City Research Online

City St George's, University of London

Citation: Kapar, B. (2013). The effects of 2007-2008 crisis on the CDS and the interbank markets: Empirical investigations. (Unpublished Doctoral thesis, City University London)

This is the unspecified version of the paper.

This version of the publication may differ from the final published version. To cite this item please consult the publisher's version.

Permanent repository link: https://openaccess.city.ac.uk/id/eprint/2958/

Copyright and Reuse: Copyright and Moral Rights remain with the author(s) and/or copyright holders. Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge, unless otherwise indicated, provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way. For full details of reuse please refer to City Research Online policy.

City Research Online: http://openaccess.city.ac.uk/ publications@citystgeorges.ac.uk

The Effects of 2007-2008 Crisis on the CDS and Interbank Markets: Empirical Investigations

Burcu Kapar

July, 2013

A thesis submitted to

the Academic Faculty

by

Burcu Kapar

In partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Department of Economics

City University

London, United Kingdom

July, 2013

© Copyright 2013

Burcu Kapar

Contents

1 Introduction **1**

1.1 The 2007-2008 Financial Crisis 2

1.2 Credit Default Swap Market 5

1.2.1 The Characteristics of Credit Default Swaps 5

1.2.2 The Contribution of CDS Market to 2007-2008 Financial Crisis 8

1.2.3 New Regulations in the CDS Market as a Response to 2007-2008 Crisis . 12

1.2.4 Contribution of this Thesis to the Existing CDS Market Literature . . . 13

1.3 Interbank Credit Market 16

1.3.1 European Interbank Market 16

1.3.2 The Effects of 2007-2008 Crisis on European Interbank Market 17

1.3.3 New Measures as a Response to 2007-2008 Crisis 19

1.3.4 Contribution of this Thesis to the Existing Interbank Market Literature . 19

1.4 Structure of the Thesis 21

1.5 Conclusion 22

2 The Determinants of Credit Default Swap Spreads in the Presence of Counterparty Risk and Structural Breaks **23**

2.1 Introduction 24

2.2 The Determinants of CDS Spreads 29

2.2.1 CDS Data 30

2.2.2 Explanatory Variables and Expected Relationship . . . 33
2.3 Methodology and Empirical Results . . . 38
2.3.1 Structural Break Tests . . . 40
2.3.2 Multiple Regression Results . . . 44
2.3.3 Robustness Checks . . . 47
2.3.4 Marginal Contributions of Idiosyncratic and Systematic Variables . . . 49
2.3.5 Analysis of Counterparty Risk . . . 50
2.4 Conclusion . . . 52
Appendix 2.A . . . 55

3 Long-Run Risk Dynamics, Instabilities and Breaks on European Credit Markets over a Crisis Period 62

3.1 Introduction . . . 63
3.2 Econometric Methodology . . . 66
3.2.1 Unit Root Tests with Breaks . . . 67
3.2.2 Econometric Model . . . 69
3.2.3 Robustness Checks . . . 72
3.2.3.1 Exogeneity of the Factors . . . 72
3.2.3.2 Multivariate Cointegration Test-Johansen Methodology . . . 73
3.3 Empirical analysis of the CDS market . . . 73
3.3.1 European CDS data . . . 74
3.3.2 Empirical findings . . . 75
3.3.3 Application of the Model . . . 75
3.3.4 Robustness Checks . . . 79
3.3.4.1 Exogeneity of the Factors . . . 79
3.3.4.2 Multivariate Cointegration Test-Johansen Methodology . . . 80
3.4 Conclusions . . . 80
Appendix 3.A . . . 83

4 Early Warning Indicators of Money Market Distress: A Non-Parametric Approach **88**

4.1 Introduction . . . 89

4.2 The e-MID Market and Data . . . 92

4.2.1 The e-MID Market . . . 92

4.2.2 Data . . . 94

4.3 Econometric Methodology . . . 97

4.4 Empirical Findings . . . 101

4.4.1 Dynamics of Spreads: Mean and Volatility . . . 101

4.4.2 Size Matters . . . 103

4.4.3 The Role of Operating Currency and Bank's Nationality . . . 106

4.5 Conclusion . . . 109

Appendix 4.A . . . 111

5 Conclusion **127**

5.1 Introduction . . . 127

5.2 Conclusions and Implications of the Findings . . . 128

5.3 Limitations of the Study and Suggestions for Future Research . . . 130

Bibliography **132**

List of Figures

1.1 TED Spread, the interest rate between the LIBOR and the Treasury bill rate . . 4

1.2 Credit Default Swaps-Notional Amount Outstanding Semiannually 7

1.3 CDS Spreads of Main Counterparties over Time 10

1.4 European Interbank Market 18

2.1 CDS Spreads of Reference Entities over Time 32

2.2 Time Series Graphs of CDS Spreads and Potential Explanatory Variables . . . 55

4.1 Volume and Number of Transactions per Month in the e-MID Market 114

4.2 Conditional Density of Estimation of Borrower Spread-Volatility of Spread on Monthly Time Period with Conditional Quantile Functions 115

4.3 Conditional Density of Estimation of Lender Spread-Volatility of Spread on Monthly Time Period with Conditional Quantile Functions 116

4.4 Estimated Conditional Densities of Spreads for Different Sized Borrowers 117

4.5 Estimated Conditional Densities of Volatility of Spreads for Different Sized Borrowers 118

4.6 Estimated Conditional Densities of Spreads for Different Sized Lenders 119

4.7 Estimated Conditional Densities of Volatility of Spreads for Different Sized Lenders 120

4.8 Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers using Euro or other currency with Major Domestic Borrowers 121

4.9 Comparison of Estimated Conditional Densities of Spreads for Foreign Lenders using Euro or other currency with Major Domestic Lenders 122

4.10 Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers experiencing Sovereign Crisis or not with Major Domestic Borrowers 123
4.11 Comparison of Estimated Conditional Densities of Spreads for Foreign Lenders experiencing Sovereign Crisis or not with Major Domestic Lenders 124
4.12 Comparison of Estimated Conditional Densities of Spreads for Britain, Germany, Greece with Major Domestic Borrowers 125
4.13 Comparison of Estimated Conditional Densities of Spreads for Britain, Germany, Greece with Major Domestic Lenders 126

List of Tables

2.1 List of Reference Entities in the Dataset 31

2.2 Descriptive Statistics of Financial and Non-Financial CDS Spreads 32

2.3 Structural Break Dates 44

2.4 Descriptive Statistics by Reference Entity 56

2.5 Multiple Regression Results-Systematic Variables 57

2.6 Multiple Regression Results-Idiosyncratic Variables 58

2.7 Simple Regression Results-Systematic Variables 59

2.8 Simple Regression Results-Idiosyncratic Variables 60

2.9 Marginal Contributions of Systematic and Idiosyncratic Variables 61

3.1 Unit Root Test Results with a Break 83

3.2 Engle-Granger Cointegration Test Results 84

3.3 Error Correction Model Results 85

3.4 Exogeneity Test Results 86

3.5 Johansen Cointegration Test Results 87

4.1 Participation of Different Groups to the e-MID Market 111

4.2 Information about Sub-Periods 111

4.3 Optimal Bandwidth Parameters of Conditional Density Estimation of Spread & Volatility on Asset Size 112

4.4 Optimal Bandwidth Parameters of Conditional Density Estimation of Spread on Nationality Classifications 113

Acknowledgements

I would like to express my deepest gratitude to my supervisor, Dr. Jose Olmo, for his patience, encouragement and invaluable guidance throughout my study in City University. I am extremely grateful for his time for our discussions and his understanding which helped to keep my motivation high. I also would like to thank my co-supervisor, Professor Giulia Iori, for her support and feedback on my work and her kindness to involve me in Forecasting Financial Crisis (FOC) project. I would like to convey my sincere thanks to all members of City University Economics Department for their valuable comments during my presentations and for providing generous financial support including the bursary and funds to present at the conferences in Seoul and Prague. I thank to my beloved parents for their compassion and encouragement not only through the course of my studies but also during all stages of my life. Lastly, I am in great debt to my husband who encouraged me to start this program. This work could not be possible without his support, limitless understanding and endless love.

Abstract

The global crisis of 2007-2008 is the most severe crisis since the Great Depression in the financial markets. Starting with the subprime defaults in the United States, it quickly spills over into other markets leading to the collapses of many financial institutions, bail-outs of banks worldwide and downturns in asset prices. The aim of this thesis is to investigate the repercussions of this crisis on CDS and interbank market and provide empirical evidence on the changes in the pricing of CDS contracts and interbank deposits.

Chapter 2 discusses the determinants of CDS spread changes on European contracts. The most remarkable finding of the study is that the relation between credit spreads and their determinants is regime dependant and depends on the sector of economic activity. Before the crisis the underlying credit risk in the overall CDS market is sufficient to explain credit risk. During the crisis investors have a differing view on the risk of financial and non-financial contracts. Interestingly, non-financial CDS contracts reflect the credit risk of the counterparty, but financial contracts do not. This implies that governments are expected to bail out dealers to prevent systemic risk.

Chapter 3 provides further insight into the European corporate CDS spreads and proposes an equilibrium model accommodating the occurrence of structural breaks in the long-run relationship between the variables. These breaks are endogenously determined within unit root specifications used to describe the dynamics of the explanatory factors. The findings highlight that crisis shocks are persistent and have the potential to change long-run equilibrium dynamics. The systematic credit risk factor is proxied by the European iTraxx index and the idiosyncratic factor by the stock price of reference entity. The model indicates that stock market leads price discovery process. Vector error correction model confirms the strong predictive ability of the iTraxx index and the error correcting vector for changes in the CDS spreads.

Chapter 4 focuses on European interbank market and has two main contributions. First, it estimates the cross-sectional density of interbank funding rates using nonparametric kernel methods. Second, it analyzes the effect of banks size, the operating currency and banks' nationality on the cross-sectional distribution of these rates. The findings strongly support the statistical significance of these effects and highlight the importance of these factors as early warning indicators of financial distress. Prior to the crisis, the borrowing segment of the market exhibits distinctive features such as highly volatile and multimodal distributions suggesting the occurrence of distortions in the cross-section of funding rates. During crisis, large domestic banks operating in Euros enjoy the most favourable rates. Banks' nationality analysis further confirms that interbank market provided early warning signals of incoming sovereign crisis.

Chapter 1

Introduction

Financial markets experienced one of the most severe crises around the world in 2007 and 2008. Although the crisis started with the bursting of the United States housing bubble, it quickly spilled over into other markets and assets resulting in the collapse of large financial institutions, the bailout of banks by national governments and downturns in stock markets. This triggered a downturn in economic activity yielding 2008-2012 global recessions and contributing to the European sovereign debt crisis.

During this period, credit markets experienced significant disruptions posing a threat to the stability of the financial system. Counterparty risk seemed to play a greater role behind this disruption in both CDS and interbank market. In the CDS market, CDS spreads evolved dramatically reflecting the increase in default risk of the reference entities. Also, CDS contracts on the same reference entity but written by different dealers were started to be sold from different prices showing the concern about default risk of the seller. In the interbank market, transactions were almost frozen, even in short term maturities. The main reasons behind this was the increase in the default risk of the other party in the transactions, named as counterparty risk, and the increase in liquidity risk. Hence, the turmoil highlighted the importance

of counterparty risk in credit markets although this had been neglected since the beginning of the crisis.

The aim of this thesis is to investigate the repercussions of the 2007-2008 crisis on CDS and interbank market and provide empirical evidence on the changes in the pricing of CDS contracts and interbank deposits before, during and after the crisis.

The purpose of this introductory chapter is to present the reader with background information about the relevant topics of the thesis. The chapter starts by briefly describing the worldwide financial crisis in 2007-2008 considering the underlying causes of the crisis and transmission of subprime crisis to other markets. The chapter then concentrates on the characteristics of two credit markets: Credit Default Swap and interbank market. The chapter mainly explains how the crisis affects these markets and new regulations after the crisis. The chapter also highlights the main contributions of this thesis to the existing CDS and interbank market literature. Finally, the structure of the thesis is presented.

1.1 The 2007-2008 Financial Crisis

The financial market turmoil in 2007 and 2008 has been the most severe crisis since the Great Depression and led to economic downturn throughout the world. There are three main groups of factors that have driven the recent crisis: macro factors, financial factors and banking misapplications. Monetary expansion in the U.S. market, thus lower interest rates, U.S housing boom, over-generous lending and high indebtedness of U.S. households are considered as the main macro factors of the recent crisis. The development of new structured financial products (CDSs, CDOs, asset-backed commercial papers), the increase in the number of hedge funds, the emergence of structured investment vehicles and inadequate credit risk assessment tools and regulation towards financial products and companies are considered as the

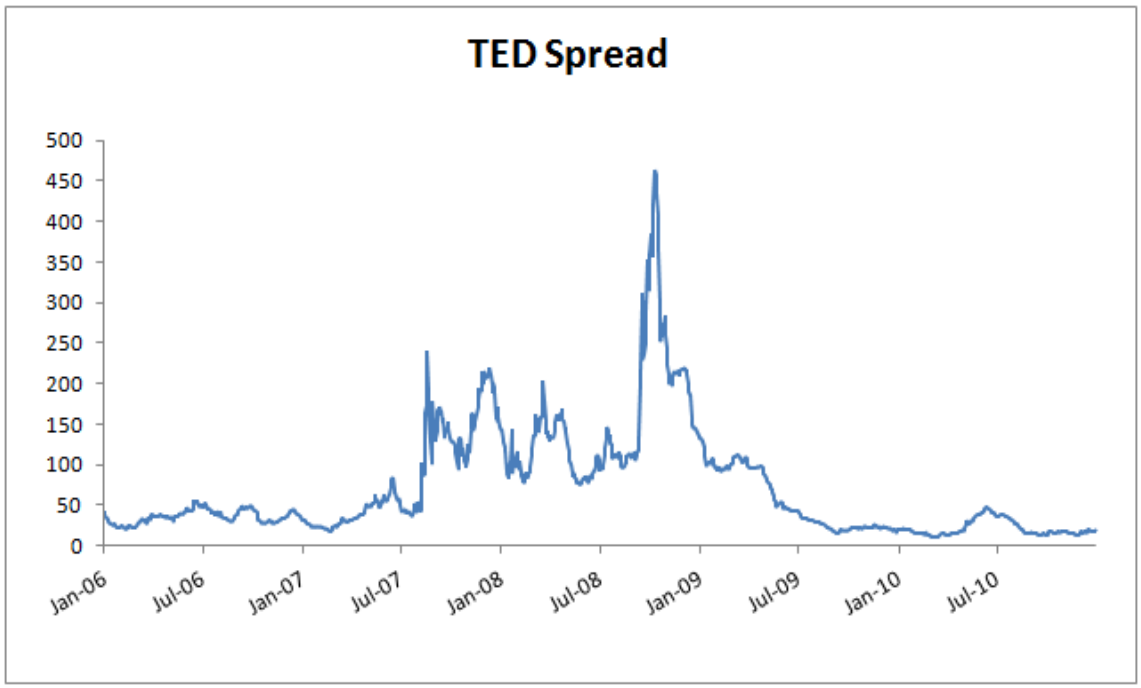
main triggering financial factors of the crisis (Orlowski, 2008). Two main misapplications of the banking sector also contributed to this crisis. First, "Originate and Distribute" model which is basically repacking the loans and transferring the risk to other investors rather than keeping the loans on banks' balance sheets. Second, financing loans with short-term instruments which leads to maturity mismatch and funding liquidity risk (Brunnermeier, 2009).

All these prevalent factors first triggered subprime mortgage defaults in February 2007 with a huge decline in mortgage credit default swap index (ABX). In June 2007, two hedge funds of Bear Sterns with vast exposures to subprime mortgage asset backed securities were exposed to large margin calls. High leverage of financial institutions accompanied by fall in house prices led to both a credit bubble and asset price booms.

Soon after, vulnerabilities in the subprime mortgage market spilled over into other types of assets. The crisis hit not only mortgage companies and investment banks but also commercial banks. Evolution in the TED spread, the difference between the interest rates on interbank loans and on short-term U.S. government debt, is one of the best examples that illustrates the transmission of the mortgage crisis into other assets and global financial institutions.

Figure 1.1 below depicts the TED spread captured by the difference between 3 month Libor and the 3 month Treasury bill yield. The outbreak of the subprime mortgage crisis on August 2007 is illustrated with the first spike in the TED spread. The second jump in December 2007 and the third jump in March 2008 shows the spillover of mortgage crisis into financial industry. In 2008, the elevated market and credit risk turned into liquidity and counterparty risk. Particularly, after the collapse of Lehman Brothers in September 2008, concern about counterparty risk increased further and institutions faced serious liquidity problems. As soon as in-

Figure 1.1: TED Spread, the interest rate between the LIBOR and the Treasury bill rate



vestors realized huge losses on credit derivatives and stock indices, they switched their investments from credit derivative and stock markets to commodities, especially crude oil futures market, triggering commodity price bubble. In the next stage of the crisis, the elevated counterparty risk and liquidity squeeze in the banking industry led to credit market freeze and concurrently flight-to-safety by investors (Orlowski, 2008). During all these stages, financial institutions that had high exposure to subprime mortgages hoarded for cash, sold their assets immediately to reduce their leverage ratio and were reluctant to lend to other institutions as they were incapable of estimating their own liquidity needs as well as evaluating the default risk of the counterparties.

1.2 Credit Default Swap Market

1.2.1 The Characteristics of Credit Default Swaps

Credit derivatives are bilateral agreements whose payoff depends on the performance of the underlying instrument. The main attraction of the agreement is that it isolates credit risk from the underlying instrument and shares the risk between two parties of the agreement. Main types of credit derivatives are Credit Default Swaps, Credit Options and Total Return Swaps, being Credit Default Swaps the most popular one with 96.7% market share.

Credit Default Swap is an over the counter contract between the seller and the buyer of protection against default risk of debt obligations issued by a specified reference entity. The reference entity can be a private or publicly traded firm, a sovereign government or governmental agency. The protection buyer pays a periodic premium over the life of the contract and in turn hedges itself against the credit risk of the reference asset. In case of the credit event, the seller is obliged to compensate the buyer for the loss according to the specified settlement procedure. In the mean time, the buyer is also exposed to counterparty risk in respect of the seller of the contract, if the seller does not have the ability to meet the obligations in case of the credit event.

According to the International Swaps and Derivatives Association (ISDA) definition 2003, there are six credit event types included in credit derivative agreements. These are bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation/moratorium, and restructuring with four specifications: full restructuring, modified restructuring, modified modified restructuring and no restructuring. The relevant credit event type is included in the contract depending on the market structure and reference entities' jurisdiction and characterization.

The price of the credit default swap, named as spread, is expressed in basis points, which is the percentage of the notional amount of the contract to be paid annually. In most of the CDS contracts, CDS premium is paid quarterly on certain reference days (March, June, September and December 20th). Spread is computed by equating the present value of premium payments to the present value of expected losses and higher spread is the indicator of higher credit risk of the reference entity.

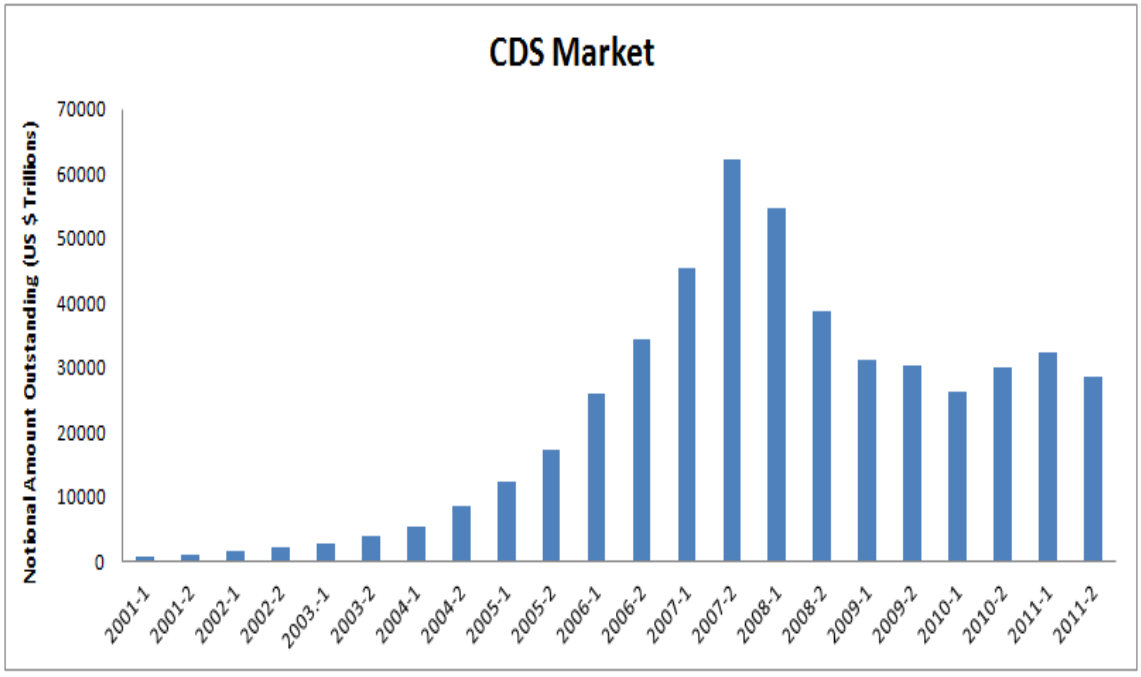
In case of a credit event, the CDS contract is settled in two ways. According to the physical settlement, the buyer delivers the reference obligation to the seller in exchange for the par value of the bond or instrument. According to cash settlement, CDS seller pays the difference between par value and market value of defaulted debt of the reference name. In March 2009, ISDA published the ISDA Credit Derivatives Determinations Committee and Auction Supplement to the 2003 ISDA Credit Derivatives Definitions. This supplement introduced auction settlement as an alternative to physical or cash settlement. According to this settlement type, a Committee, serving as a settlement auction coordinator, determine whether there has been a credit event; whether an auction will be held; or whether a particular obligation is deliverable or not.

Although the risk profile of CDS resembles to a corporate bond on the reference entity, CDS contracts have many advantages over bonds. First, CDS allows taking leveraged position as there is no need for an initial funding. Second, even if the bond of the reference entity is not available with a specific maturity; Credit Default Swap allows to take a position on that specific maturity. Finally, while shorting a bond is usually difficult in fixed income markets, via buying a CDS contract, one can easily create a short position on the reference credit.

CDS contracts are mainly categorized into three groups: Single Name CDS, CDS Indices and basket CDS. Single Name CDS is written on the default risk of

the single entity. CDS Indices compose a pool of very liquid, single name CDS contracts. Each entity in the index has equal share of the notional amount. In case of the credit event, the CDS indices proceed to be traded with the reduced notional amount. Unlike a CDS, which is an over the counter credit derivative, a CDS index is a completely standardized credit security and may therefore be more liquid and trade at a smaller bid-offer spread. CDX, iTraxx, LCDX, LevX, ABX, CMBX, MCDS and SovX are the main CDS indices traded in the market. Basket CDSs are written on CDS portfolios which can include from 3 to 100 reference entities. Nth to Default Basket is the popular type of basket CDSs. Under this contract, the seller compensates the buyer in case of the credit event of the Nth reference entity only and the CDS contract terminates after the compensation. Single name CDS contracts and index CDSs account for almost 60% and 30% of the overall market respectively in terms of gross notional amount at the end of 2011.

Figure 1.2: Credit Default Swaps-Notional Amount Outstanding Semiannually



As depicted in Figure 1.2 above, the CDS market experienced tremendous growth and increased to $ 62.173 billion at the end of 2007, even though the size of the market was only $ 631 billion at the end of 2001. However the impressive growth was impeded in 2008 and 2009 as a result of the financial crisis accentuated with the failure of Lehman Brothers. In recent years, the size of the market diminished to approximately $ 30.000 billion according to ISDA Market Survey data. Besides the effect of financial crisis, new standardization rules of the CDS contracts such as introduction of operational improvements, trade compression and offsetting of reverse positions have been influential on the fall of market size of the CDS market.

CDS contracts are mainly used for hedging and trading purposes. They are bought to hedge credit risk of the bonds or asset-backed securities. Commercial banks and other lenders are natural buyers of CDS protection for such purposes, while highly rated dealers, insurance companies, financial guarantors and credit derivative product companies are the typical protection sellers prior to the financial crisis. CDS products are also used to hedge counterparty exposure as a risk management tool and highly popular during stressful market conditions. Moreover CDS contracts are traded for speculative and arbitrage purposes in a way that speculators buy CDS contracts if they expect spreads to widen and sell contracts if they expect spreads to narrow. At the same time, CDS contract is used as a tool by the sellers to generate income via premium payments.

1.2.2 The Contribution of CDS Market to 2007-2008 Financial Crisis

Credit Default Swaps should help for the efficiency of financial markets by improving the allocation of the capital. When investors buy bonds, they are exposed to credit risk while funding companies. However via Credit Default Swaps, investors who sell

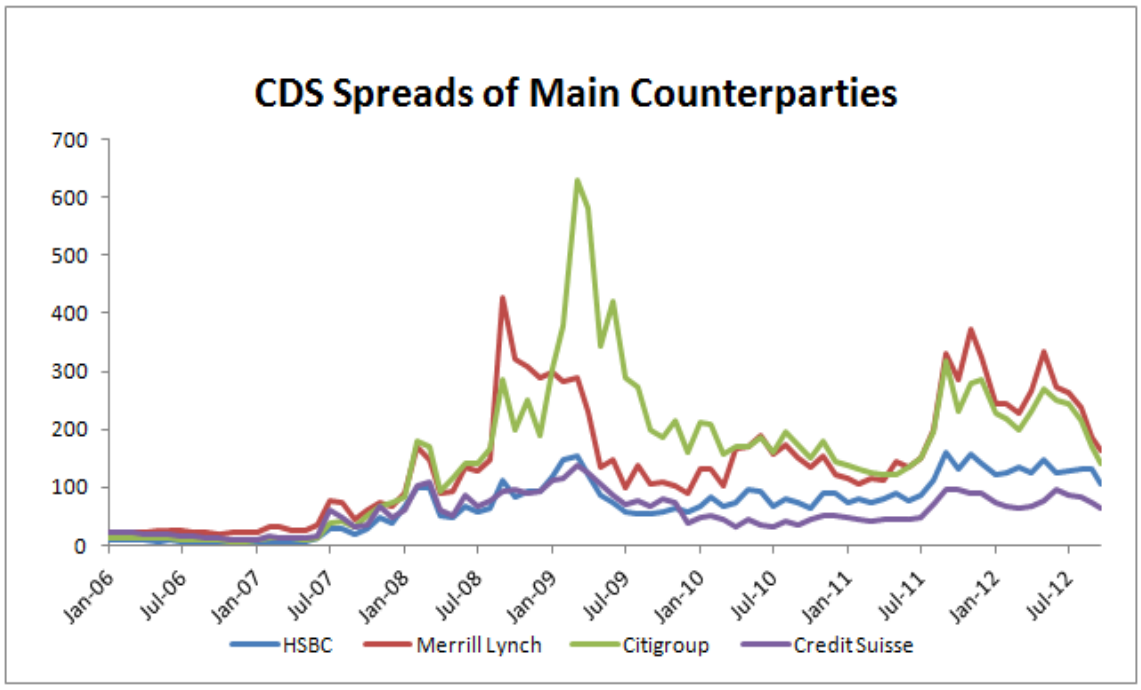
CDS written on the default risk of the bonds are subject to this risk. Hence, with the development of CDSs, the credit risk is transmitted from bond holders to CDS sellers who can best bear this risk (Stulz, 2010). Nevertheless during the recent crisis, CDSs were not able to contribute to the efficiency of financial markets as expected. The huge fall in ABX indices that composes CDS contracts written on subprime mortgages is considered as the outbreak of the recent subprime crisis.

There are many underlying reasons that explain the contribution of CDS to the recent crisis. First, due to built-in leverage of CDS contracts, investors are inclined to take riskier positions with CDSs than they can bear. However, the sellers of CDS contracts can not bear this risk during vulnerable financial times as well as during normal market conditions. AIG is one of the best examples for this. During the recent crisis, some of the hedging benefit of the contracts sold by AIG were appeared to be illusory (Stulz, 2010). Second, there was a very high concentration in the CDS market. According to data from US Treasury, at the end of 2008 five commercial banks (JP Morgan Chase, Bank of America, Citibank, Goldman Sachs and HSBC) accounted for practically 99% of the buyers and sellers of CDS in that country. Meanwhile, according to data from DTCC, in April 2009 the five largest sellers of CDS worldwide accounted for 49% of the total supply of these instruments, and the ten largest sellers accounted for 72% of the supply (ECB, 2009). The collapse of Lehman Brothers is a clear example for revealing the interconnected nature of participants in the CDS market that results in large trade replacement costs. This high concentration is one of the triggering factors for the increase in systemic risk during the crisis. Hence, the precondition in the CDS market is very vulnerable for a financial crisis.

Fourth, the opacity of over-the-counter markets played a critical role in the financial crisis. OTC markets carry a counterparty risk externality, although this

externality is absent when trading takes place in a centralized clearing mechanism that provides transparency of trade positions or a centralized counterparty that observes all trades and sets prices (Acharya and Bisin, 2010). Before the crisis, almost all of the CDS contracts were traded in over-the-counter markets and investors were exposed to counterparty risk. However until the onset of the subprime mortgage crisis, market participants perceived counterparty risk to be negligible. At this time, default risk of the seller of the contracts had not been considered in the pricing of CDS contracts. The importance of counterparty risk emerged during the 2007-2008 financial crisis when the bail-outs or collapses of many systemically important financial institutions took place. In the CDS market, the best proxy for showing the concern about counterparty risk is the CDS spreads of major dealers, CDS sellers, in the market. The Figure 1.3 below presents the spread of four major dealers from the beginning of 2006 to 2012.

Figure 1.3: CDS Spreads of Main Counterparties over Time



As depicted in Figure 1.3 above, CDS spreads started increasing in the second half of 2007 and 2008. During this time, major CDS dealers incurred substantial losses on financial contracts linked to subprime mortgages. Particularly after September 2008 with the collapse of Lehman Brothers, concern about counterparty risk surged even further. Uncollateralized transactions in which counterparties were involved triggerred this concern more. During this period, protection buyers were subject to terminated contracts before maturity due to the failure of sellers. Also, CDS contracts written by CDS dealers that had low credibility were started to be priced by lower spreads compared to those that were sold by highly credible dealers. For instance, the case of Lehman Brothers and AIG raised the awareness of CDS buyers about the credit risk of these sellers. Prior to the collapses, CDS contracts written by these dealers had been sold by lower spreads.

In principle, requiring collateral and guarantees or opening opposite positions on the existing ones are the most efficient ways of mitigating counterparty risk. However according to the ISDA Margin Survey (2008, 2009), by the end of 2008 only 66% of transactions were protected with collateral and by the end of 2009 this was even less; only 56% of transactions were collateralized. Even more, collateral agreements were employed much less frequently when the counterparty was a large dealer (Giglio, 2011). This is what we experienced during the recent crisis. The requirements of collateral increased during the turmoil, however this did not help to solve the problem of counterparty risk. Due to rating downgrades, some of the dealers like AIG and Bear Sterns were required to increase the margin calls and raise more collateral for CDS transactions, but raising capital during stressful market conditions were difficult to accomplish for distressed parties.

1.2.3 New Regulations in the CDS Market as a Response to 2007-2008 Crisis

Both CDS market participants and regulators have taken some nonstandard measures after 2007-2008 crisis. CDS market participants responded to the crisis by shifting their trading patterns. Some of them invested in contracts written on the default risk of the counterparty, in addition to the existing contracts. Although this can eliminate the losses in the event of counterparty default, it increases the total cost of buying CDS protection. Also it is obvious that switching from one counterparty to other one is not an effective solution if there is systemic concern about robustness of the counterparties in the market. Further, investors prefer shorter maturities. Even though the contracts with five year maturities are the most popular ones before the crisis, investors' preference moves from five year contracts to the contracts with less than one year maturities in order to alleviate the concern about counterparty risk (Vause, 2010).

From the regulators perspective, the most important changes in the CDS market to mitigate counterparty risk is the standardization of the contracts, trade compression and the introduction of central counterparties (CCPs). In the CDS market, standardization varies according to the type of product. While CDS indices and index tranches were highly standardized contracts, single name CDS contracts were less standardized till the outbreak of the crisis. New regulations introduced by ISDA in April 2009 in the CDS market standardize single name CDS up to a level of other CDS products such as CDS indices and index tranches. This standardization brings convenience not only for tearing up offsetting contracts but also for trade compression.

The most important development in the CDS market is the introduction of central counterparties (CCPs). CCPs stand between over-the-counter derivatives' coun-

terparties; insulating them from each others default. Instead of bilateral CDS contracts between a protection buyer and a seller, a contract between the protection buyer and a CCP and another contract between the same CCP and the protection seller are agreed via CCPs. The main goal of CCPs is to require strict collateral from counterparties and form an emergency fund to use in case of counterparty defaults. Although regulators are very hopeful about the benefit of CCPs, Duffie and Zhu (2011) investigate the efficiency of central clearing houses in reducing counterparty exposures and collateral demand. Contrary to expectations, their findings demonstrate that clearing only one types of derivative reduces netting efficiency. Only if many derivatives are cleared in the same clearing houses, efficiency increases and counterparty risk can be mitigated.

The last regulation in the CDS market is aiming to increase the transparency of the market. CDS market is highly criticized as having been not transparent during the crisis which is one of the drawbacks of over-the-counter markets. To improve transparency, as well as the establishment of clearing houses, The Depository Trust & Clearing Corporation has started providing regulators with an access to its registry of credit default swaps since November 2008.

1.2.4 Contribution of this Thesis to the Existing CDS Market Literature

Chapter 2 examines the determinants of CDS spread changes on European contracts before and after the recent crisis by taking into account systematic and idiosyncratic variables with a special emphasis on the potential effect of counterparty risk on the contracts. Different from previous contributions, the crisis period is distinguished from non-crisis period with a structural break test on CDS spread changes rather than considering the same date for all contracts. The analysis reveals that the

relation between credit spreads and their determinants in the short-term are regime dependent and relies on the sector of economic activity. Empirical findings indicate different pricing models for financial and nonfinancial firms. Non-financial firms are more sensitive to systematic variables during the tranquil period, but idiosyncratic variables during the financial crisis. However for financial firms, both systematic and idiosyncratic variables are only informative before the crisis.

As mentioned earlier, during the past several years, counterparty risk has emerged as one of the most important factors driving the financial markets and contributing to the global credit crisis. Despite the prominent role of counterparty risk in recent crisis, there is hardly any attempt that examines the effect of counterparty risk on CDS prices empirically except Arora et al. (2012). This study analyzes the contracts sold by HSBC bank to investigate the effect of default risk of HSBC on CDS contracts. It is observed that counterparty risk is reflected in the CDS prices with the outbreak of the crisis. Hence, bankruptcy or bail-out of some major dealers during crisis triggers a differentiation in CDS prices depending on the creditworthy of the sellers. The most surprising result is that whereas the default correlation is high between reference entity and protection seller, counterparty risk is not priced in the financial sector. This reveals that large dealers can be allowed to fail when non-financial firms are defaulting. However when the overall financial sector is in distress, the market expects the government to intervene to alleviate credit risk of the counterparty and fears of systemic risk.

Chapter 3 analyzes the long-run dynamics of a sample of CDS contracts in terms of systematic and idiosyncratic factors. The choice of systematic factor as iTraxx index is motivated by capital asset pricing models that consider the equity market portfolio as the only driver of the variation on excess stock returns. The choice of stock price as an idiosyncratic variable is motivated by the literature on credit

risk price discovery. Different from previous contributions, the effect of the crisis is contemplated by incorporating the occurrence of endogenous structural breaks to the pricing of CDS contracts. These breaks are incorporated into the long run equilibrium model making allowance for different long run dynamics depending on the dates of occurrence of the different outlying observations. It is observed that crisis shocks are persistent and have the potential to change long-run equilibrium dynamics. With this respect, introducing a break to account for financial crisis is an important addition to price discovery literature. In contrast to most of the related literature, cointegrated threshold model indicates that CDS market is not contributing price discovery. The leading variables are iTraxx index and firm's stock price.

In terms of methodology, as well as introducing structural break tests to account for financial crisis, this thesis corrects an important technical oversight in this literature that considers standard ordinary least squares (OLS) dynamic regressions to describe CDS spreads in levels, see for example Aunon-Nerin et al. (2002), Benkert (2004), or Ericsson et al. (2009). Many previous contributions analyzing CDS spreads do not apply any statistical test to check the stationarity of the series. They either take the first difference to work on stationary dataset or apply standard OLS regression on CDS spread levels, nonstationary variables, without considering that the estimations can be biased and unreliable. In this thesis, conducting a unit root test, CDS spreads are analyzed in changes in Chapter 2 and in levels with a co-integration framework in Chapter 3.

1.3 Interbank Credit Market

1.3.1 European Interbank Market

In Europe, the institutional environment of money market consists of four main elements. The central bank decides on the monetary policy and performs the strategy of this policy. Monetary policy instruments such as open market operations, standing facilities and reserve requirement are carried out as an operational framework for the implementation of the monetary policy and management of liquidity. For liquidity needs and hedging purposes, different financial instruments such as deposits, repos and derivatives are traded in organised exchange or over-the-counter markets. Lastly, large value payment and securities settlement systems, clearing and netting facilities assure the smooth functioning of payments and settlements.

The main function of the Euro-interbank market is to allow participant banks to effectively reallocate deposit imbalances among themselves. They allow liquidity to be readily transferred from banks with a surplus to banks with a deficit. Interbank market rates are key part of the monetary policy transmission mechanism and they are crucial for implementing interest rate monetary policy targets by central banks. The variations in interbank rates are rapidly transmitted to the entire term structure, affecting borrowing conditions of households and firms and pricing of many important derivative contracts.

For the gross liquidity need; banks prefer ECB liquidity facilities, however for daily liquidity need; banks trade in the interbank market. In Europe, interbank market transactions are organized in different ways: physically on the floor, by telephone calls or on electronic platforms. The vast majority of transactions in Europe take place on over-the-counter market without a specific trading regulation through telephone. Besides over-the-counter market, an electronic market for liquidity is also

developed in Italy called 'e-MID'.

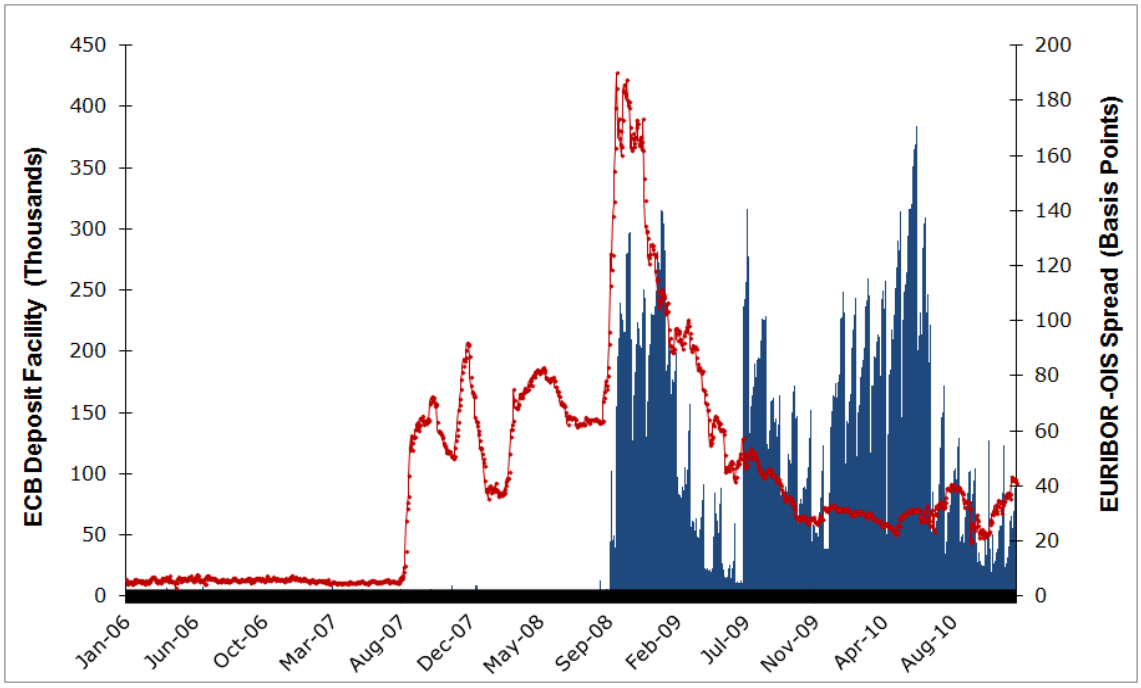
e-MID is the only electronic platform for interbank deposits in the Euro area and in the U.S. This screen based electronic market is under the supervision of Bank of Italy. The platform has 246 members from 29 countries before the crisis. The platform is fully transparent and buy and sell proposals appear on the platform with the identity of the banks posting them. In this market, each trader can choose any counterparty to start the trade. The two parties can negotiate the terms and conditions of the specific trade, change the quantity/price or refuse the transaction at all. e-MID, the supplier of the dataset of Chapter 4, represents the only readily available source of micro data on interbank transactions in the Euro area as either majority of the transactions are conducted over the counter or the Euro OverNight Index Average (EONIA) rate disseminated by European Banking Federation has daily frequency and its averaging mechanism does not allow cross-sectional or market micro structure analysis.

1.3.2 The Effects of 2007-2008 Crisis on European Interbank Market

Until August 2007, euro area money markets were functioning smoothly with stable interest rates. The market was characterized by low interest rates, volatility and risk premiums and was highly liquid. However 2007-2008 crisis had serious repercussions for the European interbank market like other global financial markets.

Figure 1.4 below presents the transmission of subprime crisis to the interbank market, depicting the spread between Euribor and Euro OverNight Index Average (EONIA) swap rate in three months time, a standard indicator of relative stress in the interbank market. EONIA is an effective overnight interest rate computed as a weighted average of all overnight unsecured lending transactions in the euro area

Figure 1.4: European Interbank Market



interbank market initiated by the contributing panel banks. This plot also depicts the amounts of liquidity deposited at ECB through deposit facilities. Until August 2007, the start of the subprime mortgage crisis, spread was very low with insignificant amount of money parked at ECB. The main reason was that during normal market conditions, banks preferred to lend out their money in the interbank market as the rate offered by ECB was smaller than the rate available in the interbank market. Until the end of September 2008, the market was characterized by very high spread, but still there was no demand for ECB deposit facilities. However at the end of September 2008, after the collapse of Lehman Brothers, spread increased to unexpected levels with huge amounts of money parked at ECB. As there was evaporation of trust in the financial markets due to the collapse of Lehman Brothers, banks preferred parking their money at ECB despite the smaller rates rather than lending out in the interbank market. Especially after September 2008, asymmetric

information about counterparty risk accompanied by increase in liquidity risk impaired the functioning of interbank market despite an unprecedented increase in the liquidity provision by central banks.

1.3.3 New Measures as a Response to 2007-2008 Crisis

During the turmoil period in order to sustain the smooth functioning of the system, ECB took some nonstandard measures. It decreased the interest rate and provided extra ordinary amount of liquidity directly to the market via long and short term operations. After the collapse of Lehman Brothers, ECB introduced fixed-rate full allotment policy in all refinancing operations for the different maturities. This enabled counterparties to satisfy all their liquidity needs against adequate collateral. The maturities of longer-term refinancing operations were increased up to one year. The types of collaterals were expanded. The increase in types of collateral eased banks liquidity constraints and encouraged them to extend new credit or continue rolling over maturing loans. Moreover the Euro system started providing liquidity in foreign currencies and purchasing euro-dominated covered bonds.

1.3.4 Contribution of this Thesis to the Existing Interbank Market Literature

Chapter 4 examines e-MID interbank market by estimating cross-sectional density of funding rates using non-parametric kernel methods. More specifically, this study utilizes the cross-sectional distributions of borrowing and lending rates over time with the aim of identifying disturbances in this market. These disturbances serve for early warning indicators of financial distress and systemic risk. Previous papers focus on the first moment of the funding rate to explain the characteristics of the interbank market. In addition to this, this chapter develops analytical techniques

to capture disturbances on the second moment of the funding rates (volatility) as well.

In both borrowing and lending segments, leverage and feedback effects are observed between cross-sectional volatility of rates and their magnitude. Leverage effect implies that increases in the volatility of spreads are responded by increases in funding rates over the next periods. Hence, volatility is a useful indicator of distress in money markets. Similarly, feedback effect implies that large funding rates lead to increases in dispersion of rates.

Dynamic analysis of the spreads reveals the different effects of 2007 and 2008 crisis on interbank markets. The first crisis has widespread effect on the entire banking sector, leading to higher borrowing costs across the sector. However the second crisis triggered by the collapse of some major financial institutions produces huge level of uncertainty in whole banking sector and increases the borrowing cost of a small sample of troubled banks compared to rest of them that obtain borrowing spreads below the cross-sectional average.

Chapter 4 also analyzes the effect of several factors such as banks size, the operating currency and banks' nationality on the cross-sectional distribution of these rates. The findings strongly support the statistical significance of these effects and highlight the importance of these factors as early warning indicators of financial distress. In particular being large in terms of asset size and operating in Euros is an advantage in this market to get better rates. Also, banks based in Greece, Ireland, Portugal and Spain obtain liquidity with higher costs than other banks. Hence, this market provides early warning signals of the incoming sovereign crisis well before the actual date of the crisis.

Novelty of this chapter arises from both the methodology used and the factors considered. In terms of methodology, the most important contribution of Chapter

4 is to propose nonparametric kernel estimation methods for modeling the cross-sectional distribution of rates. This methodology is novel in this field and contrasts to most of the related literature that explains the determinants of funding rates, see Gabrieli (2011a, 2011b), Cocco et al. (2009), Angelini et al. (2011) and Afonso et al. (2011) using parametric panel data regression models. The advantage of this method is that it lets the data speak by themselves. This chapter also contributes to the literature by introducing two new factors that have influence on the determination of spreads: Euro/NonEuro or Crisis/NonCrisis classifications. These factors enable to examine whether being based in countries operating in Euro currency or experiencing sovereign crisis brings a benefit for banks in the interbank market.

One of the distinctive contributions of this chapter is the database analyzed. e-MID has many advantages over other alternatives. First, as highlighted by Beaupain and Durre (2011), this electronic platform is a reliable source of data that allows inferring the dynamics of the whole over-the-counter transactions. Second, it tracks closely their better known counterparts as banks usually arbitrage with e-MID and over the counter. Last, interest rates reflect actual transactions so that they do not suffer from potential distortions affecting offered rates such as Libor/Euribor as documented by Mollenkamp and Whitehouse (2008), Gyntelberg and Wooldridge (2008) and Snider and Youle (2010). The drawbacks of these alternative interbank rates mark the importance of the e-MID market as a reliable source of information about the whole overnight segment of the European interbank market in an international context.

1.4 Structure of the Thesis

This introductory chapter gives background information about the relevant topics of the thesis and marks the importance of this thesis to the existing literature. Chapter

2 investigates the short-run determinants of Credit Default Swap spreads written on European contracts before and after the recent crisis. Chapter 3 examines the long-run determinants of CDS spreads proposing a threshold cointegrated model and discusses price discovery literature. Chapter 4 focuses on European interbank market with the aim of detecting early warning indicators of distress in the financial sector. The last chapter presents the main conclusions of this study as well as some suggestions for future research.

1.5 Conclusion

This introductory chapter familiarizes the reader with the background information about the topics covered in this thesis. In particular, a brief information about 2007-2008 financial crisis and the characteristics of Credit Default Swaps and European interbank market are outlined. As well as the contribution of the CDS market to the recent crisis is discussed and new regulations in the CDS market are introduced. The effect of crisis on European interbank market is presented. Contributions of this thesis to the existing CDS and interbank market literature are highlighted.

Chapter 2

The Determinants of Credit Default Swap Spreads in the Presence of Counterparty Risk and Structural Breaks

Abstract

By investigating the determinants of CDS spreads on European contracts before and after the recent crisis, we observe significant differences in the explanatory power of systematic and idiosyncratic variables. Before the crisis the underlying credit risk in the overall CDS market is sufficient to explain credit risk. During the crisis investors have a differing view on the risk of financial and non-financial contracts; whereas non-financial CDS contracts reflect the credit risk of the counterparty, financial contracts do not. Our results suggest that in case of default of financial firms, investors expect the government to intervene to alleviate credit risk of the counterparty and fears of systemic risk.

2.1 Introduction

Bond markets have been traditionally regarded as appropriate indicators to evaluate the creditworthiness of a borrower. The risk underlying these bonds is observed in the spread between the risky and risk free bond yields. Empirical models motivated from structural form equations describing fixed income prices have been used to explain variation on bond spreads. Collin-Dufresne et al. (2001) and Avramov et al. (2007) are within this group of articles. These authors use in particular, the risk free rate, volatility and leverage.

The illiquidity of bond markets and the choice of appropriate measures to proxy the risk free bond rate make the bond spread not very suitable to analyze credit risk at high (monthly, daily) frequencies. Recently, the interest has shifted to studying credit risk indirectly by looking at derivative markets, in particular Credit Default Swap (CDS) contracts.

The study of CDS spreads for gauging credit risk can be theoretically and empirically motivated. As documented by Blanco et al. (2005) and Zhu (2006), CDS and bond spreads converge to each other in the long run but exhibit important deviations from their long-run equilibrium in the short run. These differences are due to the higher liquidity of the CDS market that is able to reflect changes in market conditions faster than bond spreads. Also, in contrast to bond prices CDS contracts are standardized products designed to reflect credit risk of the reference entity. Bond prices, on the other hand, differ depending on the characteristics of the bond, the structure of coupon payments or the maturity of the debt.

Aunon-Nerin et al. (2002) is one of the first studies that concentrates on CDS spreads to explain credit risk. These authors, following the structural model approach as in Collin-Dufresne et al. (2001), use market variables as well as credit ratings and explain 82% of variation in CDS spreads. The choice of explanatory

variables for the analysis of credit risk from CDS spreads is also an important issue highly debated in the empirical literature. Thus, Benkert (2004) describes CDS spreads by mainly concentrating on volatility measures. This author observes that the effect of option-implied volatility is higher on CDS spreads compared to the effect of historical volatility, that is, forward-looking measures of risk have a higher impact on CDS prices than historical measures. Further to Benkert (2004), Cao et al. (2010) conclude that the relation between option-implied volatility and CDS market is especially stronger when CDS spreads are more volatile, the rating of the reference entity is low and options are more liquid. Zhang et al. (2009) mainly investigate the relationship between equity return and CDS market and specifically explore the effect of stochastic volatility and jumps on CDS spreads. By calculating historical volatility from equity return data and the contribution of the jump using high frequency data, their results imply that volatility risk can alone explain 50% of CDS spread variation, while jump risk can predict 19% of the variation.

Greatrex (2009) sheds important doubts on the conclusions derived from the analysis of CDS spreads in levels obtained in other articles, the reason being the existence of spurious regression analyses that invalidate any statistical inference; Greatrex (2009) proposes instead the analysis of changes on CDS spreads. By generating a rating based index based on CDS spreads and a structural form model incorporating market variables, this author explains 35% of variation in CDS spread changes. Ericsson et al. (2009) also analyze CDS spreads in levels and changes using structural form variables. These authors explain 23% of variation in CDS spread changes and up to 70% of variation in CDS spread levels.

Hardly any attempt has been made to assess the determinants of bank credit spreads. This is probably due to opaque nature of the financial industry where traditional credit risk models are likely to be less successful. Main exceptions are

Dullmann and Sosinska (2007), Raunig and Scheicher (2009) and Annaert et al. (2010). Dullmann and Sosinska (2007) explore the usefulness of CDS prices as market indicators of bank risk based on a very limited set of variables: abnormal stock returns, market index returns, the swap spread and the bid ask spread with a sample that consists of three German banks. Raunig and Scheicher (2009) compare the risk premia embedded in CDS spreads for banks and corporations. They find that banks are perceived as less risky than corporations before the sub-prime related turmoil began in the summer of 2007. During the turmoil period, the two groups are priced broadly similar. Annaert et al. (2010) analyze Euro area bank CDS spreads before and after the start of the financial crisis with variables suggested by structural credit risk models, liquidity in the CDS market as well as variables proxying for general economic conditions. They demonstrate that the determinants of bank CDS spreads vary across time with a remarkable difference before and after the start of the crisis. They also uncover sensitivity of CDS spreads on variables suggested by structural credit risk models after the start of the crisis.

Recently, there is an interest on non-linear models to investigate the relation between CDS spreads and its determinants. Alexander and Kaeck (2008) and Giammarino and Barrieu (2009) concentrate on CDS portfolio. Alexander and Kaeck (2008) advance a Markov Switching Model to capture the changes in iTraxx Europe indices with regime switches. They find a completely different model for financial and nonfinancial indices. For financials, the explanatory power of their regression models is low and almost entirely due to adding the lagged credit spread. Giammarino and Barrieu (2009) estimate nonlinear dynamic relationship between iTraxx index and its hypothetical components with an adaptive nonparametric modelling approach. Their results indicate that systematic factors play a prominent role during market crises. However they exhibit less intense time-dependent behaviour

during normal market conditions. Even more, during market crises, the empirical relation between variables and iTraxx index is contrary to expectations. Pires et al. (2010)) concentrate on individual CDS spreads and estimate the determinants of CDS spreads with quantile regressions. They find a strong relation between CDS spreads and implied volatility, put skew and absolute bid-ask spreads. Quantile approach indicates heterogeneity in the response of low-risk versus high-risk firms in a way that both the coefficients on the explanatory variables and the goodness-of-fit of the model increase with the quantile of CDS premiums.

Since the financial crisis of 2007-2008 counterparty risk has become more apparent due to the collapse of the main counterparties such as Bear Sterns, Lehman Brothers and the bailouts of many other financial institutions. During crisis, CDS contracts have been observed to amplify and spread uncertainty in the financial sector by reducing investors confidence and also leading to financial contagion due to interconnectedness of the main counterparties. Hence, understanding the dynamics of credit spreads on these markets is now more important than ever as this financial derivative has played a critical role in the unfolding of the financial crisis. Despite the significance of counterparty credit risk in the financial markets and its role in the recent financial crisis, there are mainly only theoretical papers that investigate the role of counterparty risk and default correlation between counterparties in CDS pricing. The analysis of this risk (counterparty risk) gains importance when the seller cannot fulfill its obligations under the occurrence of default of the reference entity and the default correlation is high between protection seller and buyer. Some of the theoretical studies incorporating the effect of counterparty risk and default correlation when pricing CDS contracts are Jarrow and Yu (2001), Hull and White (2001), Yu (2007), Huge and Lando (1999), Leung and Kwok (2005), Brigo and Chourdakis (2008) and Lipton and Sepp (2009). To the best of our knowledge, the

only empirical work on analyzing this effect on CDS spreads is Arora et al. (2012).

Arora et al. (2012) analyze the effect of counterparty risk on the CDS contracts using contemporaneous CDS transaction prices and quotations provided by fourteen large CDS dealers for selling protection on the same set of underlying reference firms. They use the spread of CDS written on the default risk of the protection seller as a proxy for counterparty risk and analyze the effect of default risk of the seller in a panel regression framework. They conclude that whereas counterparty risk is priced prior to the Lehman bankruptcy, the pricing of counterparty credit risk becomes much more significant and is adopted by many more CDS dealers after the Lehman bankruptcy. Interestingly, they cannot find any evidence that counterparty risk is priced in the contracts written on the default risk of financial reference entities although default correlation is high between reference entity and protection seller in the financial sector.

The aim of this chapter is to find the drivers of credit risk by analyzing Credit Default Swap spreads priced by HSBC Bank from April 2005 to November 2010. Hence, the sample of this chapter involves data from both early stages of the CDS market and the recent financial crisis period. This enables to investigate the effect of potential breaks in the dataset and see how the recent financial turmoil has changed the way that credit risk is priced in the CDS market. To do this, an extensive and rigorous empirical analysis is carried out on the explanatory power of idiosyncratic and systematic variables. In contrast to most of the existing literature, this study also incorporates the existence of counterparty risk as an explanatory variable. Unfortunately there is no opportunity to have access to CDS contracts priced by different counterparties, therefore, this chapter can be regarded as a case study specific to CDS contracts priced by HSBC Bank, however the results of this study can be generalized to other main counterparties.

This chapter also corrects an important technical oversight in this literature that considers standard ordinary least squares (OLS) dynamic regressions to describe CDS spreads in levels, see for example Aunon-Nerin et al. (2002), Benkert (2004), or Ericsson et al. (2009). These authors report the coefficient of determination (R^2) to gauge goodness of fit measures for dynamic regression models in levels. All these authors claim to explain over 90% of variation in CDS spread level. This chapter sheds some doubts on the conclusions obtained from these analyses based on R^2 goodness of fit measures. This is so because statistical analyses on the persistence of CDS spreads in levels tend to fail to reject the null hypothesis of unit root, see for example the seminal study of Pedrosa and Roll (1998). Hence, CDS spreads in levels are usually modeled as a unit root process and as such, these processes have a variance that increases to infinity invalidating, in general, statistical analyses and conclusions based on the R^2. Further, the nonstationary character of CDS spreads implies that extra care is needed to be taken when describing the relationship between the variables explaining CDS series. Thus, to avoid spurious regressions, CDS spreads are analyzed in changes in this chapter and the presence of a break is also considered to acccount for a possible regime shift in the regressions.

The remainder of this chapter is organized as follows. In Section 2.2, the dataset is presented with the potential explanatory variables and their expected relationship with CDS spreads. In Section 2.3, the econometric methodology is explained and the findings related to CDS spread analysis are reported. Section 2.4 concludes. An appendix collects tables and figures.

2.2 The Determinants of CDS Spreads

This section introduces the dataset used for the empirical analysis; it describes the determinants of CDS spreads and discusses the expected relationship between these

variables.

2.2.1 CDS Data

In this study, monthly mid quotes of CDS spreads are obtained from Bloomberg which is one of the leading financial data providers. In particular the contracts with the following specifications are considered: senior debt, EURO currency, quarterly premium payment and five year maturity. The contracts with five year maturity are chosen specifically as it is by far the most commonly traded tenor which leads to the most liquid contracts. CDS spreads are taken as end of month values and there is no missing value for any contract for the time period considered. The dataset in this chapter covers the period from April 2005 to November 2010. This period has been selected for two reasons: First, CDS market is more mature compared to the beginning of the twenty first century, and second, after experiencing tremendous growth the market started to shrink in 2008 due to the global financial crisis. This sample period is therefore ideal to investigate the existence and effect of structural breaks in individual contracts and estimate potential different models for both volatile and tranquil periods.

In this study, large capitalization companies that are representative of the corresponding sectors of economic activity in Europe are analyzed. The name of the firms and their corresponding industry information are listed in Table 2.1.

As one of the main aims of this study is to investigate the effect of counterparty risk on CDS spreads, specifically CDS contracts sold by HSBC Bank PLC are used. HSBC Bank PLC is one of the major counterparties in the CDS Market. The data sample is obtained from Bloomberg HSBC page which displays CDS quotations on contracts that are priced and sold by HSBC Bank.

Financial firms, especially banks, differ in a number of characteristics from other

Table 2.1: List of Reference Entities in the Dataset

Reference Entity	**Sector**	**Group**
Bayer AG	Pharmaceuticals	Non-Financial
BMW AG	Automotive	Non-Financial
Imperial Tobacco Group PLC	Tobacco	Non-Financial
Philips Electronics N.V.	Technology	Non-Financial
Tesco PLC	Retail	Non-Financial
Total S.A.	Energy	Non-Financial
Vinci PLC	Construction	Non-Financial
Vodafone Group PLC	Telecommunications	Non-Financial
Allianz AG	Financials-Insurance	Financial
Assicurazioni Generali S.p.A	Financials-Insurance	Financial
Aviva PLC	Financials-Insurance	Financial
BNP Paribas	Financials-Bank	Financial
Deutsche Bank AG	Financials-Bank	Financial
Societe Generale	Financials-Bank	Financial
Standard Chartered PLC	Financials-Bank	Financial

industrial firms. The structure and composition of their balance sheet, the opacity of their assets, the role of central banks in their emergency liquidity needs, their unique capital structure and different regulation rules towards them can necessitate different pricing models for financial firms. Considering this, the findings of the analysis are reported in two groups: Financial and Non-financial firms.

To illustrate the dynamics of CDS contracts from April 2005 to November 2010, Figure 2.1 above reports CDS spreads on four firms representative of the main European economic sectors: BMW, Aviva, Deutsch Bank and Vodafone. All CDS spreads began to rise sharply due to the signals of the sub-prime mortgage crisis in the second half of 2007. At the end of 2008 and beginning of 2009 they made peaks when many collapses and bailouts in financial markets took place. At the end of 2010, CDS spreads were much lower than at their peak values but still vulnerable to financial shocks.

Figure 2.1: CDS Spreads of Reference Entities over Time

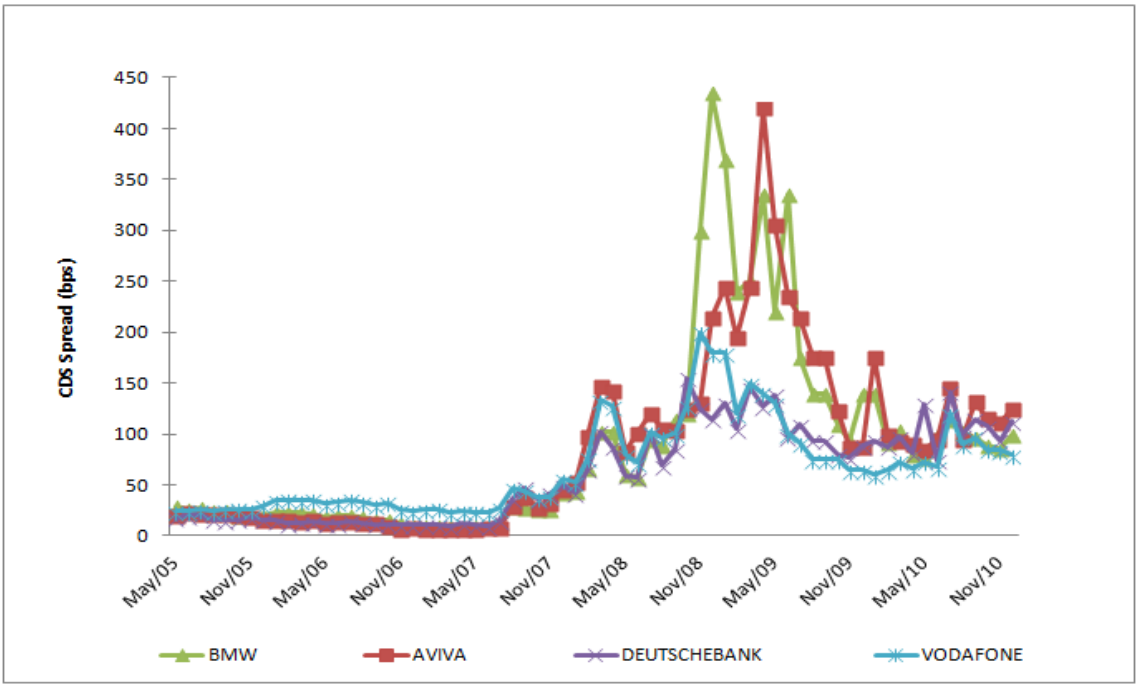


Table 2.2: Descriptive Statistics of Financial and Non-Financial CDS Spreads

	CDS Spread Level (bps)			CDS Spread Change (bps)		
	Mean	**St.Dev.**	**Range**	**Mean**	**St.Dev.**	**Range**
Non-Financial	68	64	7-435	1	26	-160-205
Financial	66	67	6-460	2	30	-145-252

Table 2.2 reports descriptive statistics for the CDS spreads and the corresponding series in differences for the two groups. Interestingly, the average CDS spread and the corresponding dispersion measures (standard deviation and range) are very similar across groups and series. The statistics for the differenced series reveal a higher positive skewness for financial than for non-financial firms.

Table 2.4 breaks down descriptive statistics by reference entity. When analyzed by firm, the cross-sectional variation in CDS spreads over the period studied is vast. The minimum spread recorded is only 6 bp (e.g. financial firms), whereas maximum spread runs up to 435 bp (BMW). Average spread ranges between 34 bp (Munich

Re) and 115 bp (Imperial). The variations over time are also huge for especially some reference entities like Imperial (97 bp) and BMW (95 bp). Spread changes on average ranges between 0 and 2 bp. Minumum spread change is -160 bp and maximum spread change increases up to 205 bp. These statistics reveal the variety in the sample.

2.2.2 Explanatory Variables and Expected Relationship

Credit Default Swaps are usually priced using two different approaches. For reduced form models, default is the outcome of a random jump process and is regarded as an unpredictable event. For structural form models, the asset value of a company is assumed to be consisting of equity and a zero coupon bond; default occurs if the value of the firms' asset is less than the promised debt payment at the maturity of the debt. Risk free rate, leverage and volatility of the asset are the main empirically tested determinants of structural form models. However, as documented in many papers, their explanatory power is empirically weak. It is certain that the structural model needs adding more explanatory variables that reflect the features of CDS contracts and of general market conditions. In particular, two sets of variables are considered in this study classified as systematic and idiosyncratic variables including counterparty risk. As systematic variables, the risk free rate, STOXX, iTraxx Europe and VSTOXX indices are considered. These variables are motivated as follows.

The structural approach predicts a negative relationship between the interest rate and credit spreads. Collin-Dufresne et al. (2001) note that a higher interest rate should increase the risk-neutral drift of the value process which reduces the probability of default and decreases spreads. In this study, one year Euro swap rate is used as a proxy for interest rate. Swap rates are preferred instead of government

bond rates, as government bonds are not regarded as benchmark for the risk free rate any more by financial markets due to illiquidity, short selling and tax considerations.

The stock market sentiment is also very relevant to this analysis. Stock market return is one of the most relevant proxies for the overall business climate. As general market conditions affect expected recovery rates, CDS spread will narrow when economic activity is high and widen when economic activity is low. Avramov et al. (2007), Collin-Dufresne et al. (2001), Greatrex (2009) and Aunon-Nerin et al. (2002) confirm a negative relationship between S&P 500 index and credit risk. In this study, Stoxx Europe 600 index is used as a proxy for general market conditions, as the study focuses on European CDS contracts. STOXX Europe 600 Index represents large, mid and small capitalisation companies across 18 countries of the European region.

A related measure of asset markets sentiment more relevant for this analysis of credit risk is the CDS Market Index. Certainly, an index constructed from CDS contracts can reflect the market condition especially in the CDS market better than an equity market index. iTraxx Europe index is made up of 125 equally-weighted European names selected by a dealer poll based on CDS volume traded over the previous six months and rating criteria. The list collecting information on liquidity is based on trading activity data from the Depository Trust & Clearing Corporation (DTCC) Trade Information Warehouse. All entities must be given an investment grade by Fitch, Moody's or S&P, and in order to be included in the index, they need to be rated over BBB for Fitch and S&P and Baa for Moody's. The index composition is updated every half-year, on March 20th and September 20th (rolling dates), and the basket resulting from the revision is labelled as a new series of iTraxx Europe. After the launch of a new series, the earlier series of the index continue to exist, but market liquidity tends to be concentrated on the most recent series

which is often referred to as on the run. This study concentrates on the index that is constructed as a concatenation of subsequent on the run series of iTraxx Europe. Therefore, each available series of the credit index cover the period from its launch date to the rolling date of the next series. This construction is motivated by the fact that the on the run series of iTraxx Europe are the most liquid and therefore more informative. This proxy for common risk factor captures not only the effect stemming from a deteriorating macroeconomic outlook, but also changing investors' risk aversion. A strong positive relationship is expected between iTraxx Europe index and CDS spread. We will also compare explanatory power of iTraxx index with stock market index to check whether an index coming from CDS market is more successful to explain variations in CDS spread changes than a stock market index.

Market wide volatility is also a proxy for business climate. Higher volatility leads higher undertainty about the economic prospects and higher credit spreads. VSTOXX index is used to measure market wide volatility as this study focuses on European market. VSTOXX captures the expected volatility for the Dow Jones EuroStoxx 50 index. Considering the U.S. market, Greatrex (2009) documents a positive relationship between VIX index and CDS spreads. Collin-Dufresne et al. (2001) conclude that an increase in VIX index raises credit spread, yet a decrease does not have an effect on credit spreads. As the dataset contains information from a very volatile period, a positive relationship is expected between CDS spreads and VSTOXX index.

As idiosyncratic variables, volatility, stock price, liquidity of the contract and credit risk of the counterparty are considered in this study. In a similar study that investigates the effect of bond liquidity on CDS-bond basis, Nashikkar et al. (2011) use instead leverage, tangible assets and current ratio (the ratio of current assets

to current liabilities) as idiosyncratic variables. The idiosyncratic variables for this study are motivated as follows.

It is an empirical fact that an increase in volatility leads to an increase in CDS spread. The intuition for this is that since default depends on the movement of the firm value, the latter is more likely to default if its value oscillates more. There are mainly two types of volatility measures in the literature: historical and option-implied volatility. Whereas option-implied volatility reflects market expectation of future volatility, historical volatility shows how volatile the asset is in the past. Benkert (2004) and Cao et al. (2010) analyze and compare the effect of these two volatility measures on CDS spread and conclude that although both have a positive relationship with CDS spreads, the effect of option-implied volatility is stronger than historical volatility. Based on previous studies and the forward-looking characteristics of option-implied volatility, only this volatility measure is considered in this study.

Stock price of the firm reflects the business and financial condition of the underlying company. Thus, any negative news about the company is observed in stock prices faster than in any other variable such as rating. Further, as documented in Welch (2004), stock price is the best proxy for capturing variation in leverage. Ideally, leverage should be computed as the ratio of the book value of debt divided by the market value of equity. However, book values of debt are reported on a quarterly basis making difficult to obtain monthly measures of leverage. Instead, a valid proxy for leverage used in the literature is the stock return. A higher stock return leads to smaller leverage and an improvement on the financial condition, and hence smaller credit risk.

Another firm-specific variable is liquidity. Literature regarding the impact of this variable on CDS spreads is contradictory. On the one hand, since it is a derivative

contract, not an asset, it is argued that CDS spreads cannot contain a liquidity premium. On the other hand, the occurrence of a large bid-ask spread is interpreted as existence of illiquidity risk. In this study, to minimize the presence of illiquidity effects, only five year contracts are analyzed as they represent the most liquid segment of the market. Nevertheless, in order to accommodate any illiquidity effect in this market, the spread between bid-ask CDS levels is considered as a proxy for illiquidity, see also Tang and Yan (2006). The expectation is that an increase in illiquidity will trigger an upward movement in CDS spreads.

Another very relevant factor in this analysis is counterparty risk. As experienced during the financial crisis with the collapse of Lehman Brothers and the bailout of Bear Sterns, the sellers of CDS contracts are not default-free. Furthermore, especially after the crisis, it is observed that different CDS contracts written on the same reference entity have a different price that is attributed to the risk of the sellers. Thus, if the seller of the contract has a higher credit rating compared to the other sellers, the corresponding CDS contract will be more expensive. Arora et al. (2012) analyze the existence of counterparty risk on CDS contracts and use CDS spreads of each counterparty in their sample as a proxy for counterparty risk. However CDS spread of the counterparty cannot be an indicator of pure counterparty risk as it also reflects general market conditions. Considering this fact, different from Arora et al. (2012), in this study the change in the iTraxx index is subtracted from the change in CDS spread of the counterparty (HSBC Bank in this case) and this premium variable is used as a proxy for counterparty risk as below:

$$CountRisk_t = \Delta CDS_t^{HSBC} - \Delta iTraxx_t$$

This allows to measure pure default risk of the seller clearing away overall credit risk in the market proxied by iTraxx index. Negative relationship is expected be-

tween the proxy for counterparty risk and CDS spreads, that is, when credit risk of the counterparty deteriorates, investors are not willing to pay a higher premium for the contracts offered by the counterparty.

2.3 Methodology and Empirical Results

In this study, monthly frequency is preferred since some CDS spreads do not change on a daily basis and can have extreme values on some days. From a technical point of view, daily data are exposed to autocorrelation problems which can lead to unreliable empirical results using standard econometric methods.

The analysis will start with an overview of CDS spreads and the potential determinants. Figure 2.2 exhibits time series plots of monthly CDS spreads of two contracts versus explanatory variables. Two contracts are selected as representatives of the data sample. One contract from the non-financial group is BMW, and the other one from the financial group is Deutsche Bank. Figure 2.2 in the Appendix plots monthly CDS spreads in levels against iTraxx, VSTOXX and STOXX indices, respectively. Until the beginning of 2008, during the tranquil period, the plots make apparent the positive relationship between CDS spreads and iTraxx and VSTOXX indices and the negative relationship between CDS spreads and STOXX index. However, after 2008 due to the effects of the financial crisis, CDS spreads generally move independently from aggregate market sentiment. Figure 2.2 also plots the relationship between CDS spreads and the risk free rate. Until April 2007, in line with the theory, CDS spreads move inversely to the risk free rate. Figure 2.2 lastly exhibits the plot of CDS spread levels versus implied volatility and stock price, respectively. As expected, a positive relationship between implied volatility and CDS spread and a negative relationship between stock price and CDS spreads are observed.

Aunon-Nerin et al. (2002), Blanco et al. (2005), Benkert (2004) and other related papers use panel data analysis to study the relation between CDS spreads and the set of explanatory variables. These panel data models assume that all the contracts in the data sample have the same relationship with the explanatory variables. For example, these models expect that every CDS contract has the same relationship with the variable gauging counterparty risk. For this reason, the results from panel data analysis can be misleading. Similarly, papers such as Greatrex (2009), Collin-Dufresne et al. (2001) and Ericsson et al. (2009) run the regressions for each contract separately, and report the average of coefficients which can also lead to invalid inferences if the actual relation between variables varies with the CDS contract. Instead, in this study a sample of sixteen CDS contracts are selected and eight of them are classified under financial, and other eight of them are classified under the non-financial group. The empirical analysis is carried out for each firm individually allowing in turn to compare the common effects due to the group (financial versus non-financial) and idiosyncratic effects due to the company/sector. To do this, the marginal effects of each set of variables and the variability of the estimates within the group are compared. For the non-financial group the individual analysis of each firm, and in particular the study of the within variability of the parameter estimates, allow to analyze common group effects but not to distinguish between firm effects and the wide economic sector that each company represents. A more detailed analysis would consider different contracts within each sector. For sake of presentation and discussion of empirical findings only one firm for each non-financial sector is selected and the wider analysis is left for future research. Finally, in contrast to the studies implemented in the literature using panel data techniques this method is less prone to show bias in the model parameter estimates although it is less efficient since there are fewer observations from each individual time series

than if the data are pooled. The method also permits to detect idiosyncratic breaks to each time series. Next section will elaborate structural break tests used in this study.

2.3.1 Structural Break Tests

Figure 2.1 reveal that all individual CDS contracts depict a tranquil and a volatile period highlighting the existence of structural breaks in the dataset resulting from subprime crisis or the collapse of Lehman Brothers. Ignoring these breaks can lead to invalid inferences about the relation between variables as parameters may change dramatically due to important economic events in empirical applications. Previous papers such as Annaert et al. (2010) and Cesare and Guazzarotti (2010) assume the fixed data for each contract as structural break in their dataset. The choice of the same break date for every contract in their study can be misleading, as the idiosyncratic properties of each contract are different. Considering this, in this study the break dates are detected with structural break tests to differentiate the tranquil and volatile periods. The following part of this section will illustrate structural break tests used in this chapter on a standard linear regression model.

Structural break tests consider the standard linear regression below and check whether the regression coefficient, β_t, remains constant or not over time.

$$y_t = x_t^T \beta_t + u_t \qquad (t = 1, ..., n), \tag{2.1}$$

where at time t, y_t is the observation of the dependant variable, $x_t = (1, x_{t2}, ..., x_{tk})^T$ is a $kx1$ vector of observations of the independent variables, with the first component usually equal to unity, u_t are iid $(0, \sigma^2)$, and β_t is the $kx1$ vector of regression coefficients, which may vary over time. Tests on structural change are concerned with testing the null hypothesis of "no structural change"

$$H_0 : \beta_t = \beta_0 \qquad (t = 1, ..., n) \tag{2.2}$$

against the alternative that at least one coefficient varies over time. If there are m breakpoints, the coefficients shift from one stable regression relationship to a different one. Thus, there are m+1 segments in which the regression coefficients are constant and the model (2.1) can be written as:

$$y_t = x_t^T \beta_j + u_t \qquad (t = t_{j-1} + 1, ..., t_j, j = 1, ..., m + 1), \tag{2.3}$$

where j is the segment index, $I_{m,n} = (t_1, ..., t_m)$ denotes the set of breakpoints and by convention $t_0 = 0$ and $t_{m+1} = n$.

$\hat{\beta}^{(t,j)}$ is the ordinary least square (OLS) estimate of regression coefficients based on the oberservations $t + 1, ..., t + j$, and $\hat{\beta}^{(t)} = \hat{\beta}^{(0,t)}$ is the OLS estimate based on all observations up to t. Hence $\hat{\beta}^{(n)}$ is the common OLS estimate in the linear regression model. Similarly $X^{(t)}$ is the regressor matrix based on all observations up to t. The OLS residuals are denoted as $\hat{u}_t = y_t - x_t^T \hat{\beta}^{(n)}$ with the variance estimate $\hat{\sigma}^2 = \frac{1}{n-k} \sum_{t=1}^{n} \hat{u}_t^2$.

Under this setting, there are mainly two classes of tests to detect structural changes: Tests based on F statistics and tests from generalized fluctuation test framework.

F type of test statistics are based on Chow (1960) test where the potential change point is known. Chow (1960) proposes to fit two seperate regressions for the subsamples discriminated by the exogeneous break point and reject the null of no structural break if F statistics gets too large. Chow (1960) test is formulated on the basis of the model (2.1) as

$$\beta_i = \begin{cases} \beta_A & (1 \leq i \leq i_0) \\ \beta_B & (i_0 < i \leq n) \end{cases}$$

where i_0 is exogeneous change point in the interval (k,n-k). Chow (1960) proposes to fit two seperate regressions for the two subsamples defined by i_0 and to reject whenever

$$F_{t_0} = \frac{\hat{u}^T\hat{u} - \hat{e}^T\hat{e}}{\hat{e}^T\hat{e}/(n-2k)} \tag{2.4}$$

is too large, where $\hat{e} = (\hat{u}_A, \hat{u}_B)^T$ are the residuals from the full model, where the coefficients in the subsamples are estimated seperately, and $\hat{u}$ are the residuals from the restricted model where the parameters are just fitted once for all observations. The test statistics F_{t_0} has an asymptotic χ^2 distribution with k degress of freedom and F_{t_0}/k has an exact F distribution with k and $n-2k$ degrees of freedom.

The natural extension of Chow test for unknown break point is to calculate F statistics for all potential change points in an interval $[\underline{t}, \bar{t}]$ and to reject if any of those statistics get too large. Andrews (1993) and Andrews and Ploberger (1994) suggest three different test statistics to aggregate the series of F statistics into a test statistics: supremum, average and exponential. According to these test statistics, null hypothesis of no break is rejected when the maximal, mean or exponential of F statistics get too large, respectively. In this study, the supremum of a family of F statistics proposed by Andrews and Ploberger (1994) is used:

$$supF = sup_{\underline{t} \leq t \leq \bar{t}} F_t \tag{2.5}$$

Generalized fluctuation tests do not assume a particular pattern of deviation from the hypothesis of parameter constancy. To be more precise, the generalized

fluctutation tests fit the model (2.1) to the given data and derive an empirical process that captures the fluctuation either in residuals or in estimates.

Under the null hypothesis, the emprical process is governed by functional central limit theorem. The boundaries for the process is determined by corresponding limitig process with fixed probability α under the null where α is the significance level. Under the alternative hypothesis, this process fluctuates too much and the empirical process path crosses the boundaries (Kuan and Hornik, 1995). In this study, OLS-CUSUM type empirical fluctation process developed by Ploberger and Kramer (1992) is used to test for the breaks in CDS spread change. This test is based on cumulative sums of standard OLS residuals as defined below:

$$W_n^0(t) = \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{t=1}^{nt} \hat{u}_t \qquad (0 \leq t \leq 1) \tag{2.6}$$

where n is the number of observations and OLS residuals are denoted as $\hat{u}_t = y_t - x_t^T \hat{\beta}^{(n)}$ with the variance estimate $\hat{\sigma}^2 = \frac{1}{n-k} \sum_{t=1}^{n} \hat{u}_t^2$.

The limiting process for $W_n^0(t)$ is the standard Brownian bridge $W^0(t) = W(t) - tW(1)$ where W(.) marks standard Brownian motion. It starts in 0 at $t = 0$ and it also returns to 0 for $t = 1$. Under the alternative, if there is just a single structural change point t_0, the path should have a peak around t_0.

In this study, the deviation in the mean of CDS spread changes are tested with OLS-CUSUM test and the supremum of a family of F test. To do this, a constant is fitted to the model as below:

$$\Delta CDS_t = \alpha_t + u_t \tag{2.7}$$

where $\Delta CDS_t = CDS_t - CDS_{t-1}$, t denotes time period and the break is detected with a change in α over time. Table 2.3 presents the results of the break dates

for each contract. Both tests indicate the same date as structural break for all the contracts. Table 2.3 shows that for most of the firms in the study the break occurs at the end of 2007 when the subprime mortgage crisis deepened, liquidity diminished and some hedge funds collapsed. For BMW, Imperial Tobacco, Tesco, Total, Allianz and Standard Chartered, the break occurred nearly 7-8 months later, in the next wave of bankruptcies when the main dealers collapsed and fears of systematic defaults triggered in financial markets.

Table 2.3: Structural Break Dates

Reference Entity	**Group**	**Structural Break Dates**
Bayer AG	Non-Financial	December 2007
BMW AG	Non-Financial	July 2008
Imperial Tobacco Group PLC	Non-Financial	May 2008
Philips Electronics N.V.	Non-Financial	December 2007
Tesco PLC	Non-Financial	August 2008
Total S.A.	Non-Financial	August 2008
Vinci PLC	Non-Financial	December 2007
Vodafone Group PLC	Non-Financial	December 2007
Allianz AG	Financial	August 2008
Assicurazioni Generali S.p.A	Financial	December 2007
Aviva PLC	Financial	December 2007
Munich Re	Financial	December 2007
BNP Paribas	Financial	December 2007
Deutsche Bank AG	Financial	December 2007
Societe Generale	Financial	December 2007
Standard Chartered PLC	Financial	August 2008

2.3.2 Multiple Regression Results

In this section, multiple regressions are applied for both idiosyncratic and systematic variables to observe which group of variables is more successful at explaining CDS spread changes before and after the break. With these analyses, the aim is to find whether the pricing of credit risk has changed due to shocks in financial markets.

Multiple regression models considered in this study are as below:

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta ImpVol_t + \alpha_2 r_t^{StockRet} + \alpha_3 Liq_t + \alpha_4 CountRisk_t + \epsilon_t \quad (2.8)$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta iTraxx_t + \alpha_2 \Delta VSTOXX_t + \alpha_3 \Delta InterestRate_t + \epsilon_t \quad (2.9)$$

where ImpVol refers to Implied Volatility, StockRet; Stock Return, Liq; Liquidity and CountRisk; Counterparty Risk.

iTraxx Europe and STOXX Indices are correlated. In order to avoid potential multi-collinearity problems, only iTraxx Europe index is considered as a market sentiment variable in the multiple regression analyses.

Multiple analyses on CDS spread changes are presented in Tables 2.8 and 2.9. According to our analysis, in the pre-crisis period, all CDS spreads are mainly dominated by systematic factors. However during the crisis, the outlook completely changes and even iTraxx Europe index loses its predictive power to explain credit risk. This finding is contrary to some studies in the literature. These contrary results stem from either considering different variables as systematic factors or considering different CDS products as dependant variable. For instance, according to Alexopoulou et al. (2009), systematic risk is the main determinants of CDS spreads after the summer of 2007. This difference results from considering different variables as systematic factors. While Alexopoulou et al. (2009) consider risk free rate, market equity return and market equity volatility as systematic factors, we consider iTraxx index as systematic variable besides interest rate and market implied volatility. We have also different conclusion from Giammarino and Barrieu (2009). This differences result from considering different credit risk product as a dependant variable. Instead of considering individual CDS spreads, Giammarino and Barrieu (2009) aim to explain the determinants of credit risk portfolio, iTraxx index. Ac-

cording to Giammarino and Barrieu (2009), the relation between iTraxx index and systematic factors such as interest rate, market equity return and market equity volatility is more stronger during financial crisis. However, in our study, we investigate the relation between corporate CDS spreads and credit risk portfolio (iTraxx index) and other macro variables.

Moreover, during the crisis, idiosyncratic variables have different effects on financial and non-financial firms. For non-financial ones, CDS spreads become more sensitive to idiosyncratic variables rather than to systematic factors. However, for financial firms both systematic and idiosyncratic variables fail to explain most of the variation in CDS spreads. Hence, the relation between credit spreads and their determinants is regime dependent and depends on the sector of economic activity. Further, as underlined by Alexander and Kaeck (2008) for CDS indices, there is a need for regime switches when modelling CDS spreads and a different pricing model is required to model financial and nonfinancial contracts.

The explanatory power of multiple models in this study is very high compared to previous related studies using stationary regression models such as Greatrex (2009) and Ericsson et al. (2009). Systematic variables explain up to 90% and 65% of variation in CDS spread changes before and after the break, respectively. On the other hand, the variables related to idosyncratic characteristics can explain the variation in CDS spread change up to 81% and 57% before and after the break, respectively. These results provide empirical evidence that incorporating iTraxx index and counterparty risk into the regressions enhance the explanatory power of empirical models for describing the variation in CDS spreads.

2.3.3 Robustness Checks

In this section, as a robustness check, the individual relationship between CDS spread and explanatory variables is explored. With this analysis, the relationship between CDS spread change and its determinants before and after the break is compared. Simple regression models considered in this study are presented below.

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta iTraxx_t + \epsilon_t \tag{2.10}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 r_t^{STOXX} + \epsilon_t \tag{2.11}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta VSTOXX_t + \epsilon_t \tag{2.12}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta InterestRate_t + \epsilon_t \tag{2.13}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta ImpliedVolatility_t + \epsilon_t \tag{2.14}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 r_t^{StockReturn} + \epsilon_t \tag{2.15}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 Liquidity_t + \epsilon_t \tag{2.16}$$

$$\Delta CDS_t = \alpha_0 + \alpha_1 CounterpartyRisk_t + \epsilon_t \tag{2.17}$$

with $\Delta CDS_t = CDS_t - CDS_{t-1}$, r^{STOXX} and $r^{StockReturn}$ is the log return on STOXX Index and Firm's Stock Prices. Counterparty risk is defined as $CountRisk_t = \Delta CDS_t^{HSBC} - \Delta iTraxx_t$. As explained in Section 2.2.2, CDS_t^{HSBC} measures default risk of HSBC as a protection seller and iTraxx index gauges overall credit risk in the market. The difference between two represents pure credit risk of the seller, namely pure counterparty risk.

This section allows to compare the explanatory power of STOXX index with iTraxx index with the aim of revealing which market variables is more effective on individual CDS contracts. Also, the marginal effect of the risk of the counterparty on changes on CDS spreads is tested.

Table 2.7 reports the results of simple regressions with systematic variables. Before the break, all CDS contracts have a positive and very strong relation with iTraxx Europe index. Nevertheless, the influence of iTraxx Europe index on individual CDS contracts is remarkably smaller after the break compared to the tranquil period. Before the break, adjusted R^2 value ranges between 88% (Vodafone) and 40% (Munich Re). After the break, R^2 value lies between 14% (Standard Chartered) and 56% (Tesco). This reveals that individual contracts break away from aggregate market movements during the turmoil period. The relationship between CDS spreads and other systematic variable, stock market index, is also similar. Before the crisis, all contracts have a negative relationship with STOXX index, however after the break, most of them do not have any relation with stock market index. Comparing the predictive power of iTraxx index on CDS spreads with stock market index, a supporting evidence is documented for the hypothesis stating that a CDS market factor can better explain variation in CDS spread changes than a stock market factor. The findings are in favor of the hypothesis not only before the crisis, but also after the start of the crisis. Hence, CDS market index is a better systemic risk factor than stock market index to explain individual CDS contracts. The relation between CDS spread changes and market wide volatility index (VSTOXX) is also in line with expectations and previous studies. During the tranquil period, all contracts have a strong positive relationship with the volatility index. However, during the crisis, half of them exhibit statistically significant positive relationship, while other half break away from market volatility index. Lastly, before the crisis, most of the contracts have a negative relationship with interest rate in line with the predictions of structural credit risk models. However, with the start of the crisis, like other market wide variables, most of CDS spreads do not have statistically significant relationship with interest rate. Summarizing, simple regression models with systematic variables

suggest that CDS spreads are more responsive to market wide factors during tranquil periods than volatile times. Moreover, the CDS market index is a better proxy than the stock market index to proxy for general economic conditions in the pricing of individual CDS contracts.

Table 2.8 presents the results of simple regressions with idiosyncratic variables. Before the crisis, half of the firms exhibit a strong positive relationship with option-implied volatility, however during crisis, it seems that most of the CDS contracts are not related to market expectation of future volatility. Stock return variable, that is proxying for business and financial condition of the reference entity and also variation in leverage, exhibits stong relation with CDS contracts during the tranquil period. After the break, as experienced with other explanatory variables, only two of them have a negative relation. Lastly, the effect of liquidity in the CDS market is investigated by looking at the relation between bid-ask CDS spread and CDS spread change. During the tranquil period, in some contracts, increase in bid ask spread, the indicator of increase in illiquidity, results in increase in CDS spreads. However during the volatile period, liquidity has no effect on CDS contracts. To sum up, simple regression results indicate that most of the contracts have expected relation with CDS spread change before the break. Nevertheless, during the crisis, only few of them have the anticipated relationship with explanatory variables.

2.3.4 Marginal Contributions of Idiosyncratic and Systematic Variables

Marginal contributions of variables reveal the relative importance of each group of variables on the determination of CDS spreads. With this aim, the marginal contributions of idiosynacratic and systematic variables to the model are compared to reveal the most effective group on the pricing of CDS spreads as suggested by

Dullman and Sosinska (2007) and Annaert et al. (2010). First the regressions with all systematic and idiosyncratic variables are estimated. Then the marginal contibution is measured with this formula: mc_k, $R^2 - R_k^2$, of the k^{th} risk driver block (idiosyncratic and systematic variables) to the total R^2. R_k^2 is the R^2 of the kitchen sink regression, when the variables of the k-th block are omitted. The marginal contribution of k-th block is calculated with the formula below:

$$mc_k = \frac{R^2 - R_k^2}{\sum_{k=1}^{2}(R^2 - R_k^2)} \tag{2.18}$$

This ratio gives the relative contribution of kth block of variables to the sum of the marginal contributions. In order to prevent negative contributions, R^2 is considered instead of adjusted R^2. Table 2.9 shows marginal contribution of idiosyncratic and systematic variables on the determination of CDS spreads for the subsamples; before and after the break. Before the crisis, CDS spreads are predominantly determined by systematic factors. Marginal contributions of systematic factors range between 63% and 95% for non-financial firms and 80% and 92% for financial firms. However idiosyncratic variables play a trivial role in the pre-crisis period. The highest contribution of idiosyncratic variables is recorded as 37% in Vodafone CDS contract. During the crisis, the decomposition of variables changes significantly. Marginal contribution of systematic variables decrease for all firms while marginal contribution of idiosyncratic variables increases considerably for all the contracts except Vodafone and Munich Re.

2.3.5 Analysis of Counterparty Risk

Counterparty credit risk is a highly debated issue in recent years as it emerges as one of the most important factors of the recent global credit crisis. In principle, standard

agreements between counterparties necessitate full collateralization and specify the details such as the nature and the type of the collateral to be provided. Hence, the market standard of full collateralization seems to imply that there should be no pricing of counterparty credit risk in CDS contracts. However in reality, collateral is not always enough to cover all the loss in case of the credit event, and there is always probability that the buyer suffers from significant credit losses. Hence, it is not always possible to mitigate counterparty credit risk entirely.

One of the aims of this study is to investigate whether counterparty risk is incorporated in the pricing of CDS spreads or CDS market is still only pricing default risk of the reference entity. This is done for contracts sold by HSBC Bank. To do this, the following simple regression model is estimated to analyze the effect of counterparty risk on CDS spread change:

$$\Delta CDS_t = \alpha_0 + \alpha_1 CountRisk_t + \epsilon_t \tag{2.19}$$

The results of this analysis presented in Table 2.8 suggest that prior to the crisis, only BMW and Imperial from the non-financial group price counterparty default risk significantly. However after the break produced by the financial crisis, all non-financial contracts start pricing the default risk of HSBC Bank. One possible explanation for this result is that collateralization could have been considered as a sufficient measure to mitigate counterparty risk for most of the contracts in the period preceding the crisis. Also, during this period, the market assesses HSBC Bank or many other banks as a risk-free entity since no major counterparties have experienced bankruptcy, bail-out or default before. However, during the financial crisis, especially with the collapse of Lehman and bail out of AIG, the market realized that even these big dealers are not too large to fail and there exits weaknesses with existing collateral protocols and legal protections. Hence, due to the fear of

systematic defaults, the default risk of HSBC has started to be reflected in CDS prices. Incorporating more explanatory variables into the analysis like model (2.8) does not seem to lead to qualitatively different results.

The empirical analysis also suggests that counterparty risk is not priced for CDS on financial contracts. This finding particularly poses a puzzle for the second period under analysis. In principle, the correlation argument suggests that the counterparty credit risk for the CDS dealers should be most evident when they are selling protection on firms in the financial industry. Following this, the observed increase on default correlation between reference entities and the major CDS counterparties in this period should lead to a decrease on the corresponding spread that is not observed empirically. This unexpected result is in line with Arora et al. (2012) which obtain similar results by examining CDS contracts priced by a cross-section of large counterparties. These authors suggest that large CDS dealers could be allowed to fail when non-financial firms are defaulting. However when other major financial firms begin to default, in order to prevent the chaos, the market expects large CDS dealers, such as HSBC in this case, to be treated as too large to fail. This is illustrated with the bail-outs of AIG and GE Capital. A similar result is observed by Nashikkar et al. (2011) in the analysis of liquidity effects on bond spreads; these authors note that for financial firms there is an implicit obligation by regulators to step in when a financial crisis unfolds in order to prevent financial contagion.

2.4 Conclusion

This chapter explores the ability of idiosyncratic and systematic variables to explain variation in credit default swap spreads in changes. Sixteen European CDS contracts priced by HSBC bank are considered and they are grouped as financial and non-financial firms. The sample period is from April 2005 to November 2010.

One of the most remarkable results from this small scale study on HSBC contracts is that the relation between credit spreads and their determinants is regime dependent and depends on the sector of economic activity. Empirical findings indicate that CDS spreads on financial firms behave quite differently from CDS spreads of non-financial firms, especially during the financial crisis. For non-financial firms, CDS spreads are mainly determined by systematic variables during the tranquil period, but by idiosyncratic variables during the volatile period. For non-financial firms, both idiosyncratic and systematic variables are informative in the tranquil period but lose their explanatory power during the financial crisis. Hence, these findings suggest different pricing models for financial and non-financial contracts.

The analysis also finds that the iTraxx Europe CDS index is the variable with the strongest predictive ability to describe variation in CDS spreads. In fact, this variable can alone explain most of variation in CDS contracts and hence can be interpreted in a similar way to the market portfolio in standard capital asset pricing models. However, this variable also loses its predictive power on single CDS contracts during the financial crisis period suggesting that CDS spreads decouple from the underlying global credit risk during this period and are mainly driven by idiosyncratic factors.

Finally, the analysis of counterparty risk using data from HSBC Bank offers some of the first insights in the literature on the pricing dynamics of counterparty risk in the CDS market. The empirical analysis indicates that counterparty risk has started to be priced in the CDS contracts on non-financial firms after the outset of the financial crisis, that is, CDS contracts written on the same reference entity are sold at different prices depending on the creditworthiness of the seller. Contrary to non-financial contracts, there is not any counterparty risk effect on financial contracts. After the financial crisis, investors expect that the implementation of regulatory

measures and government intervention are sufficient to guarantee the fulfillment of the credit derivative contract even under default of the counterparty with the aim of avoiding systemic risk. Given the prominence of HSBC in the banking sector, and in particular in the CDS market, and the similarities of this studies' results with Arora et al. (2012), the results of this study can be generalized to CDS contracts issued by other major protection sellers existing in the financial marketplace.

Appendix 2.A

Figure 2.2: Time Series Graphs of CDS Spreads and Potential Explanatory Variables

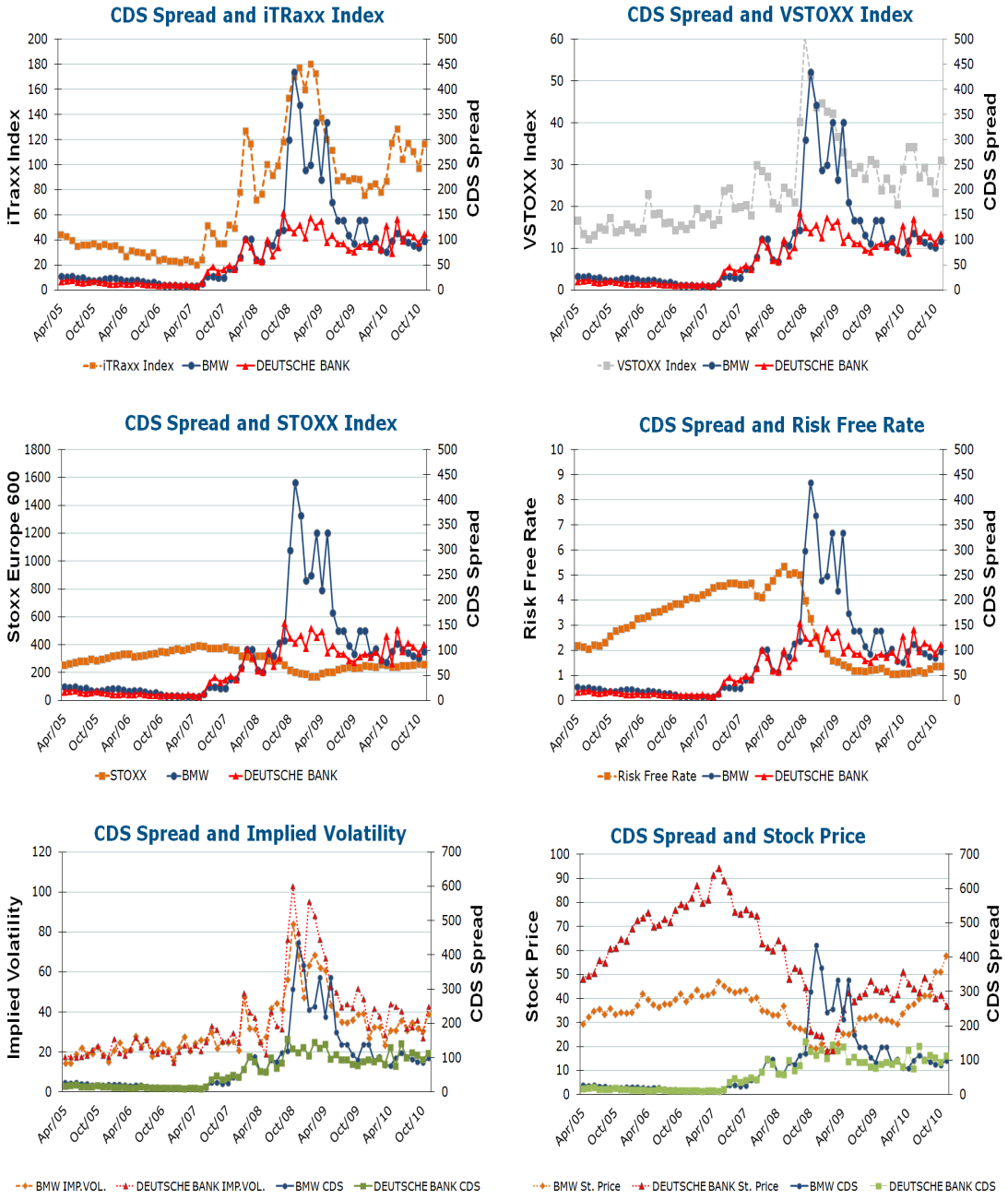


Table 2.4: Descriptive Statistics by Reference Entity

	CDS Spread Level				CDS Spread Change			
Reference Entity	**Mean**	**Minimum**	**Maximum**	**Standard Deviation**	**Mean**	**Minimum**	**Maximum**	**Standard Deviation**
Bayer	48	15	145	26	0	-35	43	12
BMW	88	9	435	95	1	-160	180	47
Imperial	115	30	415	97	1	-140	205	38
Philips	51	14	160	31	0	-55	40	14
Tesco	52	8	145	40	1	-35	42	11
Total	35	7	145	31	1	-50	55	13
Vinci	89	29	290	60	1	-105	115	25
Vodafone	67	23	200	44	1	-60	73	19
Allianz	48	7	135	36	1	-38	50	16
Assicurazione Generali	55	6	182	46	2	-60	90	24
Munich Re	34	6	80	20	0	-25	30	7
Aviva	86	7	420	85	2	-155	175	39
BNP Paribas	44	6	132	36	2	-53	69	18
Deutsche Bank	61	9	155	46	1	-55	70	22
Societe General	57	6	179	48	2	-46	66	20
Standard Chartered	67	7	325	69	1	-145	135	32

This table contains descriptive statistics of monthly CDS spreads both in levels and changes (in basis points) by reference entity. The period runs from April 2005 to November 2010.

Table 2.5: Multiple Regression Results-Systematic Variables

Reference Entity	**iTraxx Index**		**VSTOXX Index**		**Interest Rate**		**Adjusted R^2**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Bayer	0.95	0.38	-0.23	0.02	7.62	-13.4	82%	36%
	(-1.00)	(3.65)	(-0.63)	(0.07)	(1.36)	(-1.86)		
BMW	0.87	1.78	-0.16	-0.08	4.44	-55.3	83%	27%
	(8.30)	(2.49)	(-0.46)	(-0.06)	(0.88)	(-0.87)		
Imperial	0.92	0.43	0.30	3.6	9.04	-71.9	66%	48%
	(5.59)	(1.07)	(0.36)	(3.79)	(0.53)	(-3.20)		
Philips	0.55	0.63	-0.32	-0.70	-2.12	-14.2	57%	40%
	(3.41)	(3.72)	(-1.13)	(-2.15)	(-0.68)	(-1.70)		
Tesco	0.40	0.61	0.26	-0.13	-0.79	-17.6	79%	65%
	(8.58)	(5.23)	(1.71)	(-0.30)	(-0.14)	(-2.28)		
Total	0.31	0.39	0.56	-0.002	1.56	-13.5	65%	22%
	(5.32)	(1.25)	(1.47)	(-0.002)	(0.34)	(-1.16)		
Vinci	0.86	0.87	-10.5*	-2.20	-0.30	1.13	68%	40%
	(4.82)	(3.83)	(-1.97)	(-0.09)	(-0.89)	(1.18)		
Vodafone	0.89	0.92	-0.38	4.56	0.74	0.79	90%	62%
	(8.52)	(5.25)	(-3.01)	(1.22)	(0.29)	(0.43)		
Allianz	0.56	0.70	0.0009	-0.18	4.41	0.73	61%	40%
	(5.62)	(4.22)	(0.002)	(-0.47)	(0.34)	(0.13)		
Assicuraziono Generali	0.72	0.78	-0.22	-0.02	0.53	3.14	75%	23%
	(5.58)	(3.22)	(-0.90)	(-0.04)	(0.17)	(0.40)		
Munich Re	0.29	0.29	0.09	-0.09	0.46	-0.77	40%	37%
	(2.93)	(2.13)	(0.35)	(-0.41)	(0.14)	(-0.22)		
Aviva	0.77	1.63	0.10	-2.34	-20.8	-14.2	80%	28%
	(4.74)	(4.90)	(0.27)	(-2.70)	(-2.26)	(-1.08)		
BNP Paribas	0.46	0.62	0.39	-0.30	-15.3	24.3	75%	23%
	(2.93)	(3.49)	(0.77)	(-0.43)	(-2.18)	(1.49)		
Deutsche Bank	0.65	0.68	0.11	0.33	-0.75	29.7	70%	25%
	(5.11)	(3.17)	(0.24)	(0.41)	(-0.17)	(2.12)		
Societe General	0.63	0.73	0.28	-0.24	-18.8	25.0	81%	29%
	(4.17)	(3.97)	(0.57)	(-0.35)	(-2.44)	(1.93)		
Standard Chartered	0.57	0.49	1.0	2.35	-3.65	-14.5	82%	27%
	(9.14)	(1.51)	(2.01)	(3.01)	(-0.62)	(-0.94)		

This table presents estimation results of equation 2.9. The period runs from April 2005 to November 2010. The t-statistics (in square brackets) are based on the Newey-West HAC Standard Errors & Covariance matrix. Before indicates Before Break Date and After indicates After Break Date.

Table 2.6: Multiple Regression Results-Idiosyncratic Variables

Reference Entity	**Implied Volatility**		**Stock Return**		**Liquidity**		**Counterparty Risk**		**Adjusted R^2**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Bayer	0.20	-0.04	-0.47	-0.38	0.51	1.29	-0.58	-0.59	42%	40%
	(1.82)	(-0.19)	(-2.16)	(-1.15)	(0.72)	(1.16)	(-1.91)	(-3.17)		
BMW	0.18	-1.39	-0.67	-2.69	2.47	4.40	-0.62	-1.82	30%	38%
	(0.77)	(-1.24)	(-3.04)	(-1.92)	(1.91)	(0.65)	(-1.79)	(-3.75)		
Imperial	0.04	5.44	-1.41	2.47	2.71	3.26	-0.26	-1.51	26%	58%
	(0.07)	(5.10)	(-1.39)	(2.79)	(1.34)	(1.45)	(-0.50)	(-5.26)		
Philips	0.41	0.37	-0.19	-0.02	0.27	-0.19	-0.13	-0.64	24%	29%
	(1.46)	(1.21)	(-1.50)	(-0.08)	(0.27)	(-0.11)	(-0.51)	(-2.87)		
Tesco	0.83	0.58	-0.27	-0.84	0.63	0.93	0.07	-0.30	45%	55%
	(2.75)	(1.01)	(-1.04)	(-1.37)	(0.67)	(0.88)	(0.2)	(-4.58)		
Total	-0.01	-0.35	-0.53	-0.96	-2.00	0.59	0.25	-0.83	34%	47%
	(-0.09)	(-0.71)	(-2.28)	(-1.07)	(-1.63)	(0.84)	(0.87)	(-3.11)		
Vinci	0.82	-0.04	-0.10	-0.74	2.22	0.37	-0.78	-1.52	49%	55%
	(3.34)	(-0.15)	(-0.37)	(-1.16)	(3.59)	(0.36)	(-2.76)	(-4.53)		
Vodafone	0.33	0.90	-0.31	-0.41	2.86	0.33	-0.20	-0.81	37%	42%
	(1.29)	(1.77)	(-1.52)	(-0.46)	(2.49)	(0.19)	(-0.71)	(-2.65)		
Allianz	0.35	-0.12	-0.36	0.05	0.97	1.38	-0.26	-0.31	27%	7%
	(1.09)	(-0.18)	(-1.78)	(0.08)	(0.84)	(0.87)	(-1.04)	(-1.42)		
Assicuraziono Generali	0.03	0.77	-0.41	-0.42	2.50	2.08	0.01	-0.19	45%	8%
	(0.57)	(0.91)	(-1.43)	(-0.63)	(3.96)	(0.78)	(0.03)	(-0.58)		
Munich Re	0.26	0.03	-0.12	-0.19	1.35	-0.37	-0.07	-0.07	42%	5%
	(2.14)	(0.32)	(-1.41)	(-0.67)	(2.72)	(-0.60)	(-0.49)	(-0.81)		
Aviva	0.74	-1.14	-0.51	-2.71	3.13	-4.03	0.18	0.04	55%	22%
	(2.44)	(-1.25)	(-2.08)	(-1.77)	(2.02)	(-1.65)	(1.02)	(0.08)		
BNP Paribas	1.11	0.16	-0.34	-0.80	0.66	-0.37	0.08	0.65	69%	26%
	(3.70)	(0.62)	(-2.96)	(-3.57)	(0.82)	(-0.31)	(0.49)	(1.80)		
Deutsche Bank	0.55	0.50	-0.36	-0.09	0.39	-0.05	0.14	0.22	54%	10%
	(3.09)	(1.16)	(-2.39)	(-0.29)	(0.58)	(-0.07)	(0.46)	(0.51)		
Societe General	0.73	-0.09	-0.57	-0.90	0.59	-1.89	-0.19	0.53	71%	28%
	(4.53)	(-0.33)	(-4.44)	(-4.58)	(0.53)	(-2.39)	(-0.71)	(1.52)		
Standard Chartered	0.66	-0.38	-0.67	-0.93	1.22	0.17	0.12	-0.10	38%	4%
	(1.97)	(-1.24)	(-4.10)	(-0.73)	(0.89)	(0.31)	(0.24)	(-0.12)		

This table presents estimation results of equation 2.8. The period runs from April 2005 to November 2010. The t-statistics (in square brackets) are based on the Newey-West HAC Standard Errors & Covariance matrix. Before indicates Before Break Date and After indicates After Break Date.

Table 2.7: Simple Regression Results-Systematic Variables

Reference Entity	**iTraxx Index**		**VSTOXX Index**		**Stoxx Index**		**Interest Rate**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Bayer	0.8 (42%)	0.4 (27%)	1.2 (34%)	0.7 (9%)	-1.3 (43%)	-0.9 (11%)	-21.8 (16%)	-20.6 (14%)
	[10.07]	[3.19]	[4.62]	[2.05]	[-6.08]	[-1.73]	[-3.40]	[-2.15]
BMW	0.8 (82%)	2.0 (23%)	1.9 (20%)	2.8 (7%)	-1.9 (35%)	-4.8 (14%)	-20.5 (7%)	-92.7 (12%)
	[8.93]	[2.71]	[2.27]	[2.14]	[-4.06]	[-1.71]	[-1.36]	[-1.35]
Imperial	0.9 (66%)	1.6 (24%)	2.1 (23%)	4.7 (32%)	-2.8 (49%)	-3.8 (16%)	-31 (8%)	-96 (22%)
	[6.19]	[2.12]	[2.19]	[4.20]	[-3.88]	[-1.61]	[-1.88]	[-2.44]
Philips	0.4 (55%)	0.5 (30%)	0.6 (20%)	0.4 (2%)	-0.7 (31%)	-0.9 (7%)	-16 (19%)	-23 (12%)
	[6.75]	[3.47]	[2.94]	[1.07]	[-4.10]	[-1.42]	[-4.72]	[-2.14]
Tesco	0.4 (77%)	0.6 (56%)	0.9 (35%)	1.0 (16%)	-1.1 (44%)	-1.9 (55%)	-16 (14%)	-30 (30%)
	[9.48]	[4.24]	[4.34]	[2.12]	[-6.40]	[-4.33]	[-3.61]	[-2.80]
Total	0.4 (56%)	0.4 (17%)	1.0 (41%)	0.7 (6%)	-1.0 (35%)	-0.7 (5%)	-15 (10%)	-22 (11%)
	[5.20]	[2.48]	[3.62]	[1.17]	[-3.51]	[-1.15]	[-2.36]	[-1.93]
Vinci	0.8 (66%)	1.0 (35%)	1.3 (31%)	2.5 (22%)	-1.6 (47%)	-2.0 (12%)	-35.9 (32%)	-22.3 (4%)
	[9.30]	[3.74]	[2.51]	[3.36]	[-5.14]	[-1.66]	[-3.77]	[-0.71]
Vodafone	0.7 (88%)	1.0 (56%)	1.1 (35%)	2.2 (29%)	-1.1 (40%)	-2.2 (25%)	-24.7 (26%)	-15.2 (3%)
	[13.38]	[6.97]	[2.47]	[5.95]	[-3.27]	[-4.33]	[-2.62]	[-0.85]
Allianz	0.5 (61%)	0.7 (32%)	0.8 (16%)	0.6 (4%)	-1.1 (25%)	-1.1 (10%)	-13.8 (5%)	-14.0 (3%)
	[5.35]	[3.47]	[2.43]	[1.08]	[-5.23]	[-1.94]	[-0.83]	[-1.39]
Assicuraziono Generali	0.6 (74%)	0.8 (24%)	0.9 (32%)	1.2 (6%)	-1.0 (40%)	-1.4 (7%)	-21.2 (23%)	-9.3(0.7%)
	[10.38]	[4.29]	[2.86]	[1.60]	[-4.37]	[-2.91]	[-4.14]	[-1.09]
Munich Re	0.3 (40%)	0.2 (37%)	0.5 (25%)	0.3 (7%)	-0.7 (42%)	-0.4 (9%)	-11.1 (13%)	-5.5 (3%)
	[6.91]	[2.74]	[2.59]	[2.61]	[-4.25]	[-1.86]	[2.07]	[-1.51]
Aviva	1.0 (74%)	1.2 (22%)	1.8 (47%)	0.3 (0.2%)	-2.0 (59%)	-2.9 (10%)	-49.0 (49%)	-33.8 (3%)
	[4.36]	[4.28]	[2.39]	[0.30]	[-3.25]	[-2.26]	[-2.83]	[-2.11]
BNP Paribas	0.7 (67%)	0.5 (16%)	1.5 (52%)	0.4 (2%)	-1.3 (46%)	-1.0 (7%)	-37 (47%)	15.1 (3%)
	[4.03]	[2.34]	[2.32]	[0.53]	[-2.77]	[-1.41]	[-2.68]	[1.04]
Deutsche Bank	0.6 (70%)	0.6 (17%)	1.2 (41%)	1.1 (6%)	-1.1 (39%)	-1.3 (7%)	-24.8 (25%)	16.5 (3%)
	[14.02]	[3.23]	[2.42]	[1.51]	[-3.84]	[-1.96]	[-2.82]	[1.47]
Societe General	0.9 (73%)	0.6 (23%)	1.7 (52%)	0.7 (3%)	-1.7 (50%)	-1.4 (12%)	-44.9 (50%)	14.4 (2%)
	[3.98]	[2.93]	[2.20]	[0.76]	[-2.81]	[-1.90]	[-2.71]	[1.25]
Standard Chartered	0.76 (71%)	1.1 (14%)	1.9 (52%)	3.6 (18%)	-1.8 (41%)	-2.5 (9%)	-33.8 (18%)	-40.1 (5%)
	[8.56]	[2.28]	[5.66]	[3.65]	[-4.52]	[-2.03]	[-3.01]	[-1.62]

This table presents estimation results of equation 2.10-2.13. The period runs from April 2005 to November 2010. The t-statistics (in square brackets) are based on the Newey-West HAC Standard Errors & Covariance matrix. R^2 are presented in round parantheses. Before indicates Before Break Date and After indicates After Break Date.

Table 2.8: Simple Regression Results-Idiosyncratic Variables

Reference Entity	**Implied Volatility**		**Stock Return**		**Liquidity**		**Counterparty Risk**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Bayer	0.2 (7%)	0.2 (5%)	-0.6 (30%)	-0.6 (9%)	0.9 (2%)	0.5 (0.2%)	-0.7 (16%)	-0.6 (36%)
	[1.61]	[0.93]	[-2.87]	[-1.40]	[1.60]	[0.36]	[-1.84]	[-5.25]
BMW	0.4 (5%)	0.3 (0.1%)	-0.8 (21%)	-2.76 (16%)	3.9 (5%)	3.6 (0.5%)	-0.7 (8%)	-2.26 (28%)
	[1.11]	[0.16]	[-3.23]	[-1.56]	[1.52]	[0.64]	[-2.46]	[-5.82]
Imperial	0.7 (2%)	6.00 (35%)	-1.7 (21%)	-0.4 (0.1%)	3.8 (8%)	2.9 (0.4%)	-0.7 (6%)	-2.0 (35%)
	[1.12]	[3.20]	[-2.43]	[-0.18]	[2.48]	[1.25]	[-2.12]	[-3.96]
Philips	0.5 (20%)	0.3 (2%)	-0.3 (11%)	-0.5 (7%)	-0.3 (0.1%)	-1.0 (0.4%)	-0.2 (3%)	-0.6 (25%)
	[2.05]	[1.15]	[-2.44]	[-1.94]	[-0.29]	([0.48]	[-0.86]	[-3.01]
Tesco	1.0 (41%)	1.2 (33%)	-0.6 (27%)	-1.4 (40%)	0.6 (1%)	0.4 (0.6%)	-0.06 (0.3%)	-0.4 (24%)
	[5.52]	[2.66]	[-2.57]	[-3.66]	[0.53]	[0.44]	[0.28]	[-2.31]
Total	0.5 (13%)	0.5 (8%)	-0.6 (26%)	-0.7 (3%)	-2.4 (5%)	0.3 (0.2%)	0.4 (14%)	-0.7 (41%)
	[1.70]	[1.49]	[-3.01]	[-0.96]	[-3.51]	[-1.15]	[-2.36]	[-1.93]
Vinci	0.7 (18%)	0.9 (11%)	-0.3 (7%)	-1.0 (8%)	2.3 (17%)	0.9 (2%)	-0.6 (9%)	-1.5 (50%)
	[2.30]	[1.37]	[-0.97]	[-1.44]	[2.42]	[0.79]	[-1.69]	[-5.66]
Vodafone	0.5 (13%)	1.3 (21%)	-0.4 (23%)	-0.8 (4%)	3.4 (12%)	0.7 (0.4%)	-0.4 (7%)	-0.8 (28%)
	[1.93]	[3.73]	[-2.24]	[-1.29]	[2.16]	[0.45]	[-1.26]	[-3.98]
Allianz	0.5 (14%)	-0.05 (0.08%)	-0.6 (22%)	-0.01 (0.01%)	1.7 (8%)	1.4 (2%)	-0.06 (0.2%)	-0.2 (3%)
	[2.89]	[-0.15]	[-3.67]	[-0.05]	[1.79]	[0.98]	[-0.19]	[-1.30]
Assicurazione Generali	0.05 (1%)	1.0 (5%)	-0.4 (14%)	-0.6 (3%)	2.7 (35%)	1.2 (0.8%)	-0.1 (1%)	-0.2 (1%)
	[0.94]	[1.08]	[-1.77]	[-0.87]	[3.75]	[0.49]	[-0.44]	[-0.83]
Munich Re	0.4 (18%)	0.07 (1%)	-0.3 (15%)	-0.2 (2%)	1.5 (26%)	-0.4 (1%)	-0.1 (3%)	-0.07 (2%)
	[2.71]	[0.99]	[-2.23]	[-0.98]	[2.49]	[-0.78]	[-1.19]	[-1.08]
Aviva	1.2 (27%)	0.4 (2%)	-0.9 (25%)	-1.6 (14%)	4.1 (34%)	-4.0 (4%)	-0.2 (2%)	-0.08 (0.05%)
	[2.47]	[0.56]	[-2.10]	[-1.49]	[2.24]	[-1.60]	[-0.95]	[-0.19]
BNP Paribas	1.3 (61%)	0.2 (1%)	-0.7 (27%)	-0.6 (10%)	2.1 (13%)	0.07 (0%)	0.009 (0%)	0.4 (8%)
	[3.76]	[0.50]	[-1.93]	[-1.68]	[1.41]	[0.08]	[0.02]	[1.46]
Deutsche Bank	0.7 (40%)	0.6 (9%)	-0.6 (33%)	-0.3 (4%)	1.5 (8%)	0.1 (0%)	-0.02 (0%)	0.2 (2%)
	[3.32]	[1.37]	[-2.86]	[-1.00]	[1.74]	[0.16]	[-0.07]	[0.74]
Societe General	0.9 (63%)	0.3 (4%)	-0.6 (31%)	-0.6 (16%)	2.5 (13%)	-1.2 (2%)	-0.03 (0%)	0.3 (3%)
	[2.82]	[0.87]	[-2.01]	[-1.74]	[1.41]	[-1.08]	[-0.09]	[1.10]
Standard Chartered	0.9 (18%)	0.1 (1%)	-0.8 (22%)	-0.6 (3%)	2.5 (12%)	-0.4 (0.4%)	0.3 (3%)	-0.2 (0.9%)
	[1.64]	[0.18]	[-3.42]	[-0.58]	[1.14]	[-0.62]	[0.49]	[-0.32]

This table presents estimation results of equation 2.14-2.17. The period runs from April 2005 to November 2010. The t-statistics (in square brackets) are based on the Newey-West HAC Standard Errors & Covariance matrix. R^2 are presented in round parantheses. Before indicates Before Break Date and After indicates After Break Date.

Table 2.9: Marginal Contributions of Systematic and Idiosyncratic Variables

Reference Entity	**Systematic Variables**		**Idiosyncratic Variables**	
	Before	**After**	**Before**	**After**
Before	**After**			
Bayer	95%	45%	5%	55%
BMW	92%	69%	8%	31%
Imperial	91%	77%	9%	23%
Philips	93%	78%	7%	22%
Tesco	89%	81%	11%	19%
Total	78%	64%	22%	36%
Vinci	90%	70%	10%	30%
Vodafone	63%	70%	37%	30%
Allianz	92%	71%	8%	29%
Assicuraziono Generali	87%	78%	13%	22%
Munich Re	80%	82%	20%	18%
Aviva	92%	77%	8%	23%
BNP Paribas	88%	66%	12%	34%
Deutsche Bank	85%	76%	15%	24%
Societe General	88%	75%	12%	25%
Standard Chartered	93%	70%	7%	30%

The estimation of marginal contributions are based on equation 2.18.

Chapter 3

Long-Run Risk Dynamics, Instabilities and Breaks on European Credit Markets over a Crisis Period

Abstract

This article investigates the role of the long-run determinants of European corporate CDS spreads during the recent financial crisis. To do this we divide the determinants of CDS spreads in systematic and idiosyncratic factors, and propose an equilibrium model that accommodates the occurrence of structural breaks in the long-run relationship between the variables. These breaks, interpreted as outlying observations, are endogenously determined within unit root specifications used to describe the dynamics of the explanatory factors. We observe that crisis shocks are persistent and have the potential to change long-run equilibrium dynamics. The systematic credit risk factor is proxied by the European iTraxx portfolio and the idiosyncratic factor by the stock price corresponding to each CDS contract. Exogeneity tests applied to this novel econometric specification reveal that for these contracts the credit risk discovery process is in the factors and not in the CDS market. R^2 measures corresponding to the vector error correction representation of the equilibrium model confirm the strong predictive ability of the iTraxx portfolio and the error correcting vector for changes in the CDS spreads. Stock returns do not exhibit predictive power though.

3.1 Introduction

Price discovery deals with the efficient and timely incorporation of the information implicit in different markets' prices which are informative about the price of credit risk. There are two main approaches used to determine the price discovery process in asset markets: The Information Share (IS) of Hasbrouck (1995) and The Permanent-Transitory Decomposition of Gonzalo and Granger (1995). Hasbrouck (1995) considers that the information share associated with a particular market is defined as the proportional contribution of that market innovations to the innovation in the common efficient price. Gonzalo and Granger (1995) focus on the relative speed with which different markets incorporate new information and attribute superior price discovery to the markets that adjust least to deviations from the long-run equilibrium. An efficient price discovery is characterized by a quick adjustment of market prices that enables the restoration of the long-run equilibrium.

There is a growing literature on understanding information flows between credit and equity markets. Blanco et al. (2005) and Zhu (2006) observe that CDS and bond spreads converge to each other in the long run but exhibit important deviations from their long-run equilibrium in the short run. Thus Blanco et al. (2005) consider a vector error correction model (VECM) for explaining changes in bond and CDS spreads using data from a small cross-section of US and European firms and find that price discovery takes place primarily in the CDS market. Similar results are found in Zhu (2006) for a sample of 24 international issuers of CDS contracts. This author notes the leading role of the CDS market in the credit risk discovery process. The first paper to incorporate the informational content of the stock market in the analysis of CDS prices is Longstaff et al. (2003) who use a vector autoregressive (VAR) framework to examine the lead-lag relations between credit derivatives, corporate bonds and equity markets. They conclude that information tends to flow

first into credit derivative and equity markets, and then into the corporate bond market. Using a similar methodology for a sample of 58 companies during 2000-2002, Norden and Weber (2009) find that stock returns lead CDS prices and bond spreads, and that the series of changes in CDS spreads Granger causes bond spread changes. Forte and Peña (2009) also confirm the leading role of stock markets with respect to CDS and bonds in the credit risk price discovery process. These authors using a VECM representation explore the dynamic relationship between stock market-implied credit spreads, CDS spreads and bond spreads, and find that the CDS market leads the bond market.

These studies are extended to incorporate the recent crisis period. Thus, for a large set of European companies, Forte and Lovreta (2012) find that during the period 2002-2008 the stock market informational dominance documented in the literature arises especially in times of financial crisis. In tranquil times, the contribution of CDS to the credit risk discovery process proves to be equal or higher than that of the stock market. The increase of counterparty risk and illiquidity during the financial crisis seems to affect the credit risk discovery process, especially the leading role of CDS with respect to the bond market. Arce et al. (2012), in a European Monetary Union context, find that the recent financial crisis is characterized by large discrepancies between CDS and bond spreads, that should vanish otherwise in a frictionless world. These authors find that the price discovery process is state-dependent and the leading role of CDS is negatively related to the existence of counterparty risk and market risk proxied by VIX.

The aim of this chapter is to investigate the role of the long-run determinants of the spreads on major European corporate credit default swap contracts. To do this, the determinants of CDS spreads are classified as systematic and idiosyncratic factors; the systematic credit risk factor is the European iTraxx credit risk portfolio

that comprises 125 CDS contracts on major European private corporations. The idiosyncratic risk factor is the stock price of each underlying firm on which the CDS contract is written. This choice of idiosyncratic factor also allows investigating the credit risk discovery process between the CDS credit market and the equity market. During crisis, iTraxx index has started to increase reflecting the overall increase in the credit risk of the companies. Stock prices of the firm which reflect the business and financial condition of the company have started to decrease reflecting the deterioration in the financial condition of the firms.

In this study, the effect of the crisis is contemplated by incorporating the occurrence of endogenous structural breaks to the parameters. The occurrence of breaks on the parameters such as iTraxx index and stock price of the firm is tested with the implementation of unit root tests that allow a break suggested by Vogelsang and Perron (1998). The null hypothesis implies that these shocks have a permanent effect on the parameters and the alternative hypothesis corresponds to temporary shocks fluctuating around a deterministic trend function. This test also allows discriminating between additive and innovative outliers while testing the persistence of the breaks. An additive outlier occurs instantly and is not affected by the dynamics of the series; in contrast, an innovative outlier is transmitted more slowly to the series of prices and exhibits more persistence than the additive outlier.

Unit root character of CDS spreads and parameters implies that appropriate techniques for modeling the dynamic relation between variables should be based on cointegration. Hence, a long run equilibrium is proposed to describe the dynamics of corporate CDS spreads in terms of their idiosyncratic equity prices and the evolution of the iTraxx credit risk portfolio. The proposed econometric specification for modeling this long-run relationship incorporates the occurrence of the endogenous breaks to the parameters (iTraxx index and stock price) and makes allowance for

different long-run dynamics depending on the dates of occurrence of the different outlying observations. This long run equilibrium model also allows checking the relation between individual CDS spreads and market portfolio as well as price discovery process between CDS spread and stock price. To model the short run dynamics of the model, Vector Error Correction Model is also estimated. This model explains changes in CDS spreads in terms of changes in iTraxx index, stock return of the firm, the occurrence of breaks on these parameters and error correction term.

The validity of the results are checked in two ways. First, exogeneity of the parameters is checked. The exogeneity of the parameters justify the validity of the proposed model and reliability of the results. Second, Johansen (1991) maximum likelihood methodology is applied to check the validity of the model in the multivariate form.

The remainder of this chapter is structured as follows. Section 3.2 introduces the econometric methodology, estimation methods and testing techniques. Section 3.3 describes the data and discusses the empirical application to a sample of twenty five CDS contracts included in the European iTraxx index. Section 3.4 concludes. Appendix 3.A collects tables.

3.2 Econometric Methodology

This section discusses the methodology implemented in the empirical application. First unit root tests robust to the presence of additive and innovative outliers are discussed. The null hypothesis implies that these shocks have a permanent effect on the dynamics of the series. The alternative hypothesis corresponds to temporary shocks fluctuating around a deterministic trend function. The second block introduces a long-run equilibrium model that implicitly considers the occurrence of breaks to the variables and the corresponding error correction model representation.

The last block considers a test to determine the exogeneity of the factors explaining the CDS spreads. The null hypothesis of exogeneity validates the cointegrated triangular system proposed in Philips (1991) compared to a more general cointegrated VAR specification exploited in Johansen (1991) inter alios.

3.2.1 Unit Root Tests with Breaks

Vogelsang and Perron (1998) extend previous work by Perron (1989, 1990), Perron and Vogelsang (1992), Zivot and Andrews (1992) and Banerjee et al. (1992) amongst others, and propose a battery of unit root tests that allow a shift in trend at an unknown time. The shift can be due to additive or innovative outliers; an additive outlier occurs instantly and is not affected by the dynamics of the series. An innovative outlier model is applicable to cases where it is more reasonable to view the break as occurring more slowly over time. In this study, a model that accommodates the occurrence of both types of outliers is proposed to test for the statistical significance of each effect.

A convenient way to incorporate the effect of the additive outlier in the dynamics of the series is to assume an instantaneous break with a permanent effect on the drift of the model. The innovative outlier can take various forms. In this study, the literature mentioned above is followed and it is assumed that the series reacts to a break of this type in the same way that it responds to shocks to the innovation process. Let Y_t be a univariate time series with $1 \leq t \leq T$; under the null hypothesis, the econometric specification that makes allowance for an additive outlier is

$$Y_t = \mu + \delta DU_t + \beta t + Y_{t-1} + \psi^*(L)e_t \tag{3.1}$$

Similarly, the unit root specification that accommodates the occurrence of an inno-

vative outlier is

$$Y_t = \mu + \beta t + Y_{t-1} + \psi^*(L)(\theta D[T_b]_t + e_t) \tag{3.2}$$

where T_b is the break date, $D(T_b) = 1(t = T_b + 1)$, $D(U_t) = 1(t > T_b)$ and $1(\cdot)$ is the indicator function; $\psi^*(L) = A^*(L)^{-1}B(L)$ defines the moving average representation of the noise function e_t, where e_t is i.i.d. $(0, \sigma^2)$ and $A^*(L)$ and $B(L)$ being polynomials in L of order p and q, respectively. The roots of these polynomials are assumed to be strictly outside the unit circle. For the model with an additive outlier, the impact of the change in mean is δ; for the innovative outlier case the immediate impact is θ while the long run impact is $\psi^*(1)\theta$. Under the alternative hypothesis of stationary fluctuations around a deterministic trend function, Y_t is given by

$$Y_t = \mu + \beta t + \psi(L)(\delta DU_t + e_t) \tag{3.3}$$

with $\psi(L) = A(L)^{-1}B(L)$ with $A(L) = (1 - \alpha L)A^*(L)$. In the stationary case, the immediate impact of the change in mean is δ and the long run impact is $\delta\psi(1)$. The testing regression equation proposed by Vogelsang and Perron (1998) is

$$Y_t = \mu + \beta t + \delta DU_t + \theta D(T_b)_t + \sum_{i=1}^{k} \omega_i D(T_b)_{t-i} + \alpha Y_{t-1} + \sum_{i=1}^{k} c_i \Delta Y_{t-i} + e_t \tag{3.4}$$

Under the null hypothesis of a unit root, α is equal to one. These authors propose to estimate this regression by OLS and test for the unit root condition using the infimum of a vector of t-statistics for the parameter α, each corresponding to a possible break date T_b with $1 < T_b < T$. The inclusion of the dummy variables $D(T_b)_{t-i}$ $(i = 1, \ldots, k)$ in (3.4) is necessary to ensure that the limiting distribution of the t-statistic on α is invariant to the correlation structure of the errors and robust to the presence of an additive or innovative outlier. The t-statistics for the

parameters δ and θ can determine the type of break affecting the process. The case $\theta = 0$ corresponds to the occurrence of an additive outlier, $\delta = 0$ corresponds to the innovative outlier case and $\theta = \delta = 0$ corresponds to the absence of breaks in the dynamics of the time series. For details on the estimation procedure and asymptotic theory, see Vogelsang and Perron (1998).

Failure to reject the null hypothesis implies that Y_t is a unit root process with a structural break occurring at time $\widehat{T}_b$. The next stage of the modeling strategy is to propose a long run equilibrium model that explicitly considers the variations in the dynamics of the factors due to the occurrence of outlying observations.

3.2.2 Econometric Model

Let $Z_t = (Y_t, X_t)'$ be a $1 + k$-vector of unit root processes where Y_t denotes the variable under study and $\{X_{it}\}_{i=1}^{k}$ are the factors with power to explain the long-run dynamics of the response variable. Under the assumption that all variables are unit roots, the VECM representation of a general VAR(p) model for Y_t is

$$\Delta Z_t = \alpha_0 + BZ_{t-1} + \sum_{j=1}^{p} \Phi_j \Delta Z_{t-j} + \varepsilon_t \tag{3.5}$$

where α_0 is the intercept of the model, $B = \eta\gamma'$ is a matrix of rank r indicating the existence of r cointegrating relationships given by the combination $\gamma' Z_{t-1}$, where γ is an $(1+k) \times r$ vector and η a $T \times r$ matrix denoting the effect of the cointegrating errors on ΔZ_t. Johansen (1991) proposes a maximum likelihood method based on computing the rank of the matrix B for estimating the number of cointegrating relationships in Z_t and the corresponding cointegrated vectors.

All the variables in this model are potentially endogenous. In many economic models, however, certain variables can be treated as weakly exogenous for the esti-

mation of long-run relationships among other variables. The estimation of the long-run relationships can be conducted conditional on these variables. The assumption that X_t is exogenous gains importance in the context of this paper motivated by the search of the factors with power to explain the long-run dynamics of Y_t. It is shown that if a given variable is weakly exogenous for the long-run parameters (η and γ), the cointegrating vectors of interest must not appear in the generating model of that variable, that is, the variable must not be error correcting. Tests for weak exogeneity are discussed later in this section. Under weak exogeneity, model (3.5) becomes triangular, see Philips (1991), and estimation of the long-run parameters of interest is performed by OLS. The parameter estimator vector is super-consistent but its asymptotic distribution is nonstandard and depends on nuisance parameters arising from serial correlation in the errors, see Park and Philips (1988).

In this section, this triangular system is extended with a new set of variables. The relation between variables are modelled in a non-linear context where non-linearity in the parameters is modelled with dummy variables. These dummy variables are endogenously determined by the occurrence of the outliers estimated within the unit root specifications discussed above. Let $W_{i,t} = X_{i,t}D(\widehat{U}_{i,t})$ with $D(\widehat{U}_{i,t}) = 1(t > \widehat{T}_{i,b})$ and $i = 1, \ldots, k$ indicating the idiosyncratic character of the break dates. The cointegrated system modeling the long-run dynamics of Y_t is

$$Y_t = \beta_0 + \beta_1' X_t + \beta_2' W_t + \varepsilon_t \tag{3.6}$$

with $W_t = (w_{1t}, \ldots, w_{kt})'$, $\beta_1 = (\beta_{11}, \ldots, \beta_{1k})'$, $\beta_2 = (\beta_{21}, \ldots, \beta_{2k})'$ and ε_t a stationary error term. Hence, this model allows modelling the non-linear relationship in a way that the relation between variables may change due to the recent financial crisis. The VECM representation of this model is $\Delta Y_t = \lambda' M_t + u_t$ with $M_t = (X_t', W_t', \varepsilon_{t-1})'$ and u_t a zero-mean white noise process. Estimation can be carried out by OLS meth-

ods and asymptotic inference is asymptotically normal.

This modeling strategy assumes that break dates are known and assesses their impact on the long-run relationship between Y_t and the rest of variables. The discrete character of the indicator function defining the variables in W_t implies that there is no estimation effect on the OLS estimates of the β parameters of using estimated break dates instead of actual break dates as long as these estimates are statistically consistent, see Chan (1993) for a discussion of statistical inference for threshold models. This model is in the spirit of Quintos (1995) that proposes a rank test for the existence of two cointegration regimes determined by a known break date. Equation (3.6) generalizes this idea by making allowance for as many as $k+1$ cointegrating vectors to describe the dynamics between the variables. Thus, the long-run dynamics between the variables before the occurrence of $\widehat{T}_{1,b}$ are driven by the vector β_1, from time $\widehat{T}_{1,b}$ the long-run impact of X_{1t} on Y_t is $\beta_{11}+\beta_{21}$, from time $\widehat{T}_{2,b}$ the long-run dynamics of Y_t due to X_{2t} are driven by $\beta_{12}+\beta_{22}$ and so on for the rest of factors. An alternative strategy is to assume that break dates determining the nonlinearities in the cointegrating relationships are unknown; Hansen and Johansen (1993) using a rank test and Gregory and Hansen (1996) using augmented Dickey-Fuller (ADF) type tests propose methods designed to test the null hypothesis of no cointegration against the alternative of cointegration in the presence of a possible regime shift.

The omission of W_t in (3.6) yields inconsistent estimates of β_1 and λ in the regression equations for the long-run equilibrium and short-run dynamics, respectively. This omission can also yield spurious feedback effects in the linear VAR(p) representation (3.5). To show this, let $\varepsilon_t^* = Y_t - \widetilde{\beta}_1' X_t$ denote the linear long-run equilibrium relationship defined by the long-run parameters $\widetilde{\beta}_1$, that neglects Z_t from the cointegrated system. There is causality running from Y_t to X_t if the latter

variable is error correcting, more formally if $cov(\Delta X_t, \varepsilon^*_{t-1}) \neq 0$. After some algebra, it can be shown that

$$cov(\Delta X_t, \varepsilon^*_{t-1}) = cov(\Delta X_t, \varepsilon_{t-1} - (\widetilde{\beta}_1 - \beta_1)' X_{t-1} + \beta_2' W_{t-1})$$

Under exogeneity of X_t, this covariance is equal to $cov(\Delta X_t, (\beta_1 - \widetilde{\beta}_1) X_{t-1}) + cov(\Delta X_t, \beta_2' W_{t-1})$. The first term represents the bias due to considering the wrong cointegrating vector and the second term is due to the omission of the additional variable W_t. Under augmented unit root specifications of X_t, see (3.2), these covariance terms are different from zero.

3.2.3 Robustness Checks

3.2.3.1 Exogeneity of the Factors

The next step is to test for the weak exogeneity of X_t. Several tests can be implemented to assess this condition. In this study, a Wald test is proposed to simultaneously check for the weak exogeneity of all the factors in the system. The testing regression equation is

$$\Delta X_{t+1} = \rho_0 + \rho_1 \widehat{\varepsilon}_t + \sum_{j=1}^{p} \Phi_j \Delta Z_{t-j+1} + v_{t+1} \tag{3.7}$$

where Φ_j is a $(k+1) \times (k+1)$ matrix and v_{t+1} is a Gaussian white noise error vector. This formulation can be extended to accommodate the vector ΔW_t within ΔZ_t on the right hand side of the equation. For simplicity, the exogeneity is tested using the linear version of the model. It is important to note that the main feature of (3.7) is the inclusion of the error correcting variable ε_{t-1} instead of ε^*_{t-1}. By doing this, the regression model considers the existence of breaks in the factors when testing

for exogeneity of the regressors X_t.

The weak exogeneity is characterized by the joint hypothesis $H_o : \rho_1 = 0$. This regression equation is estimated by OLS and H_o is tested using the test statistic

$$D_T = T\widehat{\rho}_1' \widehat{V}(\widehat{\rho}_1)^{-1} \widehat{\rho}_1 \tag{3.8}$$

with $\widehat{V}(\widehat{\rho}_1)$ the $k \times k$ covariance matrix estimated by OLS methods. Under the null hypothesis, D_T converges to a χ^2_k distribution. Under the alternative hypothesis, some factors are endogenously determined within the system. If the factors are endogeneous in the system, in this case the factors X_t are not truly determinants of Y_t, all the variables in the model are determined endogenously within the system. The number of cointegrating vectors is likely to be larger than one to reflect other potential long-run equilibrium relationships within the variables in the system.

3.2.3.2 Multivariate Cointegration Test-Johansen Methodology

Another method to check the validity of the model is to consider general VAR(p) model (3.5) explained in the beginning of Section 3.2.2 and apply Johansen (1991) estimation and testing procedures. Obtaining similar results reinforce the validity of the model.

3.3 Empirical analysis of the CDS market

This section analyzes the drivers of CDS spreads issued on main European firms comprised in the European iTraxx credit risk portfolio. The section discusses first the data and second, the findings obtained from applying the models derived in the preceding section.

3.3.1 European CDS data

The iTraxx Europe index comprises 125 reference entities with constituents determined by a number of liquidity and ratings criteria. The list collecting information on liquidity is based on trading activity data from the Depository Trust & Clearing Corporation (DTCC) Trade Information Warehouse. This list is ranked according to trading volumes such that the entities with the highest trading volume are included in the index. All entities must be given an investment grade by Fitch, Moody's or S&P, and in order to be included in the index, they need to be rated over BBB for Fitch and S&P and Baa for Moody's. Entities from the EU and the European Free Trade Association (EFTA) given by Iceland, Norway, Switzerland, Liechtenstein, are listed in this index. The final index has the following sector decomposition. There are 30 companies on Autos & Industrials sector, 30 companies in the Consumers sector, 20 in the Energy sector, 20 in Technology, Media & Telecommunications (TMT) and 25 firms from the Financial sector. The index composition is updated every half-year, on March 20th and September 20th (rolling dates), and the basket resulting from the revision is labelled as a new series of iTraxx Europe. After the launch of a new series, the earlier series of the index continue to exist, but market liquidity tends to be concentrated on the most recent series which is often referred to as on the run. This study concentrates on the index that is constructed as a concatenation of subsequent on the run series of iTraxx Europe. Therefore, each available series of the credit index cover the period from its launch date to the rolling date of the next series. This construction is motivated by the fact that the on the run series of iTraxx Europe are the most liquid and therefore more informative.

CDS data of reference entities are collected as monthly mid quotes of CDS spreads and are obtained from Bloomberg which is one of the leading financial data providers. CBGN is a Bloomberg generic composite price, which provides a

snapshot of intraday prices taken at 5:00 pm local time in each of the three regions (New York, Tokyo, London). The Bloomberg generic intraday price is the average of all contributor prices that have been updated during the previous 24 hours. For the analysis in the next subsection, contracts with the following specifications are considered: senior debt, EURO currency, quarterly premium payment and five year maturity. The contracts with five year maturity are chosen specifically as it is by far the most commonly traded maturity which leads to the most liquid contracts. The dataset in this study covers the period from April 2005 to March 2012 (83 monthly periods).

The sample for the empirical study in the following subsection considers 25 contracts divided into the five sectors of economic activity represented in the iTraxx index. The descriptive statistics for these sectors show that the average spreads are 110 (94), 49 (30), 92 (94), 74 (60) and 78 (41), with standard deviations in brackets. The largest dispersion is found for Autos & Industrials that exhibit spreads that vary between 15 and 710 basis points. Consumers is, on the other hand, the sector that exhibits higher concentration of spreads. These descriptive statistics show that CDS spreads are for all sectors of economics activity highly skewed to the right indicating the existence of a few companies with an important contribution to the right tail of the cross-sectional distribution of spreads.

3.3.2 Empirical findings

3.3.3 Application of the Model

The aim of this empirical study is to analyze the long-run dynamics of a sample of CDS contracts comprised in the European iTraxx portfolio in terms of systematic and idiosyncratic factors. These factors can be interpreted as market-specific and firm-specific, respectively. The market-specific factor is summarized in the iTraxx

portfolio. The choice of this variable as a proxy for the systematic factor is motivated by capital asset pricing models that consider the equity market portfolio as the only driver of the variation on excess stock returns. Interestingly, preliminary analysis on the order of integration of this variable and its relation to the Stoxx 50 index and the vStoxx index, representative of the European equity market, reveal that these variables are pairwise cointegrated with iTraxx implying that it is sufficient to have the latter variable in the CDS long-run regression equation. The idiosyncratic factor is the stock price of each firm on which the CDS contract is written. The choice of this variable for proxying the idiosyncratic factors is motivated by the literature on credit risk price discovery above discussed.

The long-run equilibrium model of interest is based on the econometric specification (3.6). For each CDS contract, the vector X_t is given by the iTraxx index and the stock price, that are assumed, and later tested, to be exogenous. The variable W_t is constructed after applying the unit root test in (3.4) that accommodates the presence of additive and innovative outliers. Table 3.1 reports the estimates of model (3.4) for the iTraxx index and the 25 idiosyncratic stock prices. The purpose of this unit root test is twofold: first, it shows that the factors can be modeled as unit roots and second, it provides consistent estimates of the break points at the same time as it permits their classification as additive or innovative outliers. The sign of μ and δ reveal opposite effects of the breaks on the drift of the stock prices and the iTraxx index. The estimates and statistical significance of δ show overwhelming evidence on the existence of an additive outlier for most firms with the only exceptions of Vivendi and Credit Suisse. In general, the unit root specification with a drift being negatively affected by an additive outlier is appropriate to model the dynamics of the stock prices of the firms in our study. The statistical significance of the time trend parameter is mixed: for Autos&Industrials and Consumers is significant but of

small magnitude; for Financials, however, it is not statistically significant at 5% for any company. The occurrence of the break date also deserves some attention. The methodology proposed by Vogelsang and Perron (1998) detects a break on December 2007 for iTraxx. For most of the firms the break occurs during 2008, interestingly, for TMT firms the breaks are detected during the fall of 2007. Philips is the only firm reporting a break after the summer of 2008.

The unit root character of these series validates the long-run equilibrium model proposed above. More specifically, the model under consideration is

$$CDS_t = \beta_0 + \beta_1' X_t + \beta_2' W_t + \varepsilon_t \quad \text{for } j = 1, \ldots, n \tag{3.9}$$

with $X_t = (i_t, s_t)$, $W_t = (i_t D(\widehat{U}_{it}) s_t D(\widehat{U}_{st}))$ where i_t is the European iTraxx portfolio, s_t is the idiosyncratic log stock price corresponding to the underlying firm; $D(\widehat{U}_{it})$ and $D(\widehat{U}_{st})$ are the variables constructed from the estimated break dates. Table 3.2 presents the estimates corresponding to (3.9). The correct specification of (3.9) is assessed through the two-step procedure employing ADF tests developed by Engle and Granger (1987). The test statistic rejects the unit root null hypothesis for all firms in the study. Unreported results using Gregory and Hansen (1996) methodology corroborate these findings in all cases.

The contribution of the factors is as theoretically expected. The iTraxx is positively related to the CDS series and the stock price negatively related. The statistical relevance of the stock price is weak, being only significant for Alstom, British American Tobacco, Repsol and Vivendi. The vector W_t reflecting the discontinuities on the long-run effects of the factors on the spreads shows mixed evidence on the importance of the stock price and iTraxx. For Autos&Industrials and Consumers the marginal effect of the iTraxx index is much smaller than before the break, for TMT and Financials the discontinuity produced by the break is not statistically signifi-

cant. Interestingly, these results are reversed when analyzing the long-run effects of the stock price after the occurrence of the different breaks. This effect is positive for Financials, increases the spread, and negative for TMT. A possible explanation for this contrasting results may be in the sign and magnitude of the intercepts of the long-run equilibrium model. The Engle and Granger cointegration test shows uncontestable statistical evidence on the rejection of the unit root hypothesis in favor of the stationarity hypothesis. The likelihood ratio test reported in Table 3.2 compares the linear version of (3.9) against the extended version considering W_t. In 14 out of 25 cases the linearity hypothesis is rejected at 5% significance level. At 10% significance level, there are 16 firms rejecting the linear null hypothesis.

Table 3.3 reports the estimates of $\Delta CDS_t = \gamma_1' \Delta X_t + \gamma_2' \Delta W_t + \gamma_3 \widehat{\varepsilon}_{t-1} + u_t$, modeling the short-run dynamics of the deviations of the long-run equilibrium model. The results obtained illustrate the importance of considering the long-run dynamics for modeling the short-dynamics. The error correcting vector is statistically significant in most cases and exhibits a negative sign in line with expectations. Interestingly, there is a common message stemming from the individual regressions. Changes in CDS prices can be to a large extent explained by changes in the systematic credit risk iTraxx portfolio. In contrast, observed returns on the equity of the underlying firms hardly have explanatory power. The intercept is not significant for any firm. The main difference between this model and a standard capital asset pricing formulation is the inclusion of the error correcting variable that contributes to explaining much of the variation on the series of changes of CDS spreads. The variations corresponding to changes in W_t are significant for Energy and Financials. As for the long-run equilibrium model, the sign of the parameters is opposed between sectors. The returns on the stock price after the break have a positive effect on the change on the CDS price for Allianz and Barclays; for Enel and Repsol, the effect is negative.

These findings are reinforced by the values of the R^2 goodness of fit measure that oscillate between 46% for Enel and 81% for Allianz, providing evidence of a very reasonable goodness of fit for most CDS contracts.

3.3.4 Robustness Checks

3.3.4.1 Exogeneity of the Factors

The validity of these empirical findings hinges on the exogeneity assumption imposed on the factors X_t. This condition is statistically assessed using the Wald test (3.8) applied to the regression equation (3.7) with $Z_t = (CDS_t, i_t, s_t)'$. Overall, the p-values of the D_T test reported in Table 3.4 confirm the exogeneity of the factors for 19 out of the 25 firms in the study. Interestingly, the exogeneity is rejected for four contracts in the Energy sector and two contracts in the TMT sector. These results suggest that credit risk is not exogenously determined by the factors. Instead, there is a feedback effect between the idiosyncratic CDS spreads and the iTraxx portfolio. These results give indirect evidence on the weight of the Energy sector in the iTraxx credit risk portfolio. For BP, the bivariate long-run causality is between the idiosyncratic stock price and CDS price. Leaving aside this sector, the rest of findings are somehow surprising given the significant amount of empirical work on price discovery noting the presence of bidirectional causality between the CDS and stock markets. These exogeneity tests shed important doubts on this evidence and point towards model misspecification issues derived from applying the linear cointegrated version of the cointegrated model between stock prices and CDS spreads. The first column in Table 3.4 serves to illustrate the statistical significance of the error correcting variable implicit in the long-run econometric specification proposed in this paper.

3.3.4.2 Multivariate Cointegration Test-Johansen Methodology

A further robustness check to validate the correct specification of (3.9) is to apply the Johansen (1991) procedure to the general linear cointegrated VAR model (3.5). Table 3.5 reports the trace statistics to determine the number of cointegrating relationships in the system Z_t and the OLS estimates of the error correcting variables corresponding to each variable in the system. The lags of ΔZ_t in (3.5) are not reported for sake of space. For most firms, the null hypotheses characterized by the existence of one and two long-run equilibrium relationships, respectively, are not rejected. The error correcting variable corresponding to the CDS series is statistically significant for Autos&Industrials, Energy and TMT, but for example not for Financials. For a few firms, there is causality running from the CDS market to the iTraxx and from the CDS to the stock price. Overall, the results in Table 3.5 do not massively suggest the existence of model misspecification with the exception of a few firms. Instead, the VAR model and the Johansen procedure reinforce the validity of the exogeneity assumption.

This empirical section has provided support to the exogeneity of the iTraxx credit risk portfolio and the idiosyncratic stock price for modeling the long-run determinants of credit default swap spreads. This relationship is nonlinear and characterized by the occurrence of additive outliers affecting each factor at different dates.

3.4 Conclusions

This article investigates the determinants of the long-run risks affecting the European credit market and proxied by Credit Default Swaps on major European corporations. These determinants are divided into systematic and idiosyncratic risk

factors. The iTraxx credit risk portfolio summarizes the dynamics of the first group of market-specific variables and the idiosyncratic stock price of each firm summarizes the content in firm-specific variables.

This article uncovers that long-run risks in the European credit market are highly nonlinear during the crisis period. This nonlinearity is modeled as a cointegrated threshold model characterized by the occurrence of additive outliers to unit root models for the dynamics of the factors. This econometric model can explain the effect of unexpected shocks to the financial system that indirectly impact on the dynamics of CDS prices through the occurrence of shifts to the long-run relationship between the variables.

In contrast to models studying the price discovery process between the credit market and the equity market, it is observed that the factors are weakly exogenous and hence, the CDS market does not contribute to price discovery in financial markets. The leading markets are the iTraxx credit risk portfolio and the idiosyncratic firm's stock price. The general VAR cointegrated representation of the model and the corresponding Johansen estimation procedure give further support to this modeling strategy.

The short-run dynamics modeling changes in the series of CDS spreads can be explained by simple versions of a capital asset pricing model based on the iTraxx credit risk portfolio taking up the role of the equity market portfolio. The main difference with standard formulations of the CAPM is the inclusion of the error correcting variable measuring the departures from the long-run equilibrium relationship. In contrast, idiosyncratic stock returns are hardly significant for explaining variations in the first differences of CDS spreads.

The current literature demonstrates the strong relation between CDS spreads and option implied volatilities. A possible extension of this chapter could be to

consider option implied volatility as an idiosyncratic variable and market impled volatility such as VIX or VSTOXX as a systematic variable. This analysis can enhance our understanding about price discovery process between option implied volatilities and CDS market.

Appendix 3.A

Table 3.1: Unit Root Test Results with a Break

Group	Firms	Break Date	μ	β	δ	θ	α	t_α
Market Index	iTraxx Index	Dec-07	6.99*	0.02	18.7**	-16.9	0.78	-3.22
			(1.73)	(0.14)	(2.32)	(-1.00)		
Autos&Industrials	Akzo Nobel	May-08	91.36	0.26	-16.8	14.6	0.75	-4.29
			(2.99)	(3.09)	(-3.74)	(1.71)		
	Alstom	Oct-06	53.2	-0.24	12.8	-10.2	0.85	-3.27
			(3.67)	(-3.22)	(2.22)	(-0.98)		
	Bayer	Sep-08	72.0	0.25	-10.0	3.8	0.79	-3.49
			(3.57)	(2.67)	(-2.64)	(0.54)		
	Daimler	May-08	85.2	0.35	-21.9	12.9	0.76	-3.89
			(3.82)	(2.92)	(-3.32)	(1.17)		
	Valeo	Oct-07	39.9	0.36	-19.4	12.4	0.87	-2.95
			(2.74)	(3.05)	(-3.03)	(0.95)		
Consumers	British American Tobacco	May-08	81.0	0.42	-12.7	7.1	0.71	-4.10
			(4.12)	(4.08)	(-3.76)	(1.34)		
	Danone	May-08	106	0.24	-14.4	10.6	0.71	-4.95
			(4.96)	(3.96)	(-4.52)	(1.93)		
	Henkel	Dec-07	59.1	0.39	-16.2	13.5	0.81	-3.88
			(3.84)	(4.29)	(-4.14)	(1.94)		
	Nestle	May-08	68.8	0.29	-6.6	6.0	0.77	-3.40
			(3.43)	(3.34)	(-2.73)	(1.42)		
	Philips Electronics	Oct-09	52.6	-0.27	8.9	-8.7	0.85	-3.19
			(3.30)	(-2.87)	(2.24)	(-1.04)		
Energy	BP	Dec-07	86.6	-0.19	-8.8	10.5	0.61	-4.56
			(4.50)	(-2.27)	(-2.52)	(1.31)		
	E.ON	Oct-06	56.9	-0.26	8.1	-5.5	0.84	-3.03
			(3.13)	(-3.06)	(1.99)	(-0.71)		
	Enel	May-08	33.5	-0.06	-7.1	9.5	0.82	-3.23
			(3.19)	(-1.08)	(-2.35)	(1.56)		)
	Gas Natural	Aug-08	48.6	0.11	-17.4	15.7	0.84	-4.13
			(4.05)	(1.68)	(-4.07)	(2.06)		
	Repsol	Jun-08	78.0	0.19	-16.0	7.9	0.74	-4.01
			(3.99)	(2.54)	(-3.55)	(0.99)		
TMT	Deutsche Telekom	Aug-08	173.6	-0.03	-8.4	11.4	0.70	-4.17
			(4.09)	(-0.67)	(-3.21)	(1.82)		
	Pearson	Oct-07	40.4	0.27	-12.4	14.7	0.81	-3.64
			(3.55)	(3.64)	(-3.47)	(2.63)		
	Publicis	Aug-07	53.9	0.24	-10.9	8.9	0.83	-3.22
			(3.17)	(3.10)	(-2.83)	(1.30)		
	Reed Elsevier	Dec-07	44.5	0.06	-12.5	19.3	0.79	-4.20
			(4.04)	(1.39)	(-4.47)	(3.27)		
	Vivendi	Aug-08	77.5	-0.08	-7.2	2.75	0.77	-2.72
			(2.74)	(-1.32)	(-1.97)	(0.38)		
Financials	Allianz	Aug-08	173.6	0.17	-25.0	18.4	0.63	-4.72
			(4.69)	(1.95)	(-3.91)	(2.01)		
	Barclays	Apr-08	149.7	-0.01	-21.3	17.4	0.77	-4.08
			(4.03)	(-0.08)	(-2.80)	(1.24)		
	Credit Suisse	Oct-07	68.7	-0.08	-5.7	9.0	0.82	-3.48
			(3.50)	(-1.16)	(-1.62)	(1.07)		
	Deutche Bank	Apr-08	98.4	0.005	-18.0	20.8	0.77	-4.00
			(3.96)	(0.05)	(-2.89)	(1.76)		
	UBS	Aug-08	92.4	-0.05	-28.1	16.2	0.74	-4.26
			(4.12)	(-0.57)	(-3.94)	(1.39)		

This table reports the results of Vogelsang and Perron (1998) unit root test with a break for iTraxx index and 25 CDS spreads. The testing equation is (2.4). t-statistics are in parentheses. Under the null hypothesis of a unit root, α is equal to one. t_α represents t-statistics for the parameter α. 5% critical value for testing ($\alpha = 1$) is -5.09, 10% critical value is -4.82. Sample Period: April 2005 - March 2012

Table 3.2: Engle-Granger Cointegration Test Results

Group	Firms	Intercept	i_t	$i_t DU_{it}$	s_t	$s_t DU_{st}$	tau-statistic (Engle-Granger cointegration test)	Likelihood Ratio Test(p value)
Autos&Industrials	Akzo Nobel	46.30	0.92	-0.15	-0.12	-0.01	-5.37	0.14
		(1.49)	(5.47)	(-1.07)	(-1.73)	(-0.59)		
	Alstom	397	2.90	-1.36	-1.00	-0.08	-5.00	0.00
		(3.18)	(3.03)	(-2.06)	(-2.89)	(-1.12)		
	Bayer	0.72	0.75	-0.13	0.01	-0.02	-4.62	0.00
		(0.03)	(6.03)	(-1.38)	(0.11)	(-2.22)		
	Daimler	496	1.68	-0.48	-1.28	-0.09	-5.18	0.00
		(6.00)	(2.63)	(-1.21)	(-5.61)	(-1.90)		
	Valeo	628	1.20	0.42	-1.67	-0.12	-5.37	0.14
		(5.94)	(1.44)	(0.64)	(-5.04)	(-1.47)		
Consumers	British American Tobacco	189	0.18	0.34	-0.52	-0.04	-4.59	0.01
		(4.56)	(0.92)	(2.14)	(-3.79)	(-1.98)		
	Danone	-32.9	0.24	0.24	0.10	0.01	-4.87	0.01
		(-0.65)	(1.05)	(1.27)	(0.91)	(0.40)		
	Henkel	99.3	0.46	0.19	-0.26	-0.03	-6.22	0.16
		(3.99)	(2.65)	(0.94)	(-4.00)	(-1.25)		
	Nestle	77	-0.03	0.33	-0.20	0.02	-4.98	0.00
		(2.55)	(-0.24)	(2.38)	(-2.45)	(1.73)		
	Philips Electronics	70.7	0.66	-0.09	-0.20	0.003	-7.38	0.51
		(1.74)	(3.80)	(-0.77)	(-1.79)	(-0.27)		
Energy	BP	811	0.41	-0.67	-3.75	-0.18	-4.65	0.03
		(2.21)	(0.54)	(-0.79)	(-2.22)	(-0.93)		
	E.ON	49.7	0.40	0.14	-0.13	0.02	-5.03	0.06
		(1.59)	(1.70)	(0.87)	(-1.50)	(1.45)		
	Enel	-28.0	3.44	-0.92	-0.36	-0.22	-5.85	0.01
		(-0.23)	(3.06)	(-1.11)	(-0.68)	(-1.13)		
	Gas Natural	265	1.90	-0.39	-0.95	-0.02	-4.97	0.41
		(3.72)	(3.30)	(-0.95)	(-4.12)	(-0.20)		
	Repsol	105	0.54	-0.11	-0.34	0.04	-4.52	0.00
		(3.06)	(5.98)	(-1.70)	(-3.33)	(3.22)		
TMT	Deutsche Telekom	-46.50	0.51	0.10	0.25	0.05	-5.52	0.02
		(-0.77)	(3.37)	(0.50)	(1.10)	(1.41)		
	Pearson	76.5	0.20	0.16	-0.16	-0.05	-4.91	0.09
		(2.14)	(1.11)	(1.22)	(-1.10)	(-2.07)		
	Publicis	225	0.73	0.05	-0.60	-0.02	-7.3	0.16
		(6.47)	(4.31)	(0.43)	(-6.22)	(-2.50)		
	Reed Elsevier	6.03	0.74	0.00	0.00	-0.07	-4.67	0.50
		(0.12)	(1.89)	(0.01)	(-0.001)	(-0.71)		
	Vivendi	14.8	0.28	0.53	0.08	-0.02	-6.93	0.02
		(0.12)	(1.09)	(3.35)	(0.22)	(-0.59)		
Financials	Allianz	-61.00	0.67	0.06	0.11	0.01	-4.70	0.02
		(-1.59)	(4.78)	(0.64)	(1.54)	(1.85)		
	Barclays	-244	1.49	-0.08	0.31	0.06	-7.36	0.00
		(-1.80)	(5.98)	(-0.49)	(1.58)	(2.98)		
	Credit Suisse	-8.09	1.04	-0.02	-0.02	0.02	-6.45	0.14
		(-0.14)	(4.40)	(-0.18)	(-0.15)	(1.72)		
	Deutche Bank	-178	1.35	-0.20	0.34	0.08	-5.33	0.00
		(-1.69)	(3.92)	(-1.14)	(1.54)	(2.65)		
	UBS	80	0.65	0.49	-0.25	-0.08	-6.61	0.52
		(1.67)	(1.70)	(1.27)	(-2.12)	(-1.00)		

Note: i is the iTraxx index, s is the log stock price. DU_{it} and DU_{st} are the variables constructed from estimated break dates. tau statistics is Engle-Granger Cointegration test statistics. p value reports Likelihood Ratio test of linear versus non-linear version of the model (3.9). 5% critical value for Engle-Granger Cointegration test is -4.23. ** indicates 5% significance level, * indicates 10% significance level.

Table 3.3: Error Correction Model Results

Group	Firms	Intercept	Δi_t	$\Delta i_t DU_{it}$	Δs_t	$\Delta s_t DU_{st}$	ϵ_{t-1}	R^2
	Akzo Nobel	-0.080	1.05	-0.35	0.11	-0.31	-0.50	70%
		(-0.09)	(11.10)	(-2.36)	(0.67)	(-1.55)	(-4.73)	
Autos&Industrials	Alstom	-1.67	1.57	-0.13	-1.87	0.93	-0.40	55%
		(-0.43)	(3.28)	(-0.23)	(-2.55)	(1.05)	(-4.70)	
	Bayer	-0.06	0.84	-0.30	-0.09	-0.20	-0.37	71%
		(-0.07)	(6.80)	(-2.21)	(-1.01)	(-0.94)	(-4.32)	
	Daimler	-0.85	1.38	-0.15	-0.41	-0.60	-0.29	53%
		(-0.28)	(6.78)	(-0.44)	(-2.89)	(-1.19)	(-2.92)	
	Valeo	-0.22	1.57	-0.33	0.71	-2.67	-0.33	60%
		(-0.05)	(5.79)	(-0.80)	(1.22)	(-3.76)	(-3.95)	
	British American Tobacco	-0.21	0.64	-0.04	-0.42	-0.04	-0.36	63%
		(-0.21)	(5.01)	(-0.22)	(-2.43)	(-0.15)	(-3.80)	
Consumers	Danone	0.03	0.75	-0.13	0.04	0.56	-0.41	66%
		(0.04)	(3.78)	(-0.65)	(0.26)	(1.90)	(-3.06)	
	Henkel	-0.12	0.59	0.06	-0.07	-0.17	-0.33	70%
		(-0.14)	(8.82)	(0.57)	(-0.88)	(-0.86)	(-3.29)	
	Nestle	0.05	0.24	0.07	0.07	-0.15	-0.36	56%
		(0.08)	(1.64)	(0.52)	(0.47)	(-0.63)	(-1.98)	
	Philips Electronics	0.13	0.62	-0.15	-0.03	-0.32	-0.60	58%
		(0.13)	(4.13)	(-0.98)	(-0.14)	(-0.93)	(-4.10)	
	BP	-1.42	0.33	-0.78	-0.68	-5.33	-0.38	63%
		(-0.38)	(1.71)	(-1.35)	(-3.06)	(-1.97)	(-7.30)	
Energy	E.ON	0.23	0.49	0.09	-0.03	0.05	-0.46	57%
		(0.25)	(1.74)	(0.32)	(-0.29)	(0.20)	(-3.06)	
	Enel	-0.84	1.78	-0.30	1.19	-3.38	-0.47	46%
		(-0.19)	(5.56)	(-0.75)	(1.49)	(-2.98)	(-3.88)	
	Gas Natural	-0.29	1.45	-0.36	-0.03	-1.96	-0.47	57%
		(-0.10)	(4.97)	(-0.83)	(0.06)	(-1.89)	(-4.08)	
	Repsol	0.38	0.35	0.01	-0.23	0.33	-0.47	72%
		(0.67)	(2.97)	(0.12)	(-1.88)	(2.04)	(-4.33)	
	Deutsche Telekom	0.00	0.60	0.08	0.08	-0.07	-0.52	60%
		(0.00)	(5.01)	(0.43)	(0.69)	(-0.14)	(-4.70)	
TMT	Pearson	-0.07	0.78	-0.35	0.59	-1.49	-0.47	56%
		(-0.06)	(4.16)	(-1.66)	(2.41)	(-2.67)	(-5.42)	
	Publicis	-0.43	0.59	0.19	-0.04	-0.35	-0.78	66%
		(-0.27)	(2.62)	(0.82)	(-0.18)	(-1.22)	(-3.60)	
	Reed Elsevier	-1.18	0.72	-0.19	0.42	-2.23	-0.41	47%
		(-0.57)	(7.32)	(-0.78)	(1.73)	(-1.53)	(-3.86)	
	Vivendi	0.34	0.72	-0.05	-0.25	0.55	-0.73	55%
		(0.18)	(4.76)	(-0.28)	(-0.95)	(1.29)	(-4.10)	
	Allianz	0.19	0.58	0.23	-0.15	0.52	-0.47	81%
		(0.24)	(2.58)	(1.00)	(-1.31)	(3.62)	(-5.76)	
Financials	Barclays	0.73	1.03	0.47	-0.30	1.00	-0.86	59%
		(0.38)	(5.44)	(1.78)	(-1.55)	(2.77)	(-5.48)	
	Credit Suisse	0.47	0.71	0.37	-0.27	0.33	-0.73	74%
		(0.31)	(5.13)	(2.29)	(-1.40)	(0.77)	(-4.50)	
	Deutche Bank	0.61	0.76	0.29	-0.05	0.32	-0.54	54%
		(0.35)	(7.97)	(1.94)	(-0.40)	(1.37)	(-5.80)	
	UBS	-0.16	0.72	0.15	-0.60	-0.31	-68	55%
		(-0.06)	(4.77)	(0.50)	(-2.40)	(-0.60)	(-4.15)	

Note: i is the iTraxx index, s is the log stock price. DU_{it} and DU_{st} are the variables constructed from estimated break dates. ** indicates 5% significance level, * indicates 10% significance level.

Table 3.4: Exogeneity Test Results

Group	Firms	ϵ_{cdst}	ϵ_{it}	ϵ_{st}	Wald Test (p value)
	Akzo Nobel	0.91	0.06	0.04	0.46
		(4.80)	(0.29)	(0.41)	
Autos&Industrials	Alstom	0.44	-0.01	0.001	0.94
		(3.43)	(-0.34)	(0.03)	
	Bayer	0.93	0.13	-0.15	0.49
		(4.30)	(0.40)	(-1.11)	
	Daimler	0.47	-0.03	0.03	0.68
		(3.17)	(-0.44)	(0.74)	
	Valeo	0.35	-0.11	0.06	0.09
		(2.06)	(-1.76)	(1.23)	
	British American Tobacco	1.04	0.50	-0.05	0.07
		(8.01)	(2.09)	(-0.90)	
Consumers	Danone	0.85	0.32	0.01	0.36
		(6.25)	(1.40)	(0.11)	
	Henkel	0.82	-0.004	0.01	0.99
		(3.19)	(-0.01)	(0.10)	
	Nestle	0.61	0.01	0.09	0.47
		(5.00)	(0.03)	(1.21)	
	Philips Electronics	0.77	-0.17	0.11	0.60
		(3.94)	(-0.60)	(0.80)	
	BP	0.92	0.05	-0.06	0.00
		(7.45)	(1.29)	(-3.23)	
Energy	E.ON	0.82	0.17	-0.02	0.70
		(6.05)	(0.80)	(-0.24)	
	Enel	0.55	-0.12	0.01	0.03
		(3.77)	(-2.45)	(0.80)	
	Gas Natural	0.44	-0.15	0.04	0.01
		(3.61)	(-2.42)	(1.42)	
	Repsol	-0.15	-1.00	0.48	0.00
		(-1.19)	(-4.25)	(4.71)	
	Deutsche Telekom	0.85	0.20	-0.06	0.22
		(6.72)	(1.32)	(-1.10)	
TMT	Pearson	1.16	0.37	-0.14	0.02
		(13.45)	(1.66)	(2.20)	
	Publicis	0.6	-0.10	0.04	0.61
		(4.36)	(-0.67)	(0.71)	
	Reed Elsevier	0.86	-0.03	-0.10	0.00
		(9.60)	(-0.36)	(-3.27)	
	Vivendi	0.78	-0.11	0.03	0.59
		(5.58)	(-0.82)	(0.59)	
	Allianz	1.10	0.33	0.00	0.57
		(4.33)	(1.04)	(0.00)	
Financials	Barclays	0.86	-0.03	0.02	0.87
		(7.48)	(-0.41)	(0.31)	
	Credit Suisse	1.11	0.10	-0.05	0.73
		(5.26)	(0.48)	(-0.61)	
	Deutche Bank	0.79	0.15	-0.01	0.41
		(6.01)	(1.29)	(-0.22)	
	UBS	0.77	-0.05	-0.03	0.67
		(5.90)	(-0.67)	(-0.57)	

Note: i is the iTraxx index, s is the log stock price. Joint null hypothesis for Wald Test is ($\epsilon_{it} = 0$,$\epsilon_{st} = 0$). The number of lags is selected according to Schwarz criterion. ** indicates 5% significance level, * indicates 10% significance level.

Table 3.5: Johansen Cointegration Test Results

		Trace Statistics-Cointegration Test			Coefficients of Lagged Error Terms		
Group	Firms	None	At Most 1	At Most 2	ϵ_{cdst}	ϵ_{it}	ϵ_{st}
	Akzo Nobel	35.79	11.57	4.74	-0.55	0.01	0.14
					(-2.93)	(0.06)	(1.41)
Autos&Industrials	Alstom	32.66	14.73	5.13	-0.17	0.01	0.04
					(-2.26)	(0.65)	(2.30)
	Bayer	48.51	22.73	5.44	-0.28	0.3	-0.06
					(-1.68)	(1.30)	(-0.67)
	Daimler	42.14	11.12	4.01	-0.29	-0.002	-0.06
					(-2.94)	(-0.06)	(-2.03)
	Valeo	34.43	5.46	0.48	-0.35	0.03	-0.01
					(-3.11)	(0.80)	(-0.33)
	British American Tobacco	36.58	9.72	0.12	-0.23	0.28	-0.1
					(-1.55)	(1.53)	(-1.85)
Consumers	Danone	37.58	17.28	5.84	-0.26	0.24	-0.08
					(-1.83)	(1.29)	(-1.36)
	Henkel	45.85	6.40	0.1	-0.24	0.36	-0.15
					(-1.53)	(1.78)	(-1.86)
	Nestle	19.14	5.79	0.69			
	Philips Electronics	56.84	16.90	3.51	-0.57	0.23	-0.06
					(-3.80)	(1.11)	(-0.67)
	BP	27.20	9.29	1.76	-0.42	-0.03	0.009
					(-3.34)	(-0.85)	(0.50)
Energy	E.ON	32.40	11.45	1.65	-0.01	0.43	-0.02
					(-0.08)	(2.89)	(-0.33)
	Enel	40.38	14.51	2.21	-0.45	-0.01	-0.01
					(-4.01)	(-0.29)	(-1.16)
	Gas Natural	29.05	13.87	2.76	-0.04	0.03	0.03
					(-0.68)	(1.37)	(2.97)
	Repsol	34.58	9.80	2.67	-0.29	0.15	-0.12
					(-2.52)	(0.64)	(-1.09)
	Deutsche Telekom	36.50	19.27	3.89	-0.39	0.08	-0.02
					(-2.49)	(0.52)	(-0.36)
TMT	Pearson	31.25	3.48	0.09	-0.55	0.01	0.02
					(-4.31)	(0.09)	(0.52)
	Publicis	29.80	4.67	0.45	-0.56	0.12	-0.05
					(-2.90)	(0.72)	(-0.79)
	Reed Elsevier	32.08	10.96	1.87	-0.41	-0.01	-0.01
					(-3.73)	(-0.15)	(-0.44)
	Vivendi	33.76	9.91	1.02	-0.54	0.13	-0.04
					(-3.33)	(1.01)	(-0.83)
	Allianz	42.06	15.49	3.74	-0.25	0.17	0.05
					(-0.25)	(0.83)	(0.40)
Financials	Barclays	61.60	28.28	1.9	-0.29	0.30	-0.14
					(-1.60)	(3.26)	(-1.66)
	Credit Suisse	43.43	16.07	2.78	0.16	0.32	0.15
					(0.76)	(1.94)	(1.93)
	Deutche Bank	36.34	15.95	2.02	-0.02	0.14	0.04
					(-0.25)	(2.25)	(0.82)
	UBS	39.65	11.75	0.66	-0.66	0.06	0.003
					(-3.73)	(0.77)	(0.05)

Note: ** indicates 5% significance level, * indicates 10% significance level. i is the iTraxx index, s is the log stock price. The number of lags is selected according to Schwarz criterion.

Chapter 4

Early Warning Indicators of Money Market Distress: A Non-Parametric Approach

Abstract

One of the main interests in studying interbank money markets lies in their ability as early warning indicators of distress in the financial sector. The contributions of this paper are twofold: First, we investigate this money market by estimating the cross-sectional density of interbank funding rates using nonparametric kernel methods. Second, we analyze the effect of several factors such as banks size, the operating currency and banks' nationality on the cross-sectional distribution of these rates for the European e-MID interbank market. Our results strongly support the statistical significance of these effects and highlight the importance of these factors as early warning indicators of financial distress. In particular we observe that prior to the recent financial crises, the borrowing segment of the interbank market exhibits distinctive features such as highly volatile, multimodal distributions suggesting the occurrence of distortions in the cross-section of funding rates. During these crisis episodes, large domestic banks operating in Euros enjoy the highest lending - lowest borrowing spreads indicating the existence of optimal features defining successful banks. Banks' nationality is a particularly revealing factor in helping to uncover the existence of a link between distress in the interbank market and sovereign risk.

4.1 Introduction

Interbank markets are the main instrument for the transmission of monetary policy targets from central banks to the overall economy. These markets are responsible for distributing liquidity across the financial system by allowing the transfer of funds from banks with a surplus to banks with a deficit. This is discussed for example in Ho and Saunders (1985), Bhattacharya and Gale (1987) and Freixas, Parigi and Rochet (2000), amongst others. These authors note the insurance role of interbank markets against idiosyncratic liquidity shocks.

As well as the insurance role, interbank markets can be a threat to the stability of the financial system. The connectivity between banks offered by these markets increases their exposures to systemic risk and serves as a channel of contagion between distressed economies (Rochet and Tirole, 1996). The shock of an insolvent bank may propagate to other banks through interbank linkages, with the probability of contagion affected by the topology of the network of mutual exposure (Allen and Gale, 2000 and Freixas et al., 2000). In the empirical literature, many papers investigate the fragility of the banking system analyzing interbank market data, such as Angelini et al. (1996), Wells (2004), Furfine (2003), Upper and Worms (2004) and Sheldon and Maurer (1998). A recent paper by Mistrulli (2011) utilises a unique dataset that consists of actual bilateral exposures (as opposed to aggregate multilateral exposures) and concludes that the Italian interbank market is conducive to financial contagion, however it hardly triggers systemic risk.

During the crisis, interbank interest rates underwent record levels and trading activity in these markets saw an unprecedented decline in most market segments. The collapse of major financial institutions such as Lehman Brothers contributed to the loss of confidence in the health of the overall financial system and the rise in risk aversion levels that led to the dry up of liquidity in interbank markets. This

increase in funding rates between banks also produced the flight to quality from the interbank money market to the European Central Bank (ECB) deposit facilities. To overcome this malfunctioning of the interbank money market, central banks around the world considered nonconventional measures mainly centered on injecting liquidity into the system. The success of these measures were mixed with interest rate spreads remaining at levels well above those observed before the financial crisis.

The network studies analyse changes in the way banks form links, and assess if, as a consequences of these changes, the resulting network of exposures becomes more or less resilient to random defaults, see Furfine (2003), Iori et al. (2006), Iori et al. (2008) and Boss et al. (2006). Rather than attempting to measure systemic risk via these stress-test type of exercises, in this chapter the evolution of the cross-sectional distributions of credit spreads are monitored. Public or private information banks have about each other, should be quickly incorporated in the rates lenders charge to their borrowing counterparties. Uncertainty about the environment and the risk exposure of specific banks should lead to more volatile rates. Cross sectional distribution of spreads has the potential to quickly incorporate any worrying signal and the evaporation of trust among banks that accompanies a crisis. The aim of this chapter is to verify this hypothesis by looking at the dynamics of these distributions around recent periods of financial distress. It is therefore economically meaningful to develop analytical techniques capable of fully capturing these disturbances that can be of various forms: high volatility periods, large funding rates reflecting wide spreads between lending and borrowing rates and across banks in the system or the occurrence of different clusters around focal points. These highly asymmetric features highlight the importance of using statistical measures beyond the first moments of the funding rates distribution. The first contribution of this chapter is to propose nonparametric kernel estimation methods for modeling the cross-sectional

distribution of borrowing and lending rates in the European interbank market. This novel methodology, hardly explored in this context, provides more flexibility for accommodating the above mentioned stylized facts than standard parametric distributions such as Normal or Student-t distributions. This methodology also contrasts to most of the related literature that explains the determinants of funding rates in interbank money markets, see Gabrieli (2011a ,2011b), Cocco et al. (2009), Angelini et al. (2011) or Afonso et al. (2011), using parametric panel data regression models. The second contribution is to empirically analyze the factors that can have an influence on the level and dispersion of the interbank funding rates. Besides size of the banks, this study addresses Euro-NonEuro and Crisis-NonCrisis classifications as the potential determinants of the variation in funding rates diffferent from previous contributions. Euro refers to banks that are based in countries operating in Euro currency and NonEuro represents banks that are based in countries operating on their own currencies. Under Crisis category, banks based in countries experiencing sovereign crisis are classified. These factors allow us to investigate whether operating in Euro currency bring a benefit for the banks or whether experiencing sovereign crisis has a negative impact on the borrowing or lending spreads. The motivation for doing so is the strong relationship between interbank money markets and the overall financial system and the speed with which shocks to the money market are reflected as disturbances to the overall economy. The correct understanding of the effects of these factors on the interbank funding rates can help policy makers and financial regulators to device appropriate structures for banks in order to be able to adequately respond to their financing needs under the occurrence of shocks to the financial system.

A distinctive contribution of this work is the database analyzed. In this chapter, data on overnight transactions from July 2006 to August 2009 on the e-MID money

market trading system are used. The e-MID market represents the only readily available source of micro data on interbank transactions in the Euro area and offers the most comprehensive dataset reflecting actual transactions and not offered rates. The overnight segment is strongly influenced by the Eurosystem's operational framework implying that overnight rates are less exposed to market participant's speculative behavior.

The remainder of this chapter is organized as follows. Section 4.2 explains the properties of the e-MID interbank market and describes the dataset. Section 4.3 describes the econometric methodology based on density kernel estimation to assess the behavior of lenders and borrowers conditional on banks size, currency and banks' nationality. Section 4.4 discusses the empirical findings obtained from applying these methods to the large dataset. Lastly, Section 4.5 concludes. Tables and figures are collected in the appendix.

4.2 The e-MID Market and Data

This section introduces the characteristics of the e-MID interbank market and the dataset used for the empirical analysis.

4.2.1 The e-MID Market

The e-MID company, established in 1990, makes use of an electronic platform to manage the interbank unsecured deposit market in Europe. It is the only electronic trading platform for interbank deposits in the Euro area and in the US. Under the supervision of Bank of Italy, credit institutions and investment companies can participate in this market if their total net asset size is respectively at least 10 million US Dollars (or its equivalent in another currency) and 300 million euros (or

its equivalent in another currency). Before the financial crisis, the platform had 246 members from 29 EU countries and the US, of which 30 were central banks acting as market observers. Interbank deposit maturities range from overnight to one year with overnight contracts representing nearly 90% of total volume. After the crisis, the number of countries with banks actively participating in the e-MID market is sixteen: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Switzerland and United Kingdom.

One distinctive feature of the platform is that it is fully transparent. Buy and sell proposals appear on the platform with the identity of the bank posting them. In the overnight market segment, a buy transaction is an interbank loan proposed by the borrowing bank submitting a bid quote on the screen, hence revealing itself as liquidity-short to the market; a sell transaction is an interbank loan initiated by the lender submitting an ask quote on the screen, hence revealing itself as liquidity-long. The platform does not offset any counterparty risk; search costs are identical for all platform participants. In this market, each trader can choose any counterparty present in the book to start the trade. The two parties can negotiate the terms and conditions of the specific trade, change the quantity/price or refuse the transaction at all. During the financial crisis a decrease is observed in the volume of transactions and number of participants largely because of the transparency of the e-MID market that induces banks to search for alternative, less transparent sources of funding. Thus, before the crisis, the amount of transactions executed on the e-MID platform accounts for 17% of total turnover in unsecured money markets in the Euro Area, decreasing to around 10% of market share after the financial crisis.

Figure 4.1 presents monthly average of daily volume and number of transactions over the sample period. There is clear evidence that participation in this market

decreases during the crisis. Some of this decline can be explained by a general decrease in the interbank transactions as banks prefer to deposit their money in ECB rather than lending it to each other at the prevailing interest rates. The other obvious reason is related to the transparent nature of the market. Banks, especially borrowers, may avoid to reveal their liquidity shortage appearing on the borrowing side. Hence they may prefer to trade in a less transparent environment during financial shocks in order to avoid being openly seen in the market.

Table 4.1 presents average transaction size of different sized Italian banks and foreign ones participating in the e-MID system. These statistics reveal a correlation between transaction and institution size for domestic banks. Transaction sizes are proportional to their asset size which is in line with the findings of Furfine (1999) for the FED funds market. Table 4.1 also reports the market share of foreign and different sized domestic banks with respect to the total number of transactions and amounts traded. Foreign banks have more than 50% total volume market share in both sides of the market. High participation of foreign banks in the e-MID market acknowledges its international character.

4.2.2 Data

The dataset used for this study consists of all the transactions recorded in the platform between 12 July 2006 and 8 September 2009. For each transaction, there is comprehensive information about the date, the time of trade, quantity exchanged, the interest rate, transaction side (buy or sell) and the code of the quoting and ordering banks. The database contains 125 Italian and 90 foreign banks acting as borrowers, lenders or both during the period of study. Although the identity of the banks is not available, information on capitalization for the Italian banks and the origin country for all banks are available. Italian banks are classified into 5

groups according to their weighted asset portfolio: major banks (higher than 60 billion euro), large banks (from 26 to 60 billion euro), medium banks (from 9 to 26 billion euro), small banks (from 1.3 to 9 billion euro) and minor banks (less than 1.3 billion euro). Only overnight (O/N) and the overnight long (ONL) contracts are considered in this study where ONL refers to contracts when more than one day is present between two consecutive business days. The interest rate is expressed as an annual rate and the amount of the transaction is quoted in millions of Euros.

It is observed that the trading activity of borrowers/lenders is affected by the reserve maintenance period, announced by the ECB, rather than by calendar month effects. This is so because banks need to comply with regulatory requirements on the amount of capital held over such periods. Empirically, for the EONIA rates, Gaspar et al. (2008) report an increase in market activity towards the last days of the reserve maintenance period described by a remarkable increment in the number of transactions and in the underlying volatility of interest rates. To capture these effects, monthly periods determined by the reserve maintenance period are considered. In this dataset, there are 38 monthly periods.

The spread of each transaction is defined as the deviation of the transaction interest rate from the daily average market rate. More formally,

$$s_{b,t} = r_{b,t} - \overline{r}_{d,t} \tag{4.1}$$

with $r_{b,t}$ an individual interest rate outstanding for bank b at time t, and $\overline{r}_{d,t}$ the average rate of all transactions in the market on day t. The interest in analyzing the spread rather than the crude interest rate is for cross-comparison purposes between the banks trading in the interbank market. In order to reduce the noise due to extreme movements in funding rates, aggregate daily spreads computed over the reserve maintenance periods are considered. For a bank b executing $T_{b,m}$ transactions

on a given month m, the monthly average credit spread is calculated as below:

$$\overline{s}_{b,m} = \frac{1}{T_{b,m}} \sum_{t=1}^{T_{b,m}} s_{b,t}. \tag{4.2}$$

This statistic is complemented with a measure of volatility that provides information on the distribution of the variability of daily funding costs for each bank over the monthly maintenance period. The monthly standard deviation of the daily spread of each bank is

$$sd_{b,m} = \sqrt{\frac{1}{T_{b,m}} \sum_{t=1}^{T_{b,m}} (s_{b,t} - \overline{s}_{b,m})^2} \tag{4.3}$$

The number of borrowers varies from month to month between 62 and 127 and the number of lenders between 78 and 156. The number of observations on a particular month may be smaller than the number of banks, simply because some banks may not be active during that period.

The methodology of this study is implemented on six subperiods to control for the impact of important market events. Table 4.2 presents information about the sub-periods considered in this study. January 2007, August 2007, March 2008, September 2008 and March 2009 are considered as the dates defining the different periods in the European interbank market. February 2007 corresponds to the crash of the Shanghai Stock Exchange considered as one of the first signals of the financial crisis. Therefore, July 2006 to January 2007 is considered as the "Pre-crisis Period"; January 2007 to August 2007 as a " Financial Markets Unease Period". August 2007 is accepted as the date when sub-prime mortgage crisis spilled over into the interbank market, hence, from August 07 to March 08 is considered as the "Interbank Crisis Period". In March 2008, Bear Sterns collapsed and its collapse was the prelude to the increased tension in the investment banking sector. Right after, financial markets experienced the largest bankruptcy with the collapse of Lehman Brothers

in September 2008 triggering heightened concerns on counterparty risk and the cease in lending activities between commercial banks. Considering these important dates, March 08 to September 08 is classified as "Pre-Lehman Period" and September 08 to March 09 as "Post-Lehman Period". Lastly, the period from March 09 to September 09 is considered as the "Post-Crisis Period" when the interbank market shows the first signals of recovery.

4.3 Econometric Methodology

This section discusses the methods necessary to perform empirical analysis. The cross-section of interest rates and underlying volatility outstanding in the interbank market over the recent years will be modelled in this section. To do this, in the following, the main techniques for nonparametric kernel density estimation and the corresponding estimation of the quantile function will be presented.

Let $(x_1, x_2, ..., x_n)$ be an iid sample drawn from some distribution with an unknown density function $f(\cdot)$. Its nonparametric kernel density estimator is

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K(\frac{x - x_i}{h}) \tag{4.4}$$

where $K(\cdot)$ is a kernel function and h is a bandwidth parameter. The kernel function must be a density function, nonnegative and symmetric. The size of bandwidth chosen for kernel density estimation determines the degree of smoothing produced. The kernel function and bandwidth parameters accommodate a wide range of options that provide some flexibility in the estimation of the density. For a nice review on nonparametric kernel methods the interested reader is referred to Li and Racine (2007).

Conditional density estimation is the realization of regression where instead of

estimating the expected value $E(Y|X)$ with Y the response variable and X the regressor vector, it models the full density $f(Y|X)$. By doing this, the method provides valuable information about skewness, kurtosis, multi modality, extreme values and any other statistics that require knowledge of the underlying distribution. The following paragraphs detail the kernel method for conditional density estimation with the appropriate kernel functions chosen for each variable, conditional quantile functions and bandwidth selection method for the model specifications.

Let $g(\cdot,\cdot)$ and $\mu(\cdot)$ denote the joint and marginal densities of (X,Y) and X, respectively. Y is the dependent variable which is the spread/volatility in the models below and X as the vector of explanatory variables which in the application corresponds to a vector of ordered discrete factors such as monthly time period or banks' asset size and (unordered) discrete factors such as Euro/Non-Euro and Crisis/Non-Crisis classifications. $\hat{f}$ and $\hat{\mu}$ denote the corresponding kernel estimators and

$$\hat{f}(y|x) = \frac{\hat{g}(x,y)}{\hat{\mu}(x)} \tag{4.5}$$

for the kernel estimator of the corresponding conditional density function. It is immediate to observe that the conditional density estimation is the ratio of two kernel density estimators. As Y is a univariate continuous random variable, the kernel estimation of the joint density $g(\cdot,\cdot)$ and marginal density $\mu(\cdot)$ are given by

$$\hat{g}(x,y) = n^{-1}\sum_{i=1}^{n} K(x,X_i,\lambda)k_{h_0}(y,Y_i) \tag{4.6}$$

and

$$\hat{\mu}(x) = n^{-1}\sum_{i=1}^{n} K(x,X_i,\lambda). \tag{4.7}$$

The kernel function for the continuous dependent variable Y (spread/volatility) is

$$k_{h_0}(y, Y_i) = h_0^{-1} k((y - Y_i)/h_0) \tag{4.8}$$

where $k((y - Y_i)/h_0)$ is one of the multiple choices existing in the literature (e.g. Gaussian, Uniform, Epanechnikov) and h_0 is the smoothing bandwidth parameter corresponding to Y.

The kernel function for discrete random variables is more convoluted than for continuous random variables. Wang and van Ryzin (1981) type kernel function is used below for the ordered discrete factors, monthly time period and asset size classifications used in the posterior empirical analysis. This function takes the form:

$$K(x^d, X_i^d, \lambda) = \begin{cases} 1 - \lambda, & \text{if } X_i^d = x^d, \\ \frac{(1-\lambda)}{2} \lambda^{|X_i^d - x^d|}, & \text{if } X_i^d \neq x^d \end{cases}$$

where λ is the smoothing vector for the ordered discrete factor X^d and can lie between 0 and 1.

For the analysis focused on dichotomic conditional variables, such as Euro against Non-Euro currencies and Crisis against Non-Crisis classifications, the following kernel function developed by Aitchison and Aitken (1976) is used:

$$K(x^d, X_i^d, \lambda) = \begin{cases} 1 - \lambda, & \text{if } X_i^d = x^d, \\ \frac{\lambda}{(c-1)}, & \text{if } X_i^d \neq x^d \end{cases}$$

where λ is the smoothing vector for the discrete factor X^d and c is the number of (discrete) outcomes assumed by the factor; λ in this case lies between 0 and $(c-1)/c$. As conditional variables have two outcomes (Euro, Non-Euro or Crisis, Non-Crisis)

in this context, the bandwidth parameter λ lies between 0 and 0.5.

The estimation of conditional quantiles is also relevant in the analysis to determine the distribution of cross-sectional interest rates and volatility. A conditional quantile $q_\alpha(x)$ with $0 < \alpha < 1$, is defined as

$$q_\alpha(x) = \inf\{y \in Y : F(Y|X) \geq \alpha\}. \tag{4.9}$$

This is estimated by inverting the estimated conditional cumulative distribution function corresponding to the conditional density above. This distribution is denoted as $\hat{F}(Y|X)$ and obtained from integrating $\hat{f}(y|x)$ over the domain of the random variable Y. For a given value of α and x, the conditional quantile is obtained as follows;

$$\hat{q}_\alpha(x) = \inf\{y \in Y : \hat{F}(Y|X) \geq \alpha\} = \hat{F}^{-1}(\alpha|x), \tag{4.10}$$

with $\hat{F}^{-1}(\cdot|x)$ the inverse of the estimated cumulative distribution function $\hat{F}(\cdot|X)$.

Nonparametric kernel estimation has been established as being relatively insensitive to the choice of the kernel function. The same cannot be said for bandwidth selection. A widely employed technique to determine the optimal vector of bandwidth parameters is least squares cross-validation methods. The advantage of this method over other alternatives, such as a rule of thumb or plug-in methods, is that cross-validation automatically discards irrelevant information from the vector X (see Hall et al. (2004) and Li and Racine (2007, p. 69)). The method automatically determines which components of X are relevant and irrelevant, through assigning large smoothing parameters to the latter and consequently shrinking them toward the uniform distribution on the respective marginal distributions. Least squares cross validation produces asymptotically optimal smoothing for relevant components while eliminating irrelevant components by over-smoothing. This method is

based on the principle of selecting a bandwidth that minimizes the integrated square error of the resulting conditional density estimation, defined as

$$ISE = \int \left[\hat{f}(y|x) - f(y|x)\right]^2 \mu(x) M(x^c) dx dy \tag{4.11}$$

where $M(\cdot)$ is a weight function giving different importance to different sections of the conditional distribution.

4.4 Empirical Findings

The first block of the section studies the performance of the dynamic distributions of the spreads and the corresponding cross-sectional volatilities. This analysis allows observing the predictive ability of the underlying volatility in signalling instabilities in funding rates. The second block explores the empirical relevance of the above mentioned banks' characteristics on the cross-sectional distribution of spreads.

4.4.1 Dynamics of Spreads: Mean and Volatility

This section exploits the nonparametric quantile methods discussed in Section 4.3 for describing the dynamics of the funding rates and their volatilities. For expositional purposes, a discrete set of relevant quantiles of the distribution of these quantities are considered rather than their complete density functions. The study focuses on the 10%, 25%, 50%, 75% and 90% percentiles. This can be easily done by exploiting the flexibility of the nonparametric kernel density estimation method that allows to obtain quantiles of the relevant underlying distributions. Figure 4.2 presents this dynamic quantile analysis for the means and volatilities of the borrowing spreads; Figure 4.3 reports the analysis corresponding to the lending spreads.

The mean and volatility patterns are similar across borrowing and lending costs.

At the beginning of the evaluation period, interbank rates show very little dispersion indicating small differences in borrowing and lending conditions across banks participating in the e-MID market. The graph reports an increase in the dispersion of rates that becomes apparent from July 2007 until January 2008. This increase in the dispersion of bank rates stresses the heterogeneous performance of the cross-section of banks in both segments of the interbank market. During these months the risk premium on banks searching for liquidity varies substantially indicating important differences in borrowing and lending conditions across banks trading on the interbank market. The distribution of both borrowing and lending rates remains symmetric during this period, this is not so during the second phase of the crisis. In the borrowing segment, the median spread during this period is below zero indicating that more than 50% of the banks in the e-MID market obtain funding rates below the cross-sectional average. This implies the presence of a few problematic banks viewed as risky and receiving large borrowing rates. These findings suggest that whereas the crisis is widespread in the banking sector during the first phase of the crisis and affects all banks in the system in a similar way, during the second phase, it is more idiosyncratic and can be pinned down to the collapse of a few distressed banking institutions. The dispersion in funding rates and asymmetric cross-sectional distribution becomes more moderate during 2009 without managing to recover the levels prior to the crisis. The lending market exhibits similar findings; the asymmetric behavior of lending rates is less apparent than in the borrowing side and indicates that the increase in asked rates is of similar magnitude across the spectrum of banks in the supply side of the e-MID system.

The analysis of the quantile process of volatilities yields interesting findings. Volatility spikes characterized in this framework by increases in the upper quantiles of the distribution of volatilities are prior to the spikes observed in the distribution

of spreads. This empirical finding provides support to the existence of what is called in the analysis of equity market returns as *leverage effect*. Roughly speaking, increases in the volatility of spreads are responded by increases in funding rates over the next periods. Thus, during the period January to May 2007 banks in the upper quantiles experience important differences in funding rates over the maintenance period. This phenomenon signals high levels of uncertainty in the interbank market over the health of these banks. At the start of the crisis, July 2007, uncertainty is resolved and troubled banks receive high and stable borrowing rates over the next periods. During the second phase of the crisis, spread and volatility increases go hand in hand. Borrowing and lending rates widen over this period due to the existence of a few troubled banks. In contrast to the first phase of the crisis, this period is characterized by huge levels of uncertainty in the whole banking sector that is reflected in highly variable daily spreads over the maintenance periods.

This study on the dynamics of the quantile process is complemented with a more detailed analysis of the cross-sectional distribution of spreads obtained from conditioning on several banks' characteristics. The analysis is divided over six non-overlapping subperiods covering the period 2006 to 2009. The density functions are computed by pooling information on interest rates for each bank obtained over the months comprised in each subperiod. This methodology is very useful for obtaining aggregate measures of cross-sectional spreads over periods of economic relevance.

4.4.2 Size Matters

Asset size is an important variable to determine the characteristics of a commercial bank. In fact, Angelini et al. (2011) note that before the crisis, banks' asset size is the only relevant variable that determines borrowing spreads faced by banks. These authors also consider the rating or the capitalization ratio of banks as potential

proxies for bank characteristics, however they find that these variables are not statistically significant. This empirical finding is supported for the US money market by early studies such as Stigum (1990), Allen and Saunders (1986) and Furfine (2001) that draw attention to the tiering structure in the federal funds market by which large institutions get favorable rates compared to smaller institutions regardless the side of the transaction they are on. A recent study by Gabrieli (2011a) confirms this tiering structure of the European market during the different phases of the crisis.

By conditioning on the size of banks trading in the interbank market, nonparametric estimates of the density of the cross-sectional spreads uncover significant differences. The dataset only contains information on asset size for Italian banks. There are 125 banks in the sample. The conditioning information set is defined by a discrete categorical random variable taking five possible values where a value of 1 corresponds to the smallest group of banks and a value of 5 to the biggest banks. Table 4.3 reports bandwidth parameters for the conditional density estimation of spread on asset size classifications. Bandwidth parameters indicate that size is a relevant variable on the determination of borrowing and lending spreads in all the periods considered, even before the crisis. This is in line with previous studies such as Angelini et al.(2011) and Gabrieli (2011a) that investigate the effects of asset size on the determination of spread in a parametric setting.

Figure 4.4 reports the nonparametric densities for the borrowing spreads over the different subperiods and Figure 4.5 the nonparametric estimates of the volatilities as defined in (4.3). Figures 4.6 and 4.7 report the analogous densities for the lending rates. These charts allow to visualize the differences on the borrowing/lending conditions of different sized banks. The figures describe an interbank money market that abruptly moves from a stable market condition defined by similar funding rates across banks regardless the size to a heterogeneous market characterized by very

different borrowing/lending conditions at the start of the crisis. Figures 4.4 and 4.6 indicate that there are infinitesimal amount of differences on the spreads obtained by different sized borrowers or lenders before the crisis. Hence, even though size is a significant variable on the determination of spread according to both parametric and nonparametric analysis, this study reveals that there are not remarkable differences on the funding costs of different sized banks. The differences are only visible between the density of the largest (Italian) banks and the rest of banks after the tensions in debt markets that emerged in September 2008. During this period the differences in borrowing costs between banks of different sizes are substantial; the existence of three modes in the density of the spreads on the largest banks signals the clustering of banks in terms of their creditworthiness. Banks in the left tail of the distribution enjoy significantly smaller borrowing rates than the rest of banks. Nevertheless, there is another group of banks with rates not far from the average borrowing rate over this period. The existence of three modes also indicates that size is not the only relevant variable for explaining borrowing rates. A recent study by Gabbi et al. (2012) suggests for example that some larger banks have better exploited changing microstructure features of the interbank market during the crisis. After the crisis the differences between banks decrease but are still noticeable. The charts in Figure 4.5 reveal an increase in volatility as the collapse of Lehman Brothers approaches. This phenomenon is not observed simultaneously for all banks. The densities evolve from having one to two modes and the tails also become thicker revealing the existence of two types of banks: some banks exhibiting similar funding costs over this period and other banks exhibiting highly variable funding costs. This variability becomes systemic after the collapse of Lehman Brothers. Interestingly, after the second phase of the crisis, the group of largest banks also exhibits the largest variations in borrowing costs. This implies that for some days of the mainte-

nance period these banks obtain very favorable rates compared to the average spread on that day, and other days the funding rates are close to the average daily spread. These measures of volatility give evidence of tension and uncertainty in interbank markets over the crisis periods. After 2009, the volatility in the borrowing segment considerably declines and returns to levels before 2007.

The analysis of the lending segment in Figure 4.6 exhibits less contrast. Lending rates are similar across bank sizes. It is only after the collapse of Lehman Brothers that the group of largest banks has the highest lending rates. The corresponding densities are also bimodal giving support to the idea that not only size matters for explaining lending rates. The high spreads obtained by large banks could be the result of relationship lending, as suggested by Cocco et al. (2009), Affinito (2012), and Brauning and Fecht (2011). The analysis of volatility in Figure 4.7 shows similar patterns to those observed for the borrowing segment. The overall picture describes a market in which size is a key variable for determining bank profitability. Largest banks enjoy highest lending rates and lowest borrowing rates over the cross-section of banks acting in the e-MID market.

4.4.3 The Role of Operating Currency and Bank's Nationality

The dataset of this study covers a non-crisis and a crisis period. The number of active countries in the e-MID market over both periods is sixteen. Most of these countries have adhered the Euro currency. These countries are Austria, Belgium, France, Germany, Greece, Ireland, Luxembourg, Netherlands, Portugal and Spain. A few other participating countries such as Britain, Denmark, Norway, Poland and Switzerland do not use the common currency, though. Commercial banks in the second group of countries are not allowed to open a Euro account with ECB, and hence

they cannot use ECB deposit facilities. Table 4.4 reports bandwidth parameters for the conditional density estimation of spread on Euro/NonEuro classifications. Figures 4.8 and 4.9 describe the densities of interbank spreads conditional on the main currency on which the bank operates. The graphs show no differences in funding rates until the second phase of the crisis (Lehman Brothers collapse). After it, the nonparametric densities indicate larger funding costs for banks in non-Euro countries than for banks in countries using the Euro as main currency. On the lending side, the same results are obtained. Non-Euro banks request higher spreads for lending funds to other banks than Euro banks. These higher lending rates are likely to be due to the need of counteracting higher borrowing costs.

Although the sample does not contain information on size for foreign banks, it is plausible to assume that foreign banks are of comparable size to the largest Italian banks. This assumption is supported by the statistics on average transaction size for foreign banks reported in Table 4.1 and by observational evidence that notes that large European banks trade in international markets but smaller ones are restricted to domestic markets. Figures 4.8 and 4.9 also present the comparison between the densities of the largest Italian banks and foreign banks. These figures reveal interesting insights on the extent of asymmetric information by borrowers and lenders on large banks of different nationalities. During the 'Interbank Crisis' period and afterwards, funding conditions become tougher for foreign banks compared to their domestic counterparties. This phenomenon marks a rupture in the integration of the interbank market. From this period, a segmented market is observed that favors domestic banks. These findings are in line with the theoretical framework developed in Freixas and Holthausen (2005) on the role of asymmetric information on interbank markets.

The study of banks' nationality on the cross-sectional distribution of spreads has

recently gained importance given the unprecedented increase in spreads observed in some European sovereign debt markets. Although the sample ends in August 2009, it is investigated whether there is early evidence of any discrepancy on funding conditions between banks based in countries experiencing a sovereign crisis in posterior periods and the rest of banks. Countries exposed to sovereign crisis are Greece, Ireland, Portugal and Spain. Table 4.4 reports bandwidth parameters for the conditional density estimation of spread on Crisis/NonCrisis classifications. Figures 4.10 and 4.11 represent the densities of interbank spreads conditional on being in the latter group of countries or not. The differences reflected in borrowing conditions after the collapse of Lehman Brothers are very significant. Banks in countries under sovereign distress experience borrowing rates well above those of banks based in undistressed economies. The lending side, on the other hand, does not reflect significant differences in funding rates between banks from distressed economies and the rest of European banks. These findings show evidence of borrowing difficulties for banks in these countries well before the respective countries had trouble in funding themselves, and highlight the importance of the interbank market as an early warning indicator of sovereign debt distress when using appropriate conditioning information.

It should be noted that this is an aggregate result obtained from pooling information from banks in the four countries above mentioned. In order to extract meaningful information on which countries are mainly driving these results a more detailed analysis conditioning on specific countries and not on economic regions should be performed. With this purpose, Greece funding conditions are compared with those of banks in Britain and Germany. The results in Figures 4.12 and 4.13 illustrate the remarkable differences in borrowing conditions between banks based in Germany and Greece. These graphs also reveal a more pronounced effect of the

Lehman Brothers collapse on the borrowing rates of British banks than of German banks indicating the higher exposure of the British banking sector to the US economy. On the lending side, substantial differences are not observed on spreads conditional on banks' nationality. It is interesting to observe that in the last period Greek banks exhibit a bimodal distribution indicating the existence of a small group of, possibly troubled, banks offering lending rates well below market rates.

4.5 Conclusion

Interbank markets are the main instrument for the transmission of monetary policy targets from central banks to the overall economy. This market is responsible for supplying liquidity to the financial system through the buying and selling operations of participant commercial banks. The cross-section of interbank rates provides useful information on the performance of the banking sector.

This chapter explores the cross-sectional distribution of aggregate monthly rates obtained as the average of daily spreads in the e-MID market. In both borrowing and lending segments, it is observed that there are leverage and feedback effects between cross-sectional volatility in daily funding costs and their magnitude. More specifically, leverage implies that volatility in daily spreads is responded by increases in funding rates and suggests that volatility is a useful indicator of distress in money markets. Similarly, a feedback effect is observed implying that large funding rates feed into increases in the dispersion of rates. Both phenomena are more remarkable for the borrowing segment of the money market. The dynamic analysis of the spreads also shows that the 2007 and 2008 crises have different implications. The first crisis has widespread effects on the entire banking sector, reflected in higher borrowing spreads across the sector. The second crisis caused by the collapse of some major financial institutions produces uncertainty in daily interest rates in both borrowing

and lending segments. In this case the quantile process of spreads shows an interbank market given by a small sample of troubled banks exhibiting high spreads than the rest of banks that obtain borrowing spreads below the cross-sectional average.

The analysis of the factors with statistical significance to describe the performance of funding rates reveals that size, bank's nationality and the operating currency are influential variables that can help to predict the relative success of a bank during turmoil periods in the money market. Thus, size is a key variable for determining bank profitability; largest banks enjoy the highest lending rates and the lowest borrowing rates over the cross-section of banks acting in the e-MID market. The collapse of Lehman Brothers accentuates the differences in funding conditions between largest banks and the rest. Also, banks in the Euro currency area obtain lower funding rates than banks based in non-Euro countries. This can be due to the existence of the European Central Bank acting as a potential liquidity provider in the Euro system or to the perception that Euro countries are less risky than their non-Euro counterparts. Interestingly, non-Euro countries also have higher lending rates. The analysis of the relationship between interbank rates and sovereign crisis reveals important differences in borrowing costs between banks in Greece, Ireland, Portugal and Spain compared to the rest of banks. These results suggest that distress in the banking sector of these countries is prior to the occurrence of their respective sovereign crises, and the interbank market provided early warning signals of the incoming sovereign crisis. As a further research, we will exploit multivariate kernel methods to generalize kernel density estimation to the multivariate case. This will allow us to investigate the impact of multiple predictors such as Euro/NonEuro, Crisis/NonCrisis and asset size classifications on the density estimation of borrowing and lending spreads.

Appendix 4.A

Table 4.1: Participation of Different Groups to the e-MID Market

	Market Share (Transaction Number)		Market Share (Total Volume)		Average Transaction Size	
	Borrower	**Lender**	**Borrower**	**Lender**	**Borrower**	**Lender**
Minor-Domestic (31 Banks)	5%	10.4%	2%	3%	17	16
Small-Domestic (63 Banks)	47%	50%	16%	19%	17	19
Medium-Domestic (16 Banks)	15%	11%	10%	11%	32	31
Large-Domestic (9 Banks)	14%	9%	12%	8%	42	45
Major-Domestic (6 Banks)	7%	7%	10%	11%	67	80
Foreign Banks (90 Banks)	11%	11%	50%	51%	220	212

Table 4.2: Information about Sub-Periods

Dates	**Explanation**	**Number of Months**	**Periods**
July 06-Jan 07	2006-2 Before Crisis	6	Period 1
Jan 07-Aug 07	2007-Financial Markets Unease	6	Period 2
Aug 07-Mar 08	Interbank Crisis	8	Period 3
Mar 08-Sep 08	Before Lehman Brothers Collapse	6	Period 4
Sep 08-Mar 09	After Lehman Brothers Collapse	6	Period 5
Mar 09-Sep 09	2009-Post Crisis	6	Period 6

Table 4.3: Optimal Bandwidth Parameters of Conditional Density Estimation of Spread & Volatility on Asset Size

	Period	Asset Size	Spread	Observation Number	Asset Size	Volatility of Spread	Observation Number
Borrower	**Period 1**	0.09(1.00)	0.002	462	0.77(1.00)	0.040	431
	Period 2	0.23(1.00)	0.003	441	0.89(1.00)	0.010	407
	Period 3	0.17(1.00)	0.007	582	0.29(1.00)	0.029	532
	Period 4	0.27(1.00)	0.012	411	0.32(1.00)	0.014	389
	Period 5	0.07(1.00)	0.036	374	1.00(1.00)	0.024	334
	Period 6	0.07(1.00)	0.018	365	0.38(1.00)	0.012	324
Lender	**Period 1**	0.26(1.00)	0.002	605	0.28(1.00)	0.002	581
	Period 2	0.26(1.00)	0.003	571	0.51(1.00)	0.003	553
	Period 3	0.66(1.00)	0.004	741	0.54(1.00)	0.004	715
	Period 4	0.19(1.00)	0.008	553	0.73(1.00)	0.003	527
	Period 5	0.31(1.00)	0.023	510	1.00(1.00)	0.16	479
	Period 6	0.13(1.00)	0.014	499	1.00(1.00)	0.008	466

Note: Bandwidth Parameters of Conditional Densities are estimated with Least Squares Cross-Validation Method for each sub-period from July 2006 to August 2009. Kernel Function for Dependent Variables (Spread and Volatility) is Gaussian and Kernel Function for Independent Variables (Asset Size) is Wang and van Ryzin (1981).

Table 4.4: Optimal Bandwidth Parameters of Conditional Density Estimation of Spread on Nationality Classifications

	Period	Euro-NonEuro	Spread	Observation Number	Crisis-NonCrisis	Spread	Observation Number
Borrower	**Period 1**	0.50(0.5)	0.001	266	0.25(0.5)	0.003	266
	Period 2	0.40(0.5)	0.003	276	0.10(0.5)	0.003	276
	Period 3	0.50(0.5)	0.007	307	0.25(0.5)	0.006	307
	Period 4	0.25(0.5)	0.014	227	0.01(0.5)	0.004	227
	Period 5	0.37(0.5)	0.036	135	0.01(0.5)	0.036	135
	Period 6	0.50(0.5)	0.018	116	0.02(0.5)	0.014	116
Lender	**Period 1**	0.14(0.5)	0.002	303	0.05(0.5)	0.002	303
	Period 2	0.25(0.5)	0.002	344	0.10(0.5)	0.002	344
	Period 3	0.25(0.5)	0.006	434	0.09(0.5)	0.007	434
	Period 4	0.02(0.5)	0.011	297	0.25(0.5)	0.011	297
	Period 5	0.50(0.5)	0.038	176	0.50(0.5)	0.038	176
	Period 6	0.50(0.5)	0.026	117	0.50(0.5)	0.026	117

Note: Bandwidth Parameters of Conditional Densities are estimated with Least Squares Cross-Validation Method for each sub-period from July 2006 to August 2009. Kernel Function for Dependent Variables (Spread and Volatility) is Gaussian and Kernel Functions for Independent Variables (Euro/Non-Euro and Crisis/Non-Crisis classifications) are Aitchison and Aitken(1976).

Figure 4.1: Volume and Number of Transactions per Month in the e-MID Market

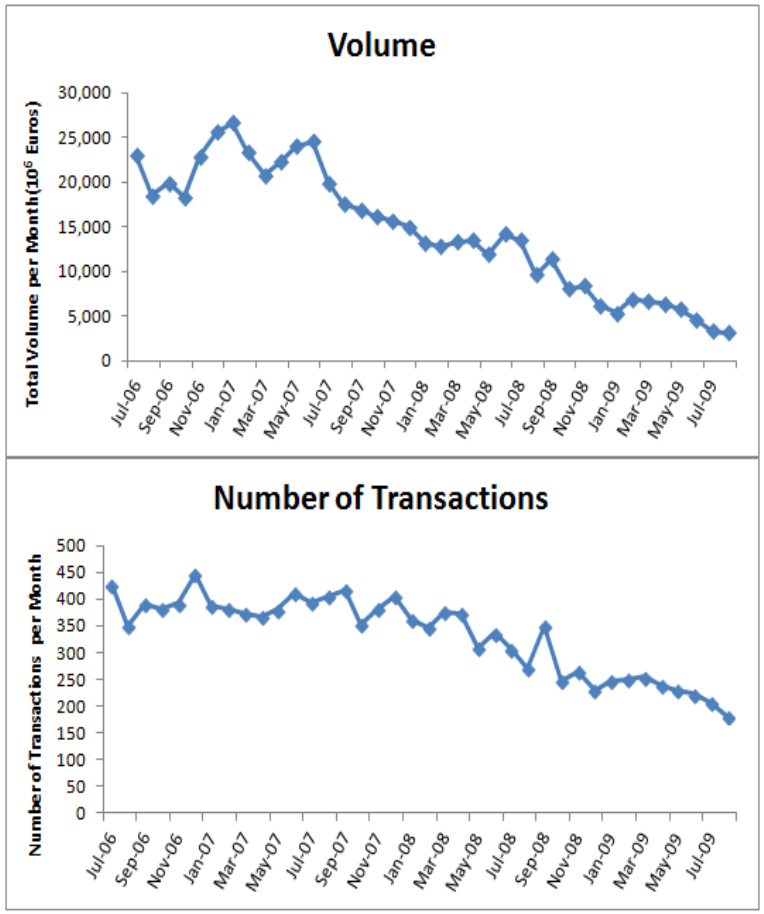
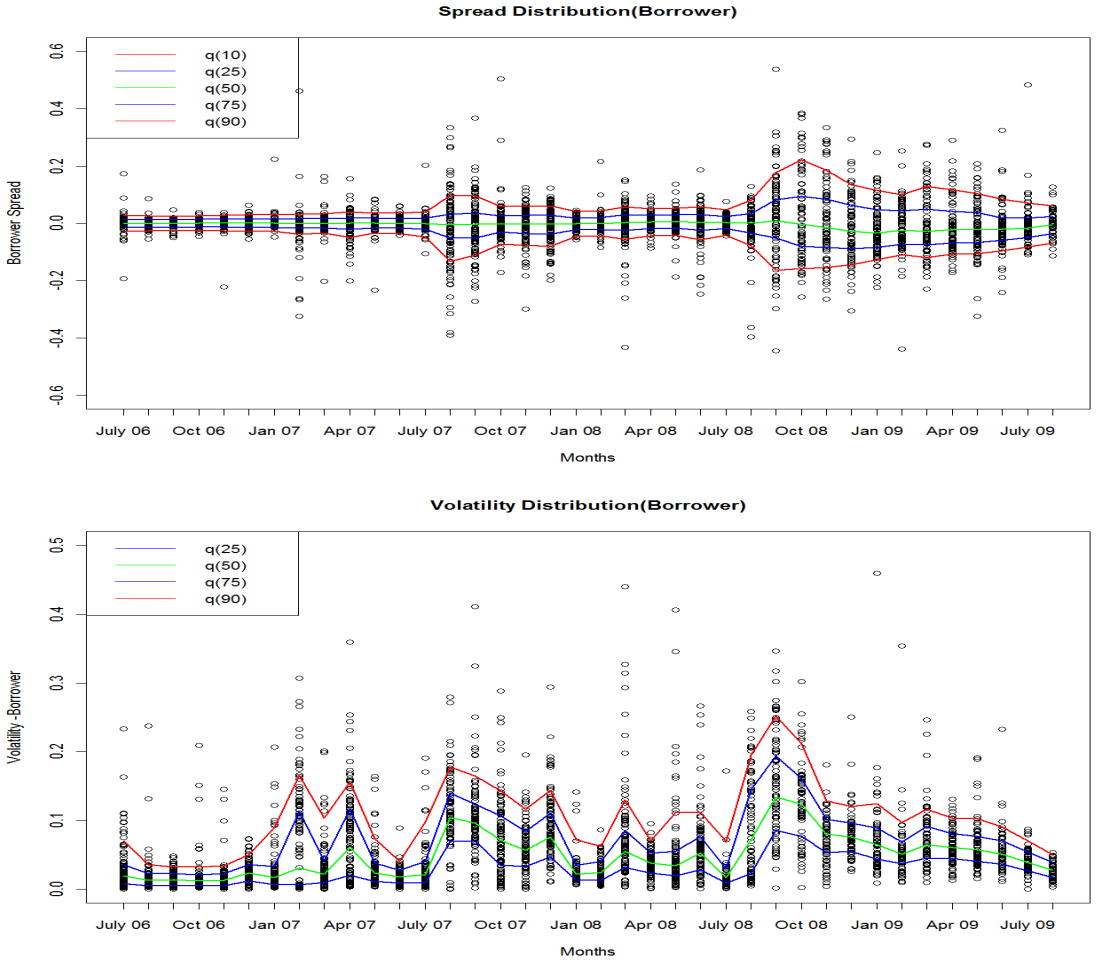
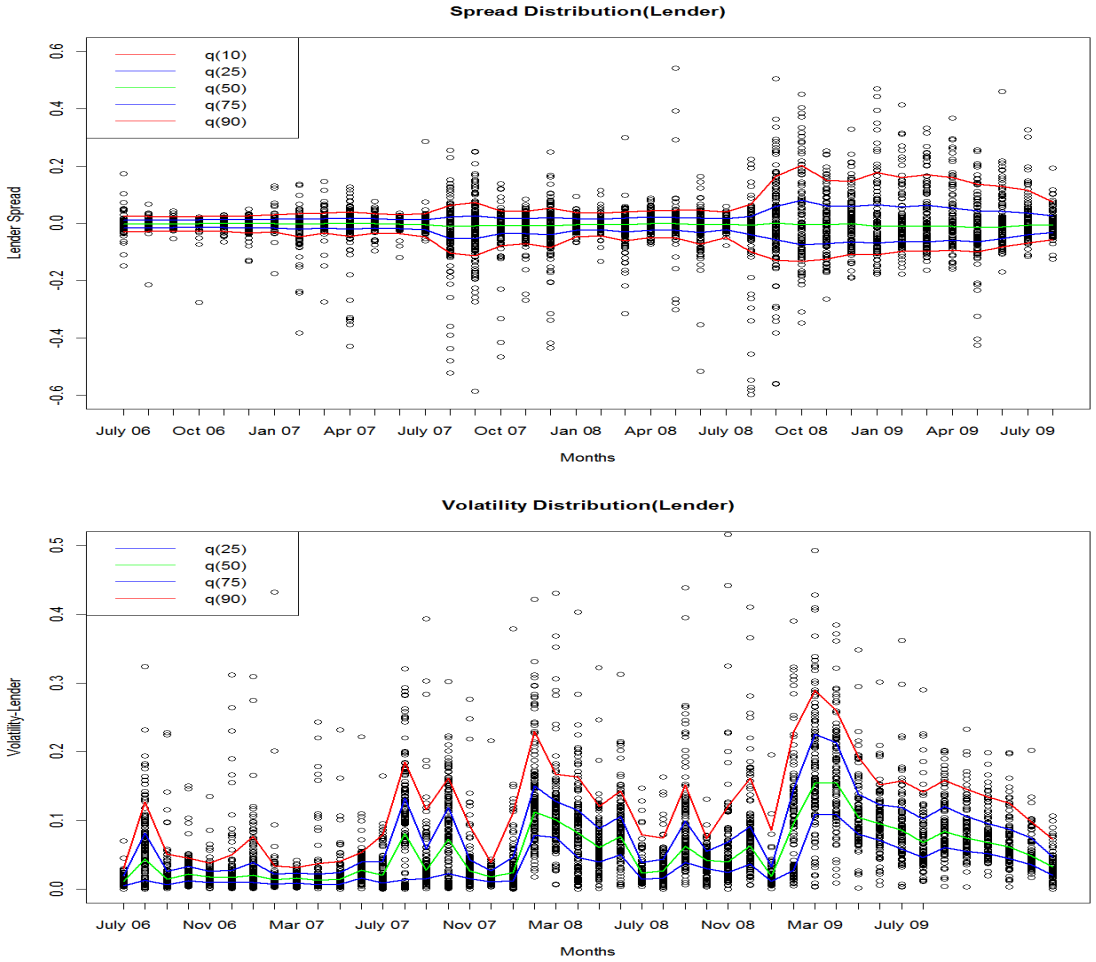


Figure 4.2: Conditional Density of Estimation of Borrower Spread-Volatility of Spread on Monthly Time Period with Conditional Quantile Functions



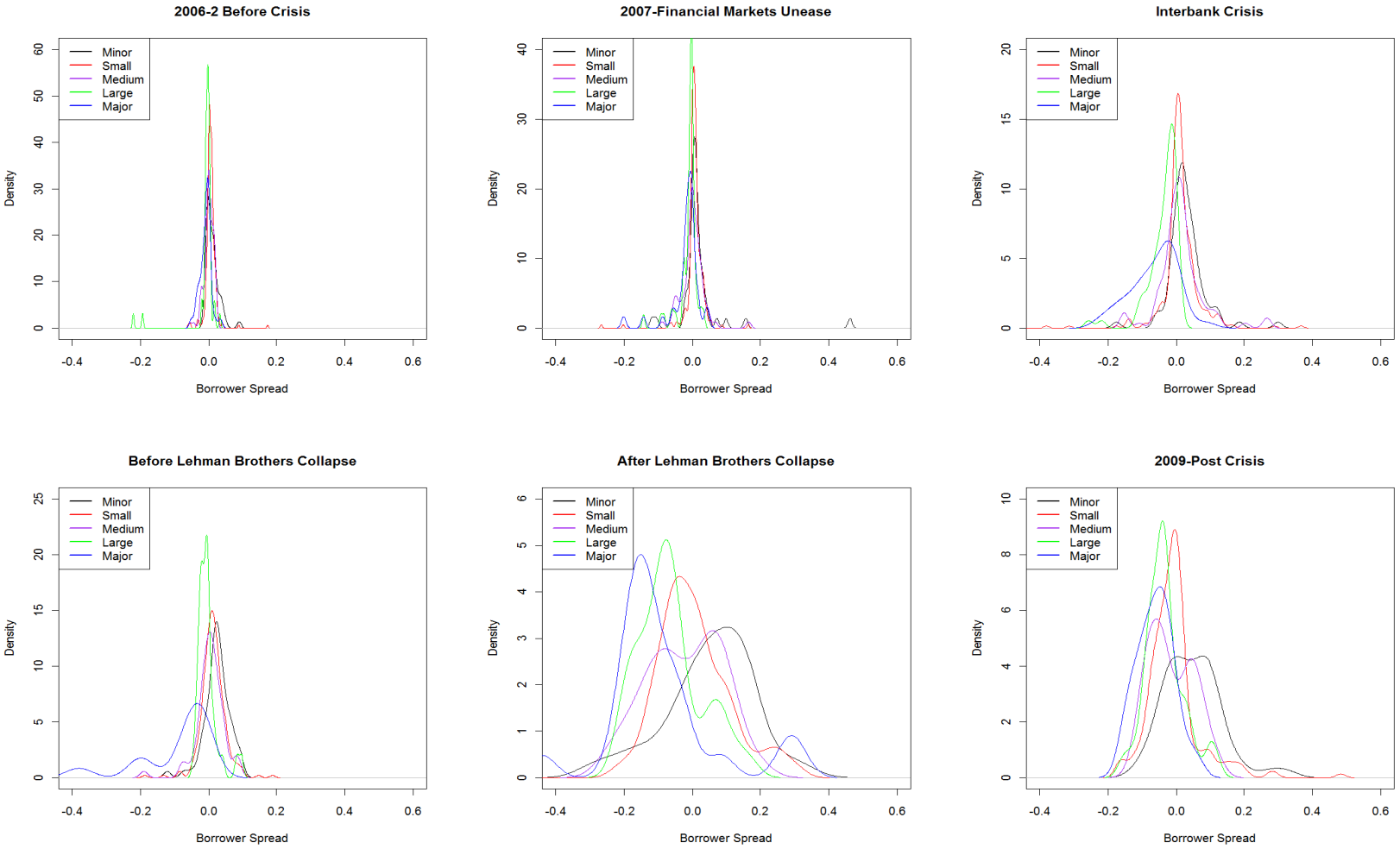
Note: Bandwidth Parameters of Conditional Densities are estimated with Least Squares Cross-Validation Method for each month for the period from July 2006 to August 2009. Dependent Variable is Spread/Volatility and Independent Variable is Monthly Time Period. Conditional Quantile Functions are estimated for 10%, 25%, 50%, 75% and 90% Percentiles.

Figure 4.3: Conditional Density of Estimation of Lender Spread-Volatility of Spread on Monthly Time Period with Conditional Quantile Functions



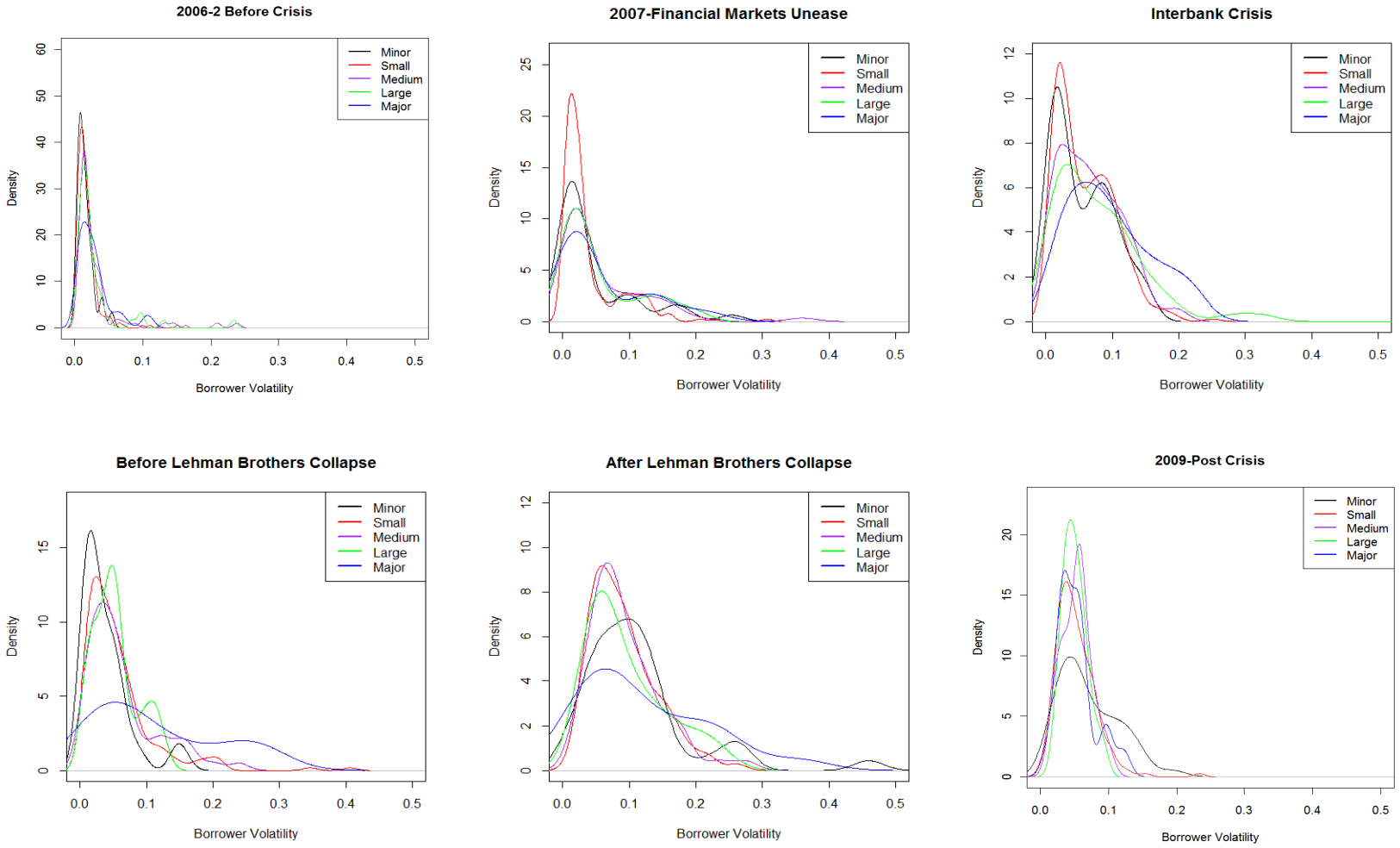
Note: Bandwidth Parameters of Conditional Densities are estimated with Least Squares Cross-Validation Method for each month for the period from July 2006 to August 2009. Dependent Variable is Spread/Volatility and Independent Variable is Monthly Time Period. Conditional Quantile Functions are estimated for 10%, 25%, 50%, 75% and 90% Percentiles.

Figure 4.4: Estimated Conditional Densities of Spreads for Different Sized Borrowers



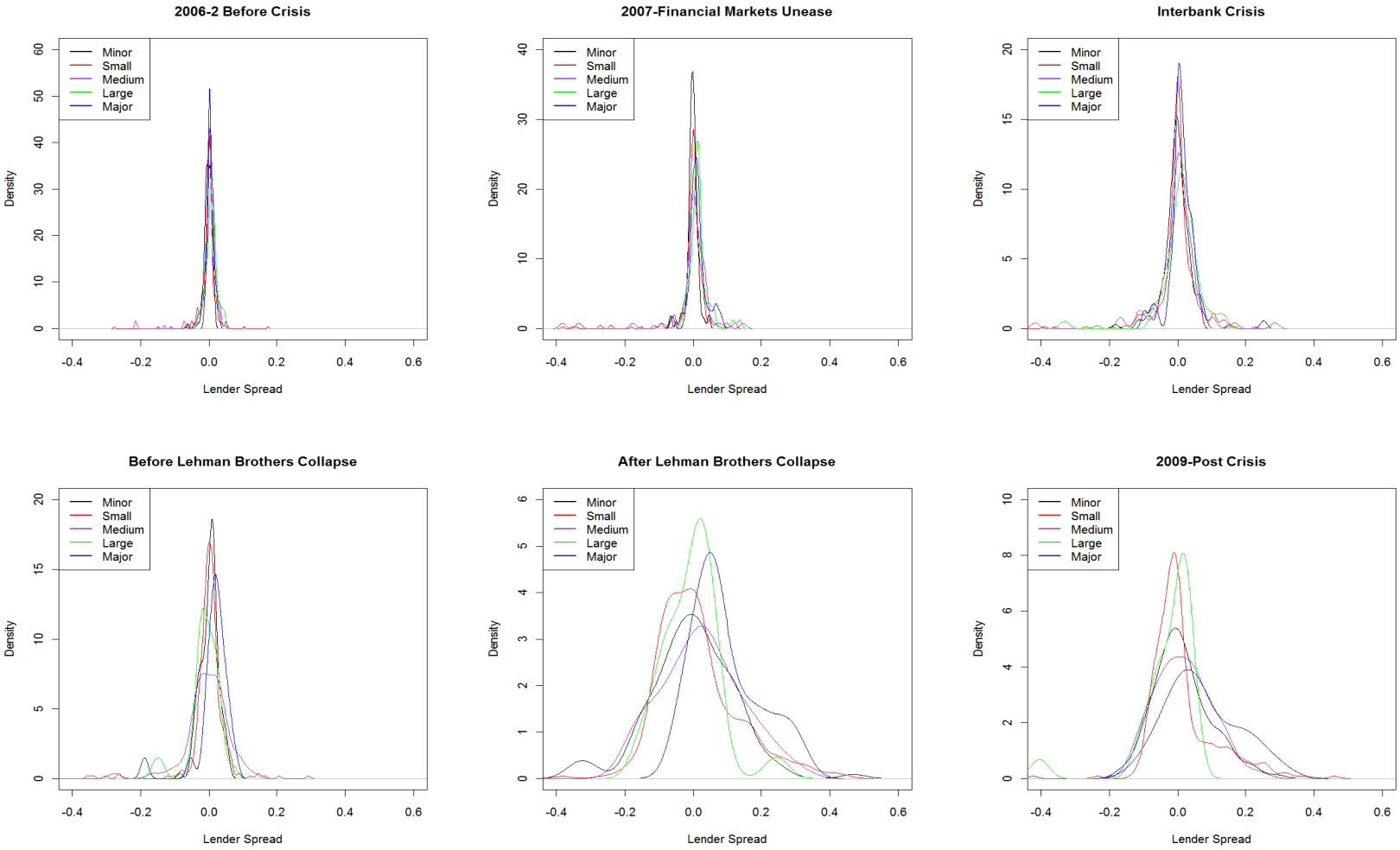
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.5: Estimated Conditional Densities of Volatility of Spreads for Different Sized Borrowers



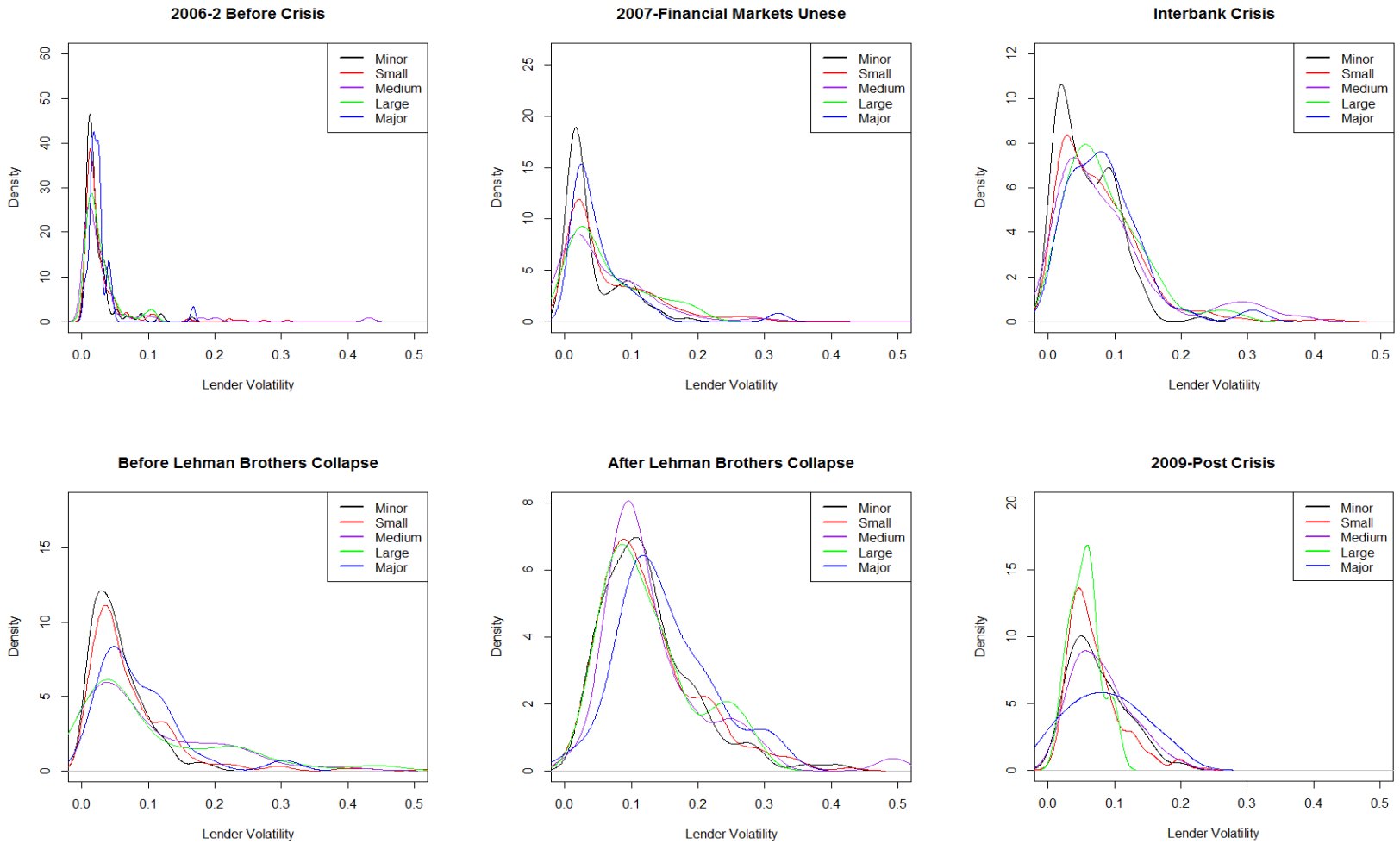
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.6: Estimated Conditional Densities of Spreads for Different Sized Lenders



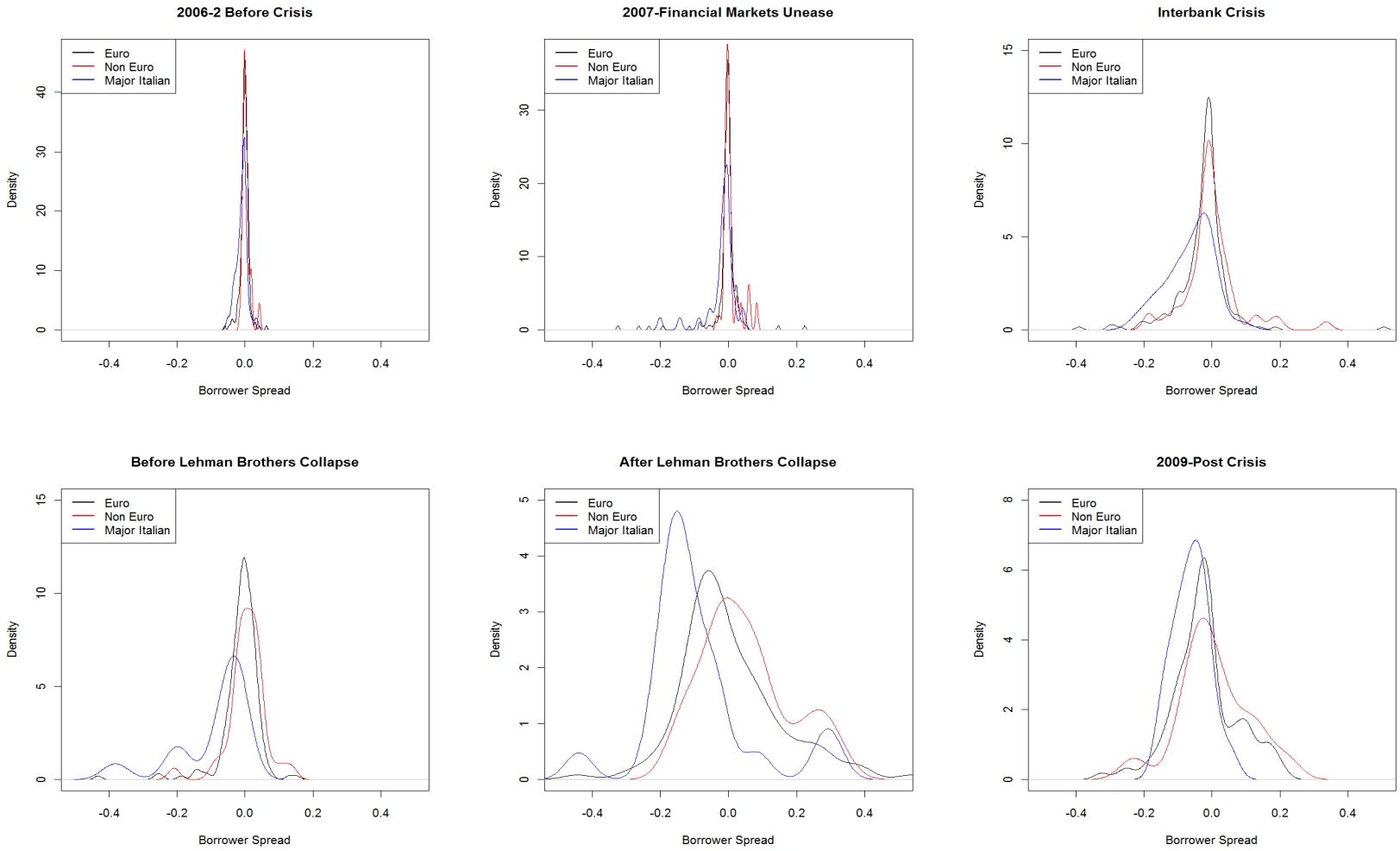
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.7: Estimated Conditional Densities of Volatility of Spreads for Different Sized Lenders



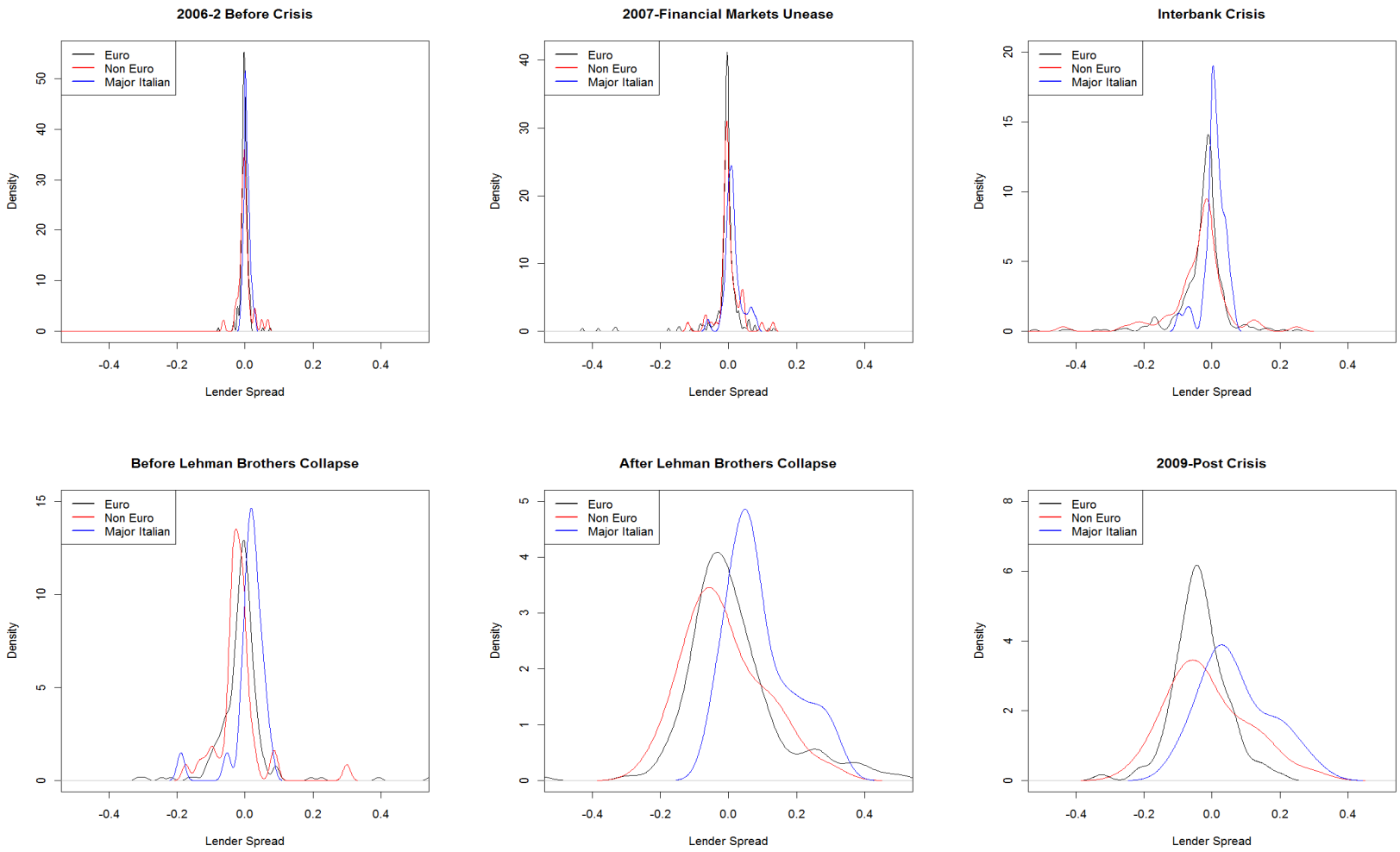
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.8: Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers using Euro or other currency with Major Domestic Borrowers



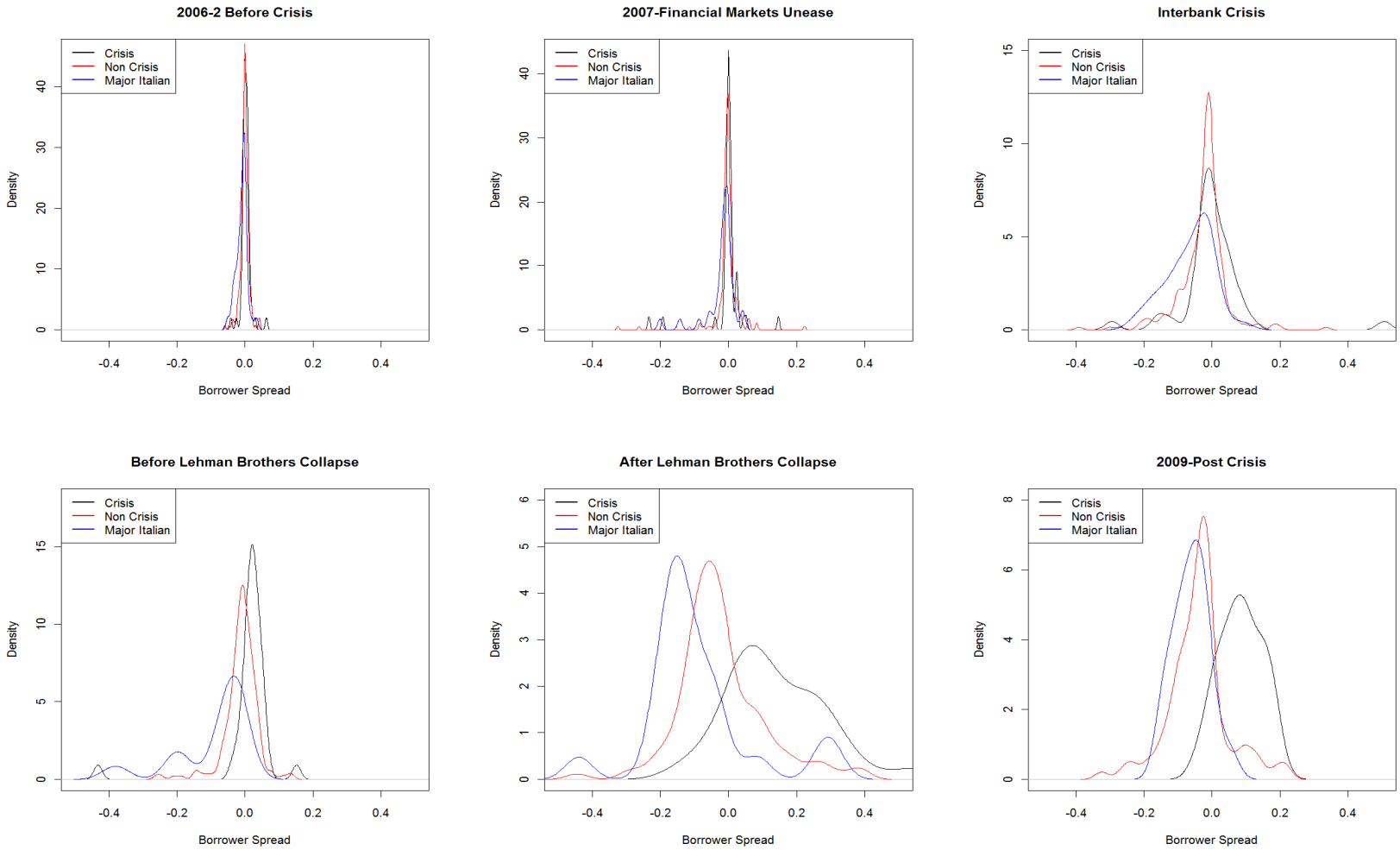
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.9: Comparison of Estimated Conditional Densities of Spreads for Foreign Lenders using Euro or other currency with Major Domestic Lenders



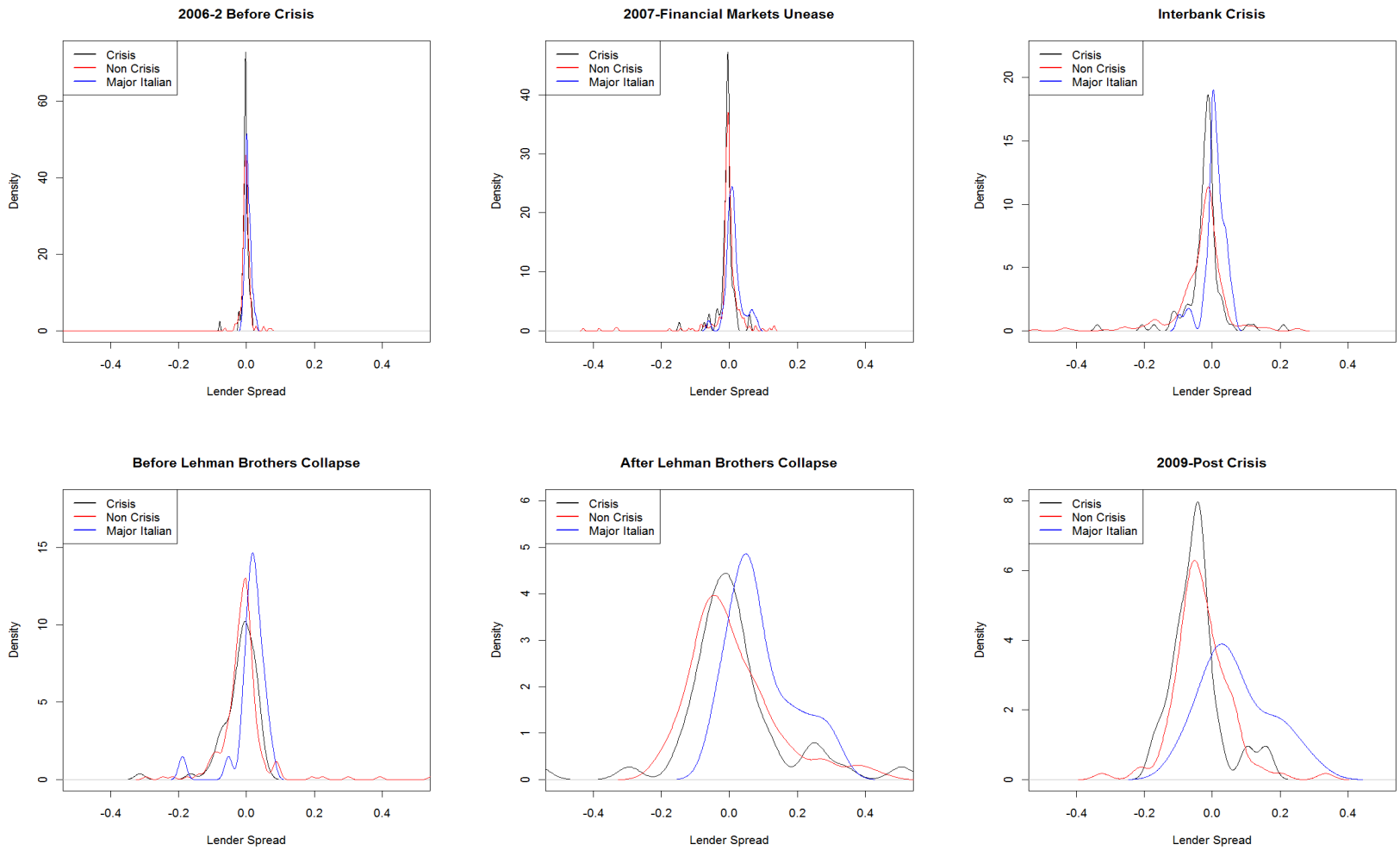
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.10: Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers experiencing Sovereign Crisis or not with Major Domestic Borrowers



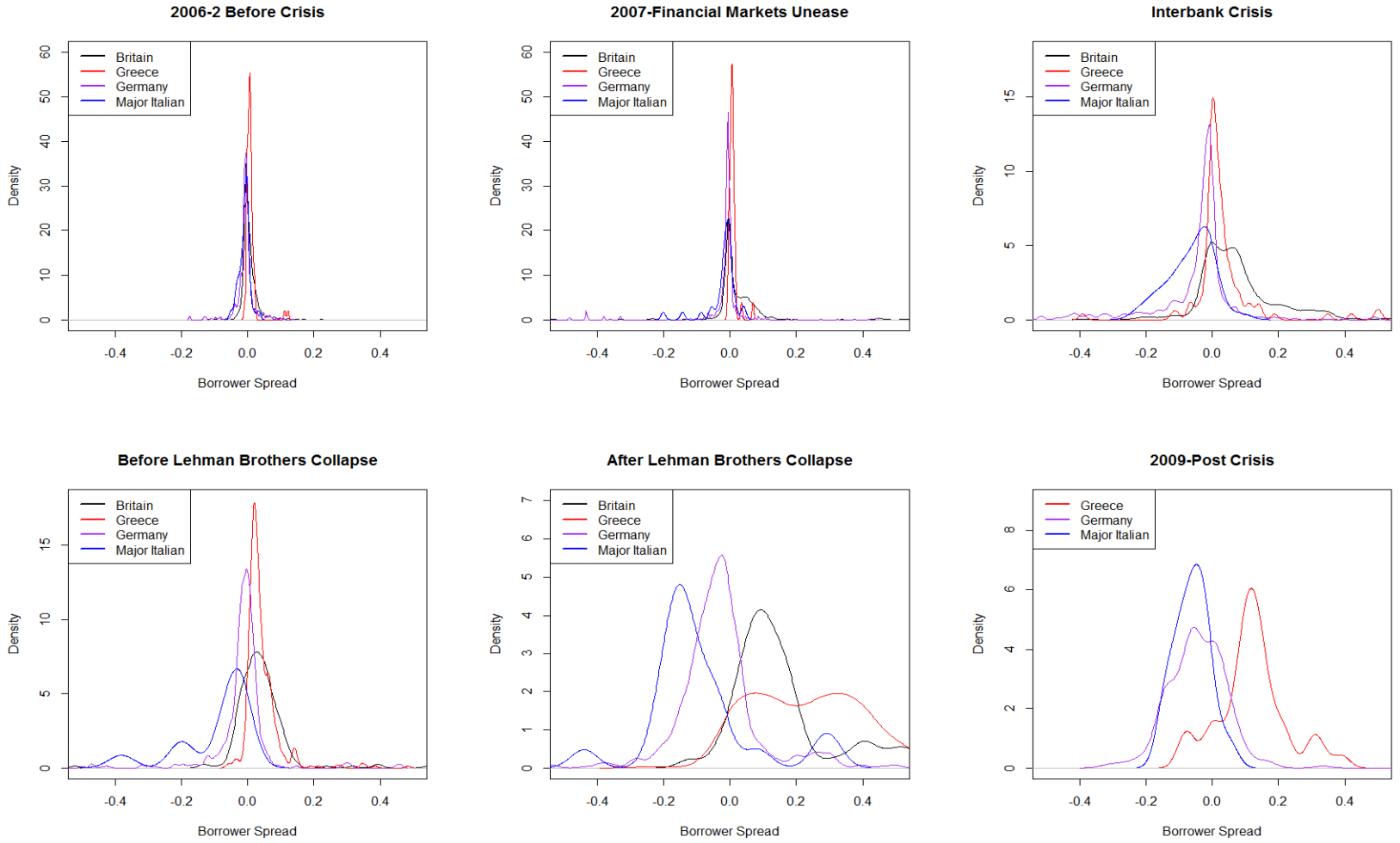
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.11: Comparison of Estimated Conditional Densities of Spreads for Foreign Lenders experiencing Sovereign Crisis or not with Major Domestic Lenders



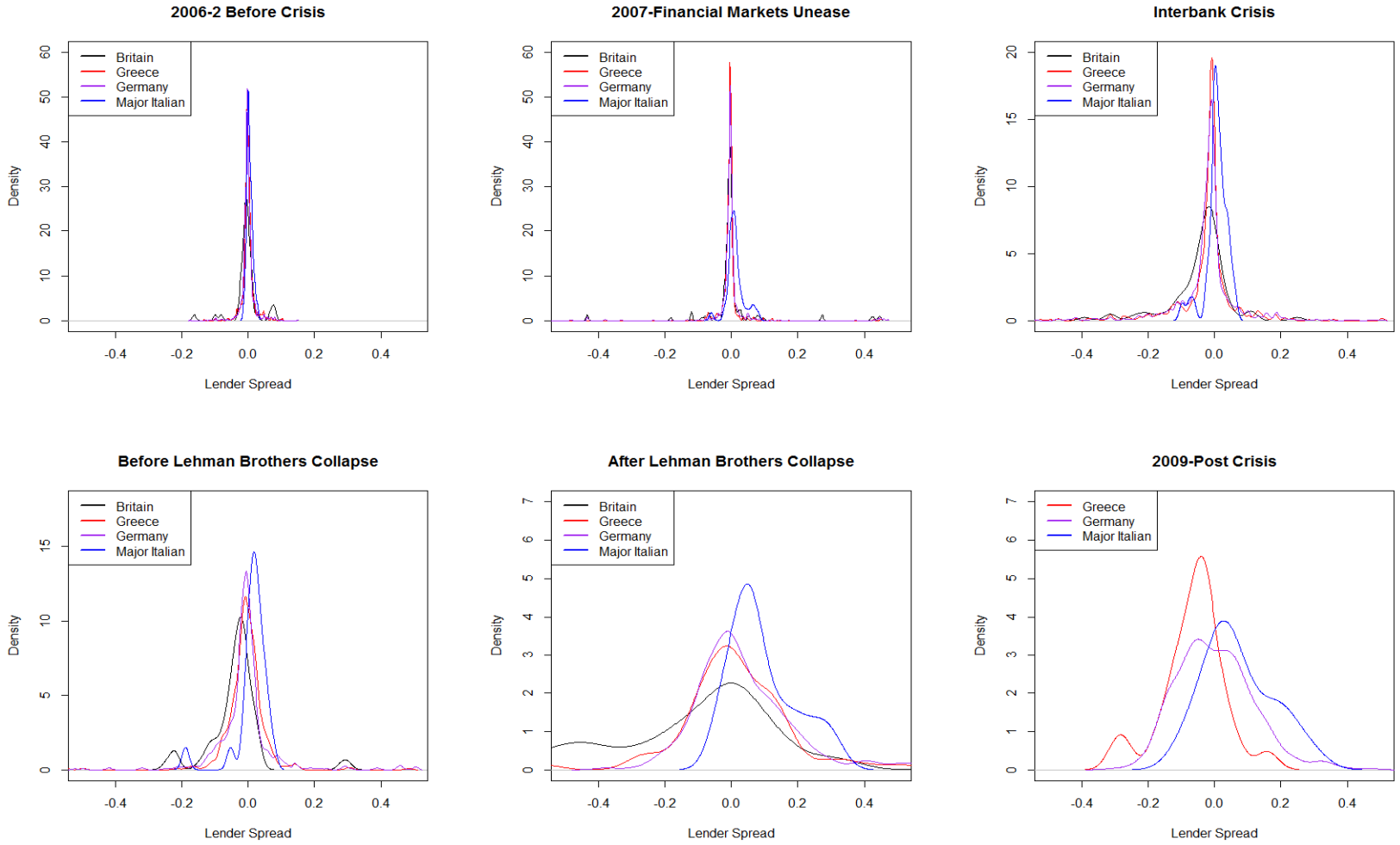
Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.12: Comparison of Estimated Conditional Densities of Spreads for Britain, Germany, Greece with Major Domestic Borrowers



Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Figure 4.13: Comparison of Estimated Conditional Densities of Spreads for Britain, Germany, Greece with Major Domestic Lenders



Note: Sample Period covers from July 2006 to August 2009. Kernel Function for Spread is Gaussian.

Chapter 5

Conclusion

5.1 Introduction

This chapter summarizes the findings and main conclusions of each empirical chapter and offers suggestions for future research. The main subject of the thesis is to provide further insight into the effect of 2007-2008 crisis on the CDS and interbank market. This is because 2007-2008 crisis poses a considerable threat to the financial stability and leads to disruptions in both Credit Default Swap and interbank market transactions.

Chapter 1 provides background information about the topics of the thesis. This chapter especially draws attention to the 2007-2008 crisis and evolution of CDS and interbank market during the crisis. The structure of this chapter is as follows. Section 5.2 discusses the conclusions of each empirical chapter as well as the implications of the findings, while Section 5.3 discusses the limitations of this thesis and proposes suggestions for future research.

5.2 Conclusions and Implications of the Findings

This thesis reveals that 2007-2008 crisis has series repercussions on CDS and interbank market. In both markets, deterioration in the financial conditions triggers the changes in the the pricing of credit risk.

Chapter 2 investigates the determinants of CDS spread in the short run and considers counterparty risk as one of the determinants of the spread different from the existing literature. Empirical findings indicate that CDS spreads display pronounced regime specific behavior in a way that financial and non-financial contracts demonstrate different sensitivity to systematic and idiosyncratic variables during tranquil and volatile periods. The credit risk of the seller, counterparty risk, is reflected in the CDS prices of non-financial contracts after the outset of the recent crisis. However the effect of counterparty risk is not observed in the financial contracts. This counterintuitive result reminds 'Too-Big-to-Fail' argument. When the overall financial industry is in distress, the government is expected to bail out the dealers to prevent systemic risk as experienced with the bail out of AIG and GE Capital.

This chapter has two main implications for regulators and CDS traders. First, different CDS pricing and risk management tools should be developed for financial and non-financial contracts. Second, strict collateral requirements should be introduced in the market or Central Counterparty Clearing Houses (CCPs) should be widespread covering all types of CDS contracts worldwide to mitigate counterparty risk.

Chapter 3 examines the long-run determinants of European CDS spreads considering iTraxx Europe index and stock price of the firm that allows investigating information flow between credit and equity markets. This chapter proposes a long-run equilibrium model incorporating an endogenous structural break to the

determinants arising from deterioration in the financial conditions during the crisis.

Chapter 3 reveals that causality runs from the iTraxx index and the stock market to the CDS market. Hence, stock market leads price discovery process. CDS market informational dominance or bidirectional causality between stock and CDS market mentioned in previous studies can be misleading and arises from neglecting the break in the series. VECM representation of cointegration model indicates that changes in CDS spreads are mainly explained by changes in iTraxx index, but not stock return. This high explanatory power of iTraxx index on CDS spread change is in line with capital asset pricing models for equity market.

Chapter 4 studies European interbank market to detect early warning indicators of financial distress in overall financial system. This is done by analyzing the cross-sectional density of interbank funding rates using nonparametric kernel methods and by investigating the effect of banks' size, operating currency, banks' nationality and time periods on the cross-sectional distribution of these rates in the European e-MID market.

In both demand and supply sides of the market, there are leverage and feedback effects between cross-sectional volatility in daily funding costs and their magnitude. Especially in the borrowing segment, volatility is a very useful indicator of distress in money markets. Subprime crisis in 2007 and the collapse of main institutions in 2008 has different implications on the interbank market. The first crisis has affected entire banking sector leading increases in all funding rates. However the second crisis has more idiosyncratic nature and characterized by higher uncertainty. Conditional density analysis of borrowing spreads on bank size, nationality and currency indicates that the market moves from homogeneous state to heterogeneous one with the start of the crisis. Especially after the collapse of Lehman Brothers, banks that have larger asset size and adopt Euro currency improve their advantageous position

in the market further. Banks based in countries that experienced sovereign crisis have to pay more than other banks well before the actual dates of the crisis.

These analytical techniques reveal the ability of interbank markets to signal early warning of distress in the overall financial sector. They have also implications for policy makers and regulators to develop appropriate structures for different types of banks in order to prevent a shock to the system during liquidity shortages in money markets.

5.3 Limitations of the Study and Suggestions for Future Research

The aim of this section is to express limitations of this thesis in terms of availability of data and econometric approaches and suggests some future directions to enhance the understanding of changes in the CDS and interbank market during financial crisis.

Chapter 2 offers some of the first insights into the pricing dynamics of counterparty risk in the CDS market. However having access to contracts sold by only one dealer (HSBC Bank PLC) poses a limitation to the generalization of the findings. Ideally, this analysis should include CDS contracts sold by other dealers. If there will be an opportunity to have an access to the dataset of many dealers, it would be of great interest to replicate the analysis to the large dataset.

In Chapter 3, the proposed model allows to test the long-run relation between variables by allowing a break in explanatory variables, thus accommodating potential changes in relation between explanatory and dependant variables. Further research can be conducted to bonds to check the long run relation between bonds and bond indices and stock prices. This allows revealing the changes in relationship arising

from the recent crisis and also exploring the price discovery between bond and stock market. An interesting extension of this chapter could be to consider option implied volatility as an idiosyncratic variable and market implied volatility as a systematic variable.This hardly explored issue in the current literature can enhance our understanding about price discovery process between CDS and option market. The methodology suggested in this thesis could be a nice option to explore this issue.

In Chapter 4, distribution of spreads and volatility of spreads serves for early warning signals for interbank distress. Generalizing kernel density estimation to the multivariate case is an interesting topic for further research. We will exploit kernel density estimation of borrowing and lending spreads with multiple predictors such as Euro/NonEuro, Crisis/NonCrisis and asset size classifications. Furthermore, a possible extension could be to investigate geographic difference in more detail. For instance, analyzing countries separately and focusing on the relation between volatility and spread distribution enhance our understanding of the effect of crisis on the interbank market.

Bibliography

Acharya, V. V. and A. Bisin, 2011. Counterparty Risk Externality: Centralized versus Over-the-counter Markets. Working Paper of NBER 17000.

Affinito, M. 2012. Do Interbank Customer Relationships Exist? And How did They Function over the Crisis? Learning from Italy. Journal of Banking and Finance 36, 3163-3184.

Afonso, G., A. Kovner and A. Schoar, 2011. Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis. Journal of Finance 66 (4), 1109-39.

Aitchison, J. and C. G. G. Aitken, 1976. Multivariate Binary Discrimination by the Kernel Method. Biometrika 63, 413-420.

Alexander, C. and A. Kaeck, 2008. Regime Dependant Determinants of Credit Default Swap Spreads. Journal of Banking and Finance 32, 1008-1021.

Alexopoulou, I., M. Andersson and O. M. Georgescu, 2009. An Empirical Study on the Decoupling Movements between Corporate Bond and CDS Spreads. Working Paper of European Central Bank 1085.

Allen, L. and A. Saunders, 1986. The Large-Small Bank Dichotomy in the Federal Funds Market. Journal of Banking and Finance 10, 219-230.

Allen, F. and D. Gale, 2000. Financial Contagion. Journal of Political Economy 108, 1-34.

Amadori, M. C., T. Lehnert, and L. Bekkour. 2011. The Relative Informational Efficiency of Stocks, Options and Credit Default Swaps. Available at SSRN: http://ssrn.com/abstract=1836894 or http://dx.doi.org/10.2139/ssrn.1836894.

Andrews, D. W. K. 1993. Tests for Parameter Instability and Structural Change with Unknown Change Point. Econometrica 61, 821-856.

Andrews, D. W. K. and W. Ploberger, 1994. Optimal Tests when a Nuisance Parameter is Present only under the Alternative. Econometrica 62, 1383-1414.

Angelini, P., G. Mariesca and D. Russo, 1996. Systemic Risk in the Netting System. Journal of Banking and Finance 20, 853-868.

Angelini, P., A. Nobili and C. Picillo, 2011. The Interbank Market after August 2007: What has Changed and Why? Journal of Money, Credit and Banking 43 (5), 923-958.

Annaert, J., M. D. Ceuster, P. V. Roy and C. Vespro, 2010. What Determines Euro Area Bank CDS Spreads? Working Paper of National Bank of Belgium 190.

Arce, O., S. Mayordomo, and J. I. Pena, 2012. Credit-Risk Valuation in the Sovereign CDS and Bonds Markets: Evidence from the Euro Area Crisis. Working Paper of Comision Nacional del Mercado de Valores 53.

Arora, N., P. Gandhi and F. A. Longstaff, 2012. Counterparty Credit Risk and The Credit Default Swap Market. Journal of Financial Economics 103 (2), 280-293.

Aunon-Nerin, D., D. Cossin, T. Hricko and Z. Huang, 2002. Exploring The Deter-

minants of Credit Risk in Credit Default Swap Transaction Data. Working Paper of University of Lausanne FAME Research Paper Series 65.

Avino, D., E. Lazar and S. Varotto. 2011. Price Discovery of Credit Spreads in Tranquil and Crisis Periods. ICMA Centre Discussion Papers in Finance DP2011-17.

Avramov, D., G. Jostova, and A. Philipov, 2007. Understanding Changes in Corporate Credit Spreads. Financial Analyst Journal 63, 90-105.

Banerjee, A., R. L. Lumsdaine, and J. H. Stock, 1992. Recursive and Sequential Tests of the Unit-Root and Trend-Break Hypotheses: Theory and International Evidence. Journal of Business and Economic Statistics 10, 271-287.

Beaupain, R . and A. Durre, 2011. Inferring Trading Dynamics for an OTC Market: The Case of The Euro Area Overnight Money Market. Quantitative Finance 11 (9), 1285-1295.

Benkert, C., 2004. Explaining Credit Default Swap Premia. The Journal of Futures Markets 24, 71-92.

Bhattacharya, S. and D. Gale, 1987. Preference Shocks, Liquidity and Central Bank Policy, in W. Barnett, and K. Singleton (eds.), New Approaches to Monetary Economics, 69-88, New York: Cambridge University Press.

Blanco, R., S. Brennan and I. W. Marsh, 2005. An Empirical Analysis of the Dynamic Relation between Investment Grade Bonds and Credit Default Swaps. The Journal of Finance 60, 2255-2281.

Boss, M., H. Elsinger, M. Summer and S. Thurner, 2006. Network Topology of the Interbank Market. Quantitative Finance 4(6), 677-684.

Brauning F. and F. Fecht, 2011. Relationship Lending and Peer Monitoring: Evidence from Interbank Payment Data. Working Paper.

Brigo, D. and K. Chourdakis, 2008. Counterparty Risk for Credit Default Swaps: Impact of Spread Volatility and Default Correlation. International Journal of Theoretical and Applied Finance 12 (7), 1007-1026.

Brunnermeier, M. K. 2009. Deciphering the Liquidity and Credit Crunch 2007-2008. Journal of Economic Perspectives 23 (1), 77-100.

Cao, C., F. Yu and Z. Zhong, 2010. The information Content of Option-Implied Volatility for Credit Default Swap Valuation. Journal of Financial Markets 13, 321-343.

Cesare, A. D., and G. Guazzarotti, 2010. An Analysis of Determinants of Credit Default Swap Spread Changes Before and During the Subprime Financial Turmoil. Working Paper of Banca DItalia 749.

Chan, K. S., 1993. Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model. Annals of Statistics 21, 520-533.

Chow, G. C. 1960. Tests of Equality between Sets of Coefficients in Two Linear Regressions. Econometrica 28, 591-605.

Cocco J. F., F. J. Gomes and N. C. Martins, 2009. Lending Relationships in the Interbank Market. Journal of Financial Intermediation 18, 24-48.

Collin-Dufresne, P., R. S. Goldstein and J. S. Martin, 2001. The Determinants of Credit Spread Changes. The Journal of Finance 56, 2177-2207.

Credit Default Swaps and Counterparty Risk, 2009. European Central Bank.

Duffie, D. and H. Zhu, 2011. Does a Central Clearing Counterparty Reduce Counterparty Risk? Working Paper of Stanford University Graduate School of Business 2022.

Dullmann, K. and A. Sosinska, 2007. Credit Default Swap Prices as Risk Indicators of Listed German Banks. Financial Markets and Portfolio Management 21 (3), 269-292.

Engle, R., and C. W. J. Granger, 1987. Cointegration and Error Correction: Representations, Estimation and Testing. Econometrica 55, 252-276.

Ericsson, J., K. Jacobs and R. Oviedo, 2009. The Determinants of Credit Default Swap Premia. Journal of Financial and Quantitative Analysis 44, 109-132.

Forte, S., and J. I. Pena, 2009. Credit Spreads: An Empirical Analysis on the Information Content of Stocks, Bonds and CDS. Journal of Banking and Finance 33, 2013-2025.

Forte, S., and L. Lovreta, 2012. Credit Risk Discovery in the Stock and CDS Markets: Who Leads in Times of Financial Crisis? Working Paper.

Freixas, X., B. M. Parigi and J. Rochet, 2000. Systemic Risk, Interbank Relations and Liquidity Provision by the Central Bank. Journal of Money, Credit and Banking 32 (3), 611-638.

Freixas, X. and C. Holthausen, 2005. Interbank Market Integration under Asymmetric Information. Review of Financial Studies 18 (2), 459-490.

Furfine, C. H., 1999. The Microstructure of the Federal Funds Market. Financial Markets, Institutions and Instruments 8 (5), 24-44.

Furfine, C. H., 2001. Banks as Monitors of Other Banks: Evidence from the Overnight Federal Funds Market. The Journal of Business 74, 33-57.

Furfine, C. H., 2003. Interbank Exposures: Quantifying the Risk of Contagion. Journal of Money, Credit and Banking 32, 611-638.

Gabbi G., G. Germano, V. Hatzopoulos, G. Iori and M. Politi, 2012. The Microstructure of European Interbank Market and Its Role in the Determination of Cross-Sectional Credit Spreads. Working Paper.

Gabrieli, S., 2011a. The Functioning of the European Interbank Market During the 2007-08 Financial Crisis. Working Paper of CEIS 158.

Gabrieli S., 2011b. Too-interconnected versus Too-Big-to-Fail: Banks' Network Centrality and Overnight Interest Rates. Working Paper of Tor Vergata University.

Gaspar, V., G. P. Quiros and H. R. Mendizabal, 2008. Interest Rate Dispersion and Volatility in the Market for Daily Funds. European Economic Review 52, 413-440.

Giammarino, F. and P. Barrieu, 2009. A Semiparametric Model for the Systematic Factors of Portfolio Credit Risk Premia. Journal of Empirical Finance 16, 655-670.

Giglio, S. 2011. Credit Default Swap Spreads and Systemic Financial Risk. Chicago Booth Research Paper, 12-45.

Gonzalo, J., and C. Granger, 1995. Estimation of Common Long-Memory Components in Cointegrated Systems. Journal of Business and Economic Statistics 13, 27-35.

Greatrex, C. A. 2009 Credit Default Swap Market Determinants. The Journal of Fixed Income 18, 18-32.

Gregory, A. W., and B. E. Hansen, 1996. Residual Based Tests for Cointegration in Models with Regime Shifts. Journal of Econometrics 70, 99-126.

Gyntelberg, J. and P. D. Wooldridge, 2008. Interbank Rate Fixings During the Recent Turmoil. BIS Quarterly Review March, 59-72.

Hall, P., J. Racine and Q. Li, 2004. Cross-Validation and the Estimation of Conditional Probability Densities. Journal of the American Statistical Association 99, 1015-1026.

Hansen, H., and S. Johansen, 1993. Recursive Estimation in Cointegrated VAR Models. Institute of Mathematical Statistics, Working Paper of University of Copenhagen 1.

Hasbrouck, J. 1995. One Security, Many Markets: Determining the Contributions to Price Discovery. Journal of Finance 50, 1175-1199.

Ho, T. and A. Saunders, 1985. A Micro-Model of the Federal Funds Market. Journal of Finance 40, 977-990.

Huge, B. and D. Lando, 1999. Swap Pricing with Two-Sided Default Risk in a Rating Based Model. European Finance Review 3, 239-268.

Hull, J. and A. White, 2001. Valuing Credit Default Swaps II: Modeling Default Correlations. Journal of Derivatives 8, 12-21.

Iori, G., S. Jafarey and F. G. Padilla, 2006. Systemic Risk on the Interbank Market. Journal of Economic Behaviour and Organisation 61, 525-542.

Iori, G., G.D. Masi, O.V. Precup, G. Gabbi and G. Caldarelli, 2008. A Network Analysis of the Italian Overnight Money Market. Journal of Economic Dynamics and Control 32(1), 259-278.

ISDA Margin Survey, 2008. International Swaps and Derivatives Association.

ISDA Margin Survey, 2009. International Swaps and Derivatives Association.

Jarrow, R., and F. Yu, 2001. Counterparty Risk and the Pricing of Defaultable Securities. Journal of Finance 56, 1765-1799.

Johansen, S., 1991. Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. Econometrica 59, 1551-1580.

Kuan, C. M. and K. Hornik, 1995. The Generalized Fluctuation Test: A Unifying View. Econometric Reviews 14, 135-161.

Leung, S. Y. and Y. K. Kwok, 2005. Credit Default Swap Valuation with Counterparty Risk. The Kyoto Economic Review 74 (1), 25-45.

Li, Q. and J. S. Racine, 2007. Nonparametric Econometrics. Princeton University Press.

Lipton, A. and A. Sepp, 2009. Credit Value Adjustment for Credit Default Swaps via the Structural Default Model. The Journal of Credit Risk 5 (2), 123-146.

Longstaff, F. A., S. Mithal, and E. Neis, 2003. The Credit-Default Swap Market: Is Credit Protection Priced correctly? Working Paper of University of California, Los Angeles.

Mistrulli, P. E., 2011. Assessing Financial Contagion in the Interbank Market: Maximum Entropy versus Observed Interbank Lending Patterns. Journal of Banking and Finance 35, 1114-1127.

Mollenkamp, C. and M. Whitehouse, 2008. Study Casts Doubt on Key Rate. The Wall Street Journal.

Nashikkar, A., M. G. Subrahmanyam and S. Mahanti, 2011. Liquidity and Arbitrage in the Market for Credit Risk. Journal of Financial and Quantitative Analysis 46, 627-656.

Norden, L., and M. Weber, 2009. The Comovement of Credit Default Swap, Bond and Stock Markets: An Empirical Analysis. European Financial Management 15, 529-562.

Orlowski, L. T. 2008. Stages of the 2007/2008 Global Financial Crisis: Is There a Wandering Asset-Price Bubble? Economics 43.

Park, J. Y., and P. C. B. Phillips, 1988. Statistical Inference in Regressions with Integrated Process: Part 1. Econometric Theory 4, 468-498.

Pedrosa, M. and R. Roll, 1998. Systematic Risk in Corporate Bond Credit Spreads. Journal of Fixed Income 8 (3), 7-26.

Perron, P., 1989. The Great Crash, the Oil Price Shock and the Unit Root Hypothesis. Econometrica 57, 1361-1401.

Perron, P., 1990. Testing for a Unit Root in a Time Series with a Changing Mean. Journal of Business and Economic Statistics 8, 153-162.

Perron, P., and T. J. Vogelsang, 1992. Nonstationarity and Level Shifts with an Application to Purchasing Power Parity. Journal of Business and Economic Statistics 10, 301-320.

Phillips, P. C. B., 1991. Optimal Inference in Cointegrated Systems. Econometrica 59, 283-306.

Pires, P., J. P. Pereira and L. F. Martins, 2010. The Complete Picture of Credit Default Swap Spreads: A Quantile Regression Approach. Working Paper of ISCTE Business School.

Ploberger, W., and W. Kramer, 1992. The CUSUM Test with OLS Residuals. Econometrica 60, 271-285.

Quintos, C. E., 1995. Sustainability of the Deficit Process with Structural Shifts. Journal of Business and Economic Statistics 13, 409-417.

Raunig, B. and M. Scheciher, 2009. Are Banks Different? Evidence from the CDS Market. Working Paper of Osterreichische National Bank 152.

Rochet, J.C. and J. Tirole, 1996. Interbank Lending and Systemic Risk. Journal of Money, Credit and Banking 28, 733-762.

Sheldon, G. and M. Maurer, 1998. Interbank Lending and Systemic Risk: An Empirical Analysis for Switzerland. Swiss Journal of Economics and Statistics 134, 685-704.

Snider, C. A. and T. Youle, 2010. Does the LIBOR Reflect Banks' Borrowing Costs? Working Paper of UCLA.

Stigum, M., 1990. The Money Market. Third Edition. Homewood: Dow Jones-Irwin.

Stulz, R. M. 2010. Credit Default Swaps and the Credit Crisis. Journal of Economic Perspectives 24 (1), 73-92.

Tang, D. Y., and H. Yan, 2006. Liquidity, Liquidity Spillover and Credit Default Swap Spreads. Working Paper.

Upper, C. and A. Worms, 2004. Estimating Bilateral Exposures in the German Interbank Market: Is There a Danger of Contagion? European Economic Review 8, 827-849.

Vause, N. 2010. Counterparty Risk and Contract Volumes in the Credit Default Swap Market. BIS Quarterly Review.

Vogelsang, T. J., and P. Perron, 1998. Additional Tests for a Unit Root Allowing for a Break in the Trend Function at an Unknown Time. International Economic Review 39, 1073-1100.

Wang, M. C. and J. van Ryzin, 1981. A Class of Smooth Estimators for Discrete Distributions. Biometrika 68, 301-309.

Welch, I. 2004. Capital Structure and Stock Returns. Journal of Political Economy 112, 106-131.

Wells, S., 2004. Financial Interlinkages in the United Kingdom's Interbank Market and the Risk of Contagion. Working Paper of Bank of England 230.

Yu, F. 2007. Correlated Defaults in Intensity-Based Models. Mathematical Finance 17, 155-173.

Zhang, B. Y., H. Zhou and H. Zhu, 2009. Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms. Review of Financial Studies 22, 5099-5231.

Zhu, H. 2006. An Empirical Comparison of Credit Spreads Between the Bond Market and the Credit Default Swap Market. Journal of Financial Services Research 29, 211-235.

Zivot, E., and D. W. K. Andrews, 1992. Further Evidence on the Great Crash, the Oil-Price Shock and the Unit-Root Hypothesis. Journal of Business and Economic Statistics 10, 251-270.