of significance. Financial wise, this is not an anticipated result, as this ratio is presenting the company's liquidity position and we would expect more significant coefficients. The cash flow to debt ratio was also regressed against changes in credit spreads, under the SUR method, on a sub-set of the original data. Results are presented in table 6.19.

Table 6.19.Liquidity Ratio (subgroup of data) – SUR Method

Ratios	All Rating Categories						
	Exp Sign	Coefficient	t-value	p-value	f-stat	No of obs	R^2
Constant		0.074	4.975	0.000	0.15 (0.00)	729	0%
Cash Flow to Debt	-	-0.000	-3.424	0.000			
	Investment Grade						
	Exp Sign	Coefficient	t-value	p-value	f-stat	No of obs	R^2
Constant		0.081	5.319	0.000	0.08 (0.00)	395	0%
Cash Flow to Debt	-	-0.027	-5.097	0.000			
	Non- Investment Grade						
	Exp Sign	Coefficient	t-value	p-value	f-stat	No of obs	R^2
Constant		0.065	2.398	0.01	0.25 (0.00)	486	0%
Cash Flow to Debt	-	-0.021	-1.890	0.05			

Coefficients are more significant than those estimated with the method of cross section weights and are statistically significant at the 95% confidence level. Higher t-statistics were obtained for investment grade companies compared to the high yield ones. But even if results obtained are statistically significant, economic wise contradict theory and intuition. As proposed by other studies[68] the performance of cash (as reflected in the cash flow) is expected to be a better predictor than traditional liquidity ratios such as the current or the quick ratio, but results don't support this.

(d) The last variable tested, was the current market capitalisation, which was used as a proxy for firm size. The estimated sign is negative, since it is expected that when a company's market capitalisation increases, changes in credit spreads are expected to tighten. An increase in a company's size is usually a good sign from the credit risk analysis point of view, especially if it is organically driven. The only time that an increase in a company's market capitalisation can be positively related to credit spreads is if it is the outcome of a debt financed acquisition or a merger, which in many instances won't be well perceived by bond investors.

Results presented in table 6.20., are based on GLS method for estimating the coefficients. Compared to results from the previous three groups of accounting ratios, the variable of a company's current market capitalisation doesn't only support strongly the negative relation between changes in spreads and a company's capitalisation but also explains one third of the variation in credit spreads in the non-investment grade band. All results are statistically and economically significant, at the 95% level of significance.

Table 6.20.Current Market Capitalisation

CMT	All Rating Categories							
	Exp Sign	Coefficient	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
CMT	-	-0.27	-26.7	0.00	0.01	706.70(0.00)	3,607	16.3%
	Investment Grade Including BBB							
	Exp Sign	Coefficient	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
CMT	-	-0.13	-8.23	0.00	0.01	74.43(0.00)	1,629	4%

[68] W. H. Beaver, "Alternative Accounting Measures as predictors of failure", The Accounting Review, 1968

	Investment Grade Excluding BBB							
	Exp Sign	Coefficient	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
CMT	-	-0.16	-4.89	0.00	0.03	41.86 (0.00)	565	6%
	Non - Investment Grade Including BBB							
	Exp Sign	Coefficient	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
CMT	-	-0.28	-18.90	0.00	0.01	657.54(0.00)	3,042	17%
	Non - Investment Grade Excluding BBB							
	Exp Sign	Coefficient	t-value	p-value	Stand. Error	f-stat	No of Obs	R^2
CMT	-	-0.36	-21.90	0.00	0.01	1,172(0.00)	1,978	37%

Table 6.21, presents the results from the regressions between the variable of the current market capitalisation and credit spreads based on the SUR method of estimating coefficients. Strongly statistically and economically significant results are also reported for the variable of the company's current market capitalisation. The negative relation is supported for all rating categories with very significant coefficients assigned to all rating levels. Coefficients based on the SUR method although statistically significant financial wise are not as significant compared to the method of cross section weights which yields higher coefficients and accompanying t-values.

Table 6.21. Current Market capitalisation(sub-group of data), SUR method

Ratios	**All Rating Categories**						
	Exp. Sign	Coefficient	t-value	p-value	f-stat	No of Obs	R^2
Constant		0.044	9.22	0.00	18.48 (0.00)	582	5%
CMT	-	-0.651	-13.25	0.00			
	Investment Grade						
	Exp. Sign	Coefficient	t-value	p-value	f-stat	No of Obs	R^2
Constant		0.018	2.055	0.00	9.24 (0.00)	294	3%
CMT	-	-0.566	-8.745	0.00			
	Non- Investment Grade						
	Exp. Sign	Coefficient	t-value	p-value	f-stat	No of Obs	R^2
Constant		0.058	3.667	0.00	15.33 (0.00)	347	9%
CMT	-	-0.586	-8.980	0.00			

From the results presented above, one can easily derive that the most statistically and economically significant coefficient is that of the current market capitalisation and the leverage ratios. The variable of the current market capitalisation, hasn't been considered in other studies, although apparently is one of the most significant variable in explaining changes in credit spreads, probably because as aforementioned is considered to be more comparable to credit spreads, in the sense that is considered more like a continuous variable.

It should be noted that the adjusted R^2s obtained have been surprisingly low, but this is rather rational since:

a. Financial ratios have been regressed on an individual basis, which by default isn't expected to provide much support for explaining the credit spread movements, and
b. If we consider that other studies, that try to predict credit ratings with the use of accounting ratios, can explain at best no more than half of the variation in credit ratings, it explains why is even harder to explain this variation when modelling credit spreads, i.e. modelling a continuous variable with the use of a discrete variable.

6.2.6. Results based on different group of ratios against individual rating categories

Results presented above, are not only based on ratio groups but also on rating groups. Therefore, it would be interesting to consider the relevance of the different ratio groups, once the broad rating categories are broken down to their constituents. In other words, a set of cross sectional regressions were performed, for the seven distinct rating categories. Table 6.22. shows the results of these regressions based on the method of cross section weights. For simplicity reasons, only the adjusted R^2s are presented in the table. The statistical significance of the results is also provided.

Table 6.22. Results based on GLS Method

Reported R^2s	Profitability Ratios	Current Market Capitalisation	Leverage Ratios	CFD ratio (Liquidity)
AAA	2%*	13%**	2%*	2%*
AA	1 %*	17%***	0%***	0%***
A	0%*	5%***	0%*	0%*
BBB	0%*	5%***	0%*	0%***
BB	1%*	10%***	0%**	0%**
B	-0%*	99%***	1%*	0%*
C	7%*	61%***	14.5%*	7%***

**** Rejected at the 1% significance level*
*** Rejected at the 5% significance levell*
** Rejected at the 10% significance level*

Results provide explicit evidence as to the financial and statistical significance of the current market capitalisation variable in explaining credit spread changes in all rating categories, but particularly important are the results provided for the "B" and "C" rating bands. In the "B" rating category alone, almost all of the variation in credit spreads is explained by the changes in that variable. Profitability ratios and the Cash Flow to Debt ratio provide very limited, almost insignificant support in explaining changes in credit spreads. Although, financially wise this could be explained by the fact that generally firms can survive an accounting loss, and although this might have a number of effects in a company's credit profile it is not really affecting their credit spread levels. But still we would expect more significant results from the CFD ratio.

6.2.7. Results based on aggregate regressions & multivariate analysis

Having tested the relation between different pools of rated companies and individual ratio groups, the next step would be to test the most important set of independent variables, provided by the analysis supplied above, against the investment and non-investment grade pool of companies. In other words, pool objects containing the different rating classes would be kept the same but all ratios (those not correlated amongst them) are going to be tested on a parallel basis within the different rating bands. Coefficients for those aggregate regressions will be estimated firstly by the method of cross section weights and whites correction for heteroscedasticity (presented in table 6.22.).

Table 6.23 All Data (Investment & Non-Investment Grade)

INVESTMENT & NON-INVESTMENT GRADE					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Adjusted R^2**
C	0.01	0.00	-3.6	0.00	**16.0%**
CFD(-1)	-0.00	0.00	-1.0	0.08	
CMT	-0.25	0.01	-25.1	0.00	
DBCP(-1)	0.02	0.01	1.5	0.09	
ROC(-1)	-0.00	0.00	-3.0	0.00	
TDEBDA (-1)	0.00	0.00	9.0	0.00	
EBDAR (-1)	-0.00	0.00	-2.7	0.01	
INVESTMENT GRADE INCLUDING BBB					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Adjusted R^2**
C	-0.01	0.00	-5.08	0.00	**7.0%**
CFD (-1)	-0.01	0.00	-3.38	0.00	
CMT	-0.12	0.01	-11.89	0.00	
DBCP(-1)	0.03	0.01	1.5	0.08	
EBITDIN(-1)	-0.01	0.00	-0.73	0.09	
TDEBDA(-1)	0.01	0.01	1.16	0.08	
ROC(-1)	-0.01	0.00	-3.02	0.00	
INVESTMENT GRADE EXCLUDING BBB					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Adjusted R^2**
C	-0.05	0.00	-9.91	0.00	**19.2%**
CFD(-1)	-0.00	0.00	-0.68	0.09	
CMT	-0.12	0.03	-3.50	0.00	
EBDAR(-1)	-0.00	0.01	-0.46	0.12	
DBCP(-1)	0.02	0.03	0.68	0.09	
TDEBDA(-1)	0.02	0.01	2.22	0.03	
ROC(-1)	-0.02	0.01	-3.14	0.00	
NON INVESTMENT GRADE EXCLUDING BBB					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Adjusted R^2**
C	0.08	0.00	16.15	0.00	**63.5%**
CFD(-1)	-0.00	0.00	-4.75	0.00	
CMT	-0.50	0.01	-19.60	0.00	
DBCP(-1)	0.25	0.05	4.85	0.00	
TDEBDA(-1)	0.00	0.00	0.28	0.11	
ROE(-1)	-0.00	0.00	-1.42	0.12	
ROC(-1)	-0.00	0.00	-4.97	0.00	
NON INVESTMENT GRADE INCLUDING BBB					
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Adjusted R^2**
C	0.04	0.00	17.34	0.00	**26.7%**
CFD(-1)	-0.01	0.00	-1.33	0.11	
CMT	-0.35	0.01	-17.65	0.00	
DBCP(-1)	0.18	0.03	6.98	0.00	
TDEBDA(-1)	0.01	0.00	1.09	0.12	
ROE(-1)	-0.00	0.00	-0.13	0.09	
ROC(-1)	-0.00	0.00	-0.55	0.09	

Generally, results show that the accounting information has the greatest impact on non –investment grade companies. These results affirm our initial intuition that changes in company specific variables should mainly affect high yield companies. The rationale is that companies which belong to the high yield category usually aren't in a good financial shape and therefore a change, even a small one in the company's financial position could greatly affect their ratings and consequently their spreads. Since low rated companies tend to be very volatile in nature, their financial standing is the most important factor considered when rating them. This should and is reflected into their ratios. It should also be noted, that except of the variable of current market capitalisation that was important and statistically significant at time t, results of the rest of the accounting ratios are referring to the lagged values (one quarter before) suggesting a lag relationhip to exist between the announcement of a company's figures and the respective change in credit spreads. This is not to say, that the rest of the accounting ratios weren't significant at time t, but rather that their lagged values provided better support for explaining the variation in credit spread changes. (For example in the high yield category, excluding BBB rated bonds, the adjusted R^2 for values at time t, was 51%).

The highest adjusted R^2s have been obtained for non-investment grade companies and once BBB rated companies are being excluded. Results also affirm that BBB band is very volatile and companies' data can vary substantially. Overall, when that category is added either to the investment or non-investment grades sample, reduces significantly the explanatory power of the model.

The results presented above are based on large number of cross sections and the coefficients have been estimated with the method of cross section weights. For comparative and illustrative purposes, results have been re-estimated on a randomly selected set of data while the only criterion set, was that a proportionate number of cross section identifiers would be selected from each rating pool. Coefficients are both estimated with the method of cross section weights but also with the SUR method on the randomly selected companies. The regression results from the new set of data are presented in tables 6.23, 6.24 & 6.25.

Estimated coefficients based on the randomly selected data and calculated by both GLS and SUR method, provide similar results to those mentioned above. The accounting ratios tend to explain more of the variation in credit spreads in the non-investment grade sample, while the variables of current market capitalisation and leverage ratios seem to be the most important variables statistically and economically in explaining the relation in all rating bands.

Overall, the coefficients of the ratio of debt to capital employed and those of CMT are the most statistically significant variables, supported by both methods of estimation and evident both from investment and non-investment rated companies' results. On a multivariate context, the fact that lagged values of the independent variables were considered, implies a time lag, of one quarter from the reporting date and the corresponding changes in credit spreads. This is not to say, that they weren't significant at time t, but rather that their lagged values provided better support for explaining the variation in credit spread changes.

Table 6.24. Cross Sectional Regressions – All Rating Categories

All Rating Categories (Investment & Non Investment grade)						
Method: GLS (Cross Section Weights)				**Method: Seemingly Unrelated Regression**		
White Heteroskedasticity-Consistent Standard Errors & Covariance						
Variable	**Coefficient**	**t-Stat**	**Prob.**	**Coefficient**	**t-Stat**	**Prob.**
C	0.07	11.92	0.00	0.06	4.42	0.00
EBDAR(-1)	-0.01	-10.09	0.00	-0.01	-5.46	0.00
CFD(-1)	-0.00	-3.66	0.00	-0.00	-3.49	0.00
DBCP(-1)	0.21	3.65	0.00	0.41	7.47	0.00
TDEBDA(-1)	0.02	2.73	0.01	0.04	5.51	0.00
CMT	-0.29	-2.98	0.00	-0.20	-4.10	0.00
Weighted Statistics						
R-squared	0.154					
Adjusted R-squared	0.148					
Unweighted Statistics				**Unweighted Statistics**		
R-squared	0.09			R-squared	0.09	
Adjusted R-squared	0.07			Adjusted R-squared	0.08	
Durbin-Watson stat	2.21			Durbin-Watson stat	2.21	

Table 6.25. Cross Sectional Regressions – Investment Grade Categories

Investment Grade						
Method: GLS (Cross Section Weights)				**Method: Seemingly Unrelated Regression**		
White Heteroskedasticity-Consistent Standard Errors & Covariance						
Variable	**Coefficient**	**t-Stat**	**Prob.**	**Coefficient**	**t-Stat**	**Prob.**
C	0.01	1.08	0.02	0.08	6.23	0.00
EBDAR(-1)	-0.11	-5.44	0.00	-0.01	-5.42	0.00
CFD(-1)	-0.00	-0.27	0.09	-0.02	-3.39	0.00
DBCP(-1)	0.22	2.33	0.02	0.79	13.27	0.00
TDEBDA(-1)	0.05	1.11	0.00	0.12	4.29	0.00
CMT	-0.32	-3.85		-0.20	-4.60	0.00
Weighted Statistics						
R-squared	0.134					
Adjusted R-squared	0.129					
Unweighted Statistics				**Unweighted Statistics**		
R-squared	0.06			R-squared	0.07	
Adjusted R-squared	0.04			Adjusted R-squared	0.05	
Durbin-Watson stat	2.27			Durbin-Watson stat	2.26	

Table 6.26. Cross Sectional Regressions – Non - Investment Grade Categories

Non-Investment Grade						
Method: GLS (Cross Section Weights)				**Method: Seemingly Unrelated Regression**		
White Heteroskedasticity-Consistent Standard Errors & Covariance						
Variable	Coefficient	t-Stat	Prob.	Coefficient	t-Stat	Prob.
C	0.03	1.45	0.06	0.05	4.90	0.00
CMT	-0.43	-3.82	0.00	-0.58	-13.05	0.00
EBDAR(-1)	-0.07	-1.94	0.06	-0.04	-1.90	0.08
CFD(-1)	-0.06	-1.85	0.07	-0.05	-3.22	0.00
DBCP(-1)	-0.20	-6.20	0.00	-0.15	-2.59	0.01
TDEBDA(-1)	0.05	1.48	0.14	0.03	1.12	0.17
Weighted Statistics						
R-squared	0.45					
Adjusted R-squared	0.39					
Unweighted Statistics				**Unweighted Statistics**		
R-squared	0.29			R-squared	0.32	
Adjusted R-squared	0.22			Adjusted R-squared	0.26	
S.E. of regression	0.33			S.E. of regression	0.33	
Durbin-Watson stat	2.44			Durbin-Watson stat	2.09	

Results provided by the randomly selected sample of companies, don't only provide support for the same accounting variables that are useful in explaining changes in credit spreads, but also are able to explain a third of a variation in spreads in the high yield category although less than 10% in the total and investment grade samples. If we consider previous studies[69] that predict corporate collapse or credit ratings, which are able to explain over half of the changes in bond ratings, by using other dummy variables, makes our results, which are based solely on accounting ratios, more significant.

[69] J.O.Horrigan, "The determination of Long-term credit standing with Financial ratios", 1966.

6.3.Conclusions

Under this chapter the relation between a company's financials and credit spread changes was examined. This section has been inspired by the limited literature provided in using accounting ratios to predict changes in credit spreads. The reason is that changes in credit spreads can partially be considered as a stochastic variable, and as such, they can't be explained to a great extent by changes in the financials of a company, which are considered to be more static.

This explains why on an individual basis, accounting variables are very weak in explaining credit-spread changes, with the exception of a company's current market capitalisation. This has been the most significant variable, statistically and financially wise, when tested in all rating categories, irrespective of the statistical model employed, since it is considered to be more of a "continuous" rather than a "static" variable. However, results do provide support as to the nature and the structure of the relation between each variable and credit spreads, and to the value of accounting ratios as determinants of credit spread changes, particularly in the non-investment grade category. In particular, we reject the null hypothesis of a positive relation between changes in credit spreads and profitability, liquidity ratios and the company's current market capitalisation, although we don't reject the second part of the same hypothesis with respect to the information content of those ratios on an individual basis in explaining changes in credit spreads. The null hypothesis of the negative relation between leverage ratios and changes in credit spreads is rejected.

However, on a multivariate basis, we find that 63.5% of the variation in high yield credit spreads is explained by the changes in the aforementioned ratios, as reflected by the adjusted R^2, compared to an adjusted R^2 of 19.2% for investment grade companies. Particularly significant coefficients are obtained for leverage ratios and the current market capitalisation. Another reason for the high explanatory power of accounting variables in the high yield sector, is that we have used ratios reflecting depreciation and amortisation expenses, which are usually very high for non-investment grade companies and which hasn't been considered in previous studies.

[69] J.O.Horrigan, "The determination of Long -term credit standing with Financial Ratios", 1965.

If we assume that there is perfect accounting transparency and complete accurate and timely accounting information to investors, these would explain about one third of the variation in credit spreads, as provided by a randomly selected sample of high yield companies. This effectively supports the idea that traditional accounting credit risk modelling can still be pursued, and can provide some significant insight to credit/bond analysts.

Of course, traditional credit risk analysis can't be used on an individual basis to explain changes in credit spreads, since even at the best case scenario, it can explain only a limited part of the variation in credit spreads. This coincides with intuition and previous literature, in the sense that there are other issues that drive credit prices and generally credit risk, which can range from technical issues to market or macroeconomic information, or more importantly as explained above, analysts' subjective judgements, which can't be quantified or modelled not even within the context of the most sophisticated credit risk model.

7.0. Estimating & back testing the final credit risk model

The purpose of this chapter is twofold:

a. To develop a model that integrates the three sets of variables into a unique framework, and
b. To find the model with the strongest predictive ability, for forecasting credit spread changes one and two years ahead.

The purpose of the analysis so far, has been to estimate and establish a relation on an individual basis, between changes in credit spreads, equity, accounting and macroeconomic factors. Also and most importantly, the overall significance of the combination of aggregate and firm specific factors hasn't been determined yet. Nor the time sensitivity and validity of the estimated coefficients has been tested. As a result, the focus of this chapter is the assessment of the validity and sensitivity of the estimated coefficients when tested upon different time frames and on randomly selected samples. In other words, the accuracy of predicting credit spreads 12, 24 and 35 months ahead will be tested, using previously estimated coefficients.

To revise, the relation we are forecasting under this section is the following:

Equation 7.1.

$$\Delta Spreads_{it+1,..n} = f\,[\alpha + (\beta 1 * (\delta X_{it})) + (\beta 2 * (\delta F_{it})) + (\beta 3 * (\delta E_{it})) + \varepsilon_{it}]$$

Where:

i = 1, 2,…n and

Δ Spreads: denotes the change in spread on corporate bonds i.e. the change in the extra yield offered to compensate investors for a variety of risks..

δX_{it}: denotes the change in a set of US macro-economic variables including GDP growth, inflation, consumer confidence, money supply, the term structure of interest rates, etc.

δF_{it}: denotes the change in a set of factors composing the company's financial performance, i.e. ratios such as ROA, ROE, Debt to capital, cash flow to debt, etc.

δE_{it}: denotes the change in the respective companies' equity prices. As an additional explanatory variable the implied volatilities are being used, as those are being provided by the VIX index and lastly the companies' historical volatilities have been calculated and used to explain changes in credit spreads.

The forecasts of credit spreads will be estimated using two different methods for estimating coefficients. In particular, section 7.1. depicts dynamic credit spread forecasts estimated with the GLS method, adjusted for heteroscedasticity while Section 7.2. provides dynamic credit spread forecasts under the SUR method. Estimated credit spreads will be forecasted and evaluated based on the dynamic solution method.

7.1. Results & Forecasts based the GLS method

7.1.1. Review of results based on individual regressions

Before proceeding with the analysis of the results based on the aggregate regressions, we should summarise some of the main findings, when individual regressions were performed, across the investment and non-investment grade samples, based on the GLS method. In particular, the main findings could be summarised to the following:
The variable with the highest explanatory power is the VIX index. Changes in individual equity values is the next most significant explanatory variable and then follow the term structure of interest rates, US consumer confidence levels and current market capitalisation. Results obtained for the total sample (investment and non-investment grade) are estimated through the GLS method, and are similar irrespective of whether we use common coefficients (i.e. there is an identical intercept for all pool members $a_{it} = a$) or "fixed effects" whereby different intercepts are estimated from each pool member, i.e. $a_{it} = a_i$, $E(a,\varepsilon_{it}) \neq 0$.

The final independent variables which are going to be included in the cross sectional regressions are those that have the highest correlation with credit spreads and those that seem to have the strongest explanatory power (on an individual basis) to credit spread changes across the rating categories. As has been mentioned above these will only include a sub-group of the above explicitly described factors while those, which are correlated amongst them, are going to be excluded.

7.1.2. Aggregate Regressions – GLS method

As a first step, the variables and weights for the total period are going to be estimated and then credit spread changes are going to be determined with the use of the following explanatory variables, i.e. VIX index, US Consumer Confidence levels, term structure of interest rates, equity, current market capitalisation and cash flow to debt, total debt to ebitda and lastly debt to capital employed. Running the cross sectional regressions yielded the results provided in table 7.1.:

Table 7.1. Aggregated Regressions on Investment & Non-investment grade sample

	Investment & Non-Investment Grade		
Variable	Coef.	t-Stat	Prob.
C	0.04	18.8	0.00
VIX	0.44	13.3	0.00
Term Structure	-0.54	-15.4	0.00
Current Market Capitalisation	-0.02	-2.07	0.00
CONF	-0.74	-10.6	0.00
Cash Flow to Debt	-0.05	-3.23	0.00
Equity	-0.21	-14.5	0.00
Total Debt to Ebitda	0.04	1.84	0.02
Weighted Statistics*			
R-squared	0.95		
Adjusted R-squared	0.95		
S.E. of regression	0.09		
Durbin-Watson stat	2.34		
Unweighted Statistics**			
R-squared	0.52		
Adjusted R-squared	0.49		
S.E. of regression	0.10		
Durbin-Watson stat	2.44		

** GLS using estimated cross-section residual variances*
***All observations are given equal weight*

As it becomes apparent, the proposed variables are very significant both in economic and statistical terms. Highly significant t-statistics[70] are reported for the term structure of interest rates, the VIX index, equity and consumer confidence index, while adjusted R-squares are particularly significant as part of the weighted statistics, while when all observations in the cross sections are given equal weights, at the best case scenario they seem to explain half of the variation in credit spreads.

Running additional regressions on a sub-set of the investment and non-investment grade sample, i.e. including fewer time series observations (to test for the time sensitivity of the results), we conclude that although results reported by unweighted statistics aren't that much different (R^2 range from 42%-54%), the output from the weighted statistic range from R^2 60% - 95%, which still is very high in explaining credit spread changes.

As a second step in the analysis, regressions are run separately for investment and non-investment grade bonds. Results provided by those regressions are presented in tables 7.2. and 7.3 respectively. As it is observed, overall the significance of results is reduced once the above regressions are run separately for the investment and non-investment grade bands, but still results are statistically and economically significant.

Table 7.2. Aggregate Regressions on Investment Grade Sample

	Investment Grade		
Variable	Coef.	t-Stat	Prob.
C	-0.02	-9.36	0.00
VIX	0.40	18.9	0.00
Term Structure	-0.06	-10.8	0.00
Current Market Capitalisation	-0.03	-5.54	0.00
CONF	-0.93	-15.9	0.00
Cash Flow to Debt	-0.06	-2.34	0.00
Equity	-0.11	-7.75	0.00
Total Debt to Ebitda	0.04	6.66	0.00
Weighted Statistics			
R-squared	0.35		
Adjusted R-squared	0.35		
S.E. of regression	0.10		
Durbin-Watson stat	2.23		
Unweighted Statistics			
R-squared	0.28		
Adjusted R-squared	0.27		
S.E. of regression	0.09		
Durbin-Watson stat	2.45		

[70] It is important to note that all t-statistics are calculated with the White test for heteroscedasticity and

Table 7.3. Aggregate Regressions on Non-Investment Grade

	Non - Investment Grade		
Variable	Coef.	t-Stat	Prob.
C	0.07	2.94	0.00
VIX	0.75	17.02	0.00
Term Structure	0.02	14.6	0.00
Current Market Capitalisation	-0.01	-4.85	0.00
CONF	-0.87	-12.08	0.00
Cash Flow to Debt	-0.07	-4.43	0.00
Equity	-0.24	-12.8	0.00
Total Debt to Ebitda	0.08	3.97	0.00
Weighted Statistics			
R-squared	0.66		
Adjusted R-squared	0.66		
S.E. of regression	0.08		
Durbin-Watson stat	2.34		
Unweighted Statistics			
R-squared	0.52		
Adjusted R-squared	0.52		
S.E. of regression	0.07		
Durbin-Watson stat	2.33		

Results provided above, are consistent with regression results provided in previous chapters and prove the higher explanatory power of these variables on non-investment grade bonds.

Results provided from the aggregate regressions, compare similarly to those reported by Huang, Jing-Zhi, Kong, Weipeng (2003)[71], which is the only other study that looks at option adjusted spreads. Although they use a different methodology and different set of explanatory variables, they also report that the eight factors considered in their model can explain more than 40% of credit spread changes for investment grade bond indices, and 67.68% and 60.82% of credit spread changes for the B and BB rated indices.

Once we have determined the most influential factors in determining credit spread changes, both from a statistical and economic standpoint the sample is divided in two sub periods, whereby the effort is focused on estimating the required credit risk model from coefficients estimated from the period of January 1997 until June 2000 and proceed with credit spread forecasts for five data points ahead, with no less than

autocorrelation consistent covariance matrix.

2,500 degrees of freedom, depending on the sub-sample used (investment or non investment grade), i.e.:

- 1 quarter ahead
- 2 quarters ahead
- 1 year ahead
- 2 years ahead
- 2 and three quarters ahead.

It is worth recalling from section 3.4 based on the table of descriptive statistics reported by average mean spread levels by year, that the standard deviation increased, with volatility levels being extremely high on average in the fall of 2000, 2001 and 2002. This makes the forecasting work a bit harder since we will be trying to estimate the credit spread levels for the last two years. On the other hand, if a robust model is found for forecasting credit spreads in years 2001 and 2002, which exhibit such high volatility, this will make results more reliable and rigorous.

The data that will be used in order to back test and calibrate the credit risk model is quarterly data. In particular, cross sectional regressions were run from observations 1 to 15 corresponding to the relevant quarters for the period January 1997 until June 2000. The independent variables used in order to estimate the model were those provided in tables 7.2-7.3.

7.1.3. Forecasts and Evaluation methodology

As a third step in the analysis, using the independent variables described above, we run pooled regressions for the individual rating categories based on data from January 1997 until June 2000 (forecasted results of those regressions are provided in section 7.1.4.). In order to proceed with the credit spreads forecasts, we created a model in "Eviews", that solves for the independent variable, i.e. changes in credit spreads for the period to be forecasted, i.e. from July 2000 until May 2002. Equations are automatically generated for each particular company within the group we are trying to

[71] The factors they consider are the Russell 2000 index, the Conference Board composite leading and coincident economic indicators, the interest rate level, the historical interest rate volatility, the yield curve slope and a high minus low factor.

forecast. Once equations are automatically processed, then we are proceeding with a dynamic solution for the required model. Specifically,

7.1.3. (a) Description of the Dynamic Solution Method

The initial observation in the forecast sample will use the actual value of lagged Y (i.e. change in spread). Thus if S is the first observation in the forecast sample then the model will compute:

$$Ys = c(1) + C(2)X_s + c(3)Z_s + c(4)Y_{s-1}$$

Where Ys-1 is the value of the lagged endogenous variable in the period prior to the start of the forecast sample. This is the one step ahead forecast.

Forecasts for subsequent observations will use the previous forecasted values of Y, i.e.

$$Y_{s+k} = c(1) + C(2)X_{s+k} + c(3)Z_{s+k} + c(4)Ys_{s+k-1}$$

These forecasts may differ significantly from the one step ahead forecasts. If there are additional lags of Y in the estimated equation, the above algorithm is modified to account of the non-availability of lagged forecasted values in the additional period. For example if there are three lags of Y in the equation:

(1) The first observation uses the actual values for all three lags, Y_{S-3}, Y_{s-2}, Y_{s-1}
(2) The second observation (S+1) uses actual values for Y_{s-2} and Y_{s-1} and the forecasted value of the first lag Y_S
(3) The third observation (S+2) will use the actual values for Y_{s-1} and forecasted values for the first and second lags Y_S and Y_{s+1}
(4) All subsequent observations will use the forecasted values of all lags

As a result the start of the forecast sample is very important for dynamic forecasting. The dynamic forecasts are true multi step forecasts (from the start of the forecast sample) since they recursively compute forecast of the lagged value of the dependent variable. These forecasts may be interpreted as forecasts for subsequent periods that would be computed using information available at the start of the forecast sample.

In order to perform dynamic forecasts, data for the exogenous variables should be available for every observation in the forecast sample and values of the dependent variables should be observed at the start of the forecast sample.

7.1.3. (b) Forecasts Evaluation

The statistical package used in this study doesn't provide forecast evaluations for coefficients estimated using pool objects and cross sectional regressions. As a result, forecast evaluations based on cross sectional estimation of coefficients will be calculated manually.

Many studies have been conducted to identify which method will provide the most accurate forecasts for a given class of time series. However, there has been no literature identifying the most accurate forecasting method in terms of cross sectional data.

Generally, comparisons of errors across series can be very complex, and as a result a single error measure is desirable. However, the choice of an error measure can vary according to the situation. For example, the choice of an error measure can vary according to the scale across series, the amount of change that occurs over the forecast horizon and the presence of extreme forecast errors (outliers). One of the main properties for an error measure is that it should be unit free.

This is something that hasn't be widely appreciated in the early 1980s according to a research made by Carbone and Armstrong (1982). They asked 145 forecasting experts which was the preferable error measure when looking at the accuracy of different forecasting methods. Most practitioners have selected the Root Mean Square Error (RMSE) and academicians had an even stronger preference for the same measure although it is not unit free.

The RMSE has been frequently used to draw conclusions about forecasting methods. For example, Zellner (1986) claimed that the Bayesian method was the most accurate method in the M-competition data, because its RMSE was the lowest. However, Chatfield (1988) in a re-examination of the M-competition data, showed that five of the 1001 series dominated the RMSE rankings. The remaining 996 series had little impact on the RMSE rankings of the forecasting methods.

Lately, there seems to be increased preference for unit-free measures for comparing methods. One such measure is the percentage of forecasts for which a given method is more accurate than the random walk (Percent better). Another way to control for scale is to calculate the error as a percentage of the actual value. The most widely used unit free measure is the Mean Absolute Percentage Error (MAPE). A disadvantage of MAPE is that it is relevant only for ratio scaled data (data with a meaningful zero). Another disadvantage of the MAPE is that it puts a heavier penalty on forecasts that exceed the actual values than on those that are less than the actual. For example the MAPE is bounded on the low side by an error of 100% but there is no bound on the high side.

Interestingly enough, there is no error measure that is 100% better than another in absolute terms. In a paper by Armstrong and Collopy (1992), they analysed 90 annual and 101 quarterly economic time series and judged error measures on reliability, validity, sensitivity to small changes, protection against outliers and their relation to the decision making process. Based on their empirical results (for reliability and construct validity) and subjective judgment they rated each error measure as good, fair or poor with respect to different criteria. The ratings are shown in the following table:

Error Measure	Reliability	Construct Validity	Outlier Protection	Sensitivity	Relationhip to decisions
RMSE	Poor	Fair	Poor	Good	Good
Percent Better	Good	Fair	Good	Poor	Poor
MAPE	Fair	Good	Poor	Good	Fair
MdAPE	Fair	Good	Good	Poor	Fair
GMRAE	Fair	Good	Fair	Good	Poor
MdRAE	Fair	Good	Good	Poor	Poor

Where:RMSE: Root Mean Square Error, Percent Better: percentage of forecasts for which a given method is better than the random walk, MAPE: Mean Absolute Percentage Error, MdAPE:Median Absolute Percentage Error, GMRAE:Geometric Mean of the Relative Absolute Error, MdRAE:Median Relative Absolute Error

As presented in the table above there is no error measure that performs well in all the criteria tested. This means that the choice of the error measure is somewhat subjective. In addition, it should be noted that these conclusions are derived for comparisons across multiple time series. The conclusions do not necessarily apply to the examination of a single time series, or when comparing times series of cross sectional data. Nevertheless they can provide some guidance as to the choice of the error measure.

In this study we will employ dynamic forecasting as mentioned above, and we will be using the mean absolute percentage error (MAPE) and the Root mean squared error (RMSE) to evaluate our forecasts. The RMSE depends on the scale of the dependent variable. The MAPE is scale invariant. These two measures are defined as follows:

Root Mean Squared Error:

$$\sqrt{\frac{1}{h+1}\sum_{t=S}^{S+h}(\hat{y}_t - y_t)^2}$$

Mean Absolute Percentage Error:

$$\frac{1}{h+1}\sum_{t=S}^{S+h}\frac{\hat{y}_t - y_t}{y_t}$$

Once the RMSEs and the MAPEs have been calculated for each time series and each cross section, they have been averaged across the sections used to give an average for each pool. Various measures of central tendency can be used to summarize the errors across each pool. Here, we will be using arithmetic means to summarize the errors for each pool. Medians have also been calculated and compared against the means, as a way to detect the outliers in the forecasts. Using medians is an extreme way to trim outliers as it removes all values higher and lower than the middle value.

Given that we are using the same dynamic method for forecasting credit spread changes, based on the error measures we can only draw conclusions on whether the model forecasts better in the investment or non investment grade companies, or perform better in the one or two years horizon. As a result a better forecast is defined when both the RMSE and the MAPE are smaller. The results are provided below.

7.1.4. Empirical Results on Credit Spread Forecasts based on the GLS method

Table 7.4.Investment Grade Forecast Errors

	Pool AAA		Pool AA		Pool A		Pool BBB	
	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE
1 quarter ahead forecast	0.19	-0.10	0.20	0.45	0.04	-0.65	0.18	0.19
2 quarters ahead forecast	0.11	-0.46	0.18	-0.06	0.02	-0.35	0.20	0.06
1 year forecast	0.11	-0.04	0.32	0.69	0.09	-0.05	0.40	0.10
2 years forecast	0.22	-2.25	0.24	-0.20	0.06	-0.02	0.17	-0.32
2 years & 3 quarters ahead	0.24	-0.28	0.51	0.61	0.11	-0.01	0.36	-0.25

Table 7.5. Non-Investment Grade Forecast Errors

	Pool BB		Pool B		Pool C	
	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE
1 quarter ahead forecast	0.33	0.33	0.31	-2.8	0.36	0.22
2 quarters ahead forecast	0.34	1.16	0.27	-1.6	0.47	-1.99
1 year forecast	0.32	46.6	0.28	-0.73	0.78	-1.64
2 years forecast	0.35	0.78	0.28	-0.60	0.21	4.76
2 years & 3 quarters ahead	0.54	17.1	0.38	-0.80	0.64	3.21

Average RMSEs are relative low in the investment grade category and higher on average in the non-investment grade. Overall, errors are less than one third within one and two year horizons with the exception of the pool C and pool B (for 2 years and 3 quarters ahead forecasts).

In order to depict the forecasted changes in credit spreads in real spread values, we worked backwards in order to calculate their respective spread levels. In particular, having as a starting point the level of spread from January 1997 and using the estimated forecasted changes in spreads, the levels of the forecasted credit spreads have been calculated. Then the mean values have been calculated for the respective observations for each particular company both for actual spread levels as well as the forecasted ones. These mean values have then been averaged to obtain an average spread for each rating category.

Tables 7.6 and 7.7., provide the average forecasted spreads per rating category and per quarter we are forecasting. Intuitively, we should expect forecasts to be more accurate for bonds in the investment grade category (due to lower volatility compared to the non-investment grade bonds) and for the immediate quarter's forecasts rather than the latter ones.

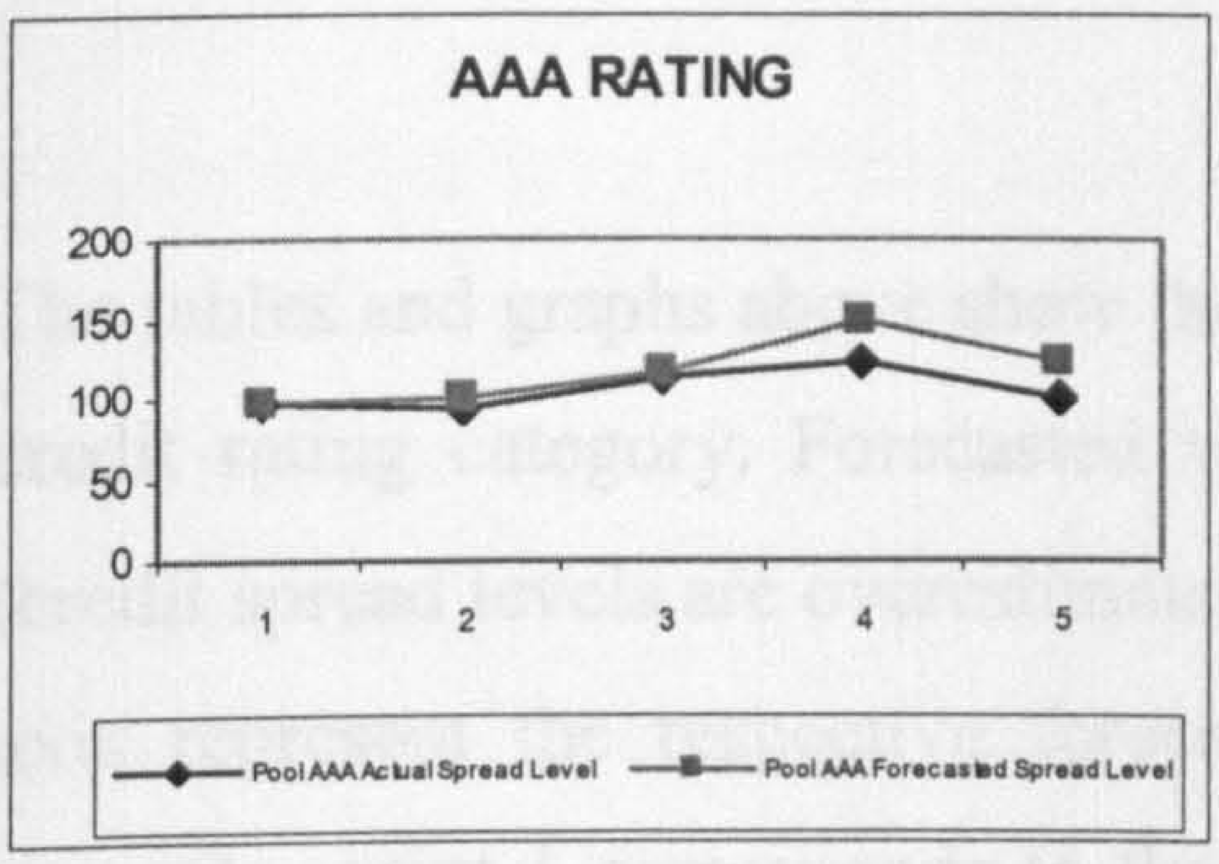
7.6. Investment Grade Forecasted Values based on the GLS method

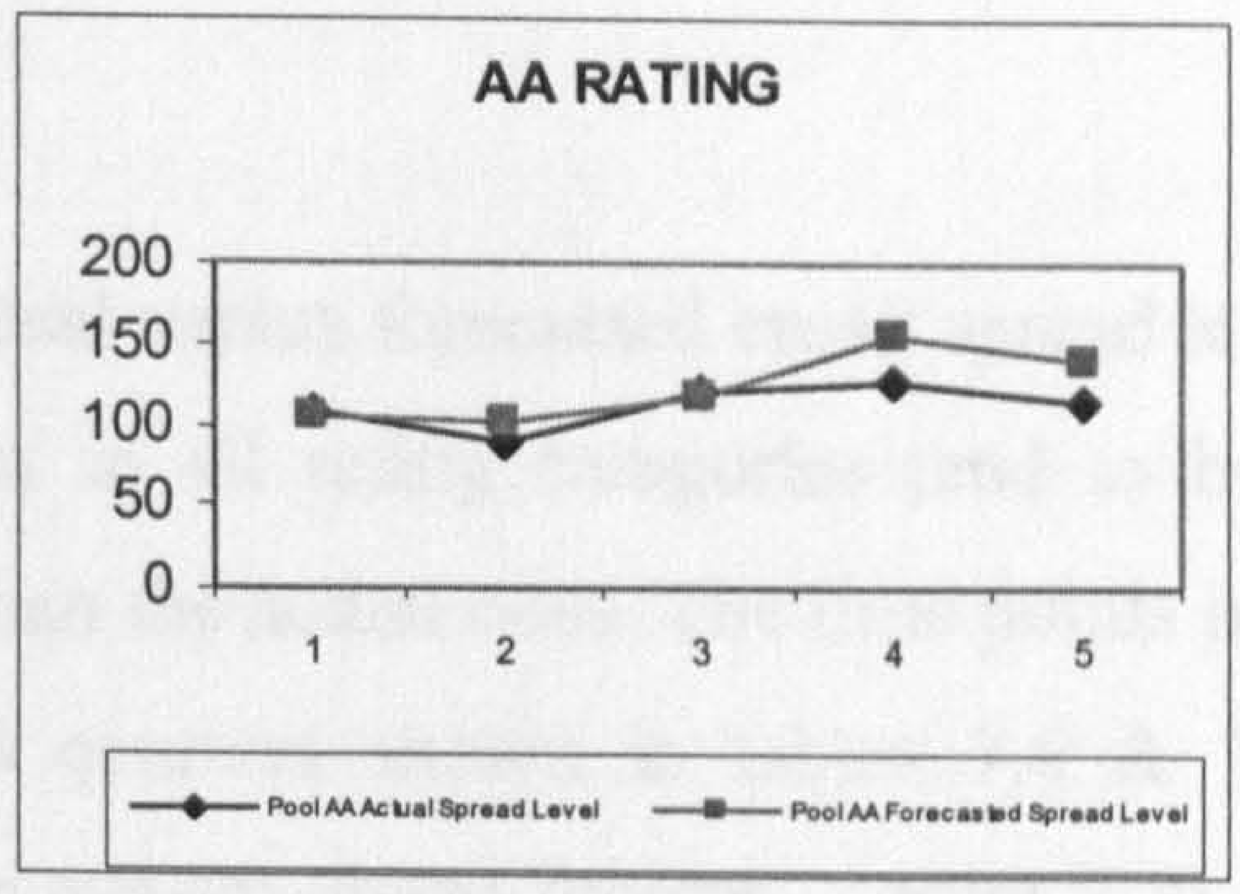
	Pool AAA		**Pool AA**		**Pool A**		**Pool BBB**	
	Average Actual Spread Level	Average Forecaste d Spread Level	Average Actual Spread Level	Average Forecaste d Spread Level	Average Actual Spread Level	Average Forecaste d Spread Level	Average Actual Spread Level	Averag e Forecas ted Spread Level
1 quarter ahead forecast	97.75	97.98	107.57	105.32	118.90	130.27	182.22	205.56
2 quarters ahead forecast	93.50	100.03	89.85	101.78	106.40	126.38	175.44	194.38
2 quarters ahead forecast (cumulative)	95.63	99.01	98.71	103.55	112.65	128.32	178.83	199.97
1 year forecast	112.81	114.59	119.71	119.02	129.31	132.39	214.22	214.75
2 years forecast	123.06	148.34	126.89	155.34	141.94	166.21	239.05	279.14
2 years forecast ***(cumulative)***	123.06	148.34	123.30	139.46	135.63	149.30	226.63	246.94
2 years & 3 quarters ahead	99.18	123.21	113.91	139.45	138.73	159.05	220.57	256.65
2 years & 3 quarters ahead ***(cumulative)***	106.93	130.31	116.02	131.27	133.05	136.92	218.26	241.42

7.7. Non-Investment Grade Forecasted Values based on the GLS method

	Pool BB		Pool B		Pool C	
	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level
1 quarter ahead forecast	232.0	296.49	318.2	364.55	608	526.05
2 quarters ahead forecast	203.8	277.32	326	353.40	646.57	2,052.56
2 quarters ahead forecast (cumulative)	217.9	286.91	322.1	358.98	627.28	1,289.35
1 year forecast	242.9	293.40	370.2	378.03	833.5	1,063.89
2 years forecast	350.7	376.38	591.75	663.21	1,598.33	1,738.54
2 years forecast ***(cumulative)***	296.8	334.89	480.97	520.62	1,215.94	1,401.22
2 years & 3 quarters ahead	350.08	373.10	562.71	626.80	1,720.24	1,795.42
2 years & 3 quarters ahead ***(cumulative)***	311.07	344.12	492.70	536.34	1,397.79	1,521.49

To make comparisons easier, the respective figures will be presented graphically in the tables that follow.


AAA RATING
200
150
100
50
0
1
2
3
4
5
Pool AAA Actual Spread Level
Pool AAA Forecasted Spread Level


AA RATING
200
150
100
50
0
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2
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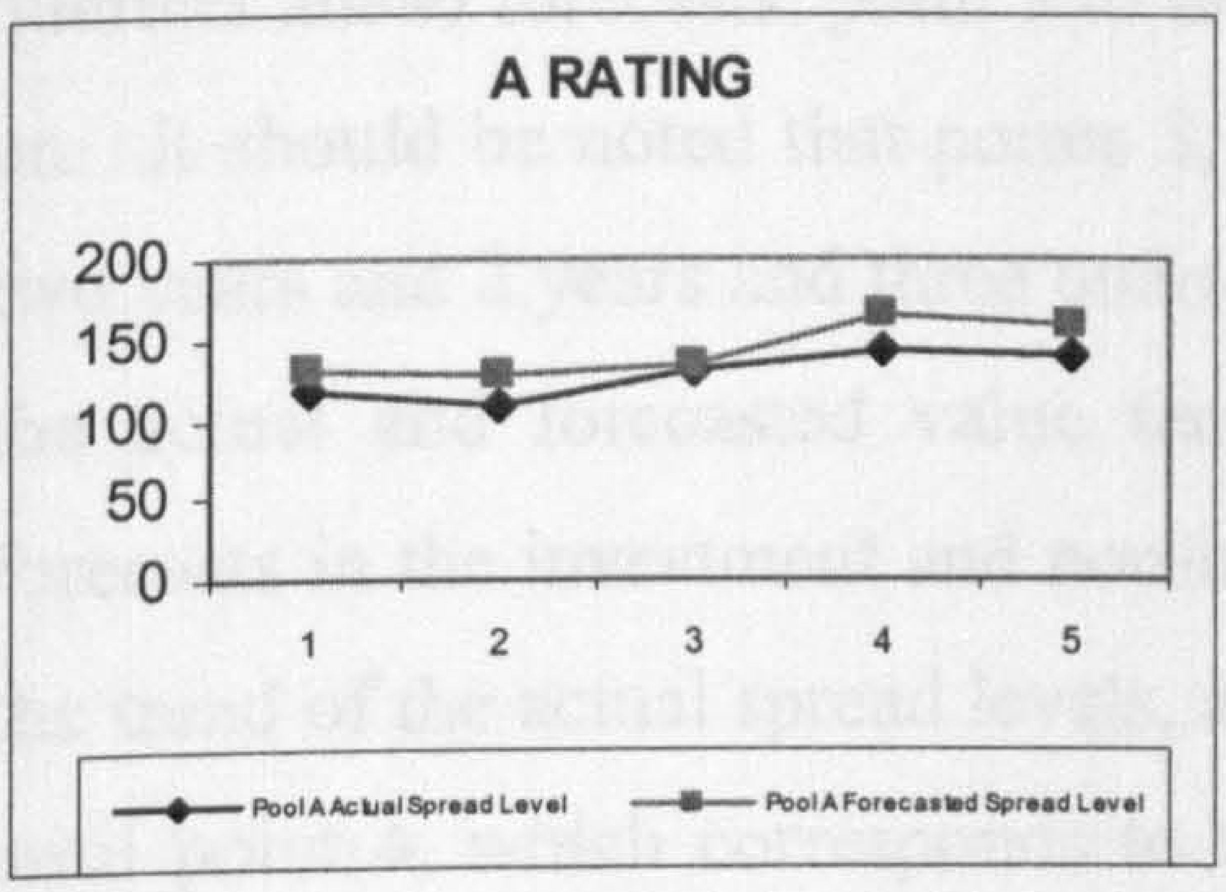
4
5
Pool AA Actual Spread Level
Pool AA Forecasted Spread Level


A RATING
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150
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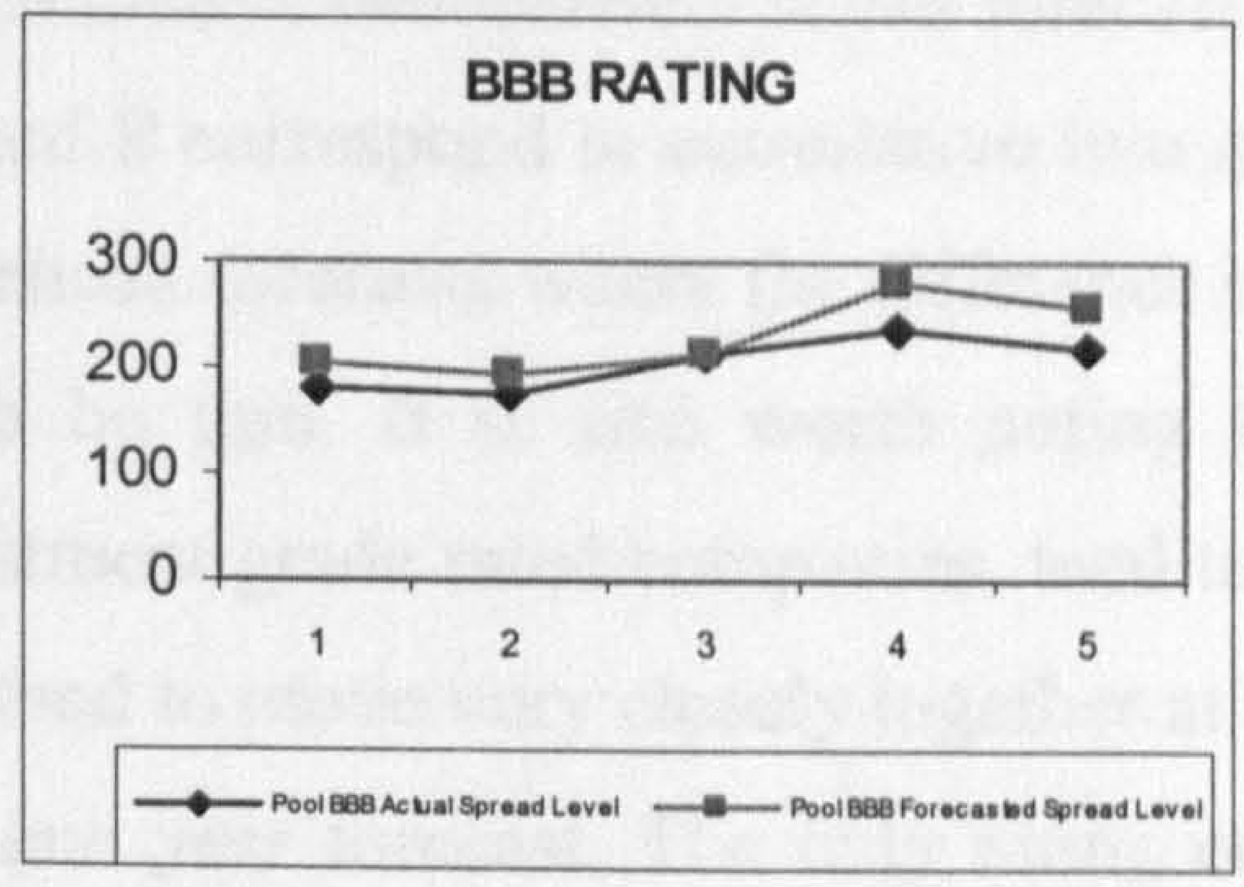
Pool A Actual Spread Level
Pool A Forecasted Spread Level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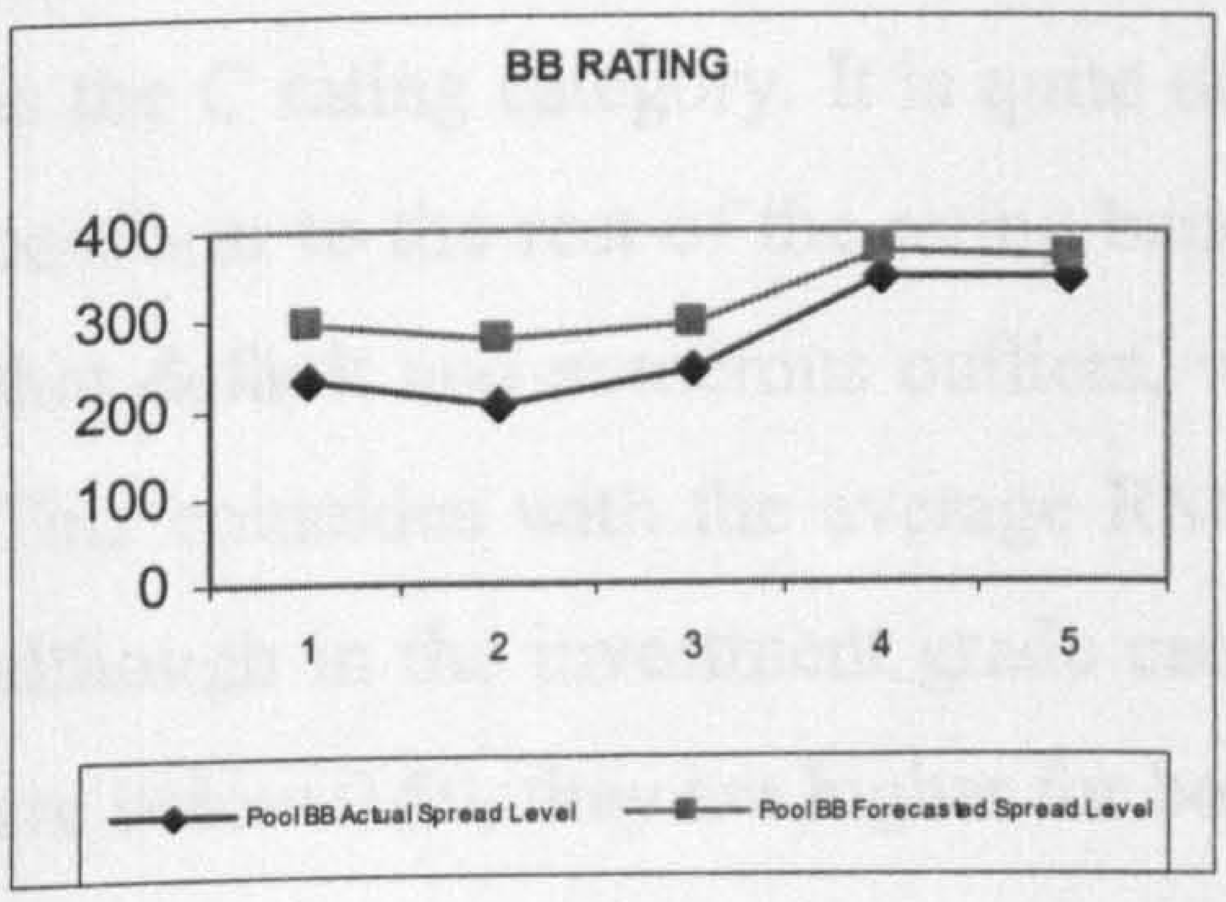
Pool BBB Actual Spread Level
Pool BBB Forecasted Spread Level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100
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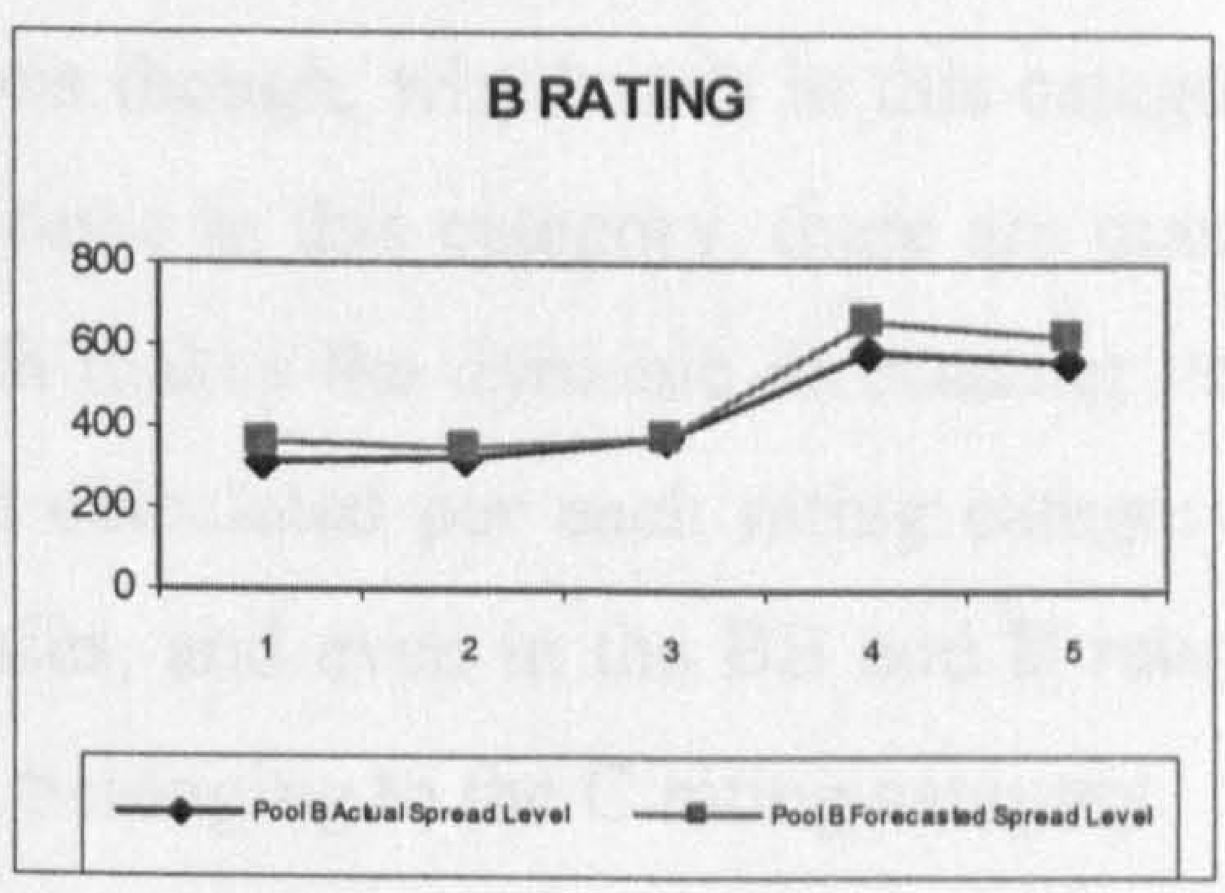
Pool BB Actual Spread Level
Pool BB Forecasted Spread Level


B RATING
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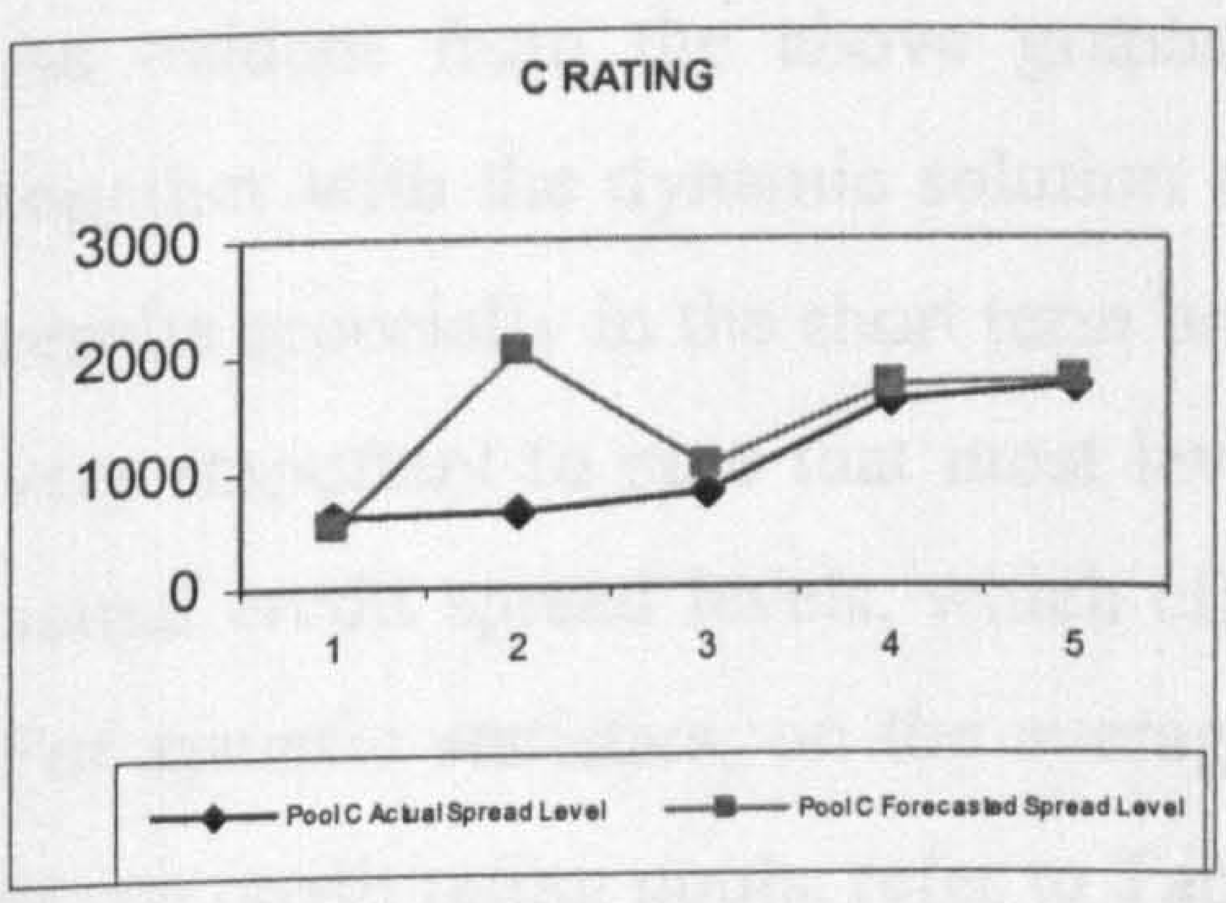
Pool B Actual Spread Level
Pool B Forecasted Spread Level


C RATING
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Pool C Actual Spread Level
Pool C Forecasted Spread Level

The tables and graphs above show the actual versus forecasted credit spread levels per credit rating category. Forecasted values in all rating categories tend to be larger (credit spread levels are overestimated) than the actual ones. The time points on the x-axis represent the respective forecasted quarters shown in tables 7.6 & 7.7. For example, point 1 corresponds to the one quarter ahead forecast, point 2 to the two quarters ahead forecasts, point 3 to the cumulative two quarters ahead forecast and so on. It should be noted that points 3, 6 and 8 correspond to cumulative two quarters, two years and 2 years and three quarters ahead forecasts where the difference between the actual and forecasted value tend to be thin. It is also worth noting that the forecasts in the investment and non-investment grade rated companies, tend to follow the trend of the actual spread levels, and tend to move very closely together at least up until point 4, which corresponds to the one year forecast. The only rating category, where forecasted values don't follow the actual ones, even in the short-term forecasts is the C rating category. It is quite obvious though, why bonds in this category don't conform to the rest of the rating bands, since in this category, there are many bonds that default and numerous outliers, which makes the dynamic forecasting very hard. This coincides with the average RMSEs calculated per each rating category, which although in the investment grade categories, and even in the BB and B rating bands are below 0.50, they are higher for bonds belonging to the C rating category.

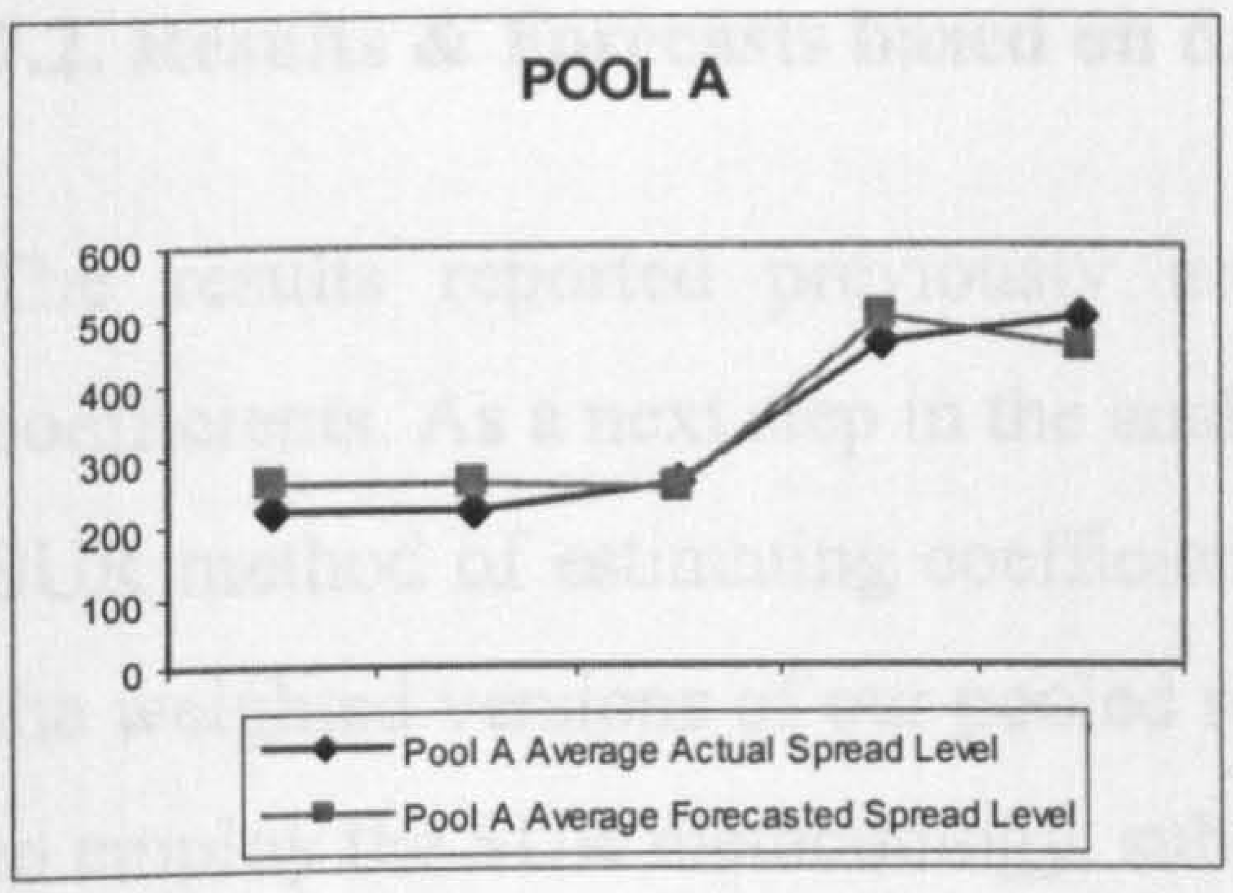
As evident from the above graphs, the GLS method for estimating coefficients together with the dynamic solution method, can provide very satisfying and reliable results especially in the short term both in investment and high yield sample. It is also very important to note that most levels of credit spread forecasts are overestimating actual credit spread levels, which effectively means that they are more conservative. For specific statistics, on the average forecasting ability in percentage terms, of the seven credit rating pools, refer to Table 1 of Appendix 7A. This shows the percentage of mean actual spread divided by mean forecasted spread, for all rating categories and all quarter forecasts ahead, where it is obvious that the only time when forecasted spread is overestimated in the 1 quarter ahead horizon is for the AA and C–rated category (102% and 115% respectively).

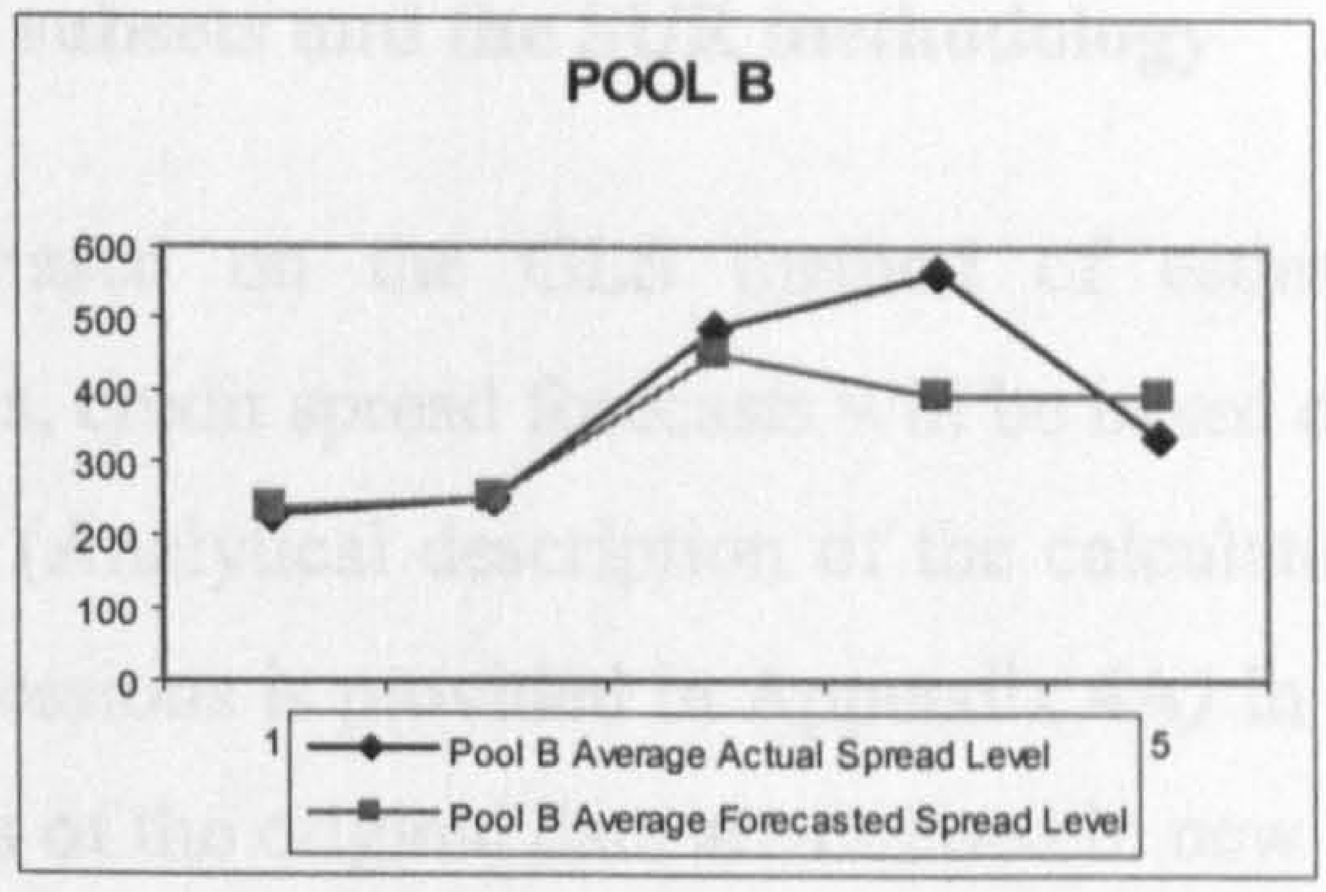
It should be mentioned though, that the estimated coefficients used in the above forecasts have been estimated separately for the investment and non-investment grade sample. This means that although forecasts, may be robust in terms of out of sample forecasting, in the sense that coefficients have been estimated from another period than the one forecasted, we haven't tested whether robust forecasts can be produced by pools which would include different rated companies, both investment and non investment grade ones.

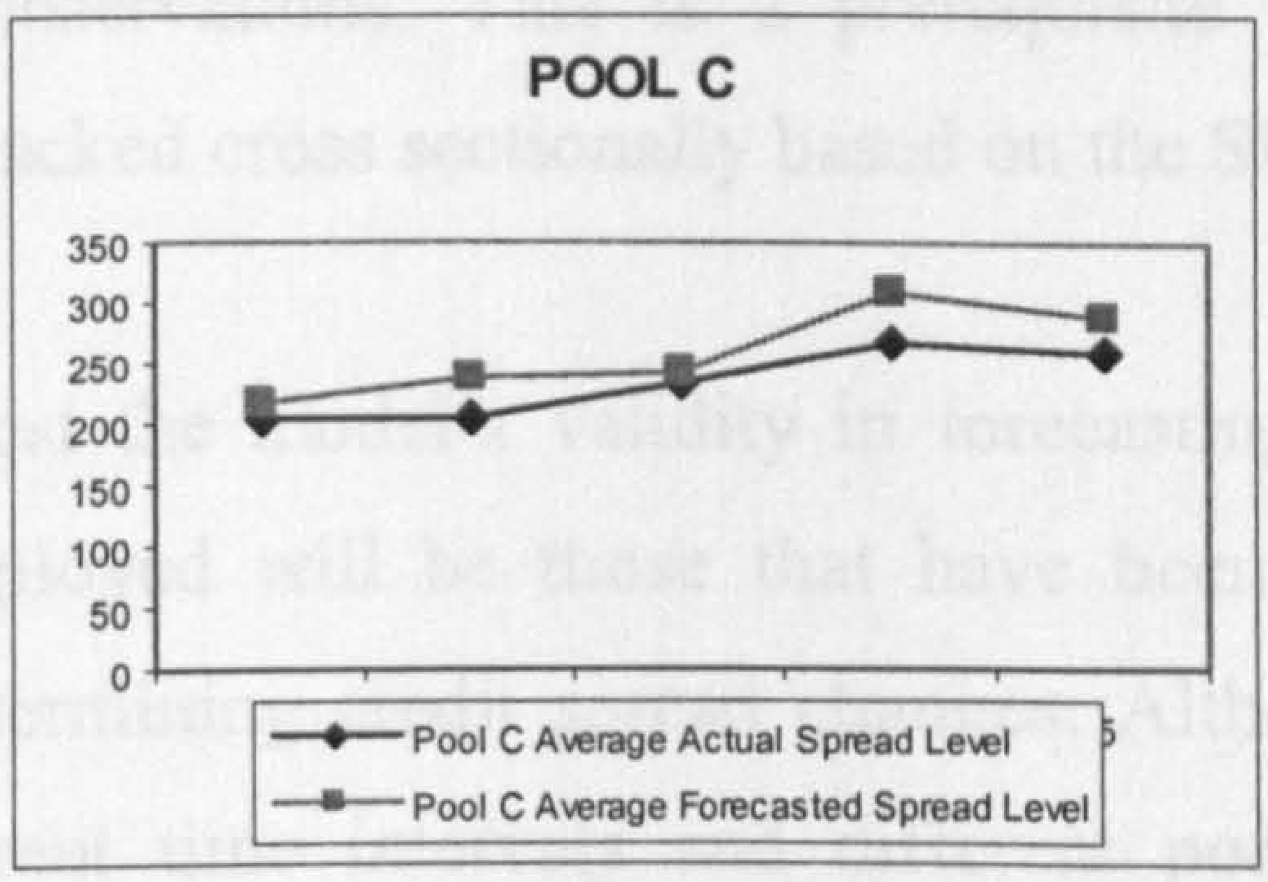
Consequently, three pools of companies have been created, each of which includes a randomly selected sample of companies belonging in the seven broad rating categories. The only restriction in these pools is, that the selection is proportionate to the number of companies in each rating band, so that the sample and results won't be biased. i.e. in the selection process, we had to satisfy the condition that not all bonds would come from the AAA rating band, nor that most would belong to the investment rating categories. The results of those randomly selected pools are shown below:

Table 7.8. Forecasted Values based on the GLS method

	Pool A		**Pool B**		**Pool C**	
	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level
1 quarter ahead forecast	223.72	261.18	225.41	239.04	204.92	218.27
2 quarters ahead forecast	220.77	261.79	249.33	247.05	203.76	237.81
2 quarters ahead forecast (cumulative)	222.25	261.49	237.37	243.04	204.34	228.04
1 year forecast	257.90	250.29	489.07	451.20	232.53	239.86
2 years forecast	456.30	500.00	564.03	392.62	265.05	308.50
2 years forecast ***(cumulative)***	357.10	375.01	307.15	327.91	248.79	274.18
2 years & 3 quarters ahead	497.84	455.20	333.79	391.50	260.29	286.29
2 years & 3 quarters ahead ***(cumulative)***	410.59	380.69	316.15	344.85	250.20	269.40







Results provided by the randomly selected pools of companies, provide very strong forecasts. In particular, in the one quarter ahead forecasts, the model can accurately predict 85%, 94% and 94% of the variation in credit spreads for the respective pools. In the second quarter, the percentage accurately forecasts is 84%, 101% and 85% while for one year ahead, it is 103%, 108% and 97% respectively.(For an analytical description of the forecasting ability in percentage terms of the three randomly selected samples, refer to Table 2, Appendix 7A). It should be noted though, that in two out of the three randomly selected pools, after the forecast of 1 quarter ahead, forecasted values of credit spreads are lower than the actual ones, while in Pool C, all forecasted values are higher than the actual ones. This underestimation of credit spreads, after the 1 quarter can be rather dangerous. In other words, a model that would provide us credit spread forecasts higher than the actual ones, is acceptable, given the current variables, in the sense that this would make forecasts more conservative. What though can be greatly misleading is a model that would provide more optimistic credit spreads forecasts than the actual ones. In other words, in the finance world, a credit risk model is much more preferable when it predicts a company's default, even if default doesn't occur, rather than a model that predicts good returns and the company goes into default.

7.2. Results & Forecasts based on data subsets and the SUR methodology

The results reported previously are based on the GLS method of estimating coefficients. As a next step in the analysis, credit spread forecasts will be based on the SUR method of estimating coefficients. (Analytical description of the calculation of the weighted versions of our pooled regressions is provided in Appendix 4A*)* In order to employ the SUR methodology, subsets of the original data are defined in new pools that include a smaller number of cross sectional observations equal to the number of time series observations. This is a prerequisite in order to perform time series regressions stacked cross sectionally based on the SUR methodology.

In order to test the model's validity in forecasting credit spreads, the independent variables employed will be those that have been identified to have the strongest impact in determining credit spread changes. Although this time they are regressed against different time intervals and different pools of companies. In particular, forecasted credit spreads based on the SUR method will be computed for:

(a) **Seven pools**, equal to the number of credit rating bands, which will include a random selection of companies in each rating pool.

(b) **Three different pools** (pool a, pool b, pool c) each of which will include a randomly selected, proportionate number of companies relative to the number of companies that exist in each rating category,

7.2.1.(a) Regression Results based on the SUR methodology

The next set of tests is focused in examining whether more reliable forecasts could be observed for the seven credit rating pools under the SUR methodology. Following the same rationale, as described under the GLS method, we estimate the regression coefficients for the period 1997 until June 2000, for the seven pools, corresponding to the seven rating categories (tables 7.12 and 7.13), then we are calculating the average RMSEs and MAPEs for investment and non-investment grade companies (tables 7.14 and 7.15) and then working backwards, as described in section 7.1.4, we are calculating the mean credit spread levels per rating bands and pools. The results of the average actual and forecasted credit spreads are shown in the tables 7.16 and 7.17.

Table 7.12.Cross Sectional Regression Results based on SUR, Investment Grade

	Pool AAA			Pool AA			Pool A			Pool BBB		
Variable	Coef.	t-Stat.	Prob.	Coef.	t-Stat.	Prob.	Coef.	t-Stat.	Prob.	Coef.	t-Stat.	Prob.
C	0.11	5.03	0.00	0.00	-0.03	0.08	0.12	7.95	0.00	0.14	13.30	0.00
VIX	0.01	0.15	0.08	0.22	1.33	0.19	0.56	7.05	0.00	0.40	11.80	0.00
Term Structure	-0.02	-1.70	0.06	-0.11	-5.4	0.00	-0.07	-8.90	0.00	-0.07	-1.84	0.00
Current Market Capitalisation	-0.04	-1.76	0.06	-0.03	-1.89	0.06	-0.09	-7.88	0.00	-0.01	-0.89	0.00
Equity	-0.01	-0.08	0.09	-1.16	-5.72	0.00	-0.05	-0.58	0.08	-0.28	-4.43	0.00
Cash Flow to Debt	0.08	1.83	0.08	1.49	5.97	0.00	0.06	1.64	0.09	0.00	4.01	0.00
CONF	-4.36	-8.58	0.00	-0.61	-0.36	0.07	-3.11	-3.58	0.00	-2.04	-6.29	0.00
EBIT	-0.19	-2.94	0.01	0.02	0.27	0.08	0.05	4.71	0.00	0.01	3.09	0.00
GDP	-0.19	-4.85	0.00	-0.30	-2.46	0.02	-0.06	-1.47	0.09	-0.06	-2.96	0.00
DBCP	-0.16	-3.10	0.01	1.86	7.61	0.00	-0.60	-3.40	0.00	-0.14	-1.84	0.07
R-squared	0.81			0.14			0.83			0.61		
Adjusted R-squared	0.75			0.01			0.79			0.56		
S.E. of regression	0.13			1.01			0.17			0.21		
Durbin-Watson	1.84			1.96			2.14			2.27		

Table 7.13.Cross Sectional Regression Results based on SUR, Non-Investment Grade

	Pool BB			Pool B			Pool C		
Variable	Coef.	t-Stat.	Prob.	Coef.	t-Stat.	Prob.	Coef.	t-Stat.	Prob.
C	0.16	12.97	0.00	0.09	3.81	0.00	0.01	0.20	0.05
VIX	0.64	12.73	0.00	0.41	5.27	0.00	0.27	4.16	0.01
Equity	-0.13	-2.94	0.01	-0.23	-2.82	0.01	-1.04	-3.84	0.02
Term Structure	0.14	5.60	0.00	0.19	7.83	0.00	0.17	9.51	0.00
CMT	-0.45	-7.80	0.00	-0.62	-8.1	0.00	-0.44	-6.99	0.00
Cash Flow to Debt	0.04	3.11	0.00	-0.05	-1.94	0.06	-0.08	2.05	0.00
CONF	-2.59	-5.52	0.00	-3.43	-4.09	0.00	-1.39	-3.94	0.02
EBIT	0.07	6.00	0.00	0.06	1.69	0.10	0.04	1.27	0.10
GDP	-0.15	-5.07	0.00	-0.20	-6.09	0.00	-0.13	-4.95	0.00
DBCP	0.51	3.40	0.00	-0.66	-2.03	0.05	1.07	7.86	0.00
R-squared	0.66			0.70			0.93		
Adjusted R-squared	0.58			0.63			0.85		
S.E. of regression	0.24			0.22			0.22		
Durbin-Watson stat	1.97			2.28			1.95		

Results presented in the tables above provide confidence as to the significance of the particular variables in explaining the variation in credit spreads, confirming results reported previously.[72] It is also important to note that the combination of the explanatory variables used under this study, together with the careful elimination process used and the assignment of firm specific information to companies' credit spreads, has been able to explain the largest part of the variation in credit spread changes, contrary to findings of Defrense, Goldstein and Martin (2001). It is worth noting that although some of the coefficients are more important in one pool compared to the other, we can draw comfort for their momentumeness for two reasons:

a. Results reported in previous chapters, based on different sets of data, support the same variables
b. These variables tend to be very important on a consistent basis, i.e. are time invariant.

Also it is important to note, that in this multi variate context, it is the only time that we get the right negative sign for the coefficient of GDP, compared to previous chapters.

Once we gained confidence in the estimated coefficients, we'll proceed with the forecast of credit spreads changes, one and two years ahead with the dynamic solution method described in the previous section.

Forecasts & evaluation based on the SUR Method

Table 7.14 Forecasted Errors based on the SUR method, Investment Grade

	Pool AAA		Pool AA		Pool A		Pool BBB	
	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE
1 quarter ahead forecast	0.26	-0.43	0.55	2.05	0.30	0.77	0.43	0.21
2 quarters ahead forecast	0.12	-0.6	0.36	0.65	0.25	-0.28	0.47	0.06
1 year forecast	0.11	1.9	0.50	0.97	0.21	-0.08	0.39	0.08
2 years forecast	0.23	2.3	0.35	0.11	0.22	-2.12	0.17	-0.44
2 years & 3 quarters ahead	0.25	0.50	0.64	0.05	0.32	-2.25	0.35	-0.34

[72] It should be noted that we get similar results for the lagged values of the above variables, although

Table 7.15. Forecasted Errors based on the SUR method, Non- Investment Grade

	Pool BB		Pool B		Pool C	
	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE	Avg RMSE	Avg MAPE
1 quarter ahead forecast	0.55	0.67	0.39	-2.4	1.09	0.36
2 quarters ahead forecast	0.55	0.08	0.34	-1.9	1.5	-0.11
1 year forecast	0.34	0.84	0.28	-0.48	0.52	0.88
2 years forecast	0.34	0.50	0.29	-0.56	0.28	0.95
2 years & 3 quarters ahead	0.60	0.04	0.37	-0.80	0.50	0.97

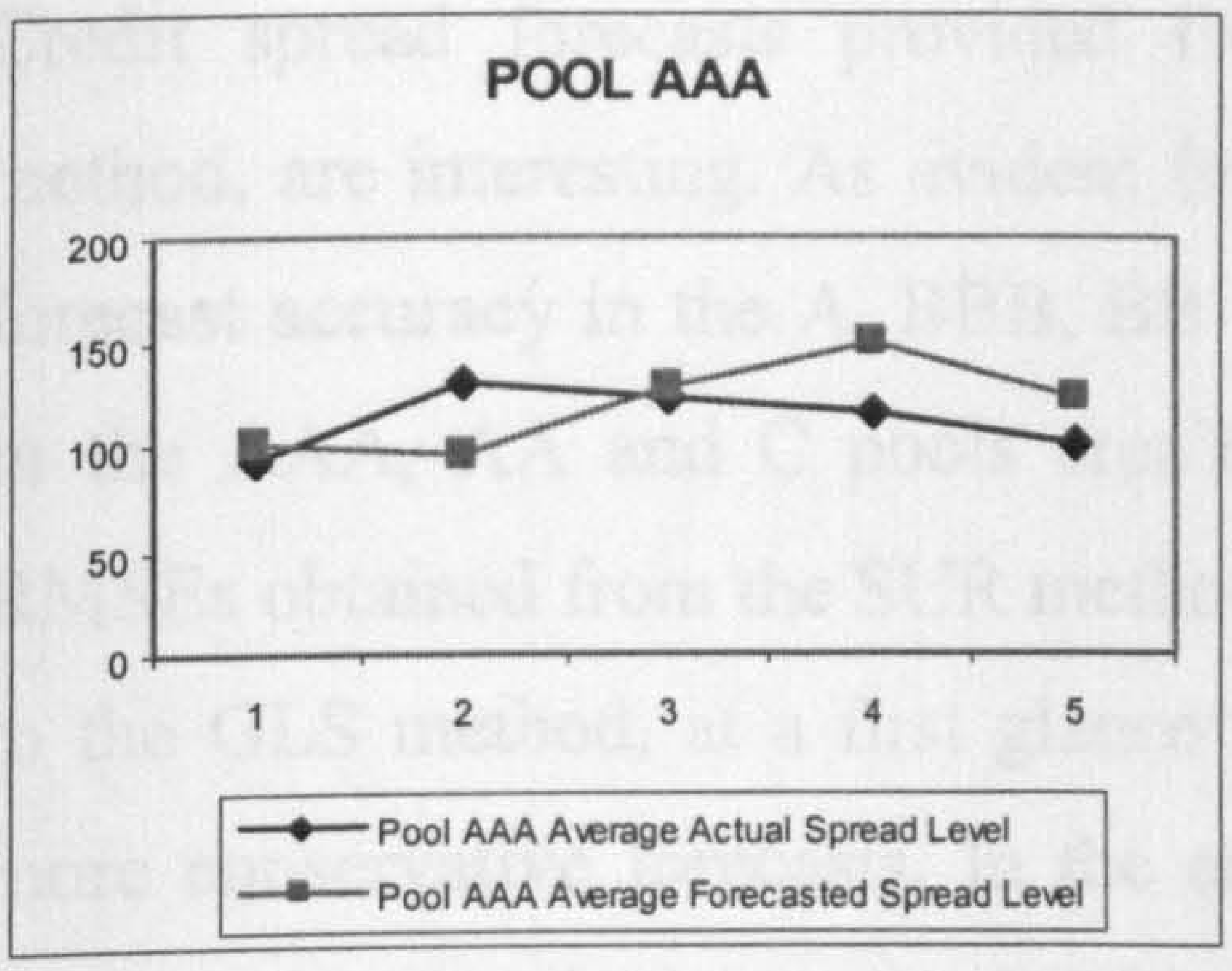
Table 7.16. Forecasted Values based on the SUR method, Investment Grade

	Pool AAA		Pool AA		Pool A		Pool BBB	
	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level
1 quarter ahead forecast	93.50	99.27	107.54	85.17	147.14	149.54	187.6	196.7
2 quarters ahead forecast	128.75	95.60	89.85	86.32	123.14	139.77	176	187.88
2 quarters ahead forecast (cumulative)	111.12	97.50	98.71	85.73	135.14	142.87	181.8	190.2
1 year forecast	121.68	127.33	119.71	119.47	145.21	150.99	213.3	225.75
2 years forecast	115.31	147.85	126.89	148.01	142.07	148.05	229.97	233.48
2 years forecast ***(cumulative)***	118.50	137.59	123.30	133.74	143.64	160.70	221.63	230.55
2 years & 3 quarters ahead	99.17	122.24	113.91	123.85	149.65	163.90	214.44	218.78
2 years & 3 quarters ahead ***(cumulative)***	107.36	124.09	116.02	121.56	148.04	158.89	214.02	219.55

not reported herein.

Table 7.17. Forecasted Values based on the SUR method, Non-Investment Grade

	Pool BB		**Pool B**		**Pool C**	
	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level
1 quarter ahead forecast	232.00	310.05	318.2	364.11	874.5	1,422.47
2 quarters ahead forecast	203.00	281.75	326.00	355.96	650.05	916.72
2 quarters ahead forecast (cumulative)	217.90	295.11	322.1	360.04	762.25	1,170.73
1 year forecast	242.9	278.95	370.2	379.68	771.62	923.65
2 years forecast	350.7	380.89	591.75	666.14	988.75	566.08
2 years forecast ***(cumulative)***	296.8	329.93	480.97	522.91	880.17	744.86
2 years & 3 quarters ahead	350.01	379.80	562.71	627.76	1,205.24	924.46
2 years & 3 quarters ahead ***(cumulative)***	311.07	343.13	492.70	537.55	1,047.54	924.17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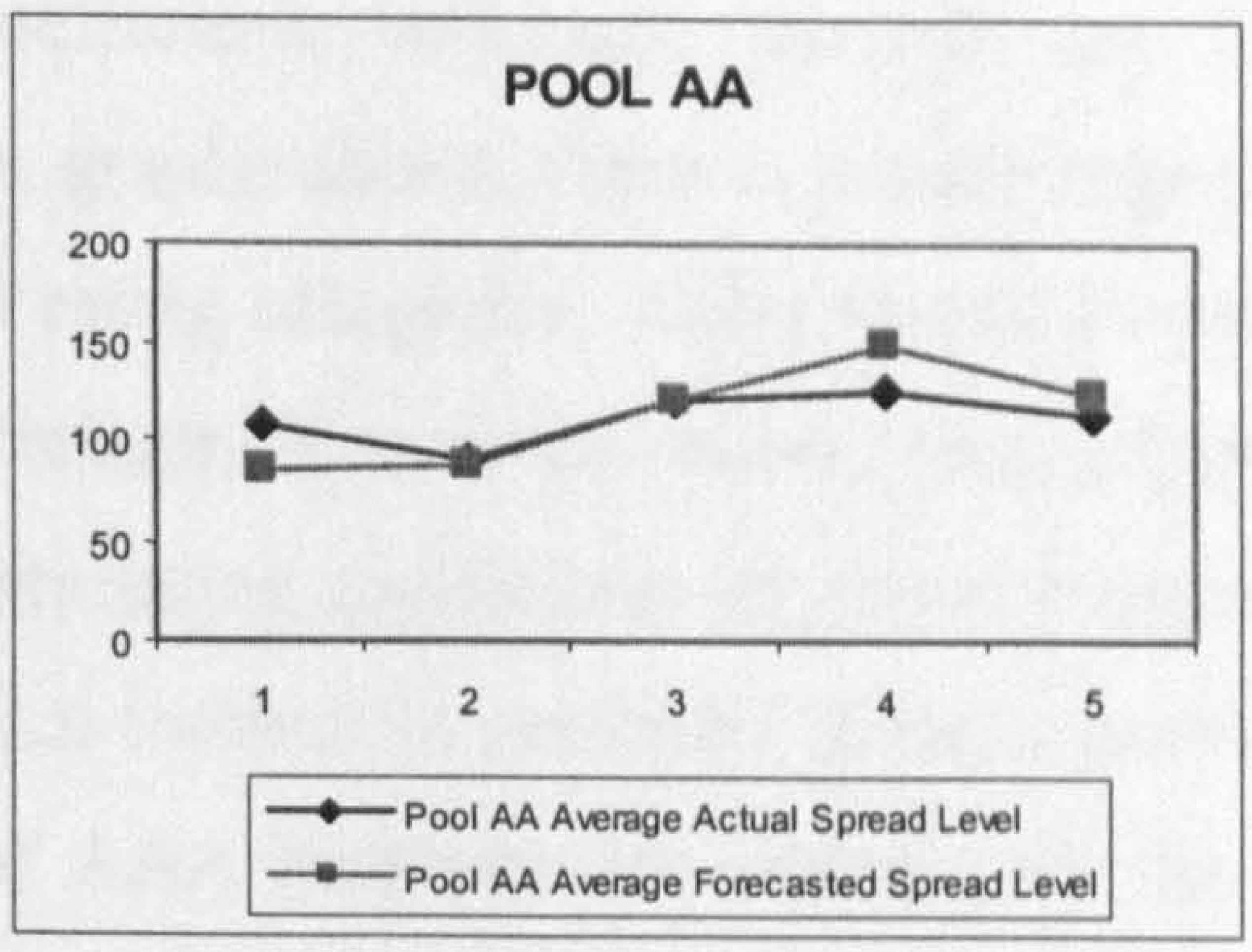
Pool AAA Average Actual Spread Level
Pool AAA Average Forecasted Spread Level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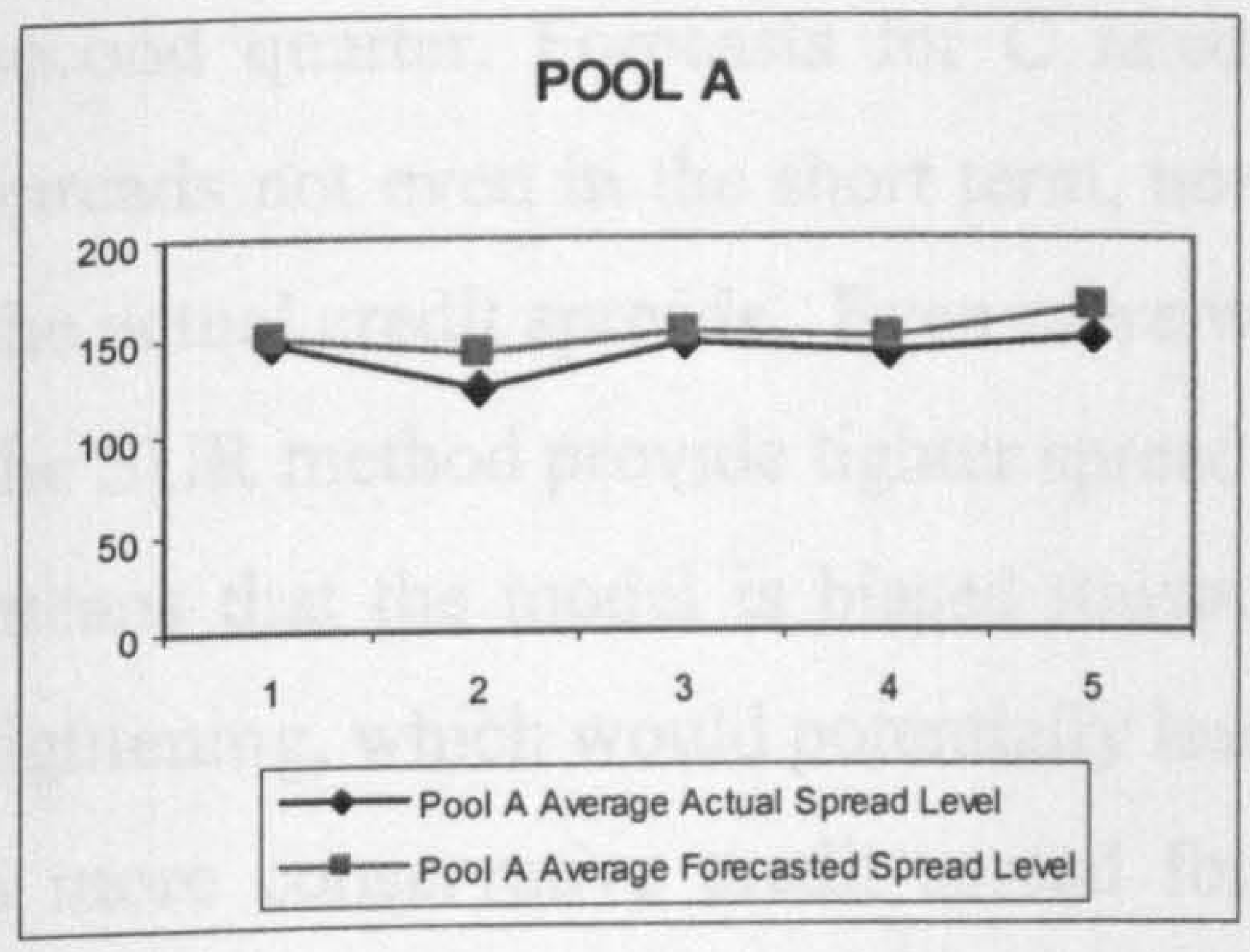
Pool AA Average Actual Spread Level
Pool AA Average Forecasted Spread Level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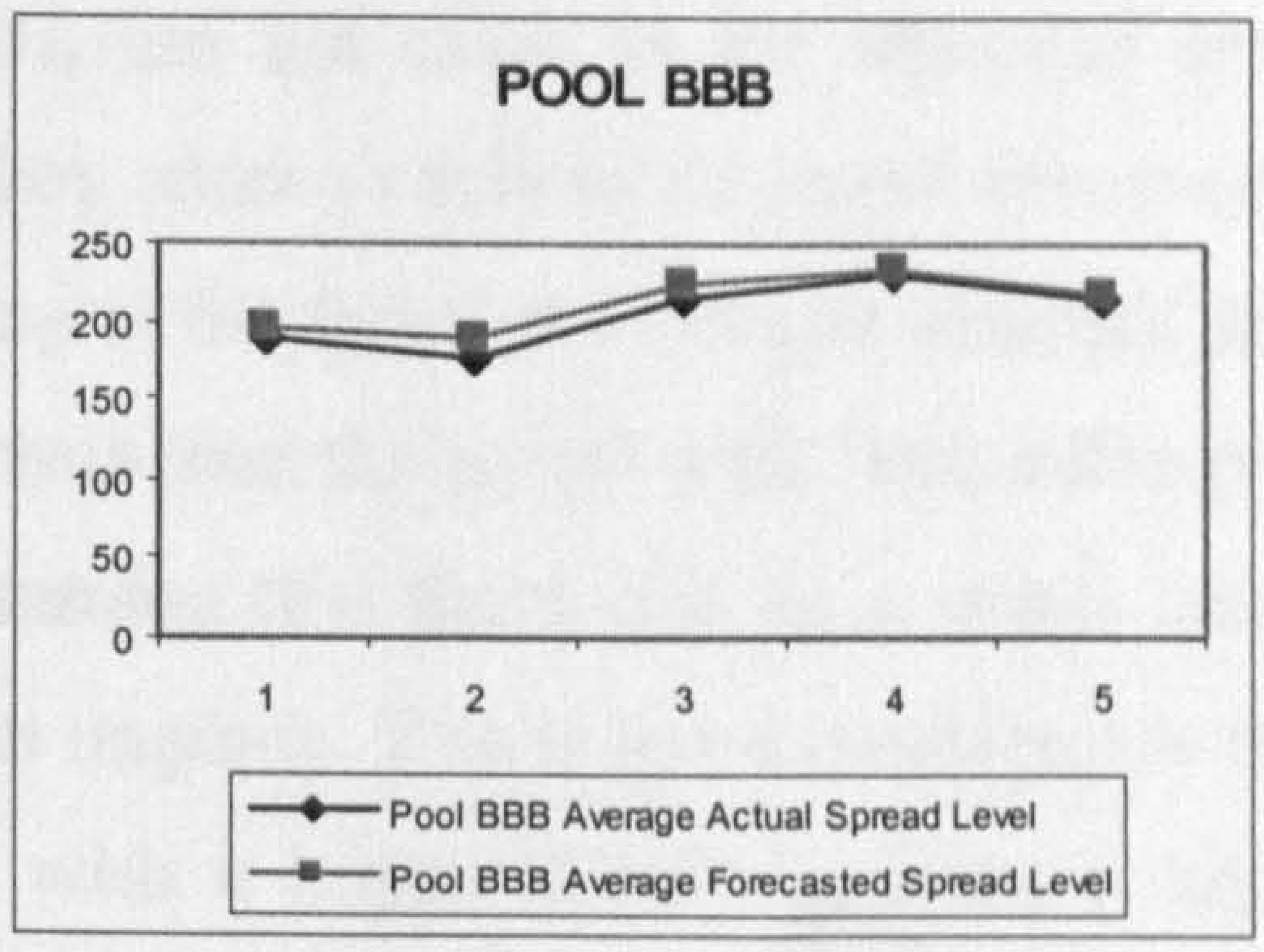
Pool A Average Actual Spread Level
Pool A Average Forecasted Spread Level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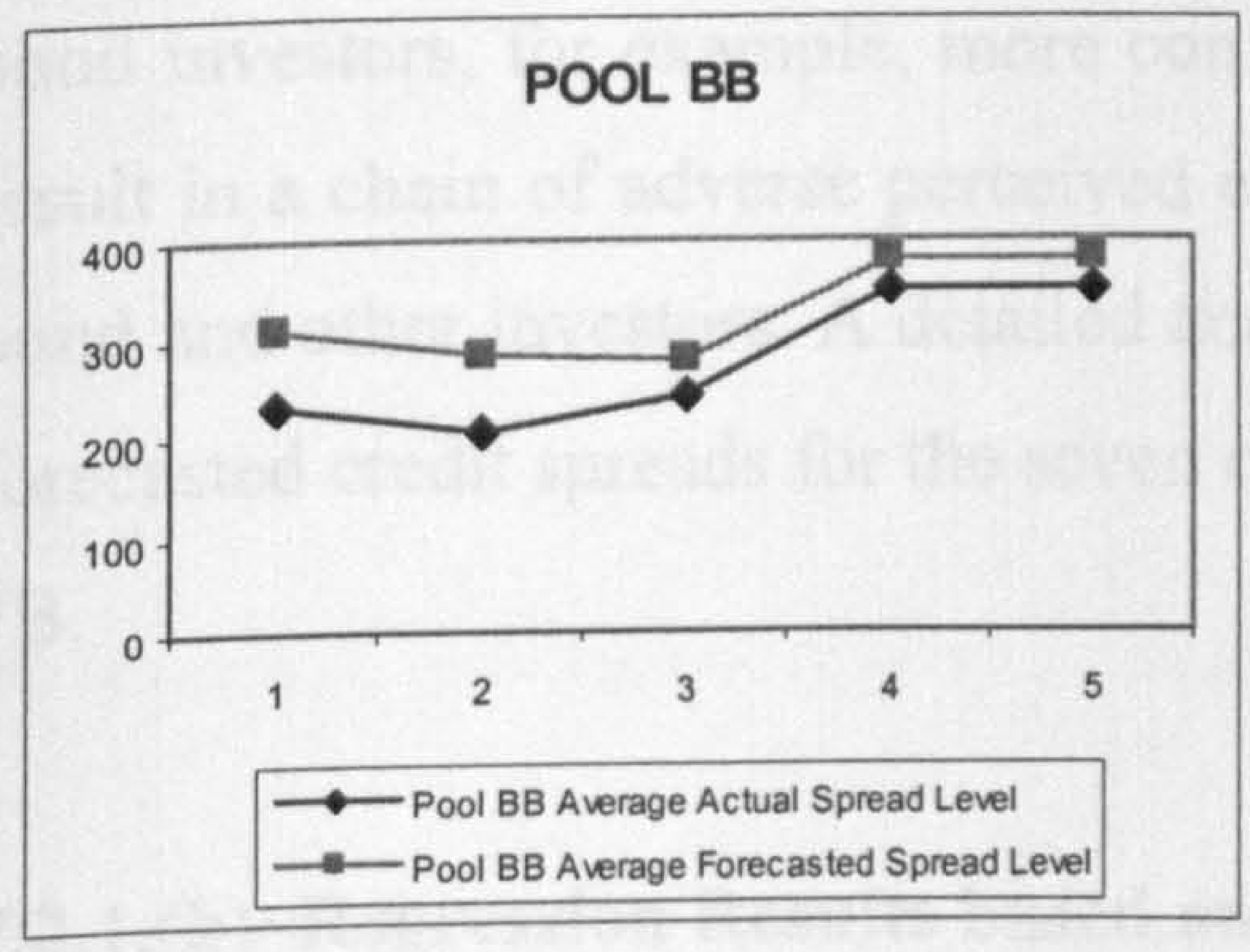
Pool BBB Average Actual Spread Level
Pool BBB Average Forecasted Spread Level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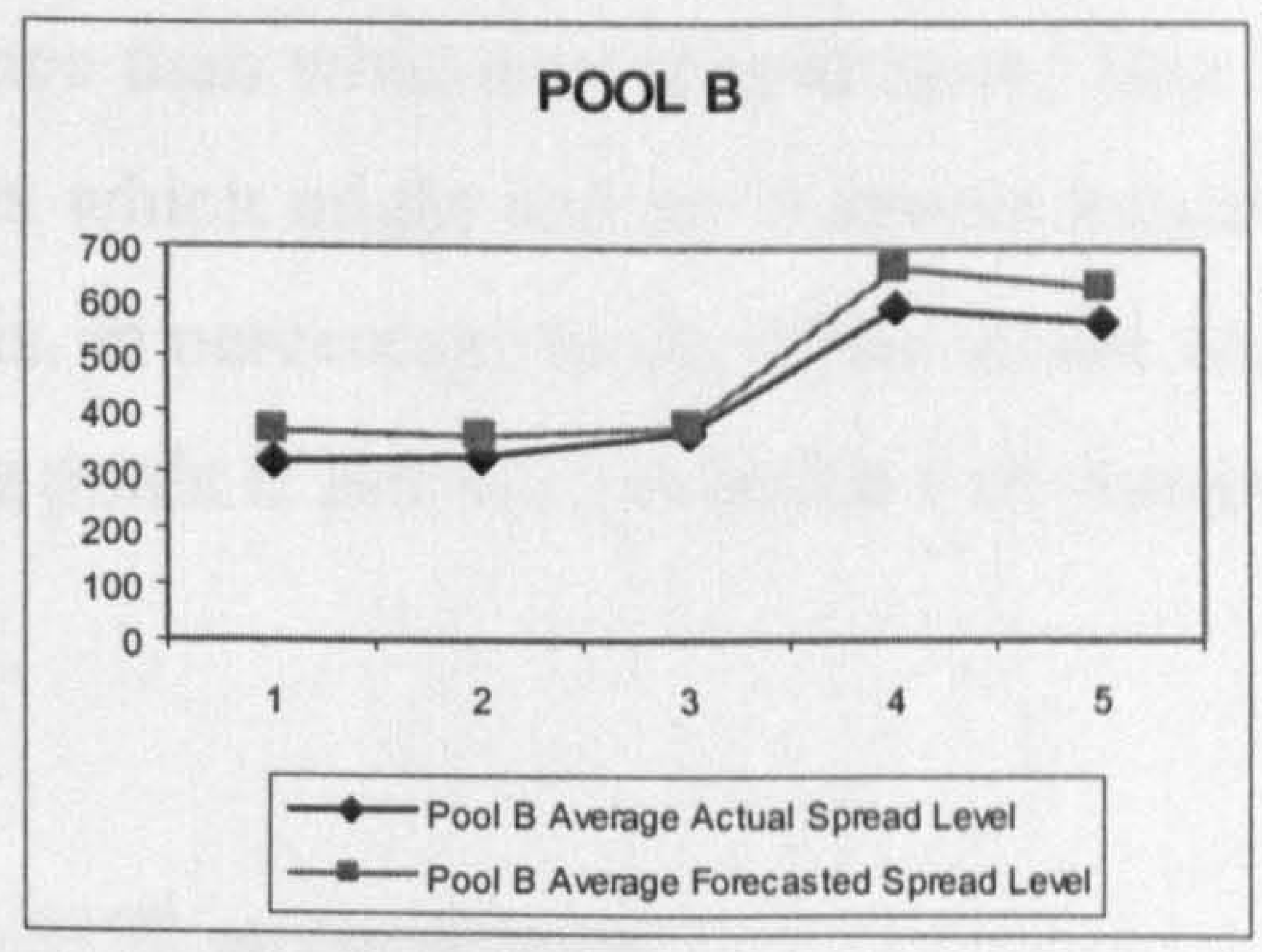
Pool BB Average Actual Spread Level
Pool BB Average Forecasted Spread Level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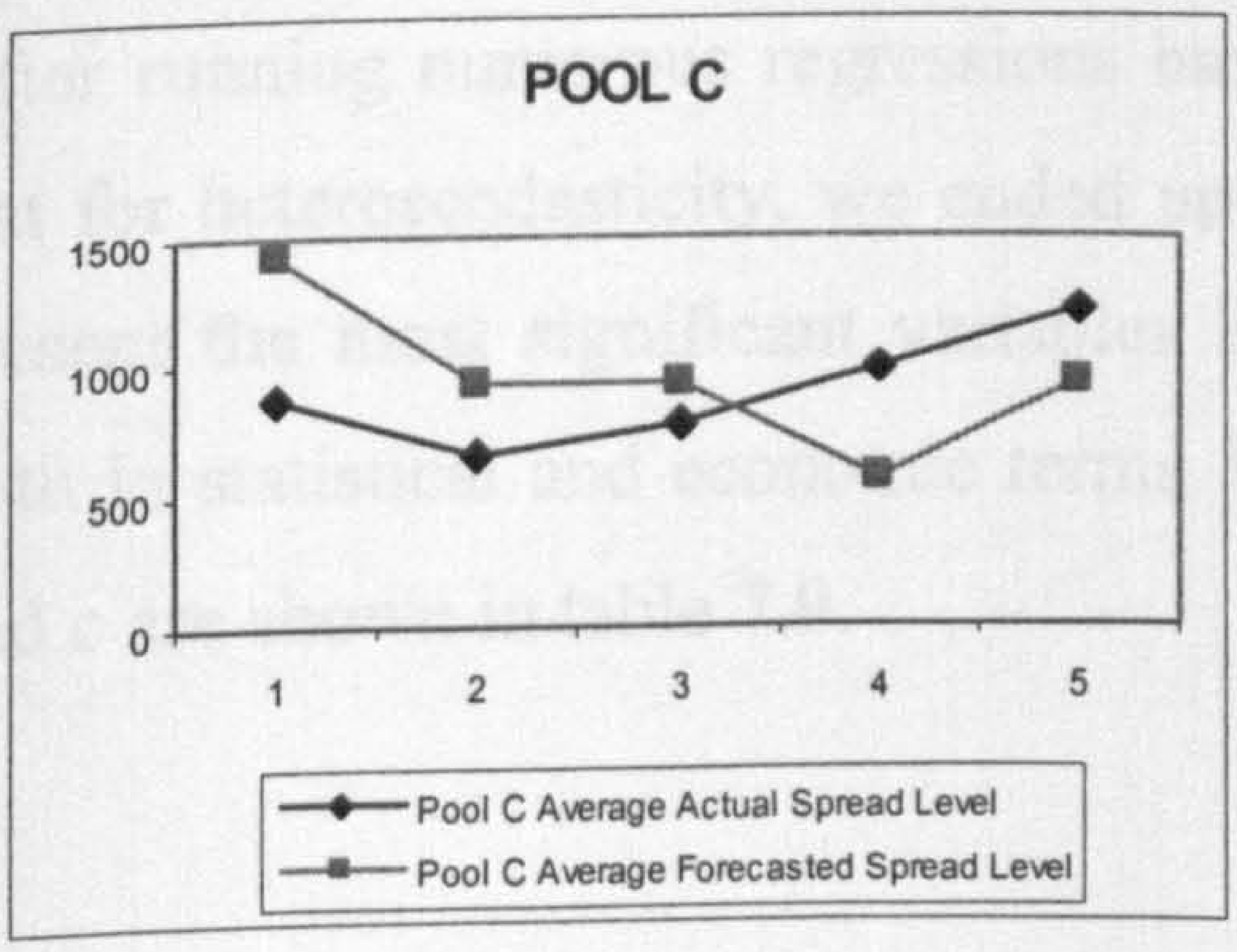
Pool B Average Actual Spread Level
Pool B Average Forecasted Spread Level


POOL C
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Pool C Average Actual Spread Level
Pool C Average Forecasted Spread Level

Credit spread forecasts provided from coefficients estimated through the SUR method, are interesting. As evident from the graphs above, there is a high degree of forecast accuracy in the A, BBB, BB and B rating categories, while spread forecasts in the AAA, AA and C pools aren't that robust. It is worth noting that although RMSEs obtained from the SUR method of estimating coefficients are lower compared to the GLS method, at a first glance the GLS method is preferred since it provides more conservative forecasts. In the cases of AAA forecasts are robust only for the first quarter ahead whereas in the AA rating band the best forecast is obtained for the second quarter. Forecasts for C rated bonds, are not close to the observed credit spreads not even in the short term, nor do they seem to follow the trend observed in the actual credit spreads. Even more worrying is the fact that forecasts obtained from the SUR method provide tighter spread forecasts than the actual ones. This effectively means that the model is biased towards assuming that there will be a credit spread tightening, which would potentially lead to an upgrade. This is more troublesome than a more conservative credit spread forecast with a higher RMSE or even a higher deviation between the actual and forecasted credit spread value, as it would provide to bond investors, for example, more confidence than what they should have. This will result in a chain of adverse perceived events which might end up in severe losses for bond and other investors. A detailed analysis, in percentage terms of the actual versus forecasted credit spreads for the seven rating pools is provided in Table 1 of Appendix 7B.

7.2.1.(b) Regression Results based on the SUR methodology

After running numerous regressions based on the SUR methodology and the White test for heteroscedasticity, we ended up with the following estimated outputs, which present the most significant variables for explaining the variation in credit spreads both in statistical and economic terms. Results of those variables for each pool, a, b and c are shown in table 7.9.

Table 7.9.Cross Sectional Regression Results based on SUR

	Pool A			Pool B			Pool C		
Variable	Coef.	t-Stat	Prob.	Coef.	t-Stat	Prob.	Coef.	t-Stat	Prob.
C	0.13	27.53	0.00	0.10	10.15	0.00	0.12	11.22	0.00
VIX	0.59	28.40	0.00	0.40	10.92	0.00	0.54	12.45	0.00
Term Structure	-0.02	-14.6	0.00	-0.04	-11.2	0.00	-0.03	-10.9	0.00
Current Market Capitalisation	-0.01	-0.85	0.08	-0.08	-1.55	0.07	-0.05	-3.70	0.00
Equity	-0.23	-15.55	0.00	-0.06	-1.60	0.11	-0.29	-4.94	0.00
Cash Flow to Debt	-0.04	-7.69	0.00	-0.03	-5.98	0.00	-0.02	-6.10	0.00
CONF	-2.96	-15.26	0.00	-2.38	-6.16	0.00	-3.85	-9.14	0.00
EBIT	-0.00	-6.71	0.00	-0.02	-2.06	0.04	-0.06	-2.36	0.02
GDP	-0.09	-7.54	0.00	-0.06	-2.86	0.01	-0.04	-5.55	0.00
DBCP	0.19	12.39	0.00	0.14	1.58	0.12	0.29	5.35	0.00
R-squared	0.73			0.68			0.65		
Adjusted R-squared	0.71			0.65			0.62		
S.E. of regression	0.20			0.16			0.26		
Durbin-Watson stat	2.34			2.21			2.29		

Results presented in this table provide confidence as to the significance of the particular variables in explaining the variation in credit spreads, confirming results reported previously. Therefore, we proceed with the forecast of credit spreads changes, one and two years ahead with the dynamic solution method described in the previous section.

Forecasts & evaluation based on the SUR Method

The tables below provide the error measures for the credit-spread forecasts for the three randomly selected pools. Two error measures have been calculated in order to evaluate the results from the credit spread forecasts.

The Root Mean Square Error and the mean absolute percentage error. Forecasted credit spreads have been evaluated for results one year ahead, two years ahead and 2 years and three quarters ahead. The results are shown below:

The forecast evaluations provided below are indeed poor.

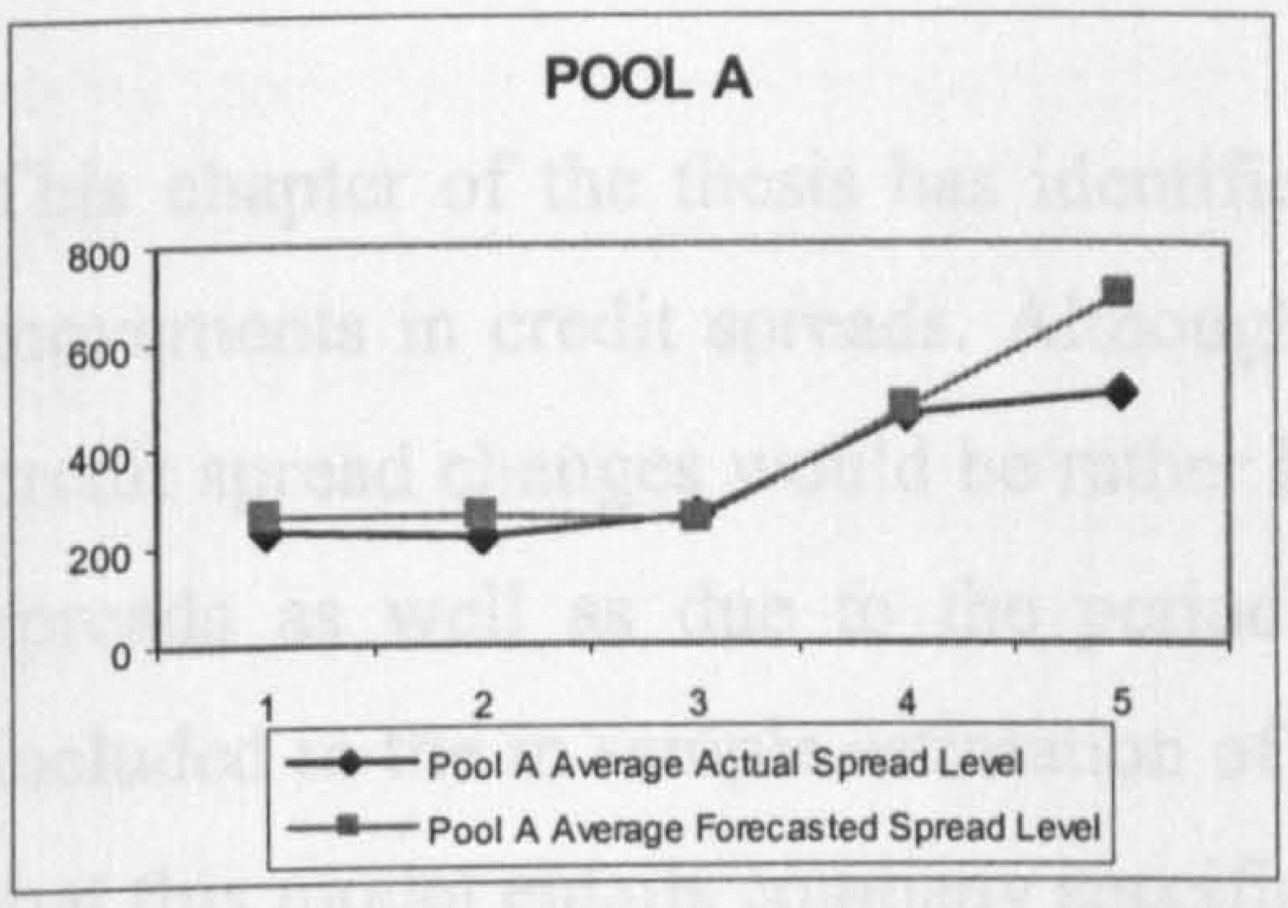
Table 7.10. Forecast Errors

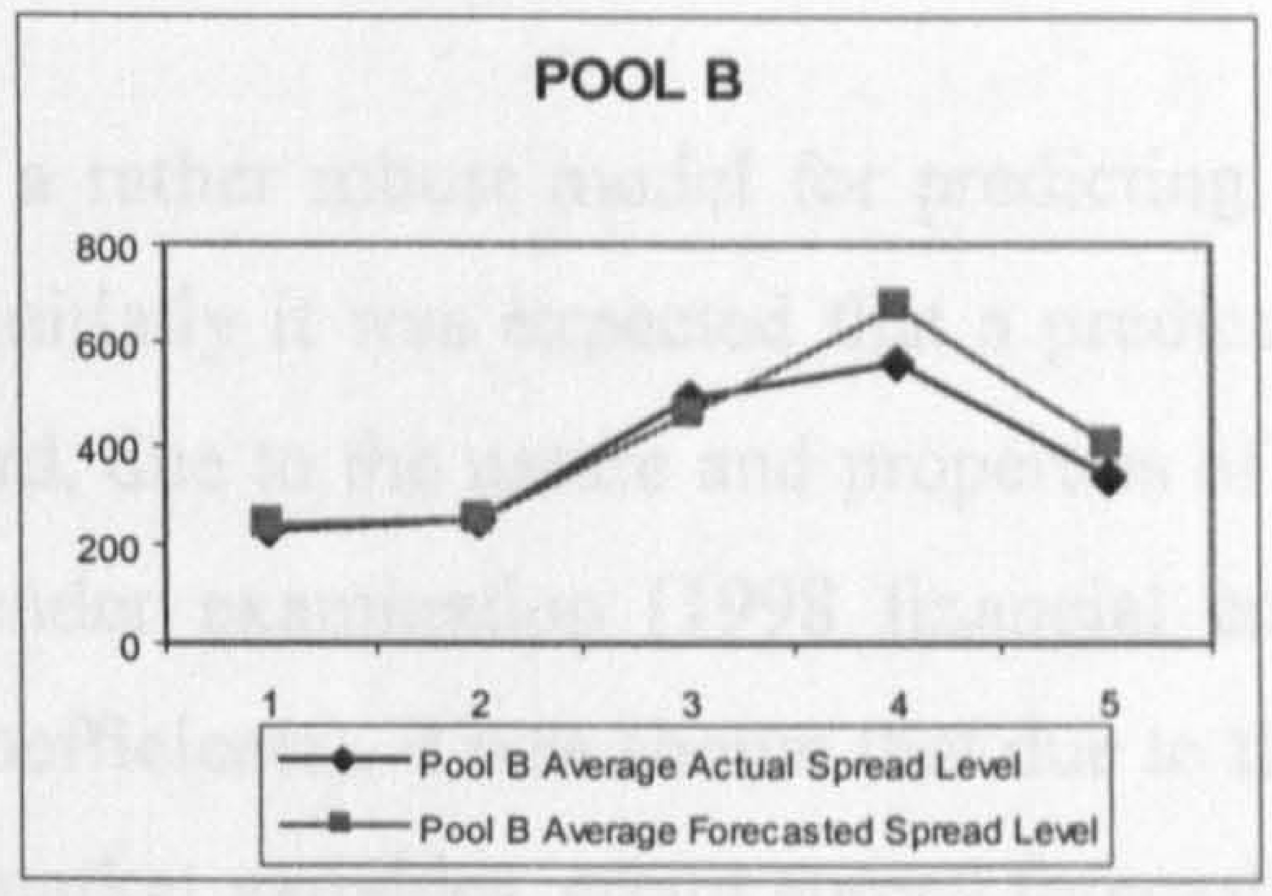
	Average RMSE	Average MAPE
Pool A		
1 quarter ahead forecast	0.41	0.72
2 quarters ahead forecast	0.41	0.42
1 year forecast	0.25	0.39
2 years forecast	0.19	0.85
2 years & 3 quarters ahead	0.30	2.98
Pool B		
	Average RMSE	Average MAPE
1 quarter ahead forecast	0.42	0.14
2 quarters ahead forecast	0.37	0.11
1 year forecast	0.30	0.29
2 years forecast	0.22	0.94
2 years & 3 quarters ahead	0.34	0.47
Pool C		
	Average RMSE	Average MAPE
1 quarter ahead forecast	0.35	-0.44
2 quarters ahead forecast	0.23	-1.74
1 year forecast	0.18	0.64
2 years forecast	0.17	1.47
2 years & 3 quarters ahead	0.28	1.14

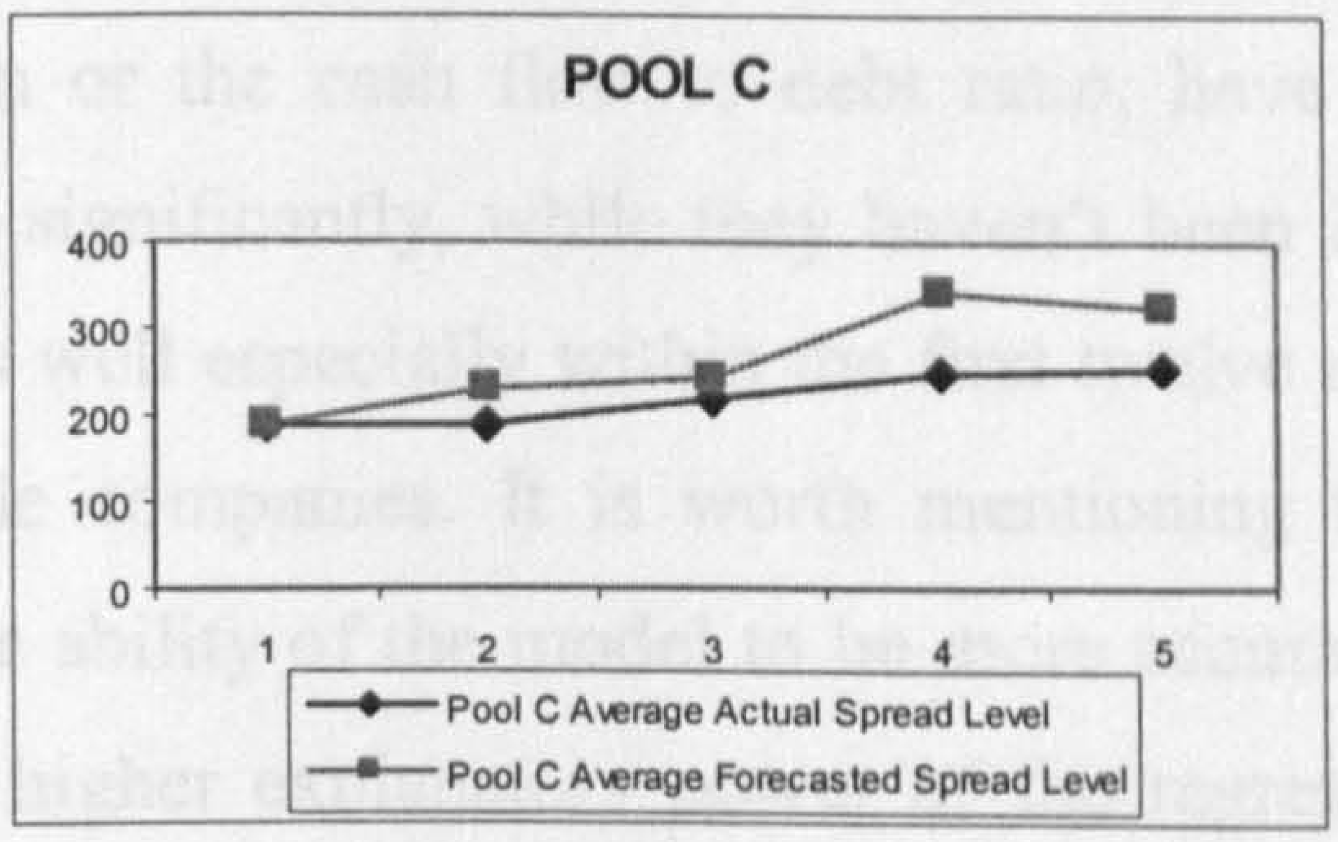
Following the same rationale as described in section 7.1.4., we are calculating the credit spread levels for the three groups of randomly selected companies.

Table 7.11. Forecasted Values based on SUR for pools A, B &C

	Pool A		Pool B		Pool C	
	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level	Average Actual Spread Level	Average Forecasted Spread Level
1 quarter ahead forecast	223.72	258.71	225.41	238.77	190.28	190.13
2 quarters ahead forecast	220.77	263.14	249.33	248.33	189.21	229.59
2 quarters ahead forecast (cumulative)	222.25	260.93	237.37	243.55	189.75	209.86
1 year forecast	257.90	249.01	489.07	456.01	215.92	243.74
2 years forecast	456.30	471.26	564.03	674.53	246.12	338.31
2 years forecast ***(cumulative)***	357.10	360.13	307.15	329.74	231.02	291.02
2 years & 3 quarters ahead	497.84	694.622	333.79	391.14	251.77	323.18
2 years & 3 quarters ahead ***(cumulative)***	410.59	442.13	316.15	345.64	238.74	294.29







Results obtained from the three randomly selected group of bonds, are similar (if not marginally better at least for forecasts one quarter ahead) to those obtained under the GLS method. In particular, the forecasting accuracy one quarter ahead is 86%, 94% and 100% for the three respective pools. The model's forecasting accuracy two quarters ahead is 83%, 100%, and 84% while for one year ahead, the percentages are 103%, 107% and 88% respectively. For an analytical description of the forecasting ability of the model under the SUR method and for the three randomly selected group of companies are provided in Appendix 7B, Table 2.

7.3. Conclusions

This chapter of the thesis has identified a rather robust model for predicting future movements in credit spreads. Although initially it was expected that a prediction of credit spread changes would be rather hard, due to the nature and properties of credit spreads as well as due to the period under examination (1998 financial crisis is included in the in sample estimation of coefficients), it was shown that due to the fact that this model entails company specific market variables, credit spread forecasts have been close to traded values. Variables incorporated in the model, such a company' market capitalisation or the cash flow to debt ratio, have increased the predictive power of the model significantly, while they haven't been included in other studies. The model performs well especially within the first twelve months and even more so for investment grade companies. It is worth mentioning that although we should expect the predictive ability of the model to be more accurate in the high yield bond spreads, due to the higher explanatory power of the regressions obtained from that pool of companies, results obtained confirm the opposite, which is mainly attributed to the higher link of bonds belonging to this category to default risk, and the cyclical behaviour in this sector. This effectively means that although the information content of those bonds is highly significant for predicting output variables, the opposite doesn't hold. This is probably due to the extreme movements in prices exhibited in high yield companies, caused most of the times by drastic/unexpected changes in issuers' creditworthiness, which effectively makes it harder to model.

Forecasts have been based on the dynamic solution method but estimated coefficients that entered the equations were accounted both under the GLS and the SUR method. Results obtained under the SUR method are similar to those provided by the GLS method applied to the randomly selected pool of companies, where the predictive accuracy of the model doesn't fall below 85% at least for credit spread forecasts within the first year (although there is a tendency for underestimation of forecasted credit spreads after the first quarter under both methods). However, RMSEs calculated for the SUR method are lower on average than those obtained from the GLS method, but we shall prefer forecasts based on GLS estimated coefficients, since they both follow the actual observed trend, but also they provide consistently more conservative forecasts. Results provided from the GLS method, contradict Jones, Mason and Ronesfeld (1984) findings and more recently, Huang and Huang (2003), show that credit spreads predicted by the structural models are significantly below the observed levels, especially for high grade bonds. Eom, Helwege and Huang (2004), also find that these models to varying degrees tend to underestimate credit spreads for high quality bonds but overestimate those for junk debt.

8.0. Concluding Remarks

The core objective of this thesis has been the modelling and prediction of credit spread changes, with the use of market continuous variables but also specific, discrete variables. Specifically the main purpose has been to explore the impact of macro, equity and accounting information on credit spreads changes.

We start this thesis by outlining the motivation, objectives and hypotheses tested. The second chapter focuses on an examination of the credit risk literature and credit risk models developed by large international banks while chapter 3, describes the data used in this thesis and the statistical properties of credit spreads and the rest of our data. Chapters 4, 5 and 6 have focused on establishing a relation between macroeconomic, equity variables, accounting data and credit spreads respectively. Chapter 7 has examined the relation between the determinants of credit spreads and all the variables examined in the previous chapters, on an aggregate basis and has employed a dynamic solution method for forecasting credit spreads one and two years ahead.

More specifically, Chapter 3 has specified the proposed credit risk model which shares some of the assumptions and variables proposed by the KMV and McKinsey's macroportfolio view models, while incorporates other variables that seem to be important based on traditional credit risk analysis. A descriptive statistical analysis of the two sets of credit spread indices employed under this thesis has also been provided, where results coincided with our anticipation that standard deviations of bonds tend to increase as credit rating categories deteriorate, and that the levels of credit spreads increase as an issuer's credit quality worsens. This is like assuming that an investor requires a higher return for higher risk. Results reported from Bloomberg indices, share some of the same properties to those reported from the ML data, with a higher volatility pattern observed from long term maturing bond indices. Results obtained from the ADF tests for both sets of data, provide confidence as to the stationarity and mean reverting properties of credit spread changes compared to credit spread levels that follow a unit root.

Chapter 4 explores the relation between macroeconomic variables and changes in credit spreads. Three issues have been identified and tested under this chapter. The first was the relation between macroeconomic variables and credit spreads, with the use of two sets of data. The second dealt with differences arising on the effect of macroeconomic variables to the different rating categories and maturities and thirdly the direction of causation between macroeconomic variables and changes in credit spreads.

With respect to the first set of tests, results provided by the OLS model, based on time series analysis, support the negative relation between changes in credit spreads and consumer confidence, trade balance money supply and the term structure of interest rates for all maturities, but only for their lagged values. (except the US confidence index which is also important at time t). The expected negative relation wasn't though supported for the variables of GDP and industrial production.

Evidence provided by the constituents of ML indices, supports strongly the consumer confidence variable, money supply and trade balance, while again we get the wrong sing for the variables of GDP and industrial production. It should be noted that relation between the term structure and changes in credit spreads is negative for investment grade companies, while is positive for the non-investment grade ones. This result is supported irrespective of the frequency of the data (monthly or quarterly) used or the methodology employed. This finding can have important implications in the contingent claims approach and the reduced form approach for valuing risky debt. It is also worth mentioning that macroeconomic variables explain more of the variation in credit spread changes of the high yield sector rather the investment grade one. Results from the OLS regressions suggest that macroeconomic variables alone, can explain at best a 17% of the variation in medium and long term maturing indices, and a 20.5% in short term indices. Findings from cross sectional regressions suggest that aggregate factors alone can explain 27.9% of the variation in credit spreads for investment grade bonds and a 44.4% for high yield ones.

With respect to the direction of causation results are a bit mixed, as provided by the empirical tests of the times series data. Results obtained from the granger causality tests for long term maturity indices generally reject the null hypotheses that macroeconomic variables don't granger cause changes in credit spread indices. However, results for unemployment in all rating categories aren't statistically sufficient to reject the null nor the alternative hypothesis. With reference to medium term maturities, the null hypothesis is rejected for the macroeconomic variables of consumer confidence, CPI, GDP, money supply and the slope of the interest rates. For the rest of the variables, results don't provide confidence to reject the null hypothesis. Short term maturity indices' results, suggest that for the variables of CPI, PPI and money supply we reject the alternate hypothesis that changes in credit indices don't granger cause the aforementioned macroeconomic variables. For the rest of the variables in short term maturing indices, we can reject the null hypothesis that macroeconomic variables don't granger cause changes in credit indices. Even though similar tests couldn't be performed for the constituents of the ML indices, due to the nature of the second set of data, results lend support, as to the higher and more significant informational content existing in companies of the high yield sector. This finding can have important implications both empirically and theoretically, in the sense that it can improve different macroeconomic output forecasts.

Chapter 5 has tested the relation between changes in credit spreads and their respective changes in equities. The main hypothesis tested was that changes in equities should prove significant for changes in spreads. Intuition would suggest that this relation should be more strongly supported for the non-investment grade category. Indeed, results provided by pooled regressions affirm our intuition, with highly statistically and economically significant results obtained for companies belonging to the B rating bucket and once implied volatilities were introduced as depicted by the VIX index. Historical volatilities didn't provide any further support for the hypothesis tested. In particular, results from pooled regressions suggest that when implied volatilities are substituted for the historical ones, adjusted R^2s fell to 6% and 28% for the investment and non-investment grade samples respectively (from 25% and 50.3% for investment and non-investment grade companies, when implied volatilities are considered).

In terms of the relation between different maturity credit spread indices and equity variables, results strongly support the negative relation amongst them for short and medium term maturing indices. Findings from OLS regressions, suggest that equity variables explain at best a 44% for short term maturing indices, and 35% and 37% for medium and long term maturing indices as reflected by the adjusted R^2s.

Furthermore, the hypothesis that the VIX index doesn't granger cause credit spreads can be rejected at the 10% level of significance, for all rating categories, for short and medium maturities, while not statistically significant results were obtained for long term maturing bonds.

In Chapter 6 the relation between a company's financials and its corporate bond spreads was examined. This section has been inspired by the limited literature provided in using accounting ratios to predict changes in credit spreads. The reason is that changes in credit spreads can partially be considered as a stochastic variable, and as such they can't be explained to a great extent by changes in the financials of a company which are considered to be more static. This explains why on an individual basis, accounting variables are very weak in explaining credit-spread changes, with the exception of the variable of the company's current market capitalisation. This has been the most significant variable, statistically and financially wise, when tested in all rating categories, irrespective of the statistical method employed, since it is considered to be more of a "continuous" rather than a "static" variable. However, results do provide statistical support as to the nature and the structure of the relation between each variable and credit spreads, and to the value of accounting ratios as determinants of credit spread changes, particularly in the non-investment grade category.

The last chapter of the thesis has identified a rather robust model for predicting future movements in credit spreads, by using variables which proved throughout this thesis to be the most statistically and economically important in explaining credit spreads. The independent variables considered are both market and firm specific variables, and their combination has provided a very meaningful combination in explaining the changes in credit spreads. Also of significant importance was the selection process used for bonds to qualify for this thesis and their immediate link to their respective firm specific factors extracted from Bloomberg. Although initially it was expected that a prediction of credit spread changes would be rather hard, on an individual basis, and even more so for the period we are trying to predict which exhibited high volatility, it was shown that due to the fact that this model entails both company specific and market variables, credit spread forecasts have been close to traded values. The model performs well especially within the first twelve months and even more so for investment grade companies.

8.1. Limitations of the current thesis & Further Research

When considering credit risk it is always very important to bear in mind that lack of data is the most important restriction to the formulation and implementation of any credit risk model. Also it is very important to consider that the line between a credit risk model's sophistication and its implementation is very thin. There is always this trade-off between the new and more sophisticated credit risk models and the simplicity and accuracy which is always worth pursuing.

This thesis has been based on data which is mostly available and by using fairly simple statistical techniques has provided a rather robust model for predicting credit spread changes. It can be argued of course that other independent variables might be more closely linked to credit spreads, than those proposed here, or that the methodology employed can be improved further. It is also important to mention that this model doesn't consider factors such as liquidity, temporary supply and demand imbalances or tax effects.

There are several issues to point out when considering the effect of macroeconomic variables on credit spread changes. Results provided have been a bit mixed with respect to the different maturity and rating categories. It is important to note that results reported under quarterly frequencies are not the same to those reported by monthly frequencies. The fact that we have derived monthly frequencies from quarterly reported figures of GDP and others, as a way to test their effects on monthly credit spreads can also be criticised.

Another point to explore further is the relation between the term structure and changes in credit spreads is negative for investment grade companies, while is positive for the non-investment grade ones. This result is supported irrespective of the frequency of the data used or the methodology employed. This finding can have important implications in the contingent claims approach and the reduced form approach for valuing risky debt.

It is worth noting at this point, that results of BBB rated bonds, also support the negative relationship between the term structure of interest rates and the changes in credit spreads. Throughout this thesis it is evident that bonds belonging to this category tend to be very volatile, but most importantly they share some of the properties specific to high yield companies. Results provided not only from macroeconomic variables but also from equity and accounting variables, show that the inclusion of this category in the investment grade lowers significantly the explanatory power of the model. This is a point that should be further researched, since results from this study, even question the justification for BBB-rated bonds to be included in the investment grade category.

Also it would be very interesting to explore further the properties of short term maturity indices, since results provided from the granger causality tests suggest that for the variables of CPI, PPI and money supply we should reject the hypothesis that changes in credit indices don't granger cause the aforementioned macroeconomic variables.

Another interesting result, which should be further explored is the high explanatory and predictive power of high yield credit spread changes for output forecasts. The strong explanatory ability of credit spreads, especially in the high yield sector, can help central bankers or other investors to improve several output forecasts. However, the high explanatory power of credit spreads in the high yield sector can be criticised, since results are based on a short time period of credit spreads. Hence the lack of historical data, limits the strength of our conclusion. Additionally, when financial markets are under stress the use of credit spreads may give the wrong signal. For example, the 1998 financial crisis, although led to a significant widening of credit spreads, was not reflected in a slowdown in economic growth in 1999. This crisis was due in part to factors idiosyncratic to this market (i.e. the Russian bond default) and not symptomatic of a systematic deterioration of credit conditions of the magnitude and kind that occurred in the late 1980s. In the 1998 crisis, banks remained in relatively good financial health and they were in position to supply funds to offset the disruptions derived from the high yield market[73]. Therefore, this result should be stress-tested on a longer sample, with more business cycles. Additionally, it may be beneficial to develop a general economic index of financial conditions that will include high yield corporate bond spread as one of its components.

Part of the results reported from chapter 5 support both theoretical and empirical evidence as to the importance for including on the one hand implied volatilities while excluding historical ones, as well as to the fact that the inclusion of equities add significant explanatory power to the modelling of credit spreads of non-investment grade companies. However, the analysis has pointed three points that should be further tested or considered:

a. It would be interesting to elaborate further on bonds belonging to the B rating class as results provided, irrespective of time attributions (data frequencies checked) have been mostly significant compared to the other rating categories and by using the same explanatory variables.
b. With respect to the time lag between changes in equities and the respective changes in credit spreads, results provided only by option adjusted spreads support the nine-month time lag. Further evidence should therefore be tested and evaluated accordingly.
c. Lastly, with respect to the index maturities, it should be noted that based on the current set, short-term maturity bonds seemed to be better modelled by changes in equities than their longer-term counterparts. Although this argument verifies that bond market aren't that far behind from equity markets, we should expect this relation to hold also for longer term maturities and therefore should be further explored.

[73] For further comments on the substitution between bonds and bank credits over the 1998 crisis, refer to Saidenberg and Strahan, 1999.

With respect to chapter 6, and the use of financial ratios in predicting changes of credit spreads, it can be argued that their economical significance might not be that vast compared to theory. However, these ratios have been selected based on empirical evidence. Surely, they could be substituted by the other ratios and further elaboration on this issue would be important, since the biggest part of the literature in credit risk has used the accounting ratio approach in the modelling of corporate collapse. It is also very important to consider the broad argument of those criticising the use of accounting ratios as they reflect the book value of companies. If we consider that asset managers and credit analysts alike, always look at the financial reports of a company issuing a bond in order to reach a conclusion on whether to buy a corporate bond or not, implies that the use of accounting ratios, is still very widely used in the finance world. As such it should get more attention in terms of more research in the academic literature. Of course, it is up to the accounting profession to come up with a better way of reporting off balance sheet risks of the company, but until that happens, improvements can be made in the prediction of credit spread changes with the use of accounting ratios.

Forecasts on credit spreads provided in chapter 7, should be further explored, if one can have access to the ML indices, in order to get more updated information and check for the predictive accuracy of the credit spreads for a longer time period. Also it is worth noting that despite the higher explanatory power for explaining changes in credit spreads in the high yield category, model's forecasts are more accurate for investment grade companies. But this can be explained by the higher volatility exhibited in non-investment grade companies.

In addition to the limitations and points to research further that were derived from the current thesis, there are two areas in credit risk modelling which are of great interest:

(1) Estimating a credit risk model as the one described in this thesis but for emerging market countries. Although this is a very interesting area of research, the difficulty is focused on the lack of time series data available in these countries. Only recently, an effort to collect data in electronic form has begun and one of the main reasons for the more systematic effort is that it constitutes one of the Basel II requirements. Also and more importantly, it would be very interesting to examine

how the amended Basel definition of default will affect the structural and reduced form approaches.

(2) The next area of focus relates to the Basel's developments related to credit risk. Although we agree that the New Accord constitutes a framework which provides guidelines for properly measuring and managing credit risk, if it is followed on a consistent basis, the argument put forward for ultimate reductions in the minimum capital requirements is questionable. In particular, whether the proposed treatments related to the measurement and management of credit risk will actually lead to a decrease in the minimum capital that banks will be required to hold or the purpose is to force banks (especially in the non-developed countries) to have some more sophisticated credit risk systems in place in order to grant and/or follow credits. If one considers the money paid and the time consumed in every financial institution in order to resolve IT issues or other legal matters in order to comply to the new Accord, the line between the financial and human resources consumed, to the potential decrease in the minimum capital requirements that banks will ultimately hold (if they follow Internal Ratings Based Approach either Foundation or the Advanced), becomes very thin. Potentially, a closer look on the resources involved especially in European banks to accomplish all issues related to Basel II, will confirm this.

APPENDICES

APPENDIX 1 – Credit Metrics

Credit VaR for a bond or loan

1. A transition matrix is created in order to specify a rating system, which will include the rating categories together with the probabilities of credit migration, within a given time frame. The main assumption made by CM is that all issuers are credit homogeneous within the same rating class with the same transition default probabilities.
2. The risk horizon should be specified. This is usually one year or a longer time frame can be specified depending on whether a longer risk horizon is required.
3. Then the forward discount curve at the pre-determined risk horizon should be specified for each credit category, and if default occurs the value of the instrument is named the recovery rate of face value of "par".
4. The information provided from above is translated in the forward distribution of the changes in portfolio value according to credit migration.

Credit VaR for a loan or bond portfolio

Using a transition matrix (as provided by one of the large rating agencies), and assuming no correlation between changes in credit quality, joint migration probabilities are derived. Each entry in the transition matrix is simply the product of the transition probabilities for each obligor.

These correlations depend upon:

- The industry in which the firms are included
- The geographical region in which the firms are located, and
- The state of the economy in the business cycle, i.e. a slowdown or growth in economic indicators. Thus, default and migration probabilities cannot remain stationary over time. Effectively this means that there is need for a structural model which bridges the default probability changes and identifies some variables with stable correlations over a period of time.

CM also uses the equity prices as a proxy for the firm's asset value, which in turn is derived as follows:

1. CM estimates correlations between equity return of different obligors, and then the model deduces correlations between changes in credit quality directly from joint distribution of equity returns. The framework used for the valuation of corporate securities was initially

developed by Merton (1974), i.e. the option pricing model, according to which the firm's assets are assumed to follow a geometric Brownian motion,(eq. 1) i.e.

$$Vt = Vo \exp\{(\mu - \frac{\sigma 2}{2})t + \sigma\sqrt{t}Z_t$$

where

V_t : Firm's asset value and follows a Brownian motion

$Z_t \sim N(0,1)$, with mean μ and variance of σ^2 of instantaneous rate of return of the firm's assets $d\,V_t / V_t$

V_t follows a log-normal distribution with an expected value at time t of $E(V_t) = V_o \exp\{\mu_t\}$

2. The firm has a very simple capital structure and is financed solely by equity and a zero coupon debt instrument maturing at time T, with a face value F, and a current market value of Bt. Default can only occur at maturity of the debt obligation if the value of the assets is less than F.

3. Merton's model is also modified by CM to include changes in credit quality. This generalisation of Merton's model assumes :

- Normalised log-returns which are normally distributed over a period of time with o mean and variance equal to one. Same distribution is followed by all obligors within the same category.

  If P_{DEF} is the probability of an obligor rated for example BB at present to default, then the critical asset value V_{DEF} is given as follows: (Eq.2)

$$P_{DEF} = Pr\,[V_t \leq V_{DEF}]$$

According to the aforementioned equation , default occurs when Zt satisfies the following relation:

$$P_{DEF} = Pr\,[\,\frac{\ln^* (V_{DEF} / V_o) - (\mu - (\sigma^2/2))\,t}{\sigma\sqrt{t}} \geq Z\,t\,] \Rightarrow$$

$$Pr\,[Z\,t \leq [\,-\ln(V_o / V_{DEF}) + (\mu - (\sigma^2/2))\,t\,]$$

Where, $r = \frac{\ln(V_t / V_0) + (\mu - (\sigma^2/2)) t}{}$, is the normalised return with N[0,1]

Zcc is the threshold point in the standard normal distribution corresponding to a cumulative probability of P_{DEF}. Then the critical asset value V_{DEF} that can trigger default is $Zcc = -d_2$. In turn,

$$d_2 = \frac{\ln (V_0 / V_{DEF}) + (\mu - (\sigma^2/2)) t}{\sigma\sqrt{t}}$$, which is called the distance to default.

Only these levels are needed to derive the joint migration probabilities and can be calculated without the need to observe the asset value or the mean and variance values. In order to find out the critical asset value V_{DEF} the asset volatility and the asset return should be estimated. It should also be noted that the normalised log-returns follow a joint normal distribution.

We could also consider the case where we have two obligors BB and A rated, with probabilities of default of P_1 (P_{DEF1}) and P_2 (P_{DEF2}), respectively and $P(_{DEF1,\ DEF2})$ being the joint probability of default, and DEF_1 and DEF_2 is the vent of default for the two obligors. From the above, the following default correlation can be derived:

$$Corr(DEF_1, DEF_2) = \frac{P(DEF_1, DEF_2) - P_1 * P_2}{\sqrt{P_1(1 - P_1) * P_2(1 - P_2)}}$$

therefore the joint probability of default is:

$$P(DEF_1, DEF_2) = Pr [V_1 \leq V_{DEF\,1}, V_2 \leq V_{DEF\,2})$$

where,

V_1, V_2: asset values for both obligors at time t

$V_{DEF\,1}, V_{DEF\,2}$: critical values which trigger default. This can also be written as:

$$P(DEF_1, DEF_2) = Pr [r_1 \leq -d_2^{\,1}, r_2 \leq -d_2^{\,2}] \equiv N_2(-d_2^{\,1}, -d_2^{\,2}, \rho)$$

where,

r_1, r_2 : are normalised asset returns for obligors 1 and 2.

$d_2^1 d_2^2$: corresponding the distance to default

$N_2(x,y,\rho)$: denotes the cumulative standard bivariate normal distribution where ρ is the correlation coefficient between x and y.

Credit VaR for large portfolios

The procedure described in the previous section cannot be applied to very large portfolios. In order to derive a model for very large portfolios, CM implements a Monte Carlo simulation to generate full distribution of the portfolio values at 1-year credit horizon. The model is derived as follows:

1. Asset return thresholds are derived for each rating class,
2. Obligors' correlation asset returns are calculated for each pair.
3. Asset return scenarios are generated according to the normal probability distribution and the "Cholesky" decomposition method is used in order to generate correlated normal variables. Every scenario made is characterised by n standardised asset returns, one for each pair of obligors making up the portfolio.
4. Asset returns are planned such as to correspond to the threshold levels derived in 1st step.
5. The portfolio is revalued given the spread curves are applying to each rating.
6. The above procedure is repeated for a number of times until credit returns represent diagrammatically a fat -tailed and highly skewed graph.
7. Then the percentiles of the distribution of the future values of the portfolio are then derived.

Some other important element inherent in the CM model are :

Credit VaR and calculation of the capital charge

Economic capital stands as a cushion to any unexpected events which might lead to default or migration. CM has also found a way to derive the capital charge related to risk, which can be expressed as follows:

$$Capital = EV - V(p)$$

Where,

EV: the expected value of the portfolio

V(p): value of the portfolio in the worst case scenario, at p% confidence level.

FV: forward value of the portfolio = Vo(1+PR)

Vo: current mark-to-market value of the portfolio

PR: promised return of the portfolio

ER: expected return of the portfolio

EL: expected loss: FV- EV

The expected loss goes into reserves and is imputed as a cost in the RAROC calculation, i.e. the capital charge comes only as a protection against unexpected losses.

APPENDIX 2 – Credit Risk +

Distribution of default losses for a portfolio

In order to derive the loss distribution of a portfolio, the losses are divided into bands, with the exposures in each band being defined as a single number. Each band is then regards as being a single portfolio of loans and bonds, whereas we have:

$$\varepsilon_j = V_j * \mu_j$$

whereas,

ε_j : is the expected loss in band j, in L units

V_j : is the common exposure in band j in L units

μ_j : is the expected number of defaults in band j

therefore we have,

$$\mu_j = \varepsilon_j / V_j$$

and the expected loss of an obligor A in units of L is:

$$\varepsilon_A = \lambda_A / L$$

then the expected loss for a 1-year period in band j, is the expected loss of all obligors belonging to the same band, i.e.

$$\varepsilon_j = \sum_{A:VA=Vj} \varepsilon_A$$

Whereby, the expected number of defaults is given by

$$\mu_j = \varepsilon_j / V_j = \sum_{A:VA=Vj} \varepsilon_A / V_j = \sum_{A:VA=Vj} \varepsilon_A / V_A$$

In order to derive for the portfolio as a whole the distribution of losses, the following are considered:

1. Probability generating function (" pgf ") for each band

Each band is taken as a portfolio of exposures, whereby the pgf for the band is given by:

∞ ∞

$$Gj(z) = \sum_{n=0} P(\text{loss } nL)\, Z^n = \sum_{n=0} P(n \text{ defautls})\, Z^{nv_j}$$

Since the number of defaults follows a Poisson distribution then:

$$Gj(z) = \sum_{n=0}^{\infty} \frac{e^{-\mu j} * \mu_j^n}{n!} Z^{nv_j} = \exp\{-\mu_j + \mu_j * Z^{vj}\}$$

2. The pgf for the entire portfolio is :

$$G(z) = \prod_{j=1}^{\infty} \exp\{-\mu_j + \mu_j * Z^{vj}\} = \exp\{-\sum_{j=1}^{m} \mu_j + \sum_{j=1}^{m} \mu_j Z^{vj}\}$$

where $\mu = \sum_{j=1}^{m}$, μ_j denotes the expected number of defaults for the entire portfolio.

3. The loss distribution of the whole portfolio

Having pgf given, $\Rightarrow$ P (loss of n L) = $(1/n!) * (d^n G(z)/ d Z^n) \mid_{Z=0}$, for n=1,2,...
Where the probabilities can be expresses in a closed form and they are dependent on ε_j and V_j

.

CR+ also proposed different extensions of the basic model which can be concluded to the following:

- The model can be extended to a multi-period,
- The variability of default rates can be assumed to result form a number of factors each of which represent an area of activity. Each factor K, is represented by a random X_k, which denotes the number of defaults in sector K, and which follow a gamma distribution. The mean default rate is also assumed to be a linear function of the X_k factors, which are also assumed to be independent. CR+ derives a closed form for the loss distribution of a bond or loan portfolio which is effective from a estimation point of view.

APPENDIX 3 – KMV Model

KMV's model can be derived in three steps:

1. Estimation of the market value and the volatility of the firm's assets
2. Calculation of the distance to default - which is an index measure
3. Scaling of the distance to default to actual probabilities.

Each of these steps are analysed in turn as shown below:

Lets assume that the market position of equity holders in a borrowing firm is equal to holding a call option on the assets of the firm –let call the firm A- which effectively means that the payoff to the equity holder has a limited downside and a long-tail upside. Then equity can be valued as follows:

$$\bar{\mathbf{E}} = \mathbf{h}\ (\mathbf{A}, \sigma_{\mathbf{A}}, \ \bar{\mathbf{r}}, \ \bar{\mathbf{B}}, \ \bar{\tau})$$

(a $^{-}$ above the variables denotes that they are directly observable)

In the above equation the market value of equity of the borrowing firm, depends on five variables, as did the BSM model for valuing a call option. However, still the values of A, σ_A are not observable. In order to resolve the problem, KMV argued that there is another relation between the observable volatility of a firm's equity value (σ_E) and the unobservable volatility of the firm's assets (σ_A), i.e.

$$\bar{\sigma}_{\mathbf{E}} = \mathbf{g}\ (\sigma_{\mathbf{A}})$$

and then the values of A and σ_A can be found, but still the formulas for the stock price –asset volatility have to be determined.

KMV also allows for dividends in the BSM model. Lets assume that B is the default exercise price – including net short term liabilities and half the book value of long term liabilities outstanding- . Even then, the strike prices have varied among different versions of the model, and therefore it was argued that this is the result of the inclusion of net rather than total short term liabilities. The maturity variable can also vary, but is usually set to be one year. Based on all the above assumption the values of A and σ_A can be specified for each obligor and generate EDF rates.

Furthermore, lets assume that the future asset values are normally distributed, then the distance to default can be calculated from t=0 to the 1year horizon as follows:

$$\textbf{Distance from Default} = \mathbf{A - B / \sigma_A}$$

The normal distribution assumption is a very important element of the KMV methodology as it can allow for joint probability distributions to be calculated, but the accuracy of such a methodology is rather questionable. In order to overcome this problem, KMV develops empirical EDFs –instead of theoretical ones- as follows:

Lets assume that a large database of companies having and not having defaulted in the past is available, and that the distance to default is calculated to be 2σ. Then we compare the percentage of the firms which had a distance to default of 2σ at time t=0 and have actually defaulted in 1-year horizon to all the other firms which had 2σ distance to default at t=0, i.e.

$$\textbf{Empirical EDF} = \frac{\textbf{Number of firms that defaulted in 1-year, with asset value of } \mathbf{2\sigma} \textbf{ from B at time t=0}}{\textbf{Total population of firms with asset values of } \mathbf{2\sigma} \textbf{ from B at time t=0}}$$

The empirical EDF can differ from the theoretical one. The EDF rates are rather sensitive due to their link to the stock market prices. However, empirical evidence shows that EDFs have been rather reliable indicators, i.e. the EDF for IBM started to rise significantly before its deterioration of the credit rating; and the EDF for Krung Thai Bank started to rise substantially before the Thai crisis in mid-1997.

It should also be noted that since EDF rates reflect information of the equity markets-given their link with stock prices- it could be argued that EDFs would be more efficient in developed rather than in emerging markets.

APPENDIX 4 – ML Industry Classification per Credit Rating Category

AAA - RATED					
IndLvl1L	IndLvl2L	IndLvl3L	IndLvl4L	ML Indst	Total
Corporate	Financial	Banking	Banking		11
			Banking Total		11
			Mortgage Banks & Thrifts		1
			Mortgage Banks & Thrifts Total		1
		Banking Total			12
		Finance & In	Cons/Comm/Lease Financing		37
			Cons/Comm/Lease Financing Total		37
		Finance & Investment Total			37
		Insurance	Life-Insurance		7
			Life-Insurance Total		7
			P&C		1
			P&C Total		1
		Insurance Total			8
	Financial Total				57
	Industrials	Consumer N	Food - Wholesale		2
			Food - Wholesale Total		2
			Food & Drug Retailers		1
			Food & Drug Retailers Total		1
			Pharmaceuticals		12
			Pharmaceuticals Total		12
		Consumer Non-Cyclical Total			15
		Energy	Integrated Energy		3
			Integrated Energy Total		3
		Energy Total			3
		Real Estate	REITs		2
			REITs Total		2
		Real Estate Total			2
		Services Cy	Airlines		9
			Airlines Total		9
			Transportation Excluding Air/Rail		3
			Transportation Excluding Air/Rail Total		3
		Services Cyclical Total			12
		Telecommuni	Telecom - Integrated/Services		1
			Telecom - Integrated/Services Total		1
		Telecommunications Total			1
	Industrials Total				33
	Utility	Utility	Electric-Distr/Trans		1
			Electric-Distr/Trans Total		1
			Electric-Integrated		4
			Electric-Integrated Total		4
		Utility Total			5
	Utility Total				5
Corporate Total					95
Quasi &	Quasi &	Agency	Agency		849
			Agency Total		849
		Agency Total			849
		Foreign Sove	Foreign Sovereign		4
			Foreign Sovereign Total		4
		Foreign Sovereign Total			4
		Government	Government Guaranteed		36
			Government Guaranteed Total		36
		Government Guaranteed Total			36
		Supranationa	Supranational		61
			Supranational Total		61
		Supranational Total			61
	Quasi & Foreign Government Total				950
Quasi & Foreign Government Total					950
Securitized/Coll	Securitized	Asset Backe	ABS Automobile		122
			ABS Automobile Total		122
			ABS Credit Cards		75
			ABS Credit Cards Total		75
			ABS Home Equity Loans		128
			ABS Home Equity Loans Total		128
			ABS Manufactured Housing		126
			ABS Manufactured Housing Total		126
			ABS Miscellaneous ABS		3
			ABS Miscellaneous ABS Total		3
			ABS Utilities		40
			ABS Utilities Total		40
		Asset Backed Total			494
		Mortgage Ba	Mortgage Backed		417
			Mortgage Backed Total		417
		Mortgage Backed Total			417
	Securitized Total				911
Securitized/Collateralized Total					911
Sovereign	Sovereign	Sovereign	Sovereign		112
			Sovereign Total		112
		Sovereign Total			112
	Sovereign Total				112
Sovereign Total					112
Grand Total					**2,068**

AA - RATED					
IndLvl1L	IndLvl2L	IndLvl3L	IndLvl4L	ML Indst	Total
Corporate	Financial	Banking	Banking		82
			Banking Total		82
			Mortgage Banks & Thrifts		3
			Mortgage Banks & Thrifts Total		3
		Banking Total			85
		Brokerage	Brokerage		77
			Brokerage Total		77
		Brokerage Total			77
		Finance & In	Auto Loans		5
			Auto Loans Total		5
			Cons/Comm/Lease Financing		65
			Cons/Comm/Lease Financing Total		65
			Investments & Misc Financial Servi		1
			Investments & Misc Financial Servi Total		1
		Finance & Investment Total			71
		Insurance	Life-Insurance		3
			Life-Insurance Total		3
			Multi-Line Insurance		8
			Multi-Line Insurance Total		8
			P&C		10
			P&C Total		10
		Insurance Total			21
	Financial Total				254
	Industrials	Basic Industr	Chemicals		7
			Chemicals Total		7
			Metals/Mining Excluding Steel		1
			Metals/Mining Excluding Steel Total		1
		Basic Industry Total			8
		Capital Good	Diversified Capital Goods		5
			Diversified Capital Goods Total		5
			Packaging		1
			Packaging Total		1
		Capital Goods Total			6
		Consumer C	Non-Food & Drug Retailers		16
			Non-Food & Drug Retailers Total		16
		Consumer Cyclical Total			16
		Consumer N	Consumer-Products		22
			Consumer-Products Total		22
			Pharmaceuticals		19
			Pharmaceuticals Total		19
		Consumer Non-Cyclical Total			41
		Energy	Energy - Exploration & Production		12
			Energy - Exploration & Production Total		12
			Integrated Energy		23
			Integrated Energy Total		23
		Energy Total			35
		Real Estate	RealEstate Dev & Mgt		2
			RealEstate Dev & Mgt Total		2
		Real Estate Total			2
		Services Cyc	Airlines		3
			Airlines Total		3
			Transportation Excluding Air/Rail		2
			Transportation Excluding Air/Rail Total		2
		Services Cyclical Total			5
		Technology &	Office Equipment		3
			Office Equipment Total		3
		Technology & Electronics Total			3
		Telecommuni	Telecom - Fixed Line		2
			Telecom - Fixed Line Total		2
			Telecom - Integrated/Services		66
			Telecom - Integrated/Services Total		66
		Telecommunications Total			68
	Industrials Total				184
	Utility	Utility	Electric-Integrated		3
			Electric-Integrated Total		3
		Utility Total			3
	Utility Total				3
Corporate Total					441
Quasi & Fore	Quasi & Fore	Agency	Agency		6
			Agency Total		6
		Agency Total			6
		Foreign Sove	Foreign Sovereign		17
			Foreign Sovereign Total		17
		Foreign Sovereign Total			17
		Government	Government Guaranteed		11
			Government Guaranteed Total		11
		Government Guaranteed Total			11
		Local-Author	Local-Authority		26
			Local-Authority Total		26
		Local-Authority Total			26
		Supranationa	Supranational		3
			Supranational Total		3
		Supranational Total			3
	Quasi & Foreign Government Total				63
Quasi & Foreign Government Total					63
Securitized/C	Securitized	Asset Backe	ABS Automobile		5
			ABS Automobile Total		5
			ABS Credit Cards		1
			ABS Credit Cards Total		1
			ABS Home Equity Loans		14
			ABS Home Equity Loans Total		14
			ABS Manufactured Housing		57
			ABS Manufactured Housing Total		57
			ABS Utilities		1
			ABS Utilities Total		1
		Asset Backed Total			78
	Securitized Total				78
Securitized/Collateralized Total					78
Grand Total					582

A - RATED					
IndLvl1L	IndLvl2L	IndLvl3L	IndLvl4L	ML	Total
Corporate	Financial	Banking	Banking		335
			Banking Total		335
			Mortgage Banks & Thrifts		17
			Mortgage Banks & Thrifts Total		17
		Banking Total			352
		Brokerage	Brokerage		49
			Brokerage Total		49
		Brokerage Total			49
		Finance & Investm	Auto Loans		24
			Auto Loans Total		24
			Cons/Comm/Lease Financing		94
			Cons/Comm/Lease Financing Total		94
			Investments & Misc Financial Servi		6
			Investments & Misc Financial Servi Total		6
		Finance & Investment Total			124
		Insurance	Life-Insurance		33
			Life-Insurance Total		33
			Multi-Line Insurance		32
			Multi-Line Insurance Total		32
			P&C		16
			P&C Total		16
		Insurance Total			81
	Financial Total				606
	Industrials	Basic Industry	Chemicals		20
			Chemicals Total		20
			Forestry/Paper		3
			Forestry/Paper Total		3
			Metals/Mining Excluding Steel		23
			Metals/Mining Excluding Steel Total		23
		Basic Industry Total			46
		Capital Goods	Aerospace/Defense		41
			Aerospace/Defense Total		41
			Building Materials		7
			Building Materials Total		7
			Diversified Capital Goods		14
			Diversified Capital Goods Total		14
			Machinery		24
			Machinery Total		24
			Packaging		3
			Packaging Total		3
		Capital Goods Total			89
		Consumer Cyclical	Apparel/Textiles		4
			Apparel/Textiles Total		4
			Household & Leisure Products		1
			Household & Leisure Products Total		1
			Non-Food & Drug Retailers		42
			Non-Food & Drug Retailers Total		42
			Restaurants		13
			Restaurants Total		13
		Consumer Cyclical Total			60
		Consumer Non-Cy	Beverage		52
			Beverage Total		52
			Consumer-Products		15
			Consumer-Products Total		15
			Food - Wholesale		42
			Food - Wholesale Total		42
			Food & Drug Retailers		2
			Food & Drug Retailers Total		2
			Pharmaceuticals		16
			Pharmaceuticals Total		16
			Tobacco		12
			Tobacco Total		12
		Consumer Non-Cyclical Total			139
		Energy	Energy - Exploration & Production		12
			Energy - Exploration & Production Total		12
			Gas Distribution		34
			Gas Distribution Total		34
			Integrated Energy		10
			Integrated Energy Total		10
			Oil Field Equipment & Services		5
			Oil Field Equipment & Services Total		5
		Energy Total			61
		Media	Media - Diversified		30
			Media - Diversified Total		30
			Printing & Publishing		17
			Printing & Publishing Total		17
		Media Total			47
		Real Estate	REITs		1
			REITs Total		1
		Real Estate Total			1
		Services Cyclical	Airlines		33
			Airlines Total		33
			Railroads		12
			Railroads Total		12
			Support-Services		1
			Support-Services Total		1
			Transportation Excluding Air/Rail		4
			Transportation Excluding Air/Rail Total		4
		Services Cyclical Total			50
		Services Non-Cycl	Health Services		10
			Health Services Total		10
		Services Non-Cyclical Total			10
		Technology & Elec	Computer Hardware		16
			Computer Hardware Total		16
			Electronics		23
			Electronics Total		23
			Software/Services		14
			Software/Services Total		14
		Technology & Electronics Total			53
		Telecommunicatior	Telecom - Integrated/Services		67
			Telecom - Integrated/Services Total		67
			Telecom - Wireless		10
			Telecom - Wireless Total		10
		Telecommunications Total			77
	Industrials Total				633
	Utility	Utility	Electric-Distr/Trans		6
			Electric-Distr/Trans Total		6
			Electric-Integrated		103
			Electric-Integrated Total		103
		Utility Total			109
	Utility Total				109
Corporate Total					1348
Quasi & Fore	Quasi & Fore	Agency	Agency		1
			Agency Total		1
		Agency Total			1
		Foreign Sovereign	Foreign Sovereign		6
			Foreign Sovereign Total		6
		Foreign Sovereign Total			6
		Government Guara	Government Guaranteed		16
			Government Guaranteed Total		16
		Government Guaranteed Total			16
		Local-Authority	Local-Authority		43
			Local-Authority Total		43
		Local-Authority Total			43
		Supranational	Supranational		5
			Supranational Total		5
		Supranational Total			5
	Quasi & Foreign Government Total				71
Quasi & Foreign Government Total					71
Securitized/C	Securitized	Asset Backed	ABS Automobile		6
			ABS Automobile Total		6
			ABS Credit Cards		39
			ABS Credit Cards Total		39
			ABS Home Equity Loans		12
			ABS Home Equity Loans Total		12
			ABS Manufactured Housing		11
			ABS Manufactured Housing Total		11
			ABS Utilities		1
			ABS Utilities Total		1
		Asset Backed Total			69
	Securitized Total				69
Securitized/Collateralized Total					69
Grand Total					**1,486**

BBB - RATED

IndLvl1L	IndLvl2L	IndLvl3L	IndLvl4L	ML Indst	Total
Corporate	Financial	Banking	Banking		38
			Banking Total		38
			Mortgage Banks & Thrifts		15
			Mortgage Banks & Thrifts Total		15
		Banking Total			53
		Brokerage	Brokerage		2
			Brokerage Total		2
		Brokerage Total			2
		Finance & In	Auto Loans		28
			Auto Loans Total		28
			Cons/Comm/Lease Financing		43
			Cons/Comm/Lease Financing Total		43
			Investments & Misc Financial Servi		11
			Investments & Misc Financial Servi Total		11
		Finance & Investment Total			82
		Insurance	Life-Insurance		9
			Life-Insurance Total		9
			Multi-Line Insurance		12
			Multi-Line Insurance Total		12
			P&C		4
			P&C Total		4
		Insurance Total			25
	Financial Total				162
	Industrials	Basic Industr	Chemicals		31
			Chemicals Total		31
			Forestry/Paper		79
			Forestry/Paper Total		79
			Metals/Mining Excluding Steel		24
			Metals/Mining Excluding Steel Total		24
			Steel Producers/Products		6
			Steel Producers/Products Total		6
		Basic Industry Total			140
		Capital Good	Aerospace/Defense		41
			Aerospace/Defense Total		41
			Building Materials		19
			Building Materials Total		19
			Diversified Capital Goods		17
			Diversified Capital Goods Total		17
			Machinery		10
			Machinery Total		10
			Packaging		4
			Packaging Total		4
		Capital Goods Total			91
		Consumer Cy	Apparel/Textiles		2
			Apparel/Textiles Total		2
			Auto Parts & Equipment		25
			Auto Parts & Equipment Total		25
			Automotive		47
			Automotive Total		47
			Household & Leisure Products		8
			Household & Leisure Products Total		8
			Non-Food & Drug Retailers		24
			Non-Food & Drug Retailers Total		24
			Restaurants		4
			Restaurants Total		4
		Consumer Cyclical Total			110
		Consumer No	Beverage		5
			Beverage Total		5
			Consumer-Products		10
			Consumer-Products Total		10
			Food - Wholesale		27
			Food - Wholesale Total		27
			Food & Drug Retailers		52
			Food & Drug Retailers Total		52
			Pharmaceuticals		6
			Pharmaceuticals Total		6
			Tobacco		6
			Tobacco Total		6
		Consumer Non-Cyclical Total			106
		Energy	Energy - Exploration & Production		87
			Energy - Exploration & Production Total		87
			Gas Distribution		107
			Gas Distribution Total		107
			Integrated Energy		74
			Integrated Energy Total		74
			Oil Field Equipment & Services		17
			Oil Field Equipment & Services Total		17
			Oil Refining & Marketing		19
			Oil Refining & Marketing Total		19
		Energy Total			304
		Media	Media - Broadcast		15
			Media - Broadcast Total		15
			Media - Diversified		58
			Media - Diversified Total		58
			Media - Services		3
			Media - Services Total		3
			Media-Cable		44
			Media-Cable Total		44
			Printing & Publishing		12
			Printing & Publishing Total		12
		Media Total			132
		Real Estate	RealEstate Dev & Mgt		10
			RealEstate Dev & Mgt Total		10
			REITs		90
			REITs Total		90
		Real Estate Total			100
		Services Cyc	Airlines		11
			Airlines Total		11
			Building & Construction		6
			Building & Construction Total		6
			Gaming		4
			Gaming Total		4
			Hotels		5
			Hotels Total		5
			Leisure		1
			Leisure Total		1
			Railroads		77
			Railroads Total		77
			Support-Services		14
			Support-Services Total		14
			Transportation Excluding Air/Rail		24
			Transportation Excluding Air/Rail Total		24
		Services Cyclical Total			142
		Services Nor	Environmental		18
			Environmental Total		18
			Health Services		17
			Health Services Total		17
		Services Non-Cyclical Total			35
		Technology &	Computer Hardware		8
			Computer Hardware Total		8
			Electronics		25
			Electronics Total		25
			Office Equipment		3
			Office Equipment Total		3
			Software/Services		2
			Software/Services Total		2
		Technology & Electronics Total			38
		Telecommuni	Telecom - Integrated/Services		65
			Telecom - Integrated/Services Total		65
			Telecom - Wireless		17
			Telecom - Wireless Total		17
		Telecommunications Total			82
	Industrials Total				1260
	Utility	Utility	Electric-Distr/Trans		8
			Electric-Distr/Trans Total		8
			Electric-Generation		28
			Electric-Generation Total		28
			Electric-Integrated		168
			Electric-Integrated Total		168
			Non-Electric Utilities		3
			Non-Electric Utilities Total		3
		Utility Total			207
	Utility Total				207
Corporate Total					1649
Quasi & Fore	Quasi & Fore	Agency	Agency		12
			Agency Total		12
		Agency Total			12
		Foreign Sove	Foreign Sovereign		30
			Foreign Sovereign Total		30
		Foreign Sovereign Total			30
		Government	Government Guaranteed		1
			Government Guaranteed Total		1
		Government Guaranteed Total			1
	Quasi & Foreign Government Total				43
Quasi & Foreign Government Total					43
Securitized/C	Securitized	Asset Backe	ABS Credit Cards		4
			ABS Credit Cards Total		4
			ABS Home Equity Loans		4
			ABS Home Equity Loans Total		4
			ABS Manufactured Housing		23
			ABS Manufactured Housing Total		23
		Asset Backed Total			31
	Securitized Total				31
Securitized/Collateralized Total					31
Grand Total					**1,723**

BB - RATED					
IndLvl1L	IndLvl2L	IndLvl3L	IndLvl4L	ML Indst	Total
Corporate	Financial	Banking	Banking		4
			Banking Total		4
			Mortgage Banks & Thrifts		3
			Mortgage Banks & Thrifts Total		3
		Banking Total			7
		Finance & In	Cons/Comm/Lease Financing		4
			Cons/Comm/Lease Financing Total		4
			Investments & Misc Financial Servi		2
			Investments & Misc Financial Servi Total		2
		Finance & Investment Total			6
		Insurance	Multi-Line Insurance		7
			Multi-Line Insurance Total		7
			P&C		1
			P&C Total		1
		Insurance Total			8
	Financial Total				21
	Industrials	Basic Industr	Chemicals		37
			Chemicals Total		37
			Forestry/Paper		36
			Forestry/Paper Total		36
			Metals/Mining Excluding Steel		6
			Metals/Mining Excluding Steel Total		6
			Steel Producers/Products		4
			Steel Producers/Products Total		4
		Basic Industry Total			83
		Capital Good	Aerospace/Defense		2
			Aerospace/Defense Total		2
			Building Materials		6
			Building Materials Total		6
			Diversified Capital Goods		3
			Diversified Capital Goods Total		3
			Machinery		8
			Machinery Total		8
			Packaging		1
			Packaging Total		1
		Capital Goods Total			20
		Consumer Cy	Apparel/Textiles		6
			Apparel/Textiles Total		6
			Auto Parts & Equipment		18
			Auto Parts & Equipment Total		18
			Automotive		3
			Automotive Total		3
			Household & Leisure Products		5
			Household & Leisure Products Total		5
			Non-Food & Drug Retailers		48
			Non-Food & Drug Retailers Total		48
			Restaurants		6
			Restaurants Total		6
		Consumer Cyclical Total			86
		Consumer No	Beverage		4
			Beverage Total		4
			Consumer-Products		6
			Consumer-Products Total		6
			Food - Wholesale		10
			Food - Wholesale Total		10
			Food & Drug Retailers		2
			Food & Drug Retailers Total		2
			Pharmaceuticals		7
			Pharmaceuticals Total		7
			Tobacco		2
			Tobacco Total		2
		Consumer Non-Cyclical Total			31
		Energy	Energy - Exploration & Production		24
			Energy - Exploration & Production Total		24
			Gas Distribution		3
			Gas Distribution Total		3
			Oil Field Equipment & Services		3
			Oil Field Equipment & Services Total		3
			Oil Refining & Marketing		5
			Oil Refining & Marketing Total		5
		Energy Total			35
		Media	Media - Broadcast		4
			Media - Broadcast Total		4
			Media - Diversified		3
			Media - Diversified Total		3
			Media-Cable		19
			Media-Cable Total		19
		Media Total			26
		Real Estate	RealEstate Dev & Mgt		2
			RealEstate Dev & Mgt Total		2
			REITs		6
			REITs Total		6
		Real Estate Total			8
		Services Cyc	Airlines		24
			Airlines Total		24
			Building & Construction		39
			Building & Construction Total		39
			Gaming		36
			Gaming Total		36
			Hotels		24
			Hotels Total		24
			Leisure		1
			Leisure Total		1
			Railroads		1
			Railroads Total		1
			Transportation Excluding Air/Rail		5
			Transportation Excluding Air/Rail Total		5
		Services Cyclical Total			130
		Services Nor	Environmental		8
			Environmental Total		8
			Health Services		38
			Health Services Total		38
		Services Non-Cyclical Total			46
		Technology &	Computer Hardware		4
			Computer Hardware Total		4
			Electronics		7
			Electronics Total		7
			Office Equipment		6
			Office Equipment Total		6
			Software/Services		1
			Software/Services Total		1
			Telecommunications Equipment		5
			Telecommunications Equipment Total		5
		Technology & Electronics Total			23
		Telecommuni	Telecom - Fixed Line		6
			Telecom - Fixed Line Total		6
			Telecom - Integrated/Services		33
			Telecom - Integrated/Services Total		33
			Telecom - Wireless		8
			Telecom - Wireless Total		8
		Telecommunications Total			47
	Industrials Total				535
	Utility	Utility	Electric-Distr/Trans		2
			Electric-Distr/Trans Total		2
			Electric-Generation		15
			Electric-Generation Total		15
			Electric-Integrated		30
			Electric-Integrated Total		30
		Utility Total			47
	Utility Total				47
Corporate Total					603
Grand Total					**603**

BB - RATED					
Count of Cusip					
IndLvl1L	IndLvl2L	IndLvl3L	IndLvl4L	ML Indst	Total
Corporate	Financial	Banking	Banking		1
			Banking Total		1
			Mortgage Banks & Thrifts		5
			Mortgage Banks & Thrifts Total		5
		Banking Total			6
		Finance & In	Cons/Comm/Lease Financing		9
			Cons/Comm/Lease Financing Total		9
			Investments & Misc Financia		2
			Investments & Misc Financial Servi Total		2
		Finance & Investment Total			11
		Insurance	Life-Insurance		2
			Life-Insurance Total		2
			Multi-Line Insurance		1
			Multi-Line Insurance Total		1
		Insurance Total			3
	Financial Total				20
	Industrials	Basic Industr	Chemicals		12
			Chemicals Total		12
			Forestry/Paper		13
			Forestry/Paper Total		13
			Metals/Mining Excluding Stee		7
			Metals/Mining Excluding Steel Total		7
			Steel Producers/Products		3
			Steel Producers/Products Total		3
		Basic Industry Total			35
		Capital Good	Aerospace/Defense		11
			Aerospace/Defense Total		11
			Building Materials		15
			Building Materials Total		15
			Diversified Capital Goods		2
			Diversified Capital Goods Total		2
			Machinery		10
			Machinery Total		10
			Packaging		14
			Packaging Total		14
		Capital Goods Total			52
		Consumer Cy	Apparel/Textiles		11
			Apparel/Textiles Total		11
			Auto Parts & Equipment		9
			Auto Parts & Equipment Total		9
			Household & Leisure Produc		9
			Household & Leisure Products Total		9
			Non-Food & Drug Retailers		21
			Non-Food & Drug Retailers Total		21
			Restaurants		6
			Restaurants Total		6
		Consumer Cyclical Total			56
		Consumer No	Beverage		2
			Beverage Total		2
			Consumer-Products		7
			Consumer-Products Total		7
			Food - Wholesale		14
			Food - Wholesale Total		14
			Food & Drug Retailers		7
			Food & Drug Retailers Total		7
			Pharmaceuticals		8
			Pharmaceuticals Total		8
		Consumer Non-Cyclical Total			38
		Energy	Energy - Exploration & Produ		29
			Energy - Exploration & Production Total		29
			Gas Distribution		2
			Gas Distribution Total		2
			Oil Field Equipment & Servic		5
			Oil Field Equipment & Services Total		5
			Oil Refining & Marketing		9
			Oil Refining & Marketing Total		9
		Energy Total			45
		Media	Media - Broadcast		21
			Media - Broadcast Total		21
			Media - Diversified		2
			Media - Diversified Total		2
			Media - Services		2
			Media - Services Total		2
			Media-Cable		25
			Media-Cable Total		25
			Printing & Publishing		15
			Printing & Publishing Total		15
		Media Total			65
		Real Estate	RealEstate Dev & Mgt		4
			RealEstate Dev & Mgt Total		4
			REITs		1
			REITs Total		1
		Real Estate Total			5
		Services Cyc	Airlines		21
			Airlines Total		21
			Building & Construction		5
			Building & Construction Total		5
			Gaming		26
			Gaming Total		26
			Hotels		6
			Hotels Total		6
			Leisure		10
			Leisure Total		10
			Railroads		3
			Railroads Total		3
			Support-Services		15
			Support-Services Total		15
			Theaters & Entertainment		1
			Theaters & Entertainment Total		1
			Transportation Excluding Air		12
			Transportation Excluding Air/Rail Total		12
		Services Cyclical Total			99
		Services Nor	Environmental		1
			Environmental Total		1
			Health Services		25
			Health Services Total		25
		Services Non-Cyclical Total			26
		Technology &	Electronics		13
			Electronics Total		13
			Telecommunications Equipm		6
			Telecommunications Equipment Total		6
		Technology & Electronics Total			19
		Telecommuni	Telecom - Fixed Line		7
			Telecom - Fixed Line Total		7
			Telecom - Integrated/Servic		7
			Telecom - Integrated/Services Total		7
			Telecom - Wireless		30
			Telecom - Wireless Total		30
		Telecommunications Total			44
	Industrials Total				484
	Utility	Utility	Electric-Generation		10
			Electric-Generation Total		10
			Electric-Integrated		6
			Electric-Integrated Total		6
		Utility Total			16
	Utility Total				16
Corporate Total					520
Grand Total					**520**

APPENDIX 4A – Calculation of weighted versions of pooled regressions

a. **Cross Section Weights:** It estimates a feasible GLS specification assuming the presence of cross section heteroscedasticity. GLS is performed by dividing the weight series by its mean then multiplying all of the data of each observation by the scaled weight series. The scaling of the weight series is a normalisation that has no effect on the parameter results, but makes the weighted residuals more comparable to the unweighted residuals. The White test of heteroscedasticity consistent covariance is accompanying the GLS results, which provides correct estimates of the coefficient covariances in the presence of heteroscedasticity of unknown form. This method accounts for cross-equation heteroskedasticity by minimizing the weighted sum-of-squared residuals. The equation weights are the inverses of the estimated equation variances, and are derived from unweighted estimation of the parameters of the system. This method yields identical results to unweighted single-equation least squares if there are no cross-equation restrictions.

b. **Seemingly Unrelated Regressions (SUR):** It estimates a feasible GLS specification correcting for both cross section heteroscedasticity and contemporaneous correlation. It is also known as the multivariate regression, or Zellner's method. It estimates the parameters of the system, accounting for heteroskedasticity, and contemporaneous correlation in the errors across equations. The estimates of the cross-equation covariance matrix are based upon parameter estimates of the unweighted system.

$$\Omega = \Sigma \otimes I_T = \begin{pmatrix} \sigma_{11} I_T \;\; \sigma_{12} I_T \;\; \ldots \\ \sigma_{1N} I_T \\ \\ \sigma_{21} I_T \; \sigma_{22} I_T \;\; \ldots.. \\ \sigma_{2N} I_T \end{pmatrix}$$

where Σ is the symmeteric matrix of the contemporaneous correlations :

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \ldots\ldots & \sigma_{1N} \\ \sigma_{21} & \sigma_{22} & \ldots\ldots & \sigma_{2N} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \end{pmatrix}$$

with typical element $\sigma_{ij} = E\ (e_{jt}\ e_{it})$, which is assumed constant across T.

The SUR model is estimated by using σ_{ij} estimated from a first stage pooled OLS regression :

$$\sigma_{ij} = \Sigma_t (y_{it} - y_{it})(y_{jt} - y_{jt}) / \max(T_i, T_j)$$

The use of the max function in the denominator handles the case of unbalanced data by downweighting the covariance terms. Provided that the number of missing values is asymptotically negligible, this approach yields a consistent estimator of Σ that is generally invertible. The parameter estimates and the covariance matrix of the parameters of the model are computed using the standard GLS formula.

APPENDIX 5a – RESULTS BASED ON MONTHLY DATA(GLS Method)

Empirical results based on ML Indices (Monthly Data)

Total Sample				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.00	6.6	0.00
US Consumer Confidence	-	-0.44	-16.3	0.00
GPD	-	0.01	8.04	0.00
Industrial Production	-	0.62	21.2	0.00
CPI	+	0.09	9.58	0.00
Term Structure	-	-0.13	-9.09	0.00
MS	-	-0.01	-8.96	0.00
Weighted Statistics – *White Heteroscedasticity Consistent Standard Errors & Covariance*				
Adjusted R-squared	7			
Durbin Watson stat	2.2			
Unweighted Statistics				
Adjusted R-squared	2			
Durbin Watson stat	2.2			

Investment Grade Sample				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.018	12.8	0.00
US Consumer Confidence	-	-0.33	-14.7	0.00
GPD	-	0.02	16.6	0.00
Industrial Production	-	0.38	10.14	0.00
CPI	+	0.08	6.45	0.00
Term Structure	-	-0.19	-9.35	0.00
MS	-	-0.011	-4.56	0.00
Weighted Statistics – *White Heteroscedasticity Consistent Standard Errors & Covariance*				
Adjusted R-squared	7			
Durbin Watson stat	2.1			
Unweighted Statistics				
Adjusted R-squared	2			
Durbin Watson stat	1.9			

Non – Investment Grade Sample				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.04	23.42	0.00
US Consumer Confidence	-	-0.78	-19.21	0.00
GPD	-	0.03	18.15	0.00
Industrial Production	-	0.7	15.58	0.00
CPI	+	-0.08	-5.09	0.00
Term Structure	-	0.48	20.46	0.00
MS	-	-0.01	-6.45	0.00
Weighted Statistics – *White Heteroscedasticity Consistent Standard Errors & Covariance*				
Adjusted R-squared	14			
Durbin Watson stat	2			
Unweighted Statistics				
Adjusted R-squared	2			
Durbin Watson stat	1.5			

APPENDIX 5b – RESULTS BASED ON MONTHLY DATA (SUR Method)

AAA - Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.04	3.76	0.00
US Consumer Confidence	-	-0.45	-2.93	0.02
Industrial Production (LAGS 3)	-	0.52	1.73	0.08
CPI (LAGS 3)	+	0.2	1.98	0.00
GDP (LAGS 3)	-	-0.03	-1.02	0.09
MS	-	-0.44	-2.96	0.00
Term Structure	-	-0.43	-3.23	0.00
Unweighted Statistics				
Adjusted R-squared	1			
Durbin Watson stat	1.9			

AA - Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.03	3.10	0.00
US Consumer Confidence	-	-0.35	-2.32	0.02
Industrial Production (LAGS 3)	-	0.52	1.73	0.08
CPI (LAGS 3)	+	0.18	2.35	0.00
Term Structure	-	-0.36	-3.45	0.00
GDP(LAGS 3)		-0.01	-1.22	0.00
MS	-	-0.04	-2.77	0.00
Unweighted Statistics				
Adjusted R-squared	2			
Durbin Watson stat	2			

A - Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.01	3.14	0.00
US Consumer Confidence	-	-0.42	-18.01	0.02
Industrial Production (LAGS 3)	-	0.43	10.67	0.00
CPI (LAGS 3)	+	0.05	3.77	0.00
Term Structure	-	-0.06	-3.21	0.00
MS	-	-0.05	-3.48	0.00
GDP(LAGS 3)	-	-0.07	-1.07	0.09
Unweighted Statistics				
Adjusted R-squared	2			
Durbin Watson stat	2.1			

BBB - Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.03	6.87	0.00
US Consumer Confidence	-	-0.43	-15.15	0.00
GPD(LAGS 3)	-	-0.01	-5.70	0.00
Industrial Production(LAGS 3)	-	0.4	7.86	0.00
CPI (LAGS 3)	+	0.21	14.5	0.00
Term Structure	-	0.32	11.7	0.00
MS	-	-0.04	-10.5	0.00
Unweighted Statistics				
Adjusted R-squared	10.8			
Durbin Watson stat	2			

BB - Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.03	14.2	0.00
US Consumer Confidence	-	-0.25	-12.3	0.00
Industrial Production (LAGS 3)	-	0.95	11.3	0.00
CPI (LAGS 3)	+	0.25	12.3	0.00
Term Structure	-	0.14	4.71	0.00
MS	-	-0.14	-5.03	0.00
GDP(LAGS 3)	-	0.02	7.26	0.00
Unweighted Statistics				
Adjusted R-squared	14			
Durbin Watson stat	2			

B – Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		-0.04	10.7	0.00
US Consumer Confidence	-	-0.67	-11.25	0.00
GDP(LAGS 3)	-	0.02	7.22	0.00
Industrial Production (LAGS 3)	-	1.13	10.44	0.00
CPI (LAGS 3)	+	0.10	2.73	0.00
Term Structure	-	0.10	2.25	0.00
MS	-	-0.02	-3.23	0.00
Unweighted Statistics				
Adjusted R-squared	13			
Durbin Watson stat	2			

C – Seemingly Unrelated Regression				
Variables	**Expected Sign**	**Coefficient**	**t-value**	**P-value**
Constant		0.04	10.7	0.00
US Consumer Confidence	-	-0.67	-11.2	0.00
GDP(LAGS 3)	-	0.02	3.62	0.00
Industrial Production (LAGS 3)	-	1.09	8.64	0.00
CPI (LAGS 3)	+	0.12	2.73	0.00
Term Structure	-	0.11	2.25	0.02
MS	-	-0.01	-3.23	0.00
Unweighted Statistics				
Adjusted R-squared	14			
Durbin Watson stat	2			

APPENDIX 6 – CORRELATIONS

5.14. Correlation Among Dependent and Independent Variables (Long Term)

LONG TERM CREDIT SPREAD INDICES AND EQUITY VARIABLES (CHANGES)											
	AAA	AA	A+	A	A-	BBB+	BBB	BBB-	RUSSELL	S&P	VIX
AAA	1.00										
AA	0.00	1.00									
A+	-0.05	-0.07	1.00								
A	-0.05	-0.05	0.77	1.00							
A-	0.01	-0.02	0.73	0.82	1.00						
BBB+	-0.07	0.04	0.65	0.74	0.79	1.00					
BBB	0.06	0.02	0.60	0.61	0.67	0.78	1.00				
BBB-	-0.03	-0.07	0.43	0.35	0.48	0.54	0.59	1.00			
RUSSELL	0.02	0.07	0.03	0.01	-0.02	0.01	-0.05	-0.02	1.00		
S&P	-0.07	-0.12	0.02	0.02	0.00	-0.04	-0.04	-0.05	-0.09	1.00	
VIX	0.03	0.02	0.06	0.00	0.00	0.05	0.04	0.14	0.08	0.62	1.00

5.15. Correlation Among Dependent and Independent Variables (Medium Term)

MEDIUM TERM CREDIT SPREAD INDICES AND EQUITY VARIABLES (CHANGES)											
	AAA	AA	A+	A	A-	BBB+	BBB	BBB-	RUSSELL	S&P	VIX
AAA	1.00										
AA	-0.73	1.00									
A+	-0.30	0.37	1.00								
A	-0.22	0.33	0.76	1.00							
A-	-0.15	0.37	0.35	0.19	1.00						
BBB+	-0.15	0.36	0.39	0.26	0.80	1.00					
BBB	-0.18	0.40	0.42	0.28	0.68	0.71	1.00				
BBB-	-0.07	0.28	0.38	0.32	0.58	0.58	0.65	1.00			
RUSSELL	0.03	-0.04	-0.04	-0.03	-0.11	-0.12	-0.13	-0.16	1.00		
S&P	-0.07	0.07	0.01	0.02	0.06	0.02	0.11	0.07	-0.07	1.00	
VIX	0.03	-0.02	-0.03	-0.03	-0.10	-0.04	-0.08	-0.01	0.08	0.61	1.00

5.16. Correlation Among Dependent and Independent Variables (Short Term)

SHORT TERM CREDIT SPREAD INDICES AND EQUITY VARIABLES (CHANGES)											
	AAA	AA	A+	A	A-	BBB+	BBB	BBB-	RUSSELL	S&P	VIX
AAA	1.00										
AA	0.14	1.00									
A+	0.34	0.47	1.00								
A	0.39	0.45	0.68	1.00							
A-	0.04	0.50	0.49	0.65	1.00						
BBB+	0.15	0.34	0.45	0.58	0.72	1.00					
BBB	0.02	0.34	0.43	0.57	0.68	0.69	1.00				
BBB-	0.13	0.37	0.41	0.56	0.61	0.58	0.66	1.00			
RUSSELL	0.07	-0.02	0.01	0.02	-0.11	-0.06	-0.15	-0.21	1.00		
S&P	-0.10	-0.11	-0.14	-0.03	0.01	0.03	-0.02	0.01	-0.07	1.00	
VIX	0.06	0.09	0.11	0.08	-0.06	-0.05	0.03	0.00	0.08	0.61	1.00

APPENDIX 7A

Table 1

Forecasting Ability in Percentage Terms under the GLS Method							
	Investment Grade				High Yield		
	AAA	AA	A	BBB	BB	B	C
1 Quarter ahead	99%	102% *	90%	88%	78%	87%	115%*
2 Quarters Ahead	93%	88%	84%	90%	73%	92.3	30%
1 Year Ahead	98%	100%	97%	99%	82%	97.8	78%
2 Years Ahead	83%	81%	85%	85%	93%	89%	91%
2 Year & ¾ ahead	81%	81%	87%	85%	93%	89%	96%
	Avergage Forecasting Ability in Percentage Terms for Investment Grade Sample				Avergage Forecasting Ability in Percentage Terms for High Yield Sample		
1 Quarter ahead	92%				93%		
2 Quarters Ahead	90%				65%		
1 Year Ahead	99%				86%		
2 Years Ahead	84%				91%		
2 Year & ¾ ahead	84%				93%		
Percentages above have been calculated as Mean Actual Spread Levels divided by Mean Forecasted Spread Levels							
* AA and C percentages imply that the forecasted spread is smaller than the actual one, hence the forecast is underestimating credit spread levels.							

Table 2

Forecasting Ability in Percentage Terms under the GLS Method on the Three Random Samples			
	A	B	C
1 Quarter ahead	85%	94%	94%
2 Quarters Ahead	84%	101%*	85%
1 Year Ahead	103% *	108% *	97%
2 Years Ahead	91%	143%*	86%
2 Year & ¾ ahead	109%*	91%	90%
Percentages above have been calculated as Mean Actual Spread Levels divided by Mean Forecasted Spread Levels.			
* Percentages imply that the forecasted spread is smaller than the actual one, hence the forecast is underestimating credit spread levels.			

APPENDIX 7B

Table 1

Forecasting Ability in Percentage Terms under the SUR Method							
	Investment Grade				High Yield		
	AAA	AA	A	BBB	BB	B	C
1 Quarter ahead	94%	126% *	98%	95%	74%	87%	61%
2 Quarters Ahead	135%*	103%*	94%	94%	72%	91%	70%
1 Year Ahead	78%	99%	94%	94%	87%	97%	83%
2 Years Ahead	82%	85%	98%	98%	92%	88%	174%*
2 Year & 3/4 ahead	81%	91%	98%	98%	91%	89%	113% *
	Avergage Forecasting Ability in Percentage Terms for Investment Grade Sample				**Avergage Forecasting Ability in Percentage Terms for High Yield Sample**		
1 Quarter ahead	90%				74%		
2 Quarters Ahead	87%				78%		
1 Year Ahead	91%				89%		
2 Years Ahead	91%				68%		
2 Year & 3/4 ahead	92%				89%		
Percentages above have been calculated as Mean Actual Spread Levels divided by Mean Forecasted Spread Levels.							
* Percentages imply that the forecasted spread is smaller than the actual one, hence the forecast is underestimating credit spread levels.							

Table 2

Forecasting Ability in Percentage Terms under the SUR Method on the Three Random Samples			
	A	B	C
1 Quarter ahead	86%	94%	100%
2 Quarters Ahead	83%	100%	84%
1 Year Ahead	103%	107% *	88%
2 Years Ahead	96%	84%	72%
2 Year & ¾ ahead	71%	85%	77%
Percentages above have been calculated as Mean Actual Spread Levels divided by Mean Forecasted Spread Levels.			
* Percentages imply that the forecasted spread is smaller than the actual one, hence the forecast is underestimating credit spread levels.			

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