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By

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Essays on Credit Risk: European studies in the context of the global financial crisis

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"Over the course of this crisis, we as an industry caused a lot of damage. Never has it been clearer how mistakes made by financial companies can affect Main Street, and we need to learn the lessons of the past few years."

Brian T. Moynihan, CEO and President, Bank of America

Dedication

To the memory of my grandfathers BEKKOUR Mustapha and AMARA Ahmed who were for me a model of rigor and wisdom;

To my beloved parents for always supporting me and standing by me.

To my brothers, Salim and Mehdi who have always been here for me.

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Chapter one

General Introduction

1.1 General context: the global financial crisis

The financial crisis that began with troubles in the US mortgage market almost brought down the entire world's financial system**.** Most of the world's banks were threatened with bankruptcy, a shock which propelled most developed countries into severe recession. The global financial crisis is considered to have been the largest contraction in the global economy since the Great Depression. It had major consequences for international financial markets, and then more generally, on the world economy. There was a profound effect on investment, consumption, jobs etc. The collapse of Lehman Brothers triggered a domino effect in Wall Street with the consequence of a rise in risk aversion in market participants. The outcome was reduced liquidity and self-reinforcing panics, which underpinned the market turbulence. Financial institutions stopped lending to each other due to the resultant crisis of confidence. Bond markets fell, cutting the industry's revenues by a third. Non-financial companies saw the supply of loans reduced dramatically, leaving many unable to pay suppliers or workers. This forced them to cut their spending, leading to further harmful impacts on the real economy.

The financial crisis had serious long term negative consequences for the Eurozone. In the decade prior to the onset of crisis, economic growth in Europe had been generally strong, fiscal deficits were limited and the euro area did not appear to have a public debt problem. The debt levels rose only modestly in most Eurozone member countries prior to the 2007-08 global financial crisis. According to Lane (2012), in 1995 the ratio of gross public debt to GDP for both the euro area and United States were quite similar (60 % for US and 70% for European countries[1]). However, after 2008, this figure rose more quickly in Europe than in the US, and this trend began to intensify during 2010. Many European banks had borrowed substantial sums on the American money markets before the crisis, often using this to make what proved to be excessively risky investments. Due to the interconnection in the financial markets, the troubles in the US thus transmitted themselves to Europe. Furthermore, Europe had its own underlying internal imbalances. When the Eurozone was created, the countries later grouped together with the acronym "PIIGS"[2] tended to have large budget deficits, while countries in northern Europe tended to have budget surpluses. Thus, Eurozone member countries had the same monetary policy but different fiscal policies, enabling countries like Greece to benefit from cheap funding costs, equal to those of Germany. This helped exacerbate overindebtedness of these countries. Furthermore, cheap interest rates in Spain and Ireland helped create a housing bubble similar to that in US. All these imbalances where amplified with the spread of US credit crisis.

The recent events point out the fact that the rise in the complexity and globalization of financial services contributes to stronger interconnections, with potentially dramatic consequences in the financial markets and the whole economy. The effects are still being felt, seven years on. It took huge taxpayer-financed bail-outs to shore up the industry. In several rich countries GDP is still below its pre-crisis peak. Fear of financial contagion and an economic breakdown was the major motivation behind massive bailouts and other interventions provided by governments during the

[1] These ratios were calculated by the author how used IMF public Debt Databased (https://www.imf.org/external/pubs/ft/gfsr/)
[2] Portugal, Italy, Ireland, Greece and Spain.

recent financial crisis. In Europe, aid measures to banks and other financial institutions amounted to more than 900 billion euros in 2008[3]. These financial injections fended off an economic depression, but were only short term solution. For the long term, better risk management and complete rewriting of the rulebook for financial services is required to prevent future crises and ensure the financial and economic stability. In this thesis we only focus on Europe.

Risk management is the process of identifying and analyzing exposure to risk and determining the optimal way to manage such exposure in order to prevent (or at least minimize) the exposure. Financial and non-financial institutions face different types of risks: Market Risk, Credit Risk, Liquidity Risk, Operational Risk, Legal Risk, etc. Given the major role of credit risk in the recent financial crisis, this thesis focuses on analysing different perspectives of credit risk in Europe during the financial crisis. We consider different markets: Credit Default Swap (CDS), options on equities and exchange rates, and finally, the equity markets. We also look at the impact on different entities: corporates, banks and sovereigns however, we focus more on banks. Credit risk is the risk of loss on a claim. More generally, it is the risk such that a third party does not honour its contractual commitments. It is a function of three parameters: the amount of the debt, the probability of default and the proportion of the debt that will not be recovered in case of default.

Analysing credit risk during the financial crisis has to start with an investigation of the causes of the global financial crisis. The exact causes are a continuous debate. Many papers address the question of the causes of the financial crisis (see further Reinhart and Rogoff, 2009, Calomiris, 2009, Claessens and Kose, 2014, Eichengreen, 2010, and Claessens et al., 2014).

The financial crisis was the result of a multiple and interlinked causes. It is hard to enumerate them separately because, in reality, most are interconnected, but for a pedagogical purpose we will try to cite some of the key causes. Firstly, banks were responsible for reckless lending. Secondly, the fast growth of credit derivatives, in particular the CDS market, became dominated by speculation. In addition, these complex financial products has enabled risk transfers that were not fully understood by financial regulators and by institutions themselves, thus complicating the assessment of counterparty risk. Thirdly, the ratings agencies miscalculated the risks associated with mortgage-backed securities to which they often gave generous ratings. In addition, the

[3] European Commission Internal Market and Services

government indirectly encouraged moral hazard risk to be taken by systemically important banks through an implicit government guarantee. Lastly, central bankers and other regulators also bear blame for lax regulatory policies.

All these elements together had added to the complexity and interconnection of the financial market, accentuating the systemic risk and endangering overall financial stability. In this thesis, we will focus on credit derivatives and the credit rating agencies which were significant contributors to the outbreak of the crisis. In the next section, we first define the concept of "systemic risk", the reason why the subprime crisis became a global crisis through a domino effect. Then we present the CDS market and credit rating agencies, and show their role in the stability of the financial market.

1.2 Financial stability

There is no widely agreed definition of financial stability. They vary significantly in academic papers and among policy makers. The European Central Bank, for instance, defines financial stability as “a condition whereby the financial system is able to withstand shocks without giving way to cumulative processes, which impair the allocation of savings to investment opportunities and the processing of payments in the economy.”

In order to enhance financial stability, there has been an increased focus on systemic risk as a key aspect of macro prudential policy and surveillance (MPS). Government and financial regulators have established entities like the Financial Stability Oversight[4] Council in the U.S., the European Systemic Risk Board in the European Union (2013), and the Financial Stability Board (FSB) in G20.

1.2.1 Definition of systemic risk

There is no consensus about the definition of systemic risk. Several definitions are proposed in the literature where some are qualitative and others are quantitative definitions.

[4] In July 2010, the U.S. Congress enacted the Dodd Frank Wall Street Reform and Consumer Protection Act (Dodd Frank Act), the most comprehensive financial reform bill since the 1930s. Among other things, the Dodd Frank Act created the Financial Stability Oversight Council (FSOC) and Office of Financial Research (OFR)

The Bank of International Settlements (BIS)[5] views systemic risk as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties". While Acharya and Yorulmazer (2007, 2008) define systemic risk as the risk of default of the banking system, considered as a whole. According to DeBandt and Hartmann (2000), systemic risk can be rather an external effect hitting one institution, market or system which then spreads onto others, or, a wide systematic shock which badly affects many institutions or markets at the same time. Another strand of the literature proposes a wider definition, Borio et al., (2001), Perotti and Suarez (2009) view systemic risk as propagation risk where shock effects go beyond their direct impact, causing disorder in the real economy. According to Borio et al. (2001), financial system turmoil can rarely raise from failure of a unique financial institution due to an idiosyncratic chock. Nevertheless, financial system problems are due to financial institutions underestimating their exposure to a common factor, most notably the financial business cycle in the economy as a whole.

These definitions above show that the concept of systemic risk is not yet clearly defined, which makes its measurement challenging. Furthermore, the estimation should include the complex nature of the financial system (cross-section dimension as well as the time-dimension). From a quantitative perspective, systemic risk corresponds to losses in the financial systems that go beyond a certain threshold. These huge losses are quite unlikely to occur but can have great harm to the financial system and the real economy, as noted by Drehmann and Tarashev (2011). The systemic risk measures are designed to capture the tail risk that reflects the interconnectedness within and across sectors. Giesecke and Kim (2011) define systemic risk as the conditional probability of failure of a large proportion of all financial institutions. This definition points out that the cause of systemic distress is the correlated failure of institutions to meet their obligations." According to the ECB (2009), systemic risk limited to the banking sector should consider several factors. Firstly, a common shock that affects the whole banking system and then is transmitted to the real economy. Secondly, the outcome of an idiosyncratic shock to a financial institution that is propagated to the rest of the financial sector and ends up affecting the real economy. Thirdly, as a

[5] Bank of International Settlements, 64th Annual Report, p 177

slow buildup of vulnerabilities in the banking system that may affect the real economy. Thus, we observe that the definition of systematic risk is a topic of ongoing debate among researchers and therefore accurate measurement of such risk involves complexities.

Now we would like to draw the attention to the role of the CDS market and credit ratings during the global financial turmoil in undermining financial stability.

1.2.2 Corporate and sovereigns CDS Market

Credit derivatives played a major role in the global financial crisis. They are defined as contracts where the payoff is related to the creditworthiness of one or more counterparties. They can be split into two categories: *unfunded credit derivatives* and funded credit derivatives. The first category is a bilateral contract between two counterparties. The second transaction involve a special purpose vehicle (SPV) to transform claims into securities that can then be sold to investors at different levels of risk using securitization and synthetic securitization. Credit derivatives are instruments that allow the transfer of part or all of the credit risk associated to an obligation (a claim) without allowing for a transfer of ownership. The price of the derivatives credit depends directly on the credit quality of the issuer. Credit derivative markets have grown exponentially in recent years. According to a BIS report (2010), the gross notional amount of outstanding credit derivative contracts rose from about $4 trillion at the end of 2003 to roughly $62 trillion at the end of 2007 i.e. an increase of 1 450%.

CDSs represent the most common type of credit derivatives. They were designed to transfer the “risk of default” of a particular *reference entity* (underlying debt instrument or debtor: a company or a sovereign entity) from a party which is seeking insurance protection (*protection buyer*) to the party that is willing to offer such a protection (*protection seller*) in exchange for a contractually determined fair premium (*CDS spread or premium*). Through a CDS contract, not only the “risk of default” can be insured, but also several triggering events against which protection can be bought, namely default, bankruptcy, restructuring, repudiation or moratorium and obligation acceleration or default. Once one of these credit events takes place, the contract has to be settled either via physical or cash settlement, as specified in the contract. CDS spread is quoted in basis points per annum and is paid in quarterly installments. It represents a credit risk proxy for the issuer: corporate or sovereign. A higher spread on the CDS implies a greater risk of default by the reference entity. It reflects the perception of the financial market on the corporate and sovereign debt. Blanco et al. (2005) suggest that CDS spreads tend to respond more quickly to changes in credit conditions compared to bond credit spreads. According to Longstaff et al. (2005) and Ericsson et al. (2009) CDS spreads seem to be a more accurate and cleaner indicator of the firm's real creditworthiness or default risk. At sovereign level, Pan and Singleton (2008) show that market prices of CDS spreads reflect the perception of financial markets about the economic-political stability of a country, and thus about the creditworthiness of a given sovereign. The credit default swaps market has grown subsequently in recent years, with the total amount outstanding at the end of 2004 at 6.4 trillion US dollars raising to 57.9 trillion US dollar in June 2007, representing a growth rate of 805%.

Initially, in the mid-1990s when CDS were introduced to the market, commercial banks used CDS to hedge the credit risk associated with large claims, such as corporate loans). Gradually this market became dominated by speculation. During the European sovereign debt crisis, speculation based on the distress of sovereigns had exacerbated the risk of sovereign default of 'vulnerable countries' particularly the "PIIGS". In addition, credit derivatives are used as a way to take additional risks without having to set aside additional capital requirements as they transfer toxic assets to investors. This kind of instrument creates interdependencies, complexity in the financial market and hence they increase systemic risk. A good example is the collapse of Lehman Brothers. Due to its exposure to one of the largest CDS market counterparties (the sub-prime mortgage market) and since it was an important CDS reference entity itself, its breakdown lead to the near-collapse of other entities though a domino effect that went hand-in-hand with worldwide financial panic.

The crisis we are living through shows how harmful consequences can result from the credit derivative market and thus the necessity of carefully analyzing this market in order to better control it through regulation. For this reason, chapters two, three and four are dedicated to analyzing sovereign and corporate CDS markets.

Previous research suggests that informed traders prefer equity option and CDS markets over stock markets to exploit their informational advantage. As a result, equity and credit derivative markets contribute more to price discovery than stock markets. The objective of **chapter two** is to investigate the dynamics behind informed investors' trading decisions in European stock, options and credit default swap markets based on a sample of 91 financial and non-financial, investment-and non-investment grade companies. This allows us to identify the predictive explanatory power of the unique information contained in each market with respect to future stock, CDS and option market movements. A lead-lag relation is found between the CDS market and the other markets, in which changes in CDS spreads are able to consistently forecast changes in stock prices and equity options' implied volatilities. This includes how the fast growing CDS market seems to play a special role in the price discovery process. Moreover, in contrast to results from US studies, the stock market is found to forecast changes in the other two markets, suggesting that investors also prefer stock market involvement to exploit their information advantages before moving to CDS and option markets. Interestingly, these patterns have only emerged during the recent financial crisis, while before the crisis the option market was found to be of major importance in the price discovery process.

Chapter three seeks to examine whether the information contained in deep-out-of-the-money put options (DOOM) put options can be combined with information on CDS contracts to estimate default arrival rates. Using a sample of European banks, it exploits a theoretical link between the equity DOOM and CDS contracts proposed by Carr&Wu (2011) from a different angle with a view to gauging their credit riskiness. In addition, we analyze the differences between the estimated default arrival rates and those rates emanating from the market (historical default arrival rates). We then find that the financial guarantees provided by governments to systemically important institutions are a significant factor in explaining those differences. The government guarantees also explain the differences in the levels of our estimates across banks. Ultimately, our results suggest that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks, but can serve, at times, as early warning signals.

In **chapter four**, we investigate empirically the impact of the credit risk of Eurozone member countries on the stability of the euro. In the absence of a common euro bond, euro-area credit risk is induced though the credit default swaps of the member countries. The stability of the euro is examined by decomposing dollar-euro exchange rate options into the moments of the risk-neutral distribution. We document that during the sovereign debt crisis changes in the creditworthiness of member countries have significant impact on the stability of the euro. In particular, an increase in member countries' credit risk results in an increase in volatility of the dollar-euro exchange rates, along with soaring tail risk induced through the risk-neutral kurtosis. We find that member countries' credit risk is a major determinant of the euro crash risk, as measured by the risk-neutral skewness. We propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure and show that our results are robust to this change in measure. We highlight that during the sovereign debt crisis, the creditworthiness of countries with vulnerable fiscal positions were the main risk-endangering factor of euro stability.

1.2.3 Credit ratings agencies

The financial crisis also highlighted the importance and implications of bank and sovereign ratings assigned by the rating agencies. Moody's Investors Service, Standard and Poor's (S&P) and Fitch Ratings dominate the global credit rating industry. Moody's and S&P account for 80% of the market, while Fitch's share is 15% (Duff and Einig, 2009). These ratings represent an estimation of the rating agency regarding the ability of an institution or a sovereign to meet its obligation. In other words, ratings reflect the creditworthiness of the bond issuer and signal improving and deteriorating fundamental credit quality. In this sense, the rating issued by credit rating agencies are considered as a credit risk indicator and determine the institutions' and countries' financing costs. The three agencies have different scales of ratings and different methods to assess credit quality.

Credit rating agencies played a key role in the financial crisis. They were blamed for precipitating the crisis, by giving excessively high ratings to risky mortgage-backed securities (MBS). The risk models on which these ratings had been based were overoptimistic about default risks on the underlying mortgages and about correlations between the different assets. These derivatives were new and were not fully comprehended or appreciated by the rating agencies. Furthermore, there is a conflict of interest; the agencies are paid by companies that issued bonds (CDO, MBS), giving them an incentive to please their client rather than giving a true assessment of risk.

Despite recent criticisms, rating agencies play a crucial role in the global financial markets and the economy in general. For these reasons, it is essential that credit ratings correctly reflect the credit risk embedded in bonds and countries, taking into consideration all the elements that could affect the creditworthiness of the issuer. In the last chapter of the thesis we investigate whether Distance to Default and systemic risk are a good predictors for banks and sovereign credit ratings.

Previous research has documented that Distance to Default from Merton Model is informative to predict future changes in credit ratings. In **chapter five** we analyze the impact of Distance to Default (DD) and systemic risk on the probability of downgrading banks and sovereigns using the panel probit model. We estimate Distance to Default using a standard option pricing framework and the systemic risk indicator by an aggregation procedure which is the standard practice in financial stability publications. For this purpose, we consider a set of 41 banks from 14 European countries over the period from 2007 to 2013. The results show that both indicators affect the downgrade probability of banks and sovereigns, however, systemic risk goes beyond Distance to Default to explain deterioration of the financial stability of banks and countries. The results show also that the three rating agencies react differently to the deterioration in banks' credit risk proxies by Distance to Default and systemic risk. Regarding banks' ratings, among the three agencies, Moody's is the one that reacts least to an increase in banks' systemic risk and Distance to Default in comparison with its competitors S&P and Fitch. As to sovereign ratings, S&P is the agency that takes the banks' systemic risk factor most into account in its assessment of the countries' risk profiles, with Fitch coming next.

1.3 Thesis structure

The thesis is organized as follows. In the next chapter we investigate the dynamics behind informed investors' trading decisions in European stock, options and credit default swap markets. In chapter three we exploit a theoretical link between the equity deep-out-of-the-money put and CDS contracts to estimate default arrival rates. Chapter four seeks to analyze the impact of countries' credit risk on the stability of the euro. In chapter five we analyze the impact of Distance to Default and systemic risk on the probability of downgrading banks and countries. Finally, in chapter six we conclude and discuss our future research directions[6].

[6] Chapter 2, 3, 4, and 5 are extended versions of the following papers:

Amadori M., Bekkour L., Lehnert T., 'The Relative Informational Efficiency of Stocks, Options and Credit Default Swaps', Published in Review of Risk Finance, volume 15, Number 5,510-532 (2014)

Bekkour L.,Lehnert T, Nadal F, Rasmouki F., 'CDS Contracts versus Put Options: A Robust Relationship?', 2014. Working paper

Bekkour L., Lehnert T., Rasmouki F, Wolff C., Jin, X., 'Euro at Risk: The Impact of Countries' Credit Risk on the Stability of the Common Currency', 2012. Working paper

Alsakka, R., Bekkour L., ap Gwilym, O, 'Does systemic risk affect credit ratings of sovereigns and banks?', 2015. Working paper

Chapter Two

The Relative Informational Efficiency of Stocks, Options and Credit Default Swaps during the Financial Crisis

2.1 Introduction

A relatively new stream of literature tries to explore the connections between the different equity, options and credit derivatives markets with respect to informed traders' investment decisions. Acharya and Johnson (2007) study the phenomenon of insider trading in the credit derivatives markets. They find evidence of its existence, especially when more banks are lending to an obligor. In fact, in the case of higher credit risk, they show that credit default swap (CDS) spreads lead stock returns. Therefore, insiders (in this case the lending institutions) tend to exploit their (insider) knowledge, which reveals their significant incremental information in the CDS market. Following this line of reasoning, Cao et al. (2010) hypothesize that if informed/insider trading is the common underpinning of price discovery in the option and CDS markets and considering that both CDS and equity options offer a low cost and effective protection against downside risk, then we should expect a contemporaneous link between CDS spreads and option-implied volatility (IV). Using a sample of US firms over a three year time span, their findings are consistent with this main hypothesis. Similar results are also obtained by Consigli (2007). The preference of informed traders for option markets over stock or bond markets is also documented in previous studies such as Pan and Poteshman (2006) and Cao et al. (2005). In an earlier version of their paper, Cao et al. (2010) further explore the lead-lag relation among stock, option, and CDS markets. Their results are consistent with the preference of informed traders to first use options and CDS markets to exploit their informational advantage. Subsequently, this information is transmitted into the stock market. They also examine the reasons why implied volatility is found to be a better explanatory variable for CDS spreads compared to historical volatility (HV) and other theoretical determinants. The results show that IV explains CDS spreads not only because it forecasts future volatility, but also because it captures a time-varying volatility risk premium. For an international sample of firms over the period 2000-2002, Norden and Weber (2009) find that first, stock returns lead CDS and bond spread changes, while CDS spread changes are found to Granger cause bond spread changes for a large number of firms. Second, the CDS market is more sensitive to the stock market than the bond market. This effect intensifies with lower credit quality and larger bond issues. Finally, they find that the CDS market contributes more to price discovery than the bond market, although this effect seems stronger among US firms compared to European ones.

The aim of this study is to empirically investigate the relative informational efficiency of stock, options and credit default swaps for European firms and a long time series, that is covering the financial crisis period. Our aim is to empirically explore the price discovery process across the three markets. Inspired by Acharya and Johnson (2007), we run a two-step time series regression analysis, incorporating the seemingly unrelated regression (SUR) approach in the second step. Given that we are confronted with a relatively small cross-section and a long time-series, a SUR approach is more appropriate than panel analysis. A lead-lag relation is found between the CDS market and the other markets, in which changes in CDS spreads are able to consistently forecast changes in stock prices and equity options' implied volatilities, indicating how the fast growing CDS market seems to play a special role in the price discovery process. Moreover, in contrast to results of US studies, the stock market is found to forecast changes in the other two markets, suggesting that investors also prefer stock market involvement to exploit their information advantages before moving to the CDS and equity option markets. Interestingly, these patterns have only emerged during the recent financial crisis, while before the crisis the option market was found to be of major importance in the price discovery process. Additionally, we find these relationships to be substantially stronger for financial firms relative to non-financial firms, as a result of the increased importance of financial firms in market participants' investment decisions during the crisis periods. With respect to informed/insider trading as the common underpinning of price discovery in the option and stock markets, we find that only for highly rated, liquid and financial firms the option market is leading the stock market. For the liquid firms and during the financial crisis, our results suggest that the option market is negatively influencing the CDS market, which is counterintuitive, and puzzling, but could possibly highlight the unique characteristics of the recent crisis.

The remainder of the paper is organized as follows. In the next section, we summarize the literature. In section 2.3 and 2.4 we describe the data and the methodology, section 2.5 explains the testing procedures and provides a discussion of the empirical results. Finally, section 2.6 concludes.

2.2 Literature review

Two different market-implied proxies are typically used to measure the creditworthiness of a firm. First of all, bond credit spreads, which are defined as "the increase in yield over comparable government debt (the benchmark) that corporate borrowers of different ratings have to pay" (Servaes and Tufano, 2006, p.12). This difference changes over time, obviously, the higher the rating of the issuer the lower the credit spread will be. Bond credit spreads have been the focus of many studies trying to identify how much of these credit spreads could be explained by default and non-default components. In particular, Collin-Dufresne et al. (2001) apply a structural credit risk model to study the determinants of monthly credit spreads changes. They use a set of variables like volatility, leverage, business climate proxies, yield curve slope etc., but they are only able to explain a maximum of 25 percent of the spreads changes. Through a Principal Component Analysis (PCA), they find that the residuals from their regression model are highly cross-correlated and mostly driven by a single common factor. They argue that bonds seem to be trading in a highly segmented market. Their findings identify local demand/supply shocks, independent of both changes in firms' credit risk and typical measures of liquidity, which are usually seen as main determinants of credit spreads. Moreover, Campbell and Taksler (2003) document the strong relationship between equity volatility and bond credit spreads, arguing that it can be an explanatory variable as powerful as the company's own credit ratings. In fact, in their analysis, both of the variables explain about one third of the variation in corporate bond yield spreads. They also find a longer-term explanatory relationship between bond spreads and idiosyncratic equity volatility. Cremers et al. (2008) use equity implied volatility and skewness as explanatory variable with respect to credit spread changes. They also perform a PCA analysis and find the existence of spillover effects between option-market liquidity and short-maturity corporate bonds indicating how individual option prices contain information about the likelihood of rating migrations.

The second proxy of a company's creditworthiness is the Credit Default Swap (CDS) spread. CDSs represent the most common type of credit derivatives. They were designed to transfer the "risk of default" of a particular *reference entity* (underlying debt instrument or debtor: a company or a sovereign entity) from a party which is seeking insurance protection (*protection buyer*) to the party that is willing to offer such a protection (*protection seller*) in exchange for a contractually determined fair premium (*CDS spread or premium*). Through a CDS contract not only the "risk of default" can be insured. There are several triggering events against which protection can be bought; namely default, bankruptcy, restructuring, repudiation or moratorium and obligation acceleration or default. Once one of these credit events takes place, the contract has to be settled either via physical or cash settlement, which is specified in the contract. The CDS spread is quoted in basis points per annum and is paid in quarterly installments. It represents the fair value of the credit risk of the institution. The credit risk that the protection buyer bears is subject to the debt instrument he is seeking to insure. The intense growth experienced in the credit derivatives market during the last decade incited researchers to better understand what drives the pricing of credit risk (CDS spread). The relationship between CDS spreads and corporate bond spreads has also been extensively examined. A theoretical arbitrage relation between the two which equals CDS spreads to the difference between bond yields and a reference risk-free rate is generally assumed. Blanco et al. (2005) consider 33 US and European investment grade firms and find support for the theoretical relationship (using the swap rate as the risk-free rate). Moreover, they find that the CDS spreads seem to lead bond credit spreads in the process of price discovery causing short-lived deviations. These results suggest that CDS spreads tend to respond more quickly to changes in credit conditions. Similar results are provided by Longstaff et al. (2005) on a set of US firms using the Treasury rate as the risk-free rate. They decompose credit spreads into default and non-default components. With respect to the non-default components, they identify individual corporate bond and market wide liquidity (illiquidity) characteristics as the main drivers. The non-default components can be considered to explain the difference between CDS spreads and bond spreads. Therefore, CDS spreads seem to be a more accurate and cleaner indicator of the firm's real creditworthiness or default risk. This is also confirmed in a study by Ericsson et al. (2009) who use a set of structural credit risk models to evaluate both the bond and the CDS spreads for a sample of US firms. They find evidence that their models tend to underestimate the bond spreads, but not the CDS spreads due to the importance of some omitted non-default risk components, bond illiquidity, in particular.

Following the testing framework of Campbell and Taskler (2003), Benkert (2004) investigates the capability of both option implied volatility and historical volatility in explaining CDS spreads. Option implied volatility is found to be a more important factor in explaining the variation of credit default swap premia compared to historical volatility. Moreover, Ericsson et al. (2005) find leverage, volatility and the risk free rate to be important determinants of the CDS spread, explaining around 60 percent of the CDS premia. Similar results are found in a study by Zhang et al. (2009), where they consider equity volatility risk and jump risk as explanatory variables. The authors are able to explain around 48 percent of the CDS spread changes considering volatility risk alone. They confirm once more the tight relationship between equity volatility and credit spreads. Most studies are mainly based on US companies; because of the availability of reliable CDS quotes (see Aunon-Nerin et al. (2002)).

Based on Acharya and Johnson (2007), Berndt and Ostrovnaya (2008) investigate the impact of announcements on companies credit conditions on both credit default swaps and option markets. Their empirical findings show that both the CDS and the option market react prior to the announcement of negative news. However, option prices reveal information about such forthcoming negative events at least as early as credit spreads. They conclude that option market participants trade on unsubstantiated rumors more than investors in the CDS market. In addition, they find that the equity market does not react to abnormal movement in options, but a strong incremental spillover is found from CDS to equity markets around adverse earnings releases.

Coudert and Gex (2010a) use a Vector Error Correction Model (VECM) and VAR model to analyze the link between the CDS and the bond market. Consistent with previous studies (Blanco et al. (2005) or Zhu (2004)) they find that the CDS market leads the bond market and the stock market leads the CDS market. Coudert and Gex (2010b) analyse the links between credit default swaps and bonds spreads, including the financial crisis period. They find that the CDS market still leads the bond market for corporates and the sovereigns in their sample. Moreover, the financial crisis seems to amplify the role of CDS market. Forte and Pena (2009) further explore the dynamic between the CDS, stock and bond markets. Thus, they investigate the relationship between changes in credit spread measures, where a modified version of Leland and Toft's (1996) structural credit risk model is calibrated based on stock and CDS data (see Forte (2011)). They apply a general VECM representation on a sample of North American and European firms. The results indicate that stocks lead credit default swaps and bonds more frequently than the other way around. However, their findings also confirm the leading role of CDS markets over bond markets. Therefore, they conclude that stock market leads the price discovery process, followed by the CDS market. This is consistent with Norden and Weber (2009). In contrast, Meng et al. (2009) find that there is not a leading market. They examine the volatility transmission among the credit default swap, equity and bond markets using a multivariate GARCH model. They find evidence of spillovers beween the three markets, in other words, volatility of one market is transmitted to the other two markets. Baba and Inada (2009) work on price discovery for four Japanese mega-banks' credit risk between subordinated credit default swaps and subordinated bond spreads. They use the price discovery measures proposed by Gonzalo and Granger (1995) and Hasbrouck (1995). Their finding suggests that the two variables are co-integrated and CDS spreads play a more dominant role in price discovery than the bond spreads. According to their results, the CDS spread has a significant effect on other financial market variables especially its own volatility and equity return. Furthermore, significant volatility spillovers are detected from the CDS to bond spreads.

Most of the samples used in the studies mentioned above include non-European firms only or a mixture of US and European firms. Byström (2005) investigates the behavior of iTraxx CDS Europe indexes. More precisely, he focuses on the relationship between CDS index spread changes and stock returns. Computing Pearson and Spearman rank correlations, he arrives at two main conclusions: The first indicates that the stock market tends to lead the CDS index market. While the second, shows a significant positive serial correlation in daily changes of the iTraxx index. As an extension of this study, Alexander and Kaeck (2008) investigate the determinants of changes in the iTraxx Europe indices by applying a Markov switching model (Goldfeld and Quandt (1973) and Cosslett and Lee (1985)). The result between credit spreads and their determinants depends in particular on the volatility of the CDS market under normal market conditions (low volatility), the CDS spreads are more sensitive to stock returns than they are to stock volatility. While, during uncertain periods, the CDS spread depends on stock volatility. Furthermore, they find that theoretical determinants of structural credit risk models - interest rates, stock returns and implied volatilities - have a significant effect on CDS spreads. This result is consistent with the Benkert (2004) and Byström (2005) empirical studies. However, their sample does not include the 2007-2009 financial crisis. Avino et al. (2011) investigates the price discovery process in single-name credit spreads obtained from four markets: bonds, credit default swaps, equities and equity options on European data from January 2006 to July 2009. Using a VECM of changes in credit spreads, they find that the equity market leads the other markets during tranquil periods, while, during the crisis, the option market leads the three other markets. This is confirmed by the strong volatility spillovers observed from the option market to the other markets. However, even if the crisis period is included, the sample contains only 12 European non-financial companies.

In this study, we investigate the lead-lag relationship among the European Stock, option and Credit Default Swap markets. Our sample is composed of 91 financial and non-financial companies of investment and non-investment grade over the period 2005–2010, covering the financial crisis period.

2.3 Data

In our analysis, we use data related to the three markets: stock prices, equity option implied volatilities and credit default swap spreads. The data is obtained from Thomson Reuters**.** The initial data set consists of 163 European companies with daily observations from November 2003 to November 2010. After matching all the variables, the companies, the periods and dealing with missing data, we obtain a final sample of 91 companies from 15 July 2005 to 30 September 2010, and therefore, a total of 123,760 observations for each variable. We consider investment-grade and non-investment grade companies from financial and non-financial sectors.

CDS market

We extract Senior CDSs with 5 year maturity, as they are the most liquid CDS contracts. We obtain data from Thomson Reuters DataStream, coming from Credit Market Analysis (CMA), the available historical data goes back to 01/01/2004. According to Thomson Reuters DataStream, "CMA datavision receives credit default swap (CDS) prices ("quote spreads") from a range of market contributors. These contributors consist of both buy and sell side institutions active in the fixed income markets such as asset managers, hedge funds and banks. These active market participants provide CMA with both real-time and delayed prices of executed trades, firm or indicative bid/offers on a specific entities (e.g. company or emerging market), tenors, seniorities (ranking of the debt receiving moneys in case of default) and restructuring types. To ensure the highest level of accuracy CMA checks these prices against previous quotes and validates those using related securities and news. For less liquid entities where market activity is infrequent, CMA calculates the fair CDS spread using a proprietary issuer/sector curve model that derives an appropriate curve using known liquid CDS spreads, bond spreads and ratings data". We use the midpoint of bid/ask rates expressed in basis points. Additionally, the **bid and ask rates** are both used in the study to construct an indicator of liquidity in the CDS market.

Option market

The relevant equity options data is also obtained from Thomson Reuters. For each firm and for both call and put options, an at-the-money implied volatility (IV) measure is retrieved. The implied volatility variable is the second most important element of our analysis. In fact, in order for a company to be included in the study, options trading volume has to be sufficiently high. In order to estimate a unique indicator of a firm's equity options IV, an average of the call IV and put IV is calculated. This is done in order to reduce the possible noise contained in the data, because the relevant calls and puts could be traded at different points in time and, therefore, at different implied volatilities. The measure of IV provided is the at-the-money (ATM) implied volatility interpolated for a continuous series of options. According to Thomson Reuters definitions, the continuous series for calls or puts are calculated using the nearest expiry month options. Using MB Risk Management (MBRM) UNIVOPT – Universal Options Add In software together with the Black-Scholes and the Cox-Rubinstein Binomial Model, interpolated ATM-IV is estimated taking into consideration: "The nearest two options series at-the-money available: One above and one below the underlying price. For example if the underlying is 655 and the two closest ATM strikes are 650 and 700, the implied volatility of the 650 strike will be weighted 45/50 against the implied volatility 700 strike which is weighted 5/50" (Thomson Reuters Definitions).

Stock market

Daily observations for the Total Return Index (TRI) are also obtained from Thomson Reuters, assuming that dividends are re-invested to purchase additional units of equity at the closing price applicable on the ex-dividend. Adjusted closing prices are used to determine price index and return index. Since, the sample also contains United Kingdom companies; the prices are converted from GBP to EUR using the actual exchange rate.

Table 2.1. Summary Statistics

Variable	Mean	Median	STDEV	Min	Max	Q1	Q3
CDS spread (bps)	106.01	70.74	92.01	27.12	605.84	54.05	128.73
Historical volatility	33.41%	32.24%	7.99%	20.58%	59.08%	27.05	39.82%
Implied volatility	33.09%	31.79%	7.44%	14.99%	53.53%	27.78%	39.07%
Stock returns (annual)	-2.02%	-0.76%	9.58%	-47.63%	14.87%	-7.06%	3.78%
CDS spread change	6.32%	4.78%	9.01%	-33.25%	44.06%	3.04%	6.94%
Implied volatility change	0.006%	0.006%	0.006%	-0.020	0.022%	0.002%	0.009%

Notes: For each variable, Table 2.1 reports the summary statistics of the time-series averages of the entire sample firms. CDS Spread is the daily five-year composite credit default swap spread; Historical Volatility is the 252-day historical volatility; Implied Volatility is the average of call and put implied volatilities at the money interpolated as available on Thomson Datastream; Firm Daily Stock Return is the annualized daily average of firm continuously compounded stock returns; CDS Spread Changes and Implied Volatility Changes are the daily change in CDS spreads and IVs of the average sample firm, respectively. The sample period covers the period from 15 July 2005 to 30 September 2010.

Table 2.1 presents summary statistics of the time series averages of variables used in the study during the period from 15 July 2005 to 30 September 2010. It can be seen that, on average, firms in the sample have performed poorly with an annualized average stock return of -2.02 percent, although, the cross-sectional standard deviation shows a high value of 9.58 percent, indicating that there is some heterogeneity between the various firms' performances in the sample. Considering the fact that CDS spreads are considered to be indicators of a firm's creditworthiness, a high mean CDS spread (106 basis points) indicates that the sample also contains risky firms, while the standard deviation of 92.01 basis points suggest that the sample firms display a representative range of default risk levels. In fact, they range from a minimum value of 27 basis points to a maximum of 606 basis points. Furthermore, the reported implied volatility and the historical volatility present similar characteristics. The heterogeneity observed in our sample leads us to split our initial sample to allow for sub-sample analysis. Hence, we also provide summary statistics for the sub samples in our analysis. The sample was divided according to: financial & non-financial sector, before & after the crisis, the credit worthiness and finally the CDS' market liquidity.

Table 2.2. Before vs. during and after the crisis

Variable	Mean	Median	STDEV	Min	Max	Q1	Q3
***Panel 1.** Before the crisis : 15/07/2005 to 31/08/2007*							
CDS spread (bps)	39.77	28.03	44.91	5.79	290.98	15.88	44.52
Historical volatility	21.62%	20.62%	4.91%	14.06%	47.48%	18.60%	23.54%
Implied volatility	23.41%	22.97%	4.73%	10.64%	47.73%	21.07%	25.52%
Stock returns (annual)	15.37%	15.37%	12.60%	-10.08%	61.74%	7.06%	21.42%
CDS spread change	0.98%	0.95%	10.75%	-63.18%	54.60%	-0.56%	2.94%
Implied volatility change	0.017%	0.016%	0.011%	-0.027%	0.048%	0.010%	0.025%
***Panel 2.** During & after the crisis: 03/09/2007 to 30/09/2010*							
CDS spread (bps)	151.82	100.74	135.22	40.24	873.41	72.37	183.28
Historical volatility	41.61%	38.69%	12.02%	25.12%	88.64%	32.05%	49.53%
Implied volatility	39.79%	37.79%	10.83%	18.00%	77.29%	31.10%	48.35%
Stock returns (annual)	-13.86%	-11.59%	14.11%	-80.39%	9.83%	-21.17%	-4.54%
CDS spread change	10.02%	7.29%	12.11%	-26.86%	62.30%	5.01%	10.77%
Implied volatility change	-0.001%	-0.001%	0.007%	-0.022%	0.021%	-0.006%	0.003%

Figure 2.1. Daily CDS spread vs. Implied Volatility

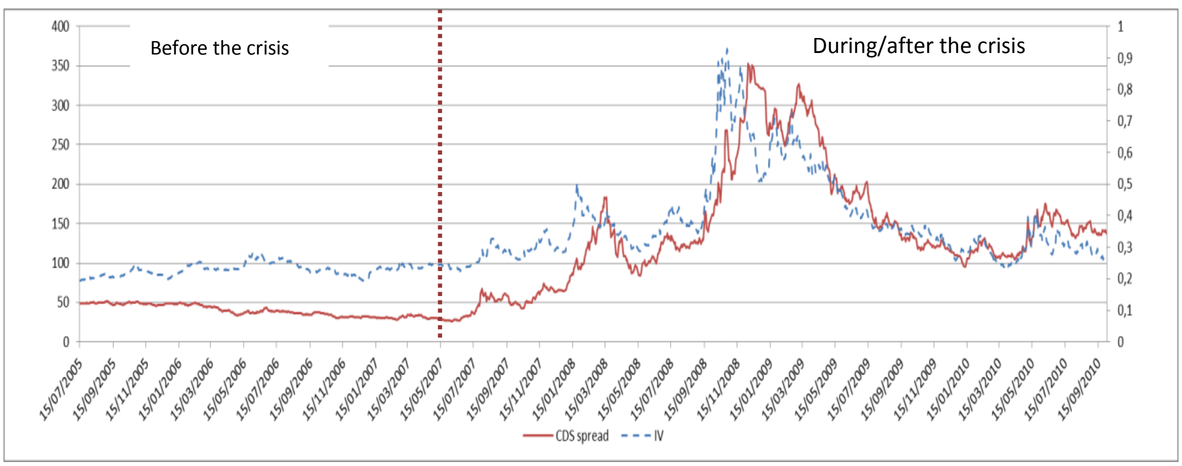


Figure 2.1 shows the daily evolution of the CDS spread (bps) and implied volatilities over the period **15 July 2005 to 30 September 2010**; The solid line represents the cross-sectional average of CDS spreads while dash line represents the cross-sectional average of implied volatility.

Table 2.2 reports the summary statistics of the times series averages of variables for two sub periods: Before (from 15 July 2005 to 31 August 2007), during, and after the crisis (from 03 September 2007 to 30 September 2010). We consider crisis period start from 3 September 2007, because the most important negative events have occurred from that date onwards[7]. The average CDS spread increased by 282% between the period before and after the crisis going from 40 to 152 basis points as illustrated in Figure 2.1. Given that the CDS spread is one of the risk measures, this increase in average spread shows that risk has increased significantly during the period of the financial crisis. Implied volatilities have also increased by 74% (from 23% to 40%) during the two periods (also illustrated in Figure 2.1). The table also shows an increase of the standard deviation between the two periods for both CDS spreads and implied volatilities, an increase of 201% and 129% respectively suggest that the financial crisis has also amplified the heterogeneity of the sample firms. Not surprisingly, the annualized average stock return decreases during the crisis to -13.86%, while the mean was 15.37% before the crisis.

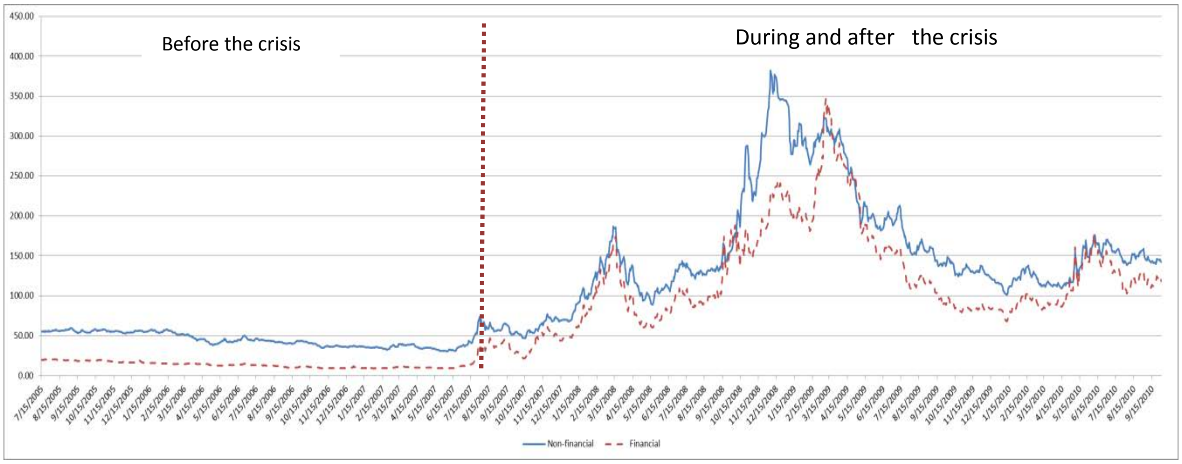
Table 2.3. Financial vs. non-financial firms

Variable	Mean	Median	STDEV	Min	Max	Q1	Q3
Panel 1. Non-financial sector							
CDS spread (bps)	112.30	70.69	100.27	27.12	605.84	52.01	145.35
Historical volatility	31.56%	30.23%	7.06%	20.58%	50.56%	25.70%	36.53%
Implied volatility	31.59%	29.72%	6.96%	14.99%	47.88%	26.71%	36.75%
Stock returns (annual)	0.00%	0.76%	7.81%	-25.96%	14.87%	-5.54%	4.79%
CDS spread change	6.12%	4.17%	9.95%	-33.25%	44.06%	2.72%	5.87%
Implied volatility change	0.004%	0.005%	0.005%	-0.020%	0.021%	0.002%	0.007%
Panel 2. Financial sector							
CDS spread (bps)	78.62	70.74	27.72	44.20	138.91	57.57	88.03
Historical volatility	41.46%	40.72%	6.86%	30.54%	59.08%	37.59%	45.28%
Implied volatility	39.65%	39.52%	5.85%	29.22%	53.53%	37.57%	41.04%
Stock returns (annual)	-10.33%	-8.82%	12.10%	-47.63%	6.55%	-15.88%	-1.76%
CDS spread change	7.22%	6.96%	2.12%	3.61%	12.45%	6.20%	8.27%
Implied volatility change	0.012%	0.012%	0.006%	0.002%	0.022%	0.008%	0.015%

Notes: For each variable, Table 2.3 reports the summary statistics of the time-series averages of the two panels: Non financial sector (panel 1) and Financial sector (panel 2). CDS Spread is the daily five-year composite credit default swap spread; Historical Volatility is the 252-day historical volatility; Implied Volatility is the average of call and put implied volatilities of at the money options; Firm Daily Stock Return is the annualized daily average of firm continuously compounded stock returns; CDS Spread Changes and Implied Volatility Changes are the daily change in CDS spreads and IV of the average sub-samples firms respectively. The sample period extends from 15 July 2005 to 30 September 2010.

[7] We perform a Chow test, which suggest August 31 2007 as the breaking-point date. Alternatively, one could use the NBER recession dates to justify the choice of the sub periods.

Figure 2.2. Financial vs. non-financial CDS spread



Notes: Figure 2.2 shows the evolution of the CDS spread (bps) of the financial and non-financial sector over the period **15 July 2005 to 30 September 2010**; The solid line represents the cross-sectional average of non-financial firms (74 firms), while the dashed line represents the cross-sectional average of financial firms (17 firms).

Table 2.3 reports summary statistics of the times series averages of variables for the financial and non-financial sectors. The CDS spread average is much higher for non-financial sector than financial sector, respectively 112 and 79 basis points. On the other hand, the average implied volatility of the financial sector exceeds the one in the non-financial sector, 40% against 32%. So, the non-financial sector appears to be more risky than the financial sector when looking at the CDS market, while, the financial sector appears to be the more risky when we evaluate option prices. The CDS spread evolution over the entire period is shown in Figure 2.2 This shows that before the financial crisis, the financial sector is less risky than the other sector, while during the financial crisis, the difference between the average spreads of the two sectors is quite volatile and at some point the financial sector becomes more risky. The standard deviation of both CDS spread and implied volatility shows that the financial sample is more homogeneous compared to the non-financial sample.

Table 2.4. Relative CDS bid-ask spread as proxy of liquidity

Variable	Mean	Median	STDEV	Min	Max	Q1	Q3
Panel 1. High liquidity							
CDS spread (bps)	148.64	119.81	121.61	47.71	605.84	70.03	164.44
Historical volatility	34.53%	34.96%	6.65%	23.67%	45.46%	28.63%	40.36%
Implied volatility	35.31%	36.71%	6.46%	24.20%	46.56%	29.37%	40.11%
Stock returns (annual)	-2.02%	-0.25%	9.58%	-25.96%	14.62%	-8.06%	4.54%
CDS spread change	9.02%	5.53%	12.02%	-9.42%	44.06%	2.60%	10.09%
Implied volatility change	0.006%	0.006%	0.005%	-0.009%	0.021%	0.004%	0.009%
Panel 2. Medium liquidity							
CDS spread (bps)	60.33	53.51	30.84	29.23	194.76	44.06	65.27
Historical volatility	31.87%	31.68%	6.52%	22.48%	46.10%	25.60%	37.08%
Implied volatility	31.39%	29.70%	6.04%	18.76%	44.68%	27.23%	36.23%
Stock returns (annual)	-0.76%	-1.01%	8.06%	-20.41%	14.87%	-6.05%	5.80%
CDS spread change	5.06%	4.22%	3.29%	2.04%	19.50%	3.39%	6.35%
Implied volatility change	0.008%	0.007%	0.006%	-0.001%	0.022%	0.003%	0.012%
Panel 3. Low liquidity							
CDS spread (bps)	108.97	81.64	79.20	27.12	357.88	56.89	135.37
Historical volatility	33.81%	31.55%	10.20%	20.58%	59.08%	25.79%	42.35%
Implied volatility	32.59%	31.84%	9.09%	14.99%	53.53%	25.46%	38.39%
Stock returns (annual)	-2.77%	-1.26%	11.34%	-47.63%	13.61%	-6.55%	2.77%
CDS spread change	4.94%	4.82%	9.10%	-33.25%	26.24%	3.49%	7.05%
Implied volatility change	0.004%	0.004%	0.006%	-0.020%	0.020%	0.002%	0.007%

Notes: For each variable, Table 2.4 reports the summary statistics of the time-series averages for the three sub sample according to CDS market liquidity subdivision. CDS Spread is the daily five-year composite credit default swap spread; Historical Volatility is the 252-day historical volatility; Implied Volatility is the average of call and put implied volatilities of at the money options; Firm Daily Stock Return is the annualized daily average of firm continuously compounded stock returns; CDS Spread Changes and Implied Volatility Changes are the daily change in CDS spreads and IV of the average sub-samples firms respectively. The sample period extends from 15 July 2005 to 30 September 2010.

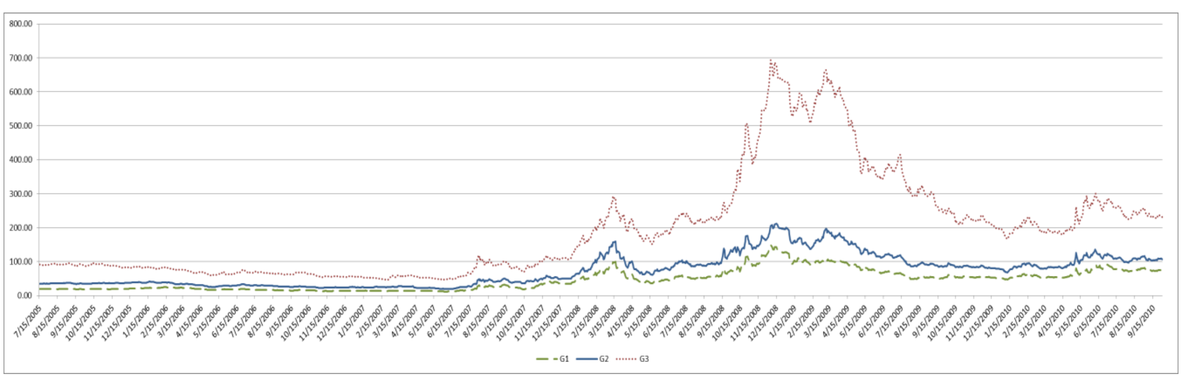
Table 2.4 reports the summary statistics of the times series averages of variables for the three sub samples according to CDS market liquidity. The liquidity of the CDS market is proxied by the relative bid-ask spread, the ratio of the bid-ask spread and the CDS mid-point. This measure is inspired by Chen, et. al. (2010), the authors refer to it as the “normalized bid-ask spread”. We can see from the table that the most liquid firms have the highest CDS spreads (149 basis points on average) and implied volatilities (35%) compared to the less liquid firms.

Table 2.5. Credit worthiness proxied by CDS spread

Variable	Mean	Median	STDEV	Min	Max	Q1	Q3
Panel 1. High-grade							
CDS spread (bps)	46.12	45.15	8.24	27.12	57.05	43.29	53.36
Historical volatility	28.38%	27.17%	5.52%	20.58%	46.10%	25.07%	29.75%
Implied volatility	28.67%	28.01%	5.46%	18.76%	44.68%	25.77%	30.39%
Stock returns (annual)	0.76%	1.26%	7.81%	-20.41%	14.87%	-3.02%	5.04%
CDS spread change	3.96%	3.59%	2.07%	1.62%	11.69%	2.66%	4.21%
Implied volatility change	0.005%	0.004%	0.005%	-0.002%	0.004%	0.002%	0.006%
Panel 2. Mid-grade							
CDS spread (bps)	73.87	69.79	12.80	57.52	97.18	63.83	86.43
Historical volatility	33.38%	31.94%	8.40%	21.94%	59.08%	28.43%	39.41%
Implied volatility	32.63%	31.63%	7.72%	14.99%	53.53%	27.49%	37.64%
Stock returns (annual)	-4.28%	-2.02%	11.09%	-47.63%	11.59%	-8.06%	1.76%
CDS spread change	5.02%	5.16%	2.88%	-3.99%	12.45%	3.33%	6.47%
Implied volatility change	0.007%	0.005%	0.006%	-0.002%	0.021%	0.003%	0.012%
Panel 3. Low-grade							
CDS spread (bps)	195.08	156.91	111.17	113.02	605.84	128.73	200.46
Historical volatility	38.30%	37.67%	6.64%	24.11%	50.56%	33.98%	42.87%
Implied volatility	37.82%	38.99%	6.08%	24.69%	47.88%	33.42%	41.64%
Stock returns (annual)	-2.27%	-0.76%	9.58%	-25.96%	14.62%	-8.06%	4.03%
CDS spread change	9.87%	6.29%	14.53%	-33.25%	44.06%	4.33%	17.89%
Implied volatility change	0.006%	0.007%	0.007%	-0.020%	0.021%	0.005%	0.009%

Notes: For each variable, Table 2.5 reports the summary statistics of the time-series averages according firms credit worthiness subdivision proxied by CDS spread (BPS). CDS Spread is the daily five-year composite credit default swap spread; Historical Volatility is the 252-day historical volatility; Implied Volatility is the average of call and put implied volatilities of at the money options; Firm Daily Stock Return the annualized daily average of firm continuously compounded stock returns; CDS Spread Changes and Implied Volatility Changes are the daily change in CDS spreads and IV of the average sub-samples firms respectively. The sample period extends from 15 July 2005 to 30 September 2010.

Figure 2.3. Credit worthiness proxied by CDS spread



Notes: Figure 2.3 shows the evolution of the CDS spread according to the credit worthiness subdivision proxied by CDS spread (bps) over the period **15 July 2005 to 30 September 2010**; The dashed line (G1) represents the cross-sectional average of the high-grade companies; The solid line (G2) represents the cross-sectional average of mid-grade companies , while the dotted line (G3) represents the cross-sectional average of low-grade companies.

Table 2.5 reports summary statistics of the times series averages of variables according to credit worthiness sub-samples. The average CDS spread for the creditworthy companies is less than one-third of that for the lowest credit grade companies (46 basis points and 195 basis points, respectively). Implied volatility is also higher for the low-grade companies 38%, while it is 29% for the high-grade companies. Figure 3 illustrates the evolution of the CDS spread for each of the three sub-samples over all the study period. It highlights that the increase in spreads during the crisis is much more severe for the low-grade companies compared to the other two groups. This shows that the financial crisis had a greater impact on companies of speculative grade, which is also found in other studies (see e.g. Avino et al. (2011)).

2.4 Methodology

We apply a methodology similar to Acharya and Johnson (2007). Though we do not implement panel data regressions, but Seemingly Unrelated Regressions (SUR) (see e.g. Zellner, 1962) and then perform a cross-sectional t-test in order to verify the statistical significance of our average cross-sectional coefficient estimates. Using panel data regression in our analysis will lead to inefficient results. Indeed, both fixed and random effect panel regressions are based on the assumption of a large cross section N and a small time-series T, while our sample is characterized by large T and small N. In this case it is more appropriate to use SUR regressions. The methodology involves two steps; the first one allows us to extract the residuals, which we use in the second step as explanatory variables, thus, the model, can be estimated using SUR methodology.

In the first step, we regress the daily changes[8] in CDS spreads, IVs and stock returns on the lagged values of CDS spread, IV changes and stock returns. To derive the CDS, option and stock market residual (respectively $r_{CDS,t}$, $r_{IV,t}$ and $r_{R,t}$), we estimate the following equations separately and for each company [9]:

[8] We perform Augmented Dickey Fuller test for unit root on the three variables: CDS spreads, IV and R. The test and the autocorrelogram show that the returns are stationary, while the CDS spreads and IV are not. To obtain stationary time series, we calculate first difference on CDS spreads and IV time series. We run the test again, which shows the absence of a unit root.

[9] Using Akaike's (1974) Information Criterion (AIC) and Schwarz's (1978) Bayesian Information Criterion (SBIC), the equation specification with three lags was found to be sufficient.

$$\Delta CDS_t = \alpha + \sum_{i=1}^{3} \beta_i \Delta CDS_{t-i} + \sum_{i=1}^{3} \gamma_i \Delta IV_{t-i} + \sum_{i=1}^{3} \delta_i R_{t-i} + r_{CDS,t} \quad (1)$$

$$\Delta IV_t = \alpha + \sum_{i=1}^{3} \beta_i \Delta CDS_{t-i} + \sum_{i=1}^{3} \gamma_i IV\Delta_{t-i} + \sum_{i=1}^{3} \delta_i R_{t-i} + r_{IV,t} \quad (2)$$

$$R_t = \alpha + \sum_{i=1}^{3} \beta_i \Delta CDS_{t-i} + \sum_{i=1}^{3} \gamma_i \Delta IV_{t-i} + \sum_{i=1}^{3} \delta_i R_{t-i} + r_{R,t} \quad (3)$$

From these three regressions, we obtain three vectors of residual. The lagged values of these residuals are then used as independent variables in the second step regression in equations 4, 5 and 6. We do this for up to three lags to absorb any lagged information transmission. The resulting residuals from each of the regressions can be interpreted as independent news from one market either not relevant or simply not appreciated by the other markets. These residuals should represent the amount of unique information contained in each market (option, stock and CDS market).

In the second step, changes in CDS spreads, IV and stock returns are regressed over the three lagged residuals. This allows us to investigate the predictive explanatory power of the unique information contained in each market with respect to future stock, CDS and option market movements.

$$R_{S,t} = \alpha_S + \beta_{S,CDS} r_{CDS,t-1} + \beta_{S,IV} r_{IV,t-1} + \beta_{S,S} r_{S,t-1} + \varepsilon_{S,t} \quad (4)$$

$$\Delta CDS_t = \alpha_{CDS} + \beta_{CDS,CDS} r_{CDS,t-1} + \beta_{CDS,IV} r_{IV,t-1} + \beta_{CDS,S} r_{S,t-1} + \varepsilon_{CDS,t} \quad (5)$$

$$\Delta IV_t = \alpha_{IV} + \beta_{IV,CDS} r_{CDS,t-1} + \beta_{IV,IV} r_{IV,t-1} + \beta_{IV,S} r_{S,t-1} + \varepsilon_{IV,t} \quad (6)$$

We use the SUR method to estimate the three equations independently. So, for each equation presented above, using the SUR approach, we estimate jointly the company-specific equations, taking into account the contemporaneous correlation of errors terms across firms. Formally:

$$E\left[\varepsilon_{i,t}, \varepsilon_{j,s}\right] = \rho_{i,j}$$ For $t=s$ and 0 otherwise.

The method involves two steps, the first one consists of running OLS regression. The residuals produced by OLS estimation will be used to construct the variance matrix $\sum$, where the elements are given by the expression:

$$\hat{\sigma}_{ij} = \frac{1}{T} \hat{\varepsilon}_i' \varepsilon_j .$$

The matrix obtained in the first step is used in the second step to run the GLS estimation to obtain the coefficients:

$$\hat{\beta} = \left(X'(\hat{\Sigma}^{-1} \otimes I_T) X \right)^{-1} \left(X'(\hat{\Sigma}^{-1} \otimes I_T) y \right).$$

X is the matrix of explanatory variables: $r_{CDS,t-1}$, $r_{IV,t-1}$ and $r_{S,t-1}$. This matrix is the same for the three equations. Y represents the vector of dependent variables: $R_{S,t}$, ΔCDS_t and ΔIV_t in equations 4, 5 and 6, respectively.

The cross-sectional average coefficient estimates (betas) and t-statistics (obtained through the cross-sectional t-test) are reported in Tables 6 through 9. Note that if errors turn out to be uncorrelated or when the set of independent variables is the same, using SUR results in a standard OLS estimation in terms of efficiency.

2.5 Empirical Results

As already outlined in the introduction section, we aim to investigate the price discovery process exploring the lead-lag relation among stock, options, and CDS markets. As mentioned before, the US results of Cao et al. (2010) are consistent with the preference of informed traders to first using both options and CDS markets to exploit their informational advantages. Inspired by those results, we examine how the price discovery process unfolds across European stock, option and CDS markets. In order to do this we apply a methodology similar to the one used in Acharya and Johnson (2007). US results suggest that CDS spread and IV changes can forecast future stock returns and they report this as evidence for informed investors' preference for the option and CDS markets to exploit their insider information compared to the stock market.

Table 2.6. Lead-Lag Analysis: Entire Sample

	Entire sample
$\beta_{S,CDS}$	-7.9 E-05 (-4.03)***
$\beta_{S,IV}$	-0.00 (-1.53)
$\beta_{CDS,S}$	-11.00 (-5.64)***
$\beta_{CDS,IV}$	-0.01 (-0.59)
$\beta_{IV,S}$	-2.37 (-2.96)**
$\beta_{IV,CDS}$	0.01 (5.29)***

Notes: Cross-sectional average coefficients and t statistics (in parentheses) of lead-lag time series SUR regressions of changes of the CDS spread, implied volatility and the stock return for the entire sample. Newey and West (1987) standard errors are used to compute t-statistics. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The regression equations and the coefficients are defined in equations (8)-(10). The sample period extends from 15 July 2005 to 30 September 2010.

Table 2.6 presents the overall results for our European sample. We report the cross-sectional average coefficient estimates (average betas from the SUR regressions) and t-statistics (obtained through the cross-sectional t-test). For example, $\beta_{IV,CDS}$ refers to the coefficient obtained with respect to the ability of the CDS market to consistently forecast changes in implied volatilities. In contrast to the US results, it is apparent that the preference of investors for the equity option markets does not entirely hold in European markets; in fact, innovations in the option markets do not predict future movements in the stock or CDS markets. Both coefficients ($\beta_{S,IV}$ and $\beta_{CDS,IV}$) are statistically insignificantly different from zero.

However, the CDS market seems to play a leading role in the price discovery process. The coefficient related to the impact of the CDS market on stock returns is negative (-7.9 E-05) and significant at 1 percent level, suggesting that an increase in the credit spread of 10 bps today will lead to a negative return in the stock price of -0.00079 (or -0.2 annualized) on the following day. In other words, negative news about the creditworthiness of a firm (in line with an increase in the spread) translates into a moderate drop in stock prices. Moreover considering the relationship between CDS and option markets, it was found in US studies that innovations in the option markets can consistently forecast changes in the CDS spreads, but not the other way around. We report contrasting results, suggested by the previously mentioned insignificant $\beta_{CDS,IV}$ and the positive and significant (at the 1 percent level) coefficient obtained with respect to the predictive power of the CDS market on changes in implied volatilities ($\beta_{IV,CDS}$). According to the estimated coefficient, an increase of 10 bps in the CDS spread today will cause a 0.1% increase in implied volatility tomorrow, on average. This confirms the strong relationship between the two markets already documented in previous studies and takes this one step further, as we show that beyond displaying a contemporaneous link, the CDS market is also leading the price discovery process in the option markets. Informed investors tend to prefer the CDS market to the option markets to exploit their informational advantages.

Furthermore, considering the predictive power of innovations in the stock market, we find that with respect to both the CDS and the option market the average coefficients ($\beta_{CDS,\,S}$ and $\beta_{IV,\,S}$) -11.00 and -2.37, respectively, are found to be negative and statistically significant (at the 1 and 5 percent level), documenting how the stock market seems to also lead the price discovery process in the other two markets. With respect to the coefficient being negative, it can be seen that a negative change of 1% in the stock return triggers a widening of the CDS spread of 11 bps and a positive change in IV of 2.37% over the next day. Regarding the option market, this phenomenon was first discovered by Black (1976, p.177), who observed that the amplitude of relative price fluctuations ("volatility") of a stock tends to increase when its price drops, which refer to the well documented "leverage effect". This effect is particularly important for option markets: option prices indeed reflect the fact that a negative volatility-return correlation induces a negative skewness in the risk-neutral distribution. Considering the positive contemporaneous relationship already documented in previous studies between IV and CDS spreads and the fact that they are both measures of a firm's riskiness, it is not surprising to find the same negative lead-lag relation between stock returns and CDS spreads. These results are also in line with Norden and Weber (2009) who find that European stock returns lead CDS and bond spread changes.

As a robustness check we subdivide our regression results into sub-samples according to sectors (financial vs. non-financial), creditworthiness (proxied by level of CDS spread) and liquidity (proxied by the bid-ask spread relative to the CDS mid-point).

Table 2.7. Lead-Lag Analysis: Financial vs. non- Financial sector subsamples

Explanatory variable	Financial / non-financial Sector	
	Financial	Non-financial
$\beta_{S,CDS}$	-1.2 E-04 (-5.70)***	-7.0 E-05 (-3.64)***
$\beta_{S,IV}$	- 2.7 E-04 (-3.60)***	- 1.1 E-04 (-1.15)
$\beta_{CDS,S}$	-8.88 (-8.05)***	-11.49 (-5.49)***
$\beta_{CDS,IV}$	-0.01 (-1.28)	-0.01 (-0.49)
$\beta_{IV,S}$	-7.47 (-5.96)***	-1.20 (-2.04)*
$\beta_{IV,CDS}$	0.01 (6.41)***	0.01 (5.05)***

Notes: Cross-sectional average coefficients and t statistics (in parentheses) of lead-lag time series SUR regressions of changes of the CDS spread, implied volatility and the stock return for each of the sub-groups. Newey and West (1987) standard errors are used to compute t-statistics. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The regression equations and the coefficients are defined in equations (8)-(10). The sample period extends from 15 July 2005 to 30 September 2010.

Tables 2.7 and 2.8 report the results for the cross-sectional average coefficient estimates (betas) and their relative t-statistics (obtained through the implementation of the afore-mentioned cross-sectional t-test). The results in Table 2.7 suggest that the overall results are partly driven by the financial companies in the sample. The results for financial firms are typically similar in terms of statistical significance, but always stronger in terms of economic significance as a result of the increased importance of financial firms in investment decisions of market participants' during the crisis periods. Interestingly, for financial firms, we find a volatility feedback effect from the option market to the stock market (see e.g. Fan et al. (2013) or Bollerslev et al. (2014)). The estimated coefficient of the impact of IV on stock return is equal to -2.7E-04, meaning that a 10% increase in IV results in a slight decrease, on average -0.0027% of the stock prices (or -0.7% annualized) on the following day.

Table 2.8 Lead-Lag Analysis: Credit worthiness and Liquidity subsample

Explanatory variable	Creditworthiness			Liquidity		
	High-grade	Mid-grade	Low-grade	High	Medium	Low
$\beta_{S,CDS}$	-8.5 E-05 (-3.54)***	-9.9 E-05 (-4.52)***	-5.3 E-05 (-5.66)***	-1.1 E-04 (-5.84)***	-2.3 E-05 (-1.00)	-1.0 E-04 (-6.81)***
$\beta_{S,IV}$	-3.6 E-04 (-2.91)***	-1.4 E-04 (-1.79)*	7.4 E-04 (1.38)	-7.9 E-05 (-1.90)*	-3.7 E-04 (-3.10)***	2.5 E-05 (0.27)
$\beta_{CDS,S}$	-4.45 (-3.69)***	-4.41 (-4.17)***	-23.71 (-9.70)***	-15.72 (-6.88)***	-2.26 (-2.74)***	-14.89 (-7.23)***
$\beta_{CDS,IV}$	-0.01 (-1.16)	0.00 (0.21)	-0.02 (-0.73)	-0.04 (-3.02)***	-0.00 (-0.28)	0.02 (0.87)
$\beta_{IV,S}$	-1.25 (-1.99)*	-4.15 (-3.92)***	-1.74 (-2.87)***	-1.08 (-2.07)**	-1.58 (-2.14)**	-4.40 (-4.35)***
$\beta_{IV,CDS}$	0.01 (5.36)***	0.01 (6.06)***	0.01 (4.65)***	0.01 (6.35)***	0.01 (5.45)***	0.01 (4.21)***

Notes: Cross-sectional average coefficients and t statistics (in parentheses) of lead-lag time series SUR regressions of changes of the CDS spread, implied volatility and the stock return for each of the sub-groups. Newey and West (1987) standard errors are used to compute t-statistics. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The regression equations and the coefficients are defined in equations (8)-(10). The sample period extends from 15 July 2005 to 30 September 2010.

Table 2.8 exhibits the lead-lag results from a company's credit quality point of view using CDS spread levels to form the sub-samples. Again, both the CDS market and the stock market seem to lead the price discovery process in the option markets across all groups. Therefore, the findings are in line with Cao et al. (2010) and Acharya and Johnson (2007), suggesting the existence of two different groups of investors: a sophisticated one, which considers to enter the CDS market and a less sophisticated one, which instead prefers the more traditional stock market involvement. The reported results are also in line with what Norden and Weber (2009) in a way that the CDS market seems to be more sensitive to the stock market as the credit quality of the reference entity decreases; in fact, looking at the average coefficients going from high to low the relationship becomes stronger.

An interesting result emerges concerning the option and stock market dynamics as $\beta_{S,IV}$ becomes negative and significant at the 1 percent level moving from low to high. An increase of 10% in IV leads to a -0.0014% (or -0.4% annualized) decrease in stock returns for mid-grade firms and -0.0036% (or -0.9% annualized) for high-grade firms the next day. This could be interpreted as a sign that for more solid firms, investors tend to exploit their knowledge through opening positions in the option markets. For those firms, despite the existence of a fairly new competitive CDS market, the option markets still plays an important role in the price discovery process. Finally, Table 2.8 also summarizes the results looking at CDS market liquidity indicators, using the bid-ask spread relative to the CDS mid-point as a proxy for liquidity. Since the results are similar we only comment on the ones involving the option market. As can be seen from Table 2.8, the stock market seems to be leading the price discovery process in both the option and CDS markets for the most liquid firms. The estimated coefficient $\beta_{CDS,\,S}$ of firms with high liquidity is large (-15.72) meaning that 1% decrease in stock returns today results in a 15.72 bps widening of CDS spreads tomorrow. This increase is less important for companies with medium liquidity; their CDS spreads increase by only 2.26 bps on average. As to $\beta_{IV,\,S}$, the coefficients are quite similar for firms with high and medium liquidity (-1.08 and -1.58, respectively), which means that a 1% negative change of stock returns causes an increase in IV of 1.08% and 1.58% on the following day.

On the other hand, there is also evidence of some spillover effect of the CDS and option markets into the stock market. In line with the results regarding creditworthiness, the more liquid the derivatives markets, the more investors tend to exploit their knowledge through opening positions in the option markets, leading to significant coefficients $\beta_{S,IV}$ and $\beta_{CDS,IV}$.. Finally, looking at the CDS and option market relationship, it can be seen that as the liquidity in the CDS market increases, the linkages between the two markets becomes stronger.

Finally, we would like to separately analyze the price discovery process of the three markets before and during/after the financial crisis. Detailed results are presented in Table 2.9.

Table 2.9. Lead-Lag Analysis: Before and during/after crisis subsamples

Explanatory variable	Sub periods	
	Before the crisis	During/after the crisis
$\beta_{S,CDS}$	7.3 E-05 (1.37)	-1.1 E-04 (-4.90)***
$\beta_{S,IV}$	-6.4 E-05 (-0.63)	-1.3 E-04 (-1.30)
$\beta_{CDS,S}$	-2.13 (-1.49)	-15.00 (-6.09)***
$\beta_{CDS,IV}$	0.04 (2.58)**	-0.03 (-1.68)*
$\beta_{IV,S}$	0.00 (0.34)	-3.14 (-3.71)***
$\beta_{IV,CDS}$	9.5 E-04 (0.09)	0.13 (5.66)***

Notes: Cross-sectional average coefficients and t statistics (in parentheses) of lead-lag time series SUR regressions of changes of the CDS spread, implied volatility and the stock return for each of the sub-groups. Newey and West (1987) standard errors are used to compute t-statistics. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The regression equations and the coefficients are defined in equations (8)-(10). The first sample period extends from 15/07/2005 to 30/08/2007 and the second sample period extends from 03/09/2007 to 30/09/2010.

A striking result is that our overall findings are very much driven by the dynamics that we observe during the financial crisis. Before the crisis, and in line with most of the US studies, we observe that the option market is leading the CDS market and therefore, the option market plays a crucial role in the price discovery process. In this period, we do not observe different spillover effects. Most of the other dynamics that we observe and previously discussed emerge during the recent financial crisis. One exception is the negative coefficient $\beta_{CDS,IV}$, suggesting that the option market is negatively influencing the CDS market, which is only marginally statistically and economically significant, but counterintuitive and puzzling, highlighting the unique characteristics of the recent crisis.

2.6 Conclusion

The aim of this European study covering the financial crisis period is to empirically investigate the relative informational efficiency of stock, options and credit default swaps. We try to answer this question by testing for a lead-lag relationship and exploring the price discovery dynamics across all three markets. Tracking the relatively recent field of research, which investigates the information content of equity options and CDS to predict returns on the underlying stock (see Cao et al. (2005 and 2010), Pan and Poteshman (2006), Acharya and Johnson (2007)), we perform another two step time-series regression analysis together with a cross-sectional t-test which, first, tries to identify the information advantage of each market with respect to the others and then uses this as explanatory variable for future changes in the other markets. Overall, it can be concluded that investors seem to first prefer stock and CDS market involvement to exploit their informational advantages and then move to option markets. Therefore, the findings suggest the existence of two different groups of investors: more sophisticated one, which considers entering the CDS market and a less sophisticated one, which instead sticks with more traditional capital markets dynamics to exploit its knowledge.

In particular, a lead-lag relation is found between the CDS market and the other markets, in which changes in CDS spreads are able to consistently forecast changes in stock prices and equity options' implied volatilities, indicating how the fast growing CDS market seems to play a special role in the price discovery process. Moreover, in contrast to US results, the stock market is found to forecast changes in the other two markets suggesting that investors also prefer stock market involvement to exploit their informational advantages and then move to CDS and option markets. Interestingly, these patterns have only emerged during the recent financial crisis, while before the crisis the option market was found to be of major importance in the price discovery process. Additionally, we find those relationships being substantially stronger for financial firms relative to non-financial firms as a result of the increased importance of financial firms in market participants' investment decisions during the crisis periods. With respect to informed/insider trading as the common underpinning of price discovery in the option and stock markets, we find that only for highly rated, most liquid and financial firms the option market is leading the stock market.

Chapter Three

CDS Contracts versus Put Options : A robust relationship?

3.1 Introduction

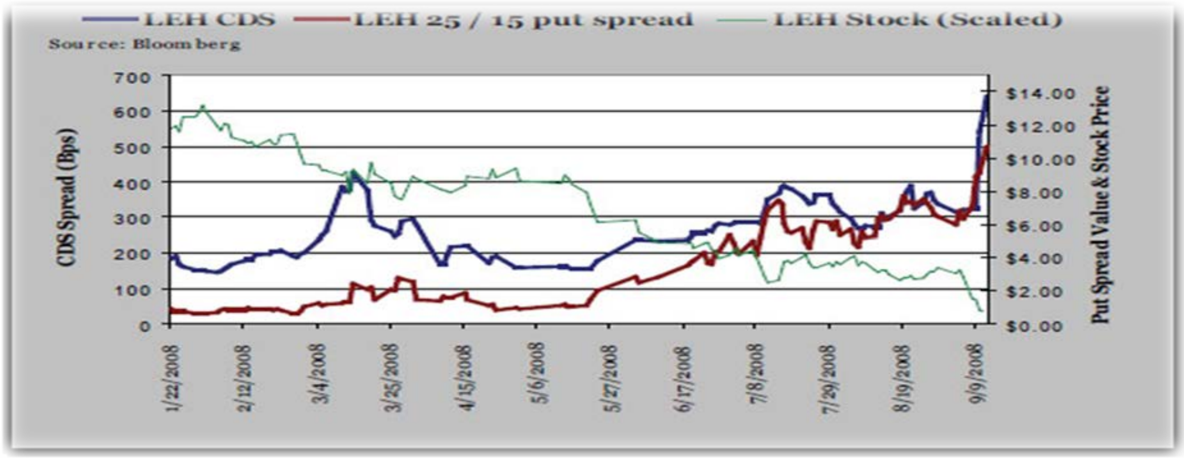
The Chicago Board Options Exchange argues in a report published in March 2009 that deep out the money options (DOOM options henceforth) can be used by investors as a “viable” and “liquid” alternative to CDS contracts[10]. Various reasons are put forward to defend this idea. Firstly, both derivatives tend to behave in the same way, particularly in times of credit crisis. Secondly, DOOM options occasionally prove to be a better indicator of credit deterioration than the CDS market. The last set of reasons is tied to the transparent feature and relatively low transaction costs of DOOM options as opposed the opaque nature and high transaction costs of CDS contracts. The whole CBOE argument is based on the work of Carr and Wu (2011). A paper where the authors propose a robust theoretical linkage between these two derivatives. In view of growing concerns about credit protection solutions, this study relies on the same model so as to verify the story put forward by the CBOE. It seems relevant to investigate the extent to which combined information contained in DOOM put options and CDS contracts can be used in the pricing of credit risk. More precisely, we exploit an existing theoretical link which proves an equivalence between a DOOM put option and a CDS contract to back out default arrival rates which are typically extracted from CDS contracts only. In this sense, we take a different empirical approach than Carr and Wu’s (2011): We do not place the focus on computing unit recovery claims values extracted from a CDS

[10] http://www.cboe.com/micro/doom/doomquickreference.aspx

contract and comparing them to values of unit recovery claims extracted from a DOOM option. Rather, we are interested in using the theoretical linkage between these two types of derivatives, and hence the combined information from CDS and DOOM options to provide estimates of default arrival rates.

The model underlying the study is a ‘simple’ theoretical link between DOOM American put options on a company’s stock and a credit insurance contract on the company’s bond. The key underpinning of the model is the presence of ‘default corridor’ [A,B] the stock price cannot penetrate. Before default the stock price remains above a barrier B before sliding below a barrier A<B after default. Under this condition a spread between two American put options struck within the corridor replicates a credit contract whose pay-off is only possible before the option expires. The most desirable attribute of the model is that the replication is materialized regardless of the details of the stock price dynamics before and after default, the interest rate dynamics, and specifications about default arrival rate, provided that the stock price is located outside the default corridor. A legitimate question arises regarding the likelihood of such a default corridor. The question is partly answered by a body of literature which models default as a strategic decision. In other words, debt holders have an incentive to spur or cause default while the value of the stock is still greater than zero, B>0 . Papers addressing the topic of strategic default include Leland and Toft (1996); Anderson, Sundaresan (1996); Mella-Baral and Perraudin (1997) and Broadie, Chernov, Sundaresan (2007). On the other hand, Car and Wu (2011) justify the assumption of the escalation of the stock price from above B to below a lower barrier by costs which are inherent to the bankruptcy process.

Futhermore, the authors clearly spell out that when the company is viewed as too big to fail (TBTF), default does not occur even when the stock price falls below the strike price of the DOOM option due to the existence of government guarantees. However, we take a particular interest in examining systemically important European banks. Our Argument is that Lehman Brothers collapsed despite being deemed TBTF. Thus, we would like to treat a sample of systemically important banks as though they would not be bailed out in the event of a default and analyse how their default arrival rates behave across time. In fact, the awareness of the systemic importance of certain institutions grew after the collapse of Lehman Brothers. Our interest in this type of banks is also justified by an empirical observation by the CBOE based on our reference model. As the plot below shows, during the crisis period of September 2008 to January 2009, The put spread and CDS spread of Lehman Brothers behaved in quite an identical fashion:



Source: http://www.cboe.com/micro/doom/doomquickreference.aspx

Thus, we apply the theoretical link of Carr and Wu (2011) and confront information about put spreads with that of CDS spreads for a sample mainly composed of systemically important institutions. More importantly we gauge the credit riskiness of such institutions, before and during the financial crisis, through the estimation of their default arrival rates.

In a second stage of our analysis we will attempt to take into account the government guarantee component provided to systemically important banks to judge whether it is necessary incorporate it to our estimation of their default arrival rates. We estimate government guarantees using the same approach as Gray and Jobst (2011)[11] and gauge their effect on the credit risk of the banks' composing our sample, and more specifically on the differences between the estimated and historical default arrival rates.

The remainder of the paper is organised as follows. In the next section we summarize the literature. Section 3.3 exposes the underpinning theoretical framework along with the estimation procedure. Section 3.4 describes the data and the related statistics. Section 3.5 outlines the main results and discusses their implications on the risk profile of the banks in our sample. Section 3.6 concludes the paper.

[11] See also the April 2014 *Global Financial Stability Report*, Gray et *al.(*2008), Gray and Malone 2008 (book) 2012

3.2 Literature review

From an academic perspective, several studies[12] demonstrate an empirical Link between CDS contracts and stock options. To cite a few, *Acharya and Johnson (2007), Berndt and Ostrovnaya (2008*) investigate the impact of announcement of negative credit news on both credit default swap (CDS) and options market. The empirical findings show that both the CDS and the option market react prior to the announcement of negative credit news. But, options prices reveal information about forthcoming adverse events at least as early as do credit spreads. *Cao et al. (2010)* show that the implied volatility (IV) explains CDS spreads not only because it forecasts future volatility, but also because it captures a time-varying volatility risk premium. *Avino et al. (2011)* investigate the price discovery process in single-name credit spreads obtained from four markets: bonds, credit default swaps, equities and equity options on European data from January 2006 to July 2009. Using a VECM of changes in credit spreads, they find that during the crisis, the option market lead the three other markets (so the option market lead the CDS market). This is confirmed by the strong volatility spillovers observed from the option market to the other markets. *Bekkour and Lehnert(2011)* work on a large European sample *and* demonstrate that the CDS market leads the option market. This pattern have only emerged during the recent financial crisis. Before the crisis the option market is found to lead the CDS market.

While is ample empirical literature looking at the relationship between stock options and CDS contracts, the main feature of these studies is that they exploit the informational aspect of the markets where these derivatives are traded and attempt to determine the direction in which information flows. Yet, the flaw with this approach is that it ignores that information extracted from the tails of the distribution is likely to reveal more about the behaviour of the markets it describes. The more interesting movements happen at the level of the tail where troublesome options can be found. That is why our data selection process is designed to extract information from the tail distribution of put options.

On the other hand, research tackling this relationship from a pricing perspective is scarce. Merton's model (1974)[13] establishes a link between corporate bond spread and stock return volatility.

[12] See also Campbell and Taskler (2002), Benkert (2004) and Alexander and Kaeck (2008).

[13] See also Merton (1973, 1976)

Despite providing a good foundation, the link is mainly based on the strong assumption whereby asset value follows a Geometric Brownian Motion and volatility is held constant. Hull, Nelken and White (2004), propose a link between CDS spreads and stock option prices through a modification in the estimation of Merton's framework .The calibration proposed by the author is nonetheless static. Carr and Wu (2010) Design a dynamic framework capable of joint estimation and valuation of put options and CDS contracts inherent to the same firm. The model decomposes the total risk of an individual stock into two components: risk in the return variance rate under normal market conditions and risk in the default arrival rate. Using data on stock options and CDS spreads they disentangle the two sources of risks and identify their respective market prices. Unlike in Carr & Wu (2011) the default arrival rate is stochastic. Nonetheless, its estimation procedure based on the Kalman Filter is costly and complex. Therefore, we opt for the framework of Carr and Wu (2011) –explained earlier- to infer default arrival rate estimates.

The objective of our study differs from that of Carr and Wu's (2011). Indeed, we do not seek to calibrate the CDS data in the model to prove that the CDS recovery claim is equivalent to the DOOM put option .Instead, we use the theoretical link to estimate a variable of interest, i.e, the default arrival rate. We do so with a specific focus on European the banking sector to gauge its credit riskiness. Altogether, our results indicate that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks but can serve, at times, as early warning signals. Furthermore, our findings suggest that higher financial guarantees from their sovereign display a lower default risk and hence have a lower CDS spread along with a lower estimated default arrival rate. Ultimately, the government guarantee explains the differences in the level of estimated default arrival rates across banks as well as the observed differences between estimated (i.e derived from Carr&Wu 's model) and historical (CDS spreads scaled by (1-recovery rate)) default arrival rates.

3.3 Methodology

Our estimation of the default arrival rates (Lambda) relies upon the framework of Carr and Wu (2011).We start off by outlining its major points of the framework . The authors develop a 'simple' theoretical link between DOOM American put options on a company's stock and a credit insurance contract on the company's bond. Under certain conditions the following relationship holds:

$$Up(t,T) = Uc(t,T) \qquad (1)$$

$$\Rightarrow \quad \frac{Pt(K2,T) - Pt(K1,T)}{K2 - K1} = \int_t^T e^{-(r+\lambda)} ds \qquad (2)$$

$$\frac{Pt(K2,T) - Pt(K1,T)}{K2 - K1} = \lambda \frac{1 - e^{-(r+\lambda)(T-t)}}{r+\lambda} \qquad (3)$$

Where :

Up(t,T) is the unit recovery claim inferred from a DOOM put option;

Uc(t,T) is the unit recovery claim inferred from a credit contract;

Pt(K2,T)-Pt(K1,T) is the spread between two observable put option prices at time t $K2 - K1$;

K2-K1 is the strike difference;

R is the interest rate;

λ is the risk neutral default arrival rate;

T is the expiry date.

The key assumption underpinning the model is the presence of 'default corridor' **[A, B]** the stock price cannot penetrate. Before default the stock price remains above a barrier B before sliding below a barrier **A≤K1<K2≤B** after default. Under this condition a spread between two American put options struck within the corridor replicates a credit contract whose pay-off is only possible before the option expires. The most desirable attribute of the model is that the replication is materialized regardless of the dynamics of the stock price before and after default, the interest rate dynamics, and specifications about default arrival rate. This implies that not only pricing of the option becomes less complex but also the inference of risk measures such as default probabilities and default arrival rates proves more parsimonious.

While Car and Wu (2009) use the theoretical linkage to show empirically that the values of credit contracts generated by CDS contracts and American put options co-move strongly, we exploit the linkage from a different angle. We use the relationship in equation (3) to infer the parameter λ , which represents the default arrival rate, based on the scaled spread in the pricing of two DOOM put options (left hand side of equation (3)). The spread corresponds to the cost of replicating a standardized default insurance contract paying 1 if the company defaults prior to T and 0 otherwise.

In order to determine a default corridor **[A, B]** in a discrete setting we work with the two lowest strike prices with non-zero bids for the highest possible time to maturity on the same trading day.

We first estimate the prices of the American put options [14] according the Bjerksund-Stensland (1993)(a) and (2002) option pricing model. Basically, the computer efficient method presented in the latter paper provides a simple approximation of the value of an American call and put options by dividing maturity into two periods, each with a flat early exercise boundary. This way, a lower bound to the option value is obtained.

In the context of complete continuous-time Black-Scholes economy, the price of the underlying asset St at a future date t will be:

$$St = Sexp\,\{(b - 0.5\sigma^2)t + \sigma W_t\}$$

Where :

S is the spot price

$b<r$ is the drift rate w/r to the equivalent martingale measure. (b) is regarded as a cost of carry

σ is the volatility

W_t is Wiener process

The value of an American call with maturity T and strike K and a given feasible strategy within the stopping date τ € [0.T] can be written as:

$$C(S, K, T, r, b, \sigma) = supEo[exp\{-r\tau\}(St - K)^+]$$

The relationship in equation (4) can be transformed to obtain the value of the put option such that:

$$P(S, K, T, r, b, \sigma) = C(S, K, T, r - b, -b, \sigma)$$

[14] Working with historical prices leads to noisy results

Once put options are estimated, and assuming constant recovery rates R^b the inference of the default rate arrival (λ) becomes possible. We take two routes with this regard: One implying the use of historical volatilities and the second involving the estimation of an implied volatility surface with a view to curing the issue of noise in the data. However, the cost of estimating an implied volatility surface does not lead to any improvements in the results.

3.3.1 Lambda (λ) using estimated option prices and historical volatilities

All variables in equation (3) are known apart from the parameter of interest. However, it is not possible to find a close form solution without having recourse to optimization technique. We set a starting value[15] of λ= 1 and we obtain a numerical value for $Up(t,T)$ (The unit recovery contract inferred from puts options) and $Uc(t,T)$ (The unit recovery contract inferred from a credit contract). Hence, on each trading day, we obtain a pair of (Up, Uc).

The optimization problem consists simply of minimizing the following objective function:

$$Up(t,T) \leq Uc(t,T) \qquad (4)$$

$$\Rightarrow \min\big(Up(t,T) - Uc(t,T)\big) \qquad (5)$$

This allows us to obtain a time series of optimal solutions for (λ), the default arrival rate corresponding to each trading day from 01/01/2006 to 31/12/2009[16].

3.3.2 Lambda (λ) using estimated option prices and estimated volatilities

In a second stage, the same methodology is applied for the Lambda inference except that we estimate implied volatilities for the American option according to the model of Bjerksund-Stensland (2002)

Important are the assumptions about: rate structure, stock specification and the continuous dividend yield (we chose a negligible level)

With a view to eliminating part of the noise inherent to option data, we further estimate a volatility surface. We use a modification of the prominent ad-hoc Black-Scholes model of Dumas, Fleming

[15] We perform the optimization with various starting values and the results remain unchanged.

and Whaley (1998). Expect that our IVs are not Black -Scholes-related but are generated from a model for American option pricing

$$IV_i = \alpha_0 + \alpha_1 \text{delta} + \alpha_2 \text{delta}^2 + \alpha_3 T + \alpha_4 T^2 + \alpha_5 \text{delta} \; T \qquad (6)$$

The regression we had for each date t and put option i , we have one observation of delta (based the theoretical model), and T . We obtain the coefficients of the equation through OLS which allows us to have a new IV for each put option. The resulting implied volatilities are then used to infer option prices, which are in turn used for the optimization in equation (5). The use of an estimated volatility surface does not necessarily lead to an improvement in our results. Therefore, we only present the results using historical volatilities and estimated option prices.

Once the default arrival rates λ are inferred based on the linkage between DOOM put options and the credit protection contract, we can compare them to default arrival rates which are computed solely based on the credit protection contract such that :

$$k = \lambda(1 - R^b)$$

$$\lambda(t,T) = {k(t,T)}/{(1 - R^b)} \qquad (7)$$

k are the historical CDS spreads

R^b *is the recovery rate fixed at* 40%

The obtained new time series represents historical default rates which are confronted to the estimated default arrival rates with a view to comparing the ‘prediction power’ of each type of indicator.

In a second stage of our analysis we will attempt to take into account the government guarantee component provided to systemically important banks and relate it to our estimation of their default arrival rates. We conjecture that government guarantees might well explain the differences in levels of default arrival rates. Essentially, banks enjoying higher financial guarantees from their sovereign should display a lower default risk and hence have a lower CDS spread along with a lower estimated default arrival rate. Furthermore, we are interested in determining whether government guarantees explain the observed differences between the estimated default arrival rates and those rates emanating from the market, i.e. historical default arrival rates (results in table 3.3). The underpinning argument is that the implicit put option derived from the equity price reflects the total expected loss of the bank while the put derived from the CDS captures the expected loss retained by the bank after accounting for financial guarantees. The difference between these two puts defines the scope of government guarantees.

Following Gray and Jobst (2011), the estimation of the implicit guarantee is possible by combining the market-implied expected losses induced through the contingent claim framework $P_E\ (t)$ (i.e. Merton's implicit put option) and information from the credit default swap markets, specifically the put option value using a CDS, $P_{CDS}\ (t)$ which is a measure of expected default net of any financial guarantee. Hence, the combination of the two types of implicit puts allows us to disentangle between the fraction of expected losses covered by the government $\propto (t)P_E\ (t)$, which represents the government implicit guarantee (i.e. contingent government liability) and the expected loss borne by the bank and translated in its CDS spread$(1-\alpha(t))P_E\ (t)$ according to the equation below:

$$\alpha(t) = 1 - \ P_{CDS}(t)/P_E\,(t) \qquad (8)$$

Where $P_E\ (t)$, the market-implied expected loss is given by the Black-Scholes- Merton equation for the value of an implicit put option :

$$P_E\ (t) = \mathrm{B}e^{-\mathrm{r}(\mathrm{T}-\mathrm{t})}\Phi(\text{-}d_2) - A(t)\ \Phi(\text{-}d_1)$$

A(t) is the asset value of the bank with strike price B which represents a distress barrier.

On the other hand , $P_{CDS}(t)$, is the expected loss net of financial guarantees.

$$P_{CDS}(t) = \left[1 - \exp(-\left(\frac{S_{CDS}(t)}{10{,}000}\right)\left(\frac{B}{D(t)} - 1\right)(T-t))\right]\ Be^{-r(T-t)}$$

Once the implied government guarantees are retrieved we relate the difference between the estimated and historical default arrival rates of bank *i* at time *t* to the corresponding government guarantee *i* at time *t* through the following panel regression with fixed effect[17]

$$|\delta\lambda|_{it} = a + b\delta GG_{it} + X_{it} + \varepsilon_{it} \quad (9)$$

Where $|\delta\lambda|$ is the difference between the estimated and historical default arrival rates in absolute value (Lambda E – Lambda H).

δGG_{it} is the government guarantee in first differences computed as (alpha*equity put option)

X_it is a set of two controls : Size as measured by market capitalization and VSTOXX which as measure of the risk appetite of the financial markets.

In addition we run two more panel regressions[18] to verify the relationship between the implied government guarantee and the estimated default arrival rates on the one hand, and the implied government guarantee and the CDS spread on the other. We expect the relationship to be negative and significant in both instances implying that banks with higher financial government guarantees display less default risk.

$$\delta Lambda_{Eit} = a + b\delta GG_{it} + X_{it} + \varepsilon_{it} \quad (10)$$

$$\delta s_{CDSit} = a + b\delta GG_{it} + X_{it} + \varepsilon_{it} \quad (11)$$

Where[19] $\delta Lambda_{Eit}$ is the estimated default arrival rate of bank i in first differences at time t , δs_{CDSit} its CDS spread in first differences and δGG_{it} is the government guarantee in first differences computed as (alpha*equity put option)

X_it is a set of two controls : Size as measured by market capitalization and VSTOXX which as measure of the risk appetite of the financial markets.

[17] We run a Haussmann test and reject the null hypothesis that the efficient random effects estimators are the same as the consistent fixed effect estimators (significant p-value = 0.000, p<Chi2=18.2)

[18] We run a Haussmann test and reject the null hypothesis that the efficient random effects estimators are the same as the consistent fixed effect estimators (significant p-value = 0.000, p<Chi2=43.98 , p-value = 0.000, p<Chi2=42.23 for Lambda E and s respectively)

[19] The Augmented Dickey Fuller test shows the presence of a unit root and so we work with first differences

3.4 Data

Data Collection

Our study spans from January 2006 to December 2009 and thus covers a pre-crisis and a crisis period. We work on a sample of large European banks. The American put options data as well as the stock data is from Thomson Reuters tick database while the CDS spreads are from Bloomberg[20]. The options data on Thomson Reuters is displayed in the form of RIC symbols which stands for 'Reuters Instrument Code' , This code encompasses information about the month-letter for the option type (Call / Put) and its strike price and the exchange identifier. The expiry date needs to be computed from complementary information. We also extract mid quotes of 14:30 p.m along with the corresponding stock prices. We extract data at this point of the day because the highest value of options trading occurs around this time.

To start with, we set a reference time series of trading days from 02/06/2006 to 30/12/2009. In constructing the sample of DOOM options, we apply a number of selection criteria. We sort the data so that for a given put option, on a given trading day, we end up with the two lowest strike prices for the highest possible time to maturity. Maturities which are lower than 200 days are discarded. The combination of low strikes and high maturities is supposed to ensure that the put options are 'deep' enough and are struck within Carr and Wu 's (2011) default corridor. Indeed, As pointed out by the authors, we are not apt of identifying this corridor ex-ante because we do not have put quotes for a continuum of strikes. Therefore, we deal with the discrete nature of strikes by selecting the lowest (K1, K2) with non-zero bid quotes and non-zero open interest rate such that K2 > K1. The non-zero(mid) bid quote and non-zero open interest rate conditions are meant to ensure the option is actually traded. Another crucial condition for the model to be implemented is that the stock represents an upper barrier B for (K1, K2) and escalades to a lower barrier A= 0 upon default such that : A<K1<K2<B. In addition, the estimated delta of the American options of our sample is lower than 15% and is another condition to help identify options struck within the corridor. We apply this filtering procedure to a sample of 50 banks and obtain 15 banks which match the requirements for the model implementation. However, the assumption related to the non-penetration of 'default corridor' is intermittently violated by some banks of our sample. When

[20] We use the German government interest rate the spot interest rate found on Bloomberg

plotting the Strike prices (K1, K2) along with the underlying asset prices (B) of each bank, we observe banks that have asset prices which never penetrate the 'default corridor' throughout the whole period of our study namely : BARC, CNKG, CRDI,DBKG, KBC, , STAN,. And, banks for which the asset price penetration of the corridor is barely ostensible, this the case of : ERTS and CSGN. The plots which can be found in appendix A.2, describe the evolution of those three variables throughout our study period for each bank and so periods over which this particular assumption is violated can be visualized.

In addition, we retrieve over-the counter- CDS quotes at 5 years maturities due to their reliability.

An additional set of data is required for the estimation of the implicit government guarantee which is obtained by recovering the difference of an implicit put option from equity and implicit put option using a CDS derivative. For 12 banks of our sample we retrieve information from Bloomberg about equity prices, the number of shares outstanding and government bond yields, the S&P 500 index, quarterly book values of short and long-term debt. The implied equity risk premiums are downloaded from Damodaran website (http://pages.stern.nyu.edu/~adamodar/).

Statistics

The number of banks which match our filtering criteria amounts to 15 over a period of 3 years (2006 through 2009). At maturities which are no lower than 200 days, we have 1044 observation for each bank.

Table 3.1 Summary statistics

	Estimated Lambda	CDS	Stock	K1	K2
Mean	49,31	44,73	655,37	12,80	13,95
STD	63,70	61,06	1144,57	14,80	16,26
Q1	52,85	59,73	29,18	7,11	7,41
Median	79,21	73,38	64,12	11,61	13,55
Q3	128,58	116,26	230,64	29,80	33,91
Skew	1,13	1,77	3,36	0,57	0,57
Kurto	0,70	2,93	11,85	-1,20	-1,21
Min	23,34	49,84	12,18	1,13	1,24
Max	248,03	264,88	4430,91	42,20	47,52

Table reports statistics calculated based on the banks time series mean values for default arrival rates (%), CDS spreads and strike prices K1 and k2

Table 3.1 reports summary statistics calculated based on the banks' time series mean values for default arrival rates, CDS spreads and strike prices K1 and K2. The mean value for the CDS is 44 bp with a standard deviation of 61%. The strikes prices K1 and K2 have mean values of 12,80 and 13,93 and standard deviations of 14,80 and 16,26. The mean on the mean values of the stocks prices is around 66 with a high standard deviation of around 1144. This gives us an indication of the large differences among the banks of our sample.

Table A.2 in appendix reports statistics related to the strike prices of the DOOM put options used in the calibration of the model along with the underlying stock prices. Despite the fact that the banks composing our sample share the common feature of being large and/or systemically important banks, the descriptive statistics show considerable difference among these banks. A major difference has to do with the volatility of the stocks. The UK banks (Barclays, RBS and Standard Chartered) have on average the most volatile stocks. Dexia and KBC have the least volatile stocks. The same applies to the mean value of stock prices of these banks. RBS has the maximum stock value (4430.91) and BBVA has the lowest (12.18). Interestingly, In terms of mean, the British banks also have very low strike prices together with German banks : STAN (0.77,094) ; BARC(1.3, 1.40); RBS (4.86, 4.93) , DB (1.97,1.96); CBKG(0.59, 0.67). Another estimate worth of comparison is the skew statistics. This estimate is negative for the put option of some banks suggesting that investors perceive a downward risk and seek protection by buying put options.

3.5 Empirical Results

Table 3.2 describes the summary statistics of estimated and historical default arrival rates. There are visible differences in the estimates of each bank.

The mean for the estimated default arrival rates ranges from 248% to 23%. According to the descriptive statistics the banks with the most volatile stocks and the deepest out of the money strike prices are not necessarily the banks for which the default arrival rate is highest. The first set of results reported in table 3.2 is characterized by dramatic differences across banks. The highest mean values of estimated default rates are registered by CSGN (248%), Barclays (197%), STAN (153%), whereas the lowest mean values are registered by CBKG (23%), ERSTE (30%).The mean value computed based on the cross section of the default arrival rates mean value of the banks of our sample is around 49%. When computing summary statistics based on the mean estimates of all bank, we obtain a standard deviation from the mean of 63,70 % which indicates that there are considerable differences in the level of default arrival rates across banks.

The standard deviation values also give us an indication for the volatility of our estimates and hence the degree of variation in the credit risk of the banks composing our sample. The sharpest variations are observed for CAGRA, CSGN, KBC with standard deviations of 150.79, 149, 104.84 respectively and corresponding minimum and maximum values of (33;609),(44;656),(14;539). (table3)

Table 3.2. Summary statistics of estimated, historical default arrival rates

Bank	Variable	Mean	Median	STDEV	Min	Max	Q1	Q3	Skew	Kurto
Barclay	Lambda E	**167,34**	197,08	89,80	28,31	322,31	76,96	253,60	0,08	-1,49
	Lambda H	**116,01**	101,12	107,90	9,08	435,20	14,38	198,84	0,74	-0,49
BBVA	Lambda E	**52,42**	28,29	52,45	13,56	301,85	23,14	63,72	2,80	8,93
	Lambda H	**156,51**	155,00	42,79	70,64	295,60	130,00	171,67	0,72	0,66
CAGRA	Lambda E	**187,86**	121,59	150,79	33,59	609,25	50,73	311,32	0,78	-0,55
	Lambda H	**83,07**	71,26	69,69	9,72	276,12	12,22	142,03	0,33	-1,32
CBKG	Lambda E	**23,34**	16,48	24,38	4,28	320,68	11,65	28,76	6,23	62,02
	Lambda H	**89,78**	98,66	66,87	13,09	274,16	20,32	138,14	0,41	-0,90
CRDI	Lambda E	**74,55**	72,27	32,52	25,69	170,67	41,35	91,73	0,61	-0,25
	Lambda H	**100,67**	84,16	86,11	12,46	460,39	20,50	158,85	1,03	1,05
DBKG	Lambda E	**50,64**	43,85	35,93	12,63	265,08	23,72	60,04	2,01	6,19
	Lambda H	**98,42**	91,95	75,66	15,92	286,66	21,74	159,21	0,44	-1,08
DEXIA	Lambda E	**71,07**	59,85	52,92	12,24	208,53	27,09	96,01	0,96	-0,15
	Lambda H	**444,36**	401,38	138,44	160,00	983,33	320,47	522,83	0,78	-0,20
ING	Lambda E	**88,32**	65,88	64,48	21,80	281,80	36,17	108,55	1,29	0,81
	Lambda H	**119,09**	115,35	77,47	9,54	305,03	50,80	172,27	0,20	-0,82
KBC	Lambda E	**103,67**	50,48	104,84	14,26	539,87	28,55	162,90	1,65	3,06
	Lambda H	**328,98**	366,67	120,54	96,25	570,83	247,81	429,17	-0,47	-0,84
RBS	Lambda E	**79,21**	68,83	45,76	33,36	240,99	53,92	87,72	2,01	4,13
	Lambda H	**122,31**	107,80	112,80	6,61	508,16	12,40	214,18	0,57	-0,70
UBS	Lambda E	**88,32**	65,88	64,48	21,80	281,80	36,17	108,55	1,29	0,81
	Lambda H	**174,92**	160,04	135,66	9,33	607,80	54,81	230,22	0,85	0,38
BNP	Lambda E	**53,29**	38,26	36,64	12,13	223,04	22,35	72,85	0,99	0,70
	Lambda H	**86,58**	94,43	49,95	10,95	239,21	48,09	119,66	0,07	-0,54
CSGN	Lambda E	**248,03**	237,67	149,79	43,89	656,58	117,34	360,86	0,51	-0,75
	Lambda H	**143,26**	131,35	94,17	18,33	443,81	76,11	194,79	0,68	-0,04
ERSTE	Lambda E	**30,23**	23,72	22,17	4,05	133,18	16,43	33,71	1,53	2,53
	Lambda H	**212,62**	205,91	170,51	18,06	803,36	59,17	307,47	0,99	0,95
STAN	Lambda E	**153,48**	135,30	47,21	99,91	265,42	118,58	166,00	1,04	-0,10
	Lambda H	**238,59**	222,50	124,84	93,50	583,33	129,79	292,71	1,01	0,28

Table 3.2 reports summary statistics of the Estimated , historical default arrival rates and CDS spreads for each bank. Respectively Lambda E, Lambda H over the period of January 2006 to December 2009. Lambda E whereas Lambda H is expressed in %

The plots displayed in Figure 3.1 clearly show that the estimated default arrival rates constitute a less noisy measure than the historical default rates. The historical measure being largely based on information stemming from the CDS market is bound to have liquidity issues leading to noisy information. Therefore, combining information from the CDS market together with information from the put option market appears to improve the quality of information about the default risk of the financial institution composing our sample.

In the following section we discuss the patterns observed in our estimated default arrival rates and confront them to major events of the financial turmoil that marked the period of our study 2006 - 2009. We do so with a view to finding evidence of the ability of our estimates co move with the patterns of the financial markets or provide warning signals as to the deterioration of the credit profile of the financial institutions.

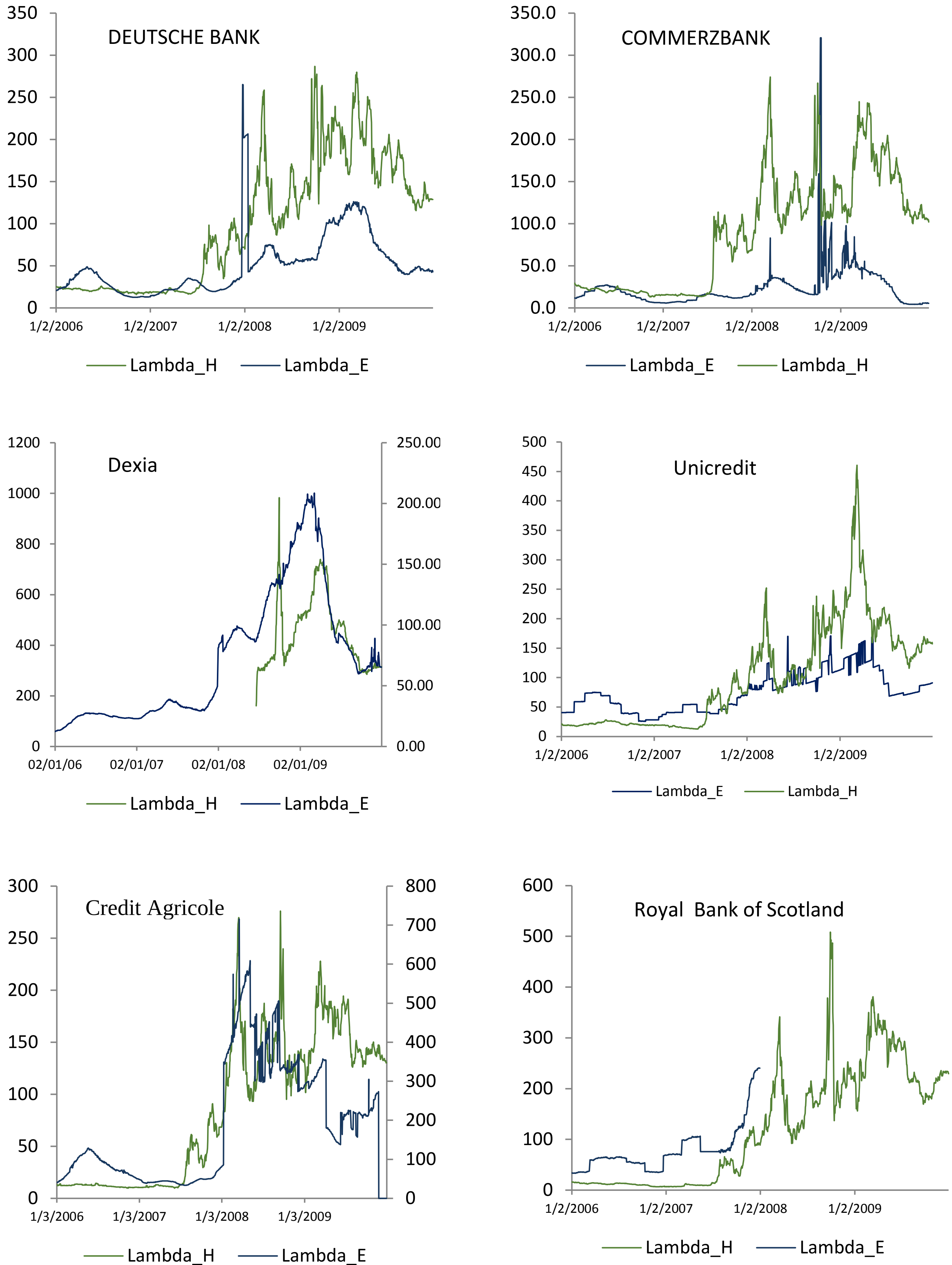
Figure 3.1 shows that the default arrival rates increased around beginning of 2007 which precedes the start of the credit crunch with BNP Paribas being the first bank to declare exposure to subprime mortgage risk through the collateralised debt obligations. In the following month, the British bank Northern Rock (albeit not part of our sample) faces liquidity strain and causes the first bank run in Britain in 150 years. Banks displaying heightened default arrival rates include Deutsche Bank, Dexia, Unicredit, Barclays, , Erste Group Bank, Credit Suisse. For RBS and Standard Chartered, the increase in the estimate before the credit crunch is slightly less stable but still intelligible.

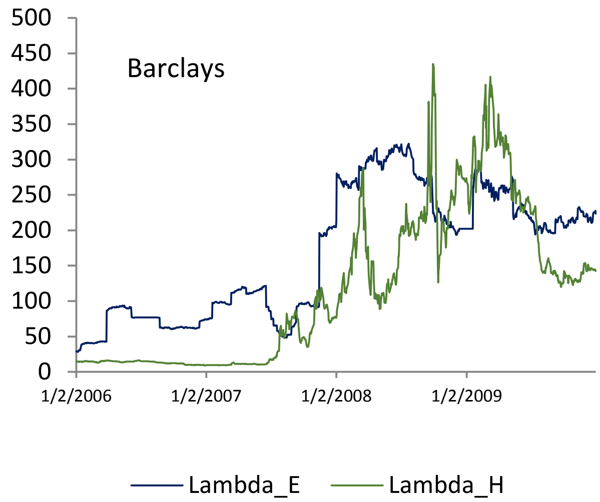
In the case of BNP Paribas, we do not observe an increase in our credit risk estimates prior to the burst of the credit crunch crisis. Admittedly, this may be due to the fact has BNP Paribas already announced its troublesome situation with regard to the valuation of CDOs to the financial markets thus becoming one of the institutions which played a major role in triggering the subprime crisis.

More pronounced spikes occurred in early 2008, Before Lehman Brothers spread off panic in the financial markets worldwide by filing for bankruptcy. We observe the spikes notably for Credit Agricole, BNP, Credit Suisse and BBVA. Over this period, the subprime crisis in the US was intensified by a series of events, the most consequential being the purchase of Bearn Stern by JP Morgan in March 2008 ,followed by the US government bail-out of Fanny Mae and Freddie Mac in September prior to the collapse of Lehman Brothers the same month. In the particular case of RBS where we only possess data for 2006 and 2007, we observe a sharp and abrupt rise of default arrival rates towards the end of 2007. RBS happens to be one of the banks which were bailed out in October 2008 by the British government to prevent a collapse of the banking sector in the UK. The observation of spikes prior to the intensification of the crisis suggests that our estimated default arrival rates could potentially send early warning signals. In the case of some banks no spikes are observed but the increase in our estimates is very clear and the trend appears more upward than downward for the following months (Barclays, UniCredit, ING Group) .Hence, when not providing early warning signals, our estimates reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks.

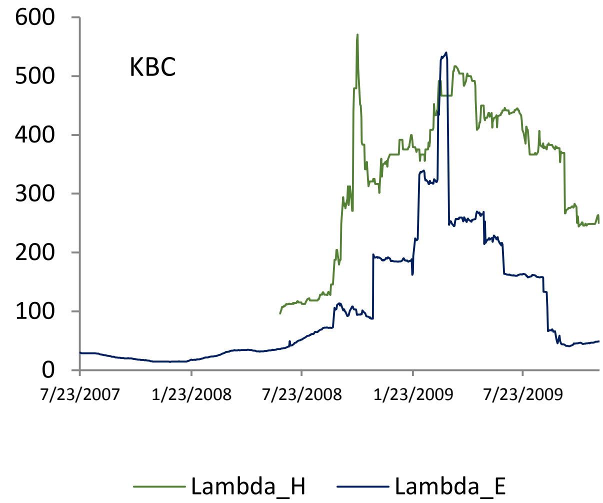
Sharp spikes are also observed towards the beginning of 2009. However for most banks the default arrival rates appear to decrease gradually after the increase or stabilize towards the end of the year. One should note that this period was marked by the start of recovery of European banks thanks to the various interventions carried out by governments and central banks. An example of such interventions is the 5tn dollars global stimulus package issued on the G20 meeting in April2009. However, an interesting observation emerges for 2009. Indeed BBVA displays a trend upward throughout year. This coincides with the Spanish sovereign being hit during the sovereign debt crisis starting in October in Greece. One could argue that the rising default arrival rates of BBVA suggests the worry of the markets about a struggling sovereign potentially unable to bail out their banks.

Figure 3.1. Plots of Estimated versus Historical Default

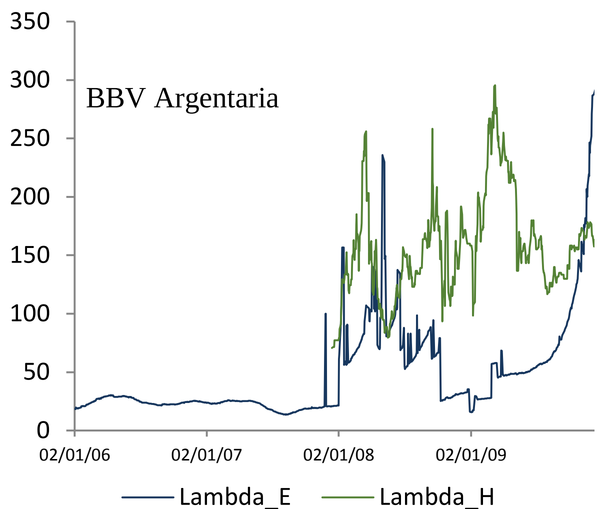




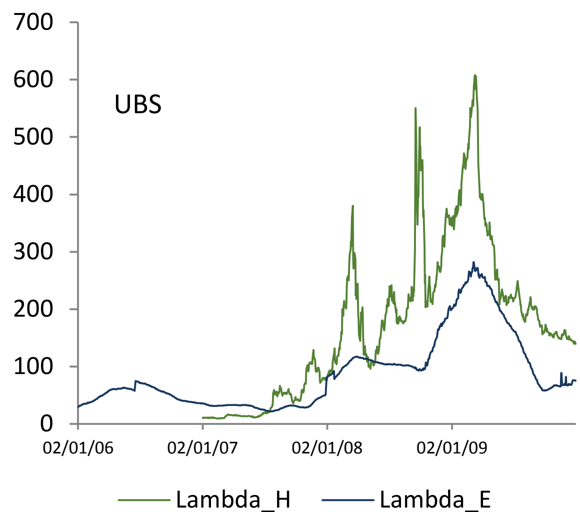
Barclays
500
450
400
350
300
250
200
150
100
50
0
1/2/2006
1/2/2007
1/2/2008
1/2/2009
Lambda_E
Lambda_H



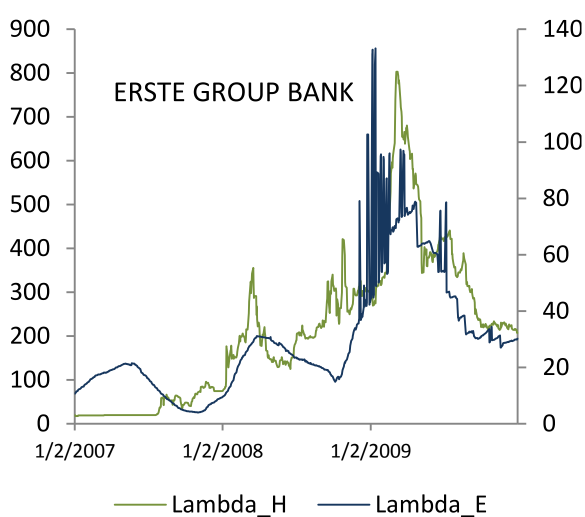
KBC
600
500
400
300
200
100
0
7/23/2007
1/23/2008
7/23/2008
1/23/2009
7/23/2009
Lambda_H
Lambda_E



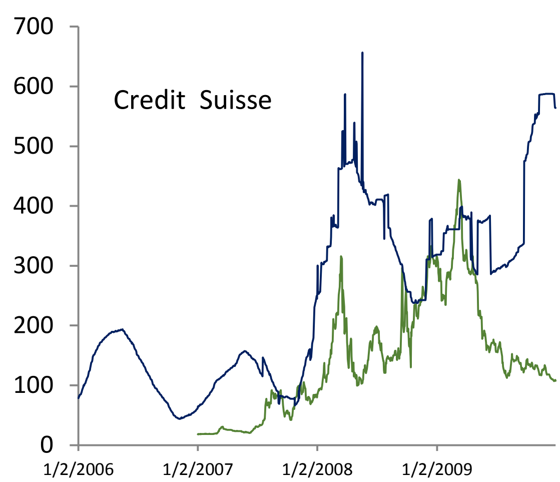
BBV Argentaria
350
300
250
200
150
100
50
0
02/01/06
02/01/07
02/01/08
02/01/09
Lambda_E
Lambda_H



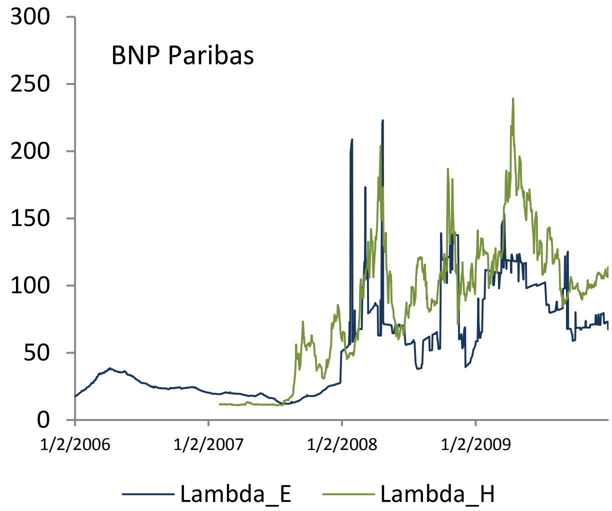
UBS
700
600
500
400
300
200
100
0
02/01/06
02/01/07
02/01/08
02/01/09
Lambda_H
Lambda_E

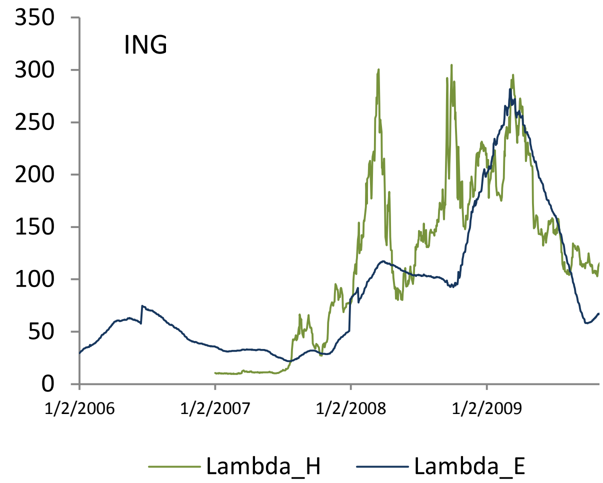


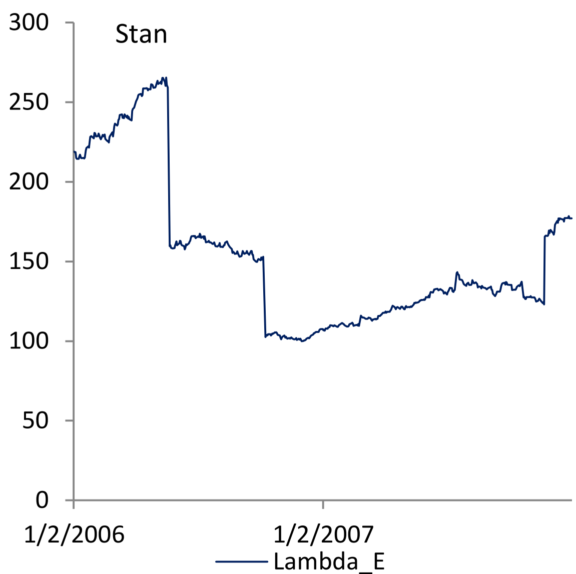
ERSTE GROUP BANK
900
800
700
600
500
400
300
200
100
0
140
120
100
80
60
40
20
0
1/2/2007
1/2/2008
1/2/2009
Lambda_H
Lambda_E



Credit Suisse
700
600
500
400
300
200
100
0
1/2/2006
1/2/2007
1/2/2008
1/2/2009







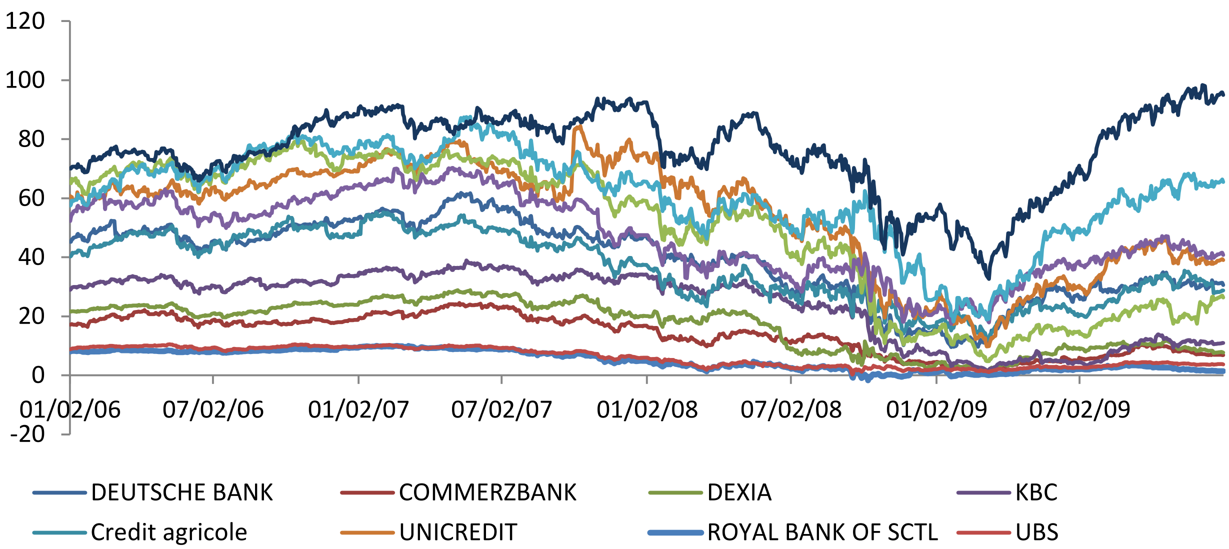
The second part of our analysis involves the estimation of financial government guarantee[21]. The purpose of that is to look at the extent to which this component help explain the differences in levels between the estimated and historical default arrival rates. Government guarantee also help explain the dramatic differences across the banks of our sample. The level of financial guarantee provided by the governments -reflecting primarily the ability of a sovereign to bail out a troubled

[21] The estimation of the government guarantee involves the estimation of a faction alpha (α) $such\ that\ \alpha(t)P_E\ (t)$. While the alphas should never be negative from a conceptual viewpoint .This factor takes a negative value for a very limited number of observations in our sample but it worth pointing out reasons which may be at the origin of this deviation from theory, these include: Differences between the put option values of the Merton model may differ from the put option values from CDS spreads due to, e.g., illiquidity in CDS markets, distortions in pricing due to irrational behaviour, recovery value perceived as different from the 40% used in pricing CDS, the effects of government interventions such as capital injections that dilute banks' equity.

blank- plays a role in reducing the default risk of the bank. Figure 3.2 represents the times series plot of the Government guarantees.

Around the beginning of 2008 we observe a rise in levels which supposedly reflects the intervention of European governments to prevent banks from suffering the effect of the US credit crunch. The rise in level is however more pronounced towards the beginning of 2009, a period where the financial crisis repercussions spread to Europe and were amplified by the start of the sovereign debt crisis.

Figure 3.2. Plots of Government guarantees



The Government guarantees which represents the government implied liability and is calculated as alpha*equity put option where alpha is factor defines as (1- Put on CDS/ Put on equity)

Table 3.3 reports regression analysis (Equation 9 through 11) relating to the government guarantee component. The First equation (9) relates differences between estimated and historical default arrival rates to government guarantees. The coefficient is negative and significant. The higher the level of guarantee, the lower the difference in levels between the two types of default arrival rates. This is in line with the fact that CDS spreads represent the default exposure of the bank after taking into account the government guarantee. Put differently, a higher government guarantee, results into a lower the CDS spread, and so we obtain a lower historical default arrival rate which in turn reduces the differences between the historical and estimated default arrival rates. Equation (10) and (11) verify the relationship between the government guarantee variable and default risk indicators, namely our estimates of default arrival rates and CDS spreads. In both instances we find strong evidence of the expected relationship (negative and significant coefficients), that is, banks with higher guarantees have less default risk.We introduce size and an indicator of the risk appetite of the European financial markets and our results remain unchanged.

Table 3.3. Regression results of equations 9 through 11

Variable	Coefficients	
	Model 1 (| $\Delta\lambda$ |)	
GG	-2.426*** (0.000)	-1.696*** (0.000)
VSTOXX	-	-0.002 ** (0.014)
Size	-	0.883 *** (0.000)
R-squared	*0.164*	*0.175*
	Model 2 (Lambda)	
GG	-3.340*** (0.000)	-0.995 *** (0.000)
VSTOXX	-	-0.002 *** (0.000)
Size	-	0.598 *** (0.000)
R-squared	*0.316*	*0.381*
	Model 3 (CDS)	
GG	-3.216 *** (0.000)	-0.412 *** (0.000)
VSTOXX	-	-0.002 *** (0.000)
Size	-	1.473*** (0.000)
R-squared	*0.473*	*0.655*

Table 3.3 reports fixed effect panel[22] regression results over the period 2006-2009. The depend variables are:$|\delta\lambda|$,$\delta Lambda_{Eit}$ and δs_{CDSit}Where $|\delta\lambda|$ is the difference between the estimated and historical default arrival rates in absolute value (Lambda E – Lambda H); $\delta Lambda_{Eit}$ is the estimated default arrival rate of bank i in first differences at time t and δs_{CDSit} its CDS spread in first differences. The independent variables are: GG_{it} , size and VSTOXX $\delta GG_{it}$is the government guarantee in first differences computed as (alpha*equity put option); Size as measured by market capitalization and VSTOXX which as measure of the risk appetite of the financial markets.

[22] We run the fixed effect model after performing Haussman test

3.6 Conclusion

The contribution of this work is twofold. First, we contribute to the literature linking CDS spreads to put options. Second, and more importantly we exploit the theoretical link between these two derivatives to estimate the default arrival rate in a novice way. We do so with a specific focus on European the banking sector to gauge its credit riskiness. Altogether, our results indicate that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks but can serve, at times, as early warning signals. Furthermore, our findings suggest that higher financial guarantees from their sovereign display a lower default risk and hence have a lower CDS spread along with a lower estimated default arrival rate. Ultimately, the government guarantee explains the differences in the level of estimated default arrival rates across banks as well as the observed differences between estimated (i.e derived from Carr&Wu ‘s model) and historical (CDS spreads scaled by (1-recovery rate)) default arrival rates.

A practical goal of the paper is to verify whether combined with information from the CDS market, DOOM put options could prove to be an alternative indicator of credit deterioration instead of solely relying on CDS derivatives deemed to have an opaque nature

Chapter four

Euro at Risk: The Impact of Member Countries' Credit Risk on the Stability of the Common Currency*

4.1 Introduction

In view of the current sovereign debt crisis, understanding the dynamics of the credit risk of the euro-area countries proves urgent so as to prevent dire scenarios. At worst, the default of a major country would unleash the currency break-up, ravage the European banking system and ultimately engender a global economic slump. In this study, we view the Eurozone sovereign debt crisis through the twin lenses of sovereign credit swaps and currency option markets. In the absence of Eurobonds, we empirically examine the impact of the credit risk of member countries on the stability of the Euro.

The credit risk of a country can be measured through its sovereign credit default swap (CDS)[23]. Market prices of CDS spreads reflect the perception of financial markets about the economic-political stability of a country, and thus about the creditworthiness of a given sovereign. As shown by Pan and Singleton (2008), the changes in credit risk premiums of sovereign markets which translate into changes in sovereign CDS spreads, do not emanate from changes in fundamentals of

[23] A sovereign CDS contract provides protection against the non-payment of sovereign debt. Typically, it involves one counterparty agreeing to sell protection to another. The "protected" party pays a yearly premium known as the CDS spread in exchange for a guarantee that in the event of a default, the seller of protection will provide compensation.

the underlying economies. Rather, these variations mirror a change in the risk appetite of market participants in terms of credit exposure. A negative change in the creditworthiness of a sovereign inevitably translates into a depreciation of its currency along with soaring currency volatility. Furthermore, currency option prices are instruments which are capable of predicting the changes in the realized volatility of currency returns. Based on data from the Mexican and Brazilian Markets, Car and Wu (2007) establish a relationship between sovereign CDS spreads and currency return volatilities induced through implied-volatilities of currency options and risk reversals[24]. Their results indicate that the sovereign CDS spreads covary substantially with the risk reversals. In the same spirit, Hui and Fong (2011) report similar results while focusing on the interconnectivity between the US and Japan sovereign CDS markets and the currency option market characterized by risk reversals of options on the dollar-yen exchange rate. Compared to Japan, The US sovereign credit risk is shown to have a significant impact on the risk reversal. Therefore it is deemed to play a more significant role in the way markets form expectations on the dollar-yen exchange rate.

Turning to the European context, Hui and Chung (2011) document information transmission from the sovereign CDS market to the currency option market. Using implied volatilities of options on the dollar-euro exchange rate as a measure of crash risk, they conclude that the credit risk of the Eurozone is a distinct factor which determines the prices of the out-of-the-money euro put options prices. The recent Eurozone crisis is viewed from various angles by the literature. Azerti et al. (2011) and Alfonso et al. (2011) use the perspective of credit rating agencies and show that sovereign rating announcements have spillovers effect on the European financial markets. They firstly study the response of sovereign CDS spread, banking stock index, insurance stock index and country stock while they secondly focus on the response of government yield spreads. Either way news about downgrades is found to have significant spillover effects. However, the linkages with currency option markets are not considered. Another perspective is that of Calice et al. (2011) who analyse the Eurozone crisis by modelling liquidity in the sovereign CDS markets. They find evidence that the liquidity of CDS markets of struggling countries such as Greece, Portugal and Ireland has a substantial impact on sovereign debt spreads. An earlier strand of literature tackles

[24] Risk reversal is the difference in volatility (delta) between similar out-of-the-money call and put options. A positive risk reversal implies that market participants are expecting an appreciation rather than a depreciation of the local currency. The risk reversal conveys information about the skewness of the exchange rate distribution.

the question of currency crash risk from a macro-economic angle and explains currency crash risk by economic fundamentals. It provides empirical evidence from developing countries of a relationship between macro-economic indicators and weak currencies. Countries with weak fundamentals are less likely to be able to defend their currencies against speculative attacks (Wolff (1987), Eichengreen et al. (1996); Frankel and Rose (1996); Kaminsky et al. (2003) are a few examples).

Our study also relates to a recent strand of literature which attempts to link currency crash risk to the distribution of exchange rate. Notwithstanding the sound models and explanations established by this strand, it does not take into account sovereign credit risk. Brunnermeier et al. (2009) detect negative skewness in the movements of exchange rates involving a low-level interest rate currency and a high-level one. This boils down to saying that carry trade strategies are exposed to crash risk. The authors argue that the skewness is triggered when such strategies take place in an abrupt manner reflecting lower risk appetite and higher liquidity constraints. Currency risk with respect to Carry trade strategies are also examined in work by Fahri et al. (2009).The main risk of these strategies emerges from the value of the exchange rate at the end. The authors propose an exchange model to distinguish between "disaster" and "Gaussian" premia in the currency option markets. The model entails a strong relationship between interest rates, changes in exchange rates and levels of risk reversals. The main empirical implication indicates that disaster premium explains 25% of carry trades returns. In others words, crash risk drives currency returns considerably. Other papers, which find a similar result by analyzing crash risk from the perspective of currency options include the work of Jurek (2009) and Burnside et al. (2011).

Moreover, our study is related to the literature examining the linkage between corporate CDS and stock option markets and the information transmission inherent to these markets. Examples include work by Acharya and Johnson (2007), which presents empirical evidence on the existence of information transmission from the corporate CDS to the stock market. This phenomenon is detected for firms which were subject or are likely to be subject to negative credit news and which maintain strong ties with banks. The analysis of the relation between CDS spreads and implied-volatilities in the work of Cao et al. (2010) shows that the information embedded in the implied volatilities of deep out of the money put options is able to explain the variations in CDS spreads. The skew of the implied volatilities is also computed so as to examine its effect on CDS spreads.

Important to note is the fact that this implied volatility is related to the negative tail of the risk neutral probability. Besides, the information embedded in it reflects both future volatility and risk premium.

In an effort to shed more light on the current sovereign debt crisis, our study proposes the use of a sound and state-to-the art measure to assess the stability of the Euro. Based on the framework of Bakshi et al. (2003), the stability of the euro is examined by decomposing dollar-euro[25] exchange rate options into the moments of the risk-neutral distribution. The method is partly used in the recent empirical option pricing literature (see e.g. Bams et al. (2009) and Neumann and Skiadopoulos (2012)). In particular, we compute model-free risk-neutral volatility, skewness and kurtosis measures from the cross-section of currency option prices, which allow us to evaluate the stability of the euro. Skewness is typically interpreted as the euro crash risk, while risk-neutral kurtosis as the tail risk of the exchange rate distribution. The first measure gives an indication in which direction market participants are expecting the dollar-euro exchange rate to move. A negative skewness reflects concerns about a depreciation of the euro, which translates into the willingness of investors to pay a higher risk premium for put options relative to call options in order to obtain protection for the potential drop in value. Tail risk refers to the extreme events whose probability is low but whose impact on prices is large should they materialize. In particular, during the European sovereign debt crisis, we expect that possible concerns about the stability of the euro should be reflected in a negative skewness of the dollar-euro exchange rate options. The focus of this study is to examine the impact of the credit risk of Eurozone member countries on the stability of the Euro.

We document that changes in the creditworthiness of a member country on one day have a significant impact on the stability of the euro on the following day. On the one hand, an increase in member countries' credit risk results in an increase of the volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. On the other, we find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. Based on those results, we propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure and show that our results are robust to this change in measure. Noticeable is the fact the creditworthiness of countries with

[25] The quotation 'dollar-euro' refers to the amount of dollars needed to obtain one unit of euro.

vulnerable fiscal positions is the main, but not the only risk-endangering factor of the euro-stability. While the creditworthiness of the latter countries has a significant impact on the skewness measure (i.e. crash risk) and the stability indicators, healthier countries equally drive the relationship between the creditworthiness and the volatility as well as the kurtosis (i.e. tail risk) of the risk-neutral distribution.

The remainder of this paper is structured as follows: The next section outlines the conceptual framework. Section 4.3 describes the data and presents some summary statistics. Then, the methodologies with respect to the option pricing aspects and the regression analyses are explained. Subsequently, the empirical results are outlined and discussed. The last section contains concluding remarks.

4.2 A Conceptual Framework

In this section, we attempt to provide a conceptual explanation for the channels through which the sovereign CDS market might impinge on the currency option market. We build on the contingent claim balance sheet framework of (Gray et al. (2007)), which is an adaptation of Merton's contingent claim analysis to the sovereign context. Under this structure, the sovereign balance sheet in Figure 4.1, representing a combined balance sheet of the government and the monetary authority, can be expressed in terms of foreign currency units (here US Dollar) to analyze the values of assets and liabilities in an international context.

Figure 4.1. The sovereign balance sheet

Assets	Liabilities	
Foreign Reserves	Foreign-currency Debt	Default-free value of debt minus put option
Net Fiscal Asset		
Other Public Assets	Local-Currency Debt Base Money	Call option
- Guarantees		

Sovereign assets consist of foreign reserves, net fiscal assets and other public assets. The item "-guarantees" results from subtracting the guarantees to too-big-to-fail entities from both sides of the balance sheet. The value of local currency liabilities in foreign currency terms, $LCL_{€}$, which comprises local-currency debt and base money, can be viewed as a call option on sovereign assets (in foreign currency terms), $V_{€Sov}$. The strike price for this option, B_f, is the distress barrier for foreign currency-denominated debt, which is derived from the interest payments and promised payments on foreign currency debt up to time T in the future. Similar to the Black-Scholes-Merton pricing framework for equity, this call option can be expressed as:

$$LCL_{\$} = V_{\$Sov}\, N(d_1) - B_f e^{-r_f T} N(d_2)$$

With:

$$\mathrm{d}_1 = \frac{\ln(\mathrm{A}_{\$\mathrm{Sov}} / B_f) + \left(r_f - r_d + 0.5\sigma^2_{\$Sov}\right) T}{\sigma^2_{\$Sov}\sqrt{T}} \quad \text{and} \quad \mathrm{d}_2 = \frac{\ln(\mathrm{A}_{\$\mathrm{Sov}} / B_f) + \left(r_f - r_d - 0.5\sigma^2_{\$Sov}\right) T}{\sigma^2_{\$Sov}\sqrt{T}}.$$

Where r_f and r_d are the foreign and local interest rates, respectively, and $\sigma^2_{\$Sov}$ is the volatility of sovereign assets in foreign currency terms. The local currency debt and money are claims on sovereign assets. In principle, governments can always inflate or dilute local currency debt in case of distress, instead of defaulting on foreign currency debt. Therefore, local currency debt can be assumed to be junior while foreign currency debt is assumed to be senior[26]. In this line of thinking, local currency liabilities can be considered to be similar to equity issued by firms and multiplied by the exchange rate being the "market cap" of the sovereign[27].

The two unknowns that cannot be observed, but need to be computed are implied sovereign assets, $V_{\$Sov}$ and asset volatility $\sigma^2_{\$Sov}$. Asset volatility $\sigma^2_{\$Sov}$ can be derived by applying Ito's lemma to the pricing formula of the call option, suggesting a relationship with the volatility of sovereign "equity", $LCL_{\$}$:

[26] See Gapen et al. (2005) for a discussion on how it could be inconsistent to consider money and local currency debt as senior and sovereign currency debt as Junior.

[27] One can easily make the analogy between the value of local currency debt and the value of equity for a firm. If the market value of assets at time t is the sum of the market value of equity and market value on debt, then equity is modeled as a call option on the assets A with strike price B, which represents the promised debt payments.

$LCL_{\$}\ \sigma_{\$LCL} = V_{\$Sov}\sigma_{\$Sov}N(d_1)$

The local currency liabilities $LCL_{\$}$, can be directly computed from the sovereign balance sheet data using actual exchange rates. The volatility of local currency liabilities, $\sigma_{\$LCL}$, is a function of the volatility of the money base and local currency debt, as well as exchange rate volatility. In case the exchange rate is floating, exchange rate volatility is the major part of uncertainty. The model can be implemented similarly to the Merton model, solving the two equations with two unknown variables. The probability of default of the sovereign is given by N(-*d*2). In order to find the model-implied credit spread, we first need to find the current value of the risky debt with promised payments B_f. From the balance sheet of the sovereign, the value of risky debt D_f can be expressed as the difference between the asset value, $V_{\$Sov}$, and the value of the local currency liabilities $LCL_{\$}$. Then the yield-to-maturity of the risky debt is $y = \frac{\ln\left(\frac{B_f}{D_f}\right)}{T}$ and the model-implied "fair value" of the credit spread is equal to $s = y - r_f$.

The sovereign CCA model provides a framework for valuing sovereign foreign-currency debt, local-currency debt, foreign currency value of base money and local-currency debt. However, the CCA model is not only useful for the valuation of the different constituents of a sovereign's capital structure, but also for the valuation of other claims such as CDS on foreign currency debt. The book-based 'fair' estimates can be compared with market-based spreads of sovereign CDS's and relative value strategies can be employed. This makes it possible to benefit from capital structure arbitrage strategies using various instruments, FX options and sovereign CDS, in particular. Similarly to the relationship between the volatility skew implied by equity options and CDS spreads, a trade strategy on the sovereign capital structure is to trade currency against the CDS. A "fair value" CDS spread can be obtained from the contingent claims model using currency market information. If currency volatility is expensive relative to observed CDS spreads, resulting in a 'fair value' CDS spread being too high compared to the observed spread, a strategy is to sell currency volatility (e.g. a straddle) and to buy protection. If volatility declines or spreads widen the strategy earns money. Another strategy, if currency volatility is cheap relative to the observed CDS spreads, the strategy is to buy currency volatility and to sell protection. If volatility increases or spreads decline the strategy earns money. Many different sovereign capital structure arbitrage trading strategies are possible using a variety of instruments, including FX spot and forwards, FX options, local-currency debt, foreign-currency debt, CDS on foreign-currency debt, and inflation or indexed debt. These strategies are reasonable because exchange rates (which affect the value of local currency liabilities) tend to co-move with the credit spreads of foreign currency debt. As a result, sovereign capital structure arbitrage also ensures that relevant information from the sovereign CDS market is transmitted into the currency options market. For example, if the sovereign CDS spread increases, the "fair value" model-implied spreads appears to be cheap or the foreign currency appears to be undervalued, the strategy is to buy a put on the local currency and to sell protection. If the local currency subsequently depreciates the strategy earns money. In the European context, it suggests, that relevant information regarding sovereign distress risk might affect the stability of the Euro.

However, one might argue that there are several reasons why the sovereign CCA model is not applicable to European countries. First, countries have direct access to large and liquid markets to issue debt in their domestic currency and that is why European countries have only a relatively small amount of foreign currency debt. Moreover, countries from the Economic and Monetary Union (EMU) have only limited control over the money supply of the European Central Bank (ECB) and, therefore, the analogy between local currency liabilities and equity is not complete. However, countries like Greece are indebted in terms of a currency (the euro) that they cannot print on demand. This makes their local currency debt similar to foreign currency debt. Furthermore, the recent interventions of the European Central Bank give rise to the perception that the member countries jointly took over some control over the money supply. As a result, debt of the member countries can be partly considered to be senior debt, equivalent to foreign currency debt, and partly to be junior debt, equivalent to local currency debt. This suggests that the CCA framework can be used as an ad-hoc model for relative value strategies like sovereign capital structure arbitrage.

4.3 Data

We collect data on daily 5-year sovereign CDS spreads for 11 countries: Belgium, France, Germany, Netherlands, Austria, Finland, Greece, Spain, Italy, Ireland, Portugal. The source used to obtain the sovereign CDS quotes is Bloomberg's CMAT portal. In addition, we obtain a complete cross-section of daily over-the-counter dollar/euro option prices together with the underlying spot exchange rates, as well as interest rates for Europe and the US through Thomson Reuters' Tick History system. Our data sample covers the period from September 10th 2007 to January 31st 2012[28]. Our data underwent a rigorous cleaning process in order to obtain the final dataset.

Currency option prices

We obtain OTC European type dollar/euro option prices quoted in implied volatilities at fixed maturities. We used the 1, 3, 6 and 9 months maturity options, because they are the most frequently traded ones. The option quotes are in terms of implied volatilities for particular put and call deltas categories, which is a common industry practice. The different delta categories cover the complete moneyness range of the currency options, e.g out-of-the-money calls and puts at 10-15-20-25-30-35-40-45-delta and at-the-money-options at 50-delta. Using the available delta- and maturity categories of all option contracts, on each day, we fit a functional form to the observed implied volatilities of the options, which allows us to obtain implied volatilities for every possible delta-maturity combination. That allows us to calculate call and put option prices through the Black-Scholes model. Thereafter, on a daily frequency, we are able to derive the moments of the risk-neutral distribution of the dollar-euro exchange rate options.

Sovereign CDS spread

The sovereign credit default swaps, expressed in basis points, are traded at various maturities of up to 30 years. We retrieve the 5-years maturity quotes for the 11 euro-area countries in the analysis since they are the most liquid.

Summary Statistics

Table 4.1 portrays the summary statistics of individual countries' CDS spreads. We report summary statistics for the subprime crisis period and the sovereign debt crisis period separately. In line with previous research (Hui and Chung (2011)), we assume that October 14th 2009 was the onset of the European sovereign debt crisis. Therefore, the subprime crisis covers the period from

[28] However, we had to reduce the sample period for the regression analysis due to lack of reliable sovereign CDS data for certain countries before September 5th 2008. Nonetheless, our sample period still covers the subprime and the sovereign debt crises.

September 5th 2008 until October 13th 2009. The period starting on October 14th 2009 and ending at January 31st 2012 represents the sovereign debt crisis period.

Table 4.1. Summary Statistics: CDS spreads per country

	BE	FR	DE	NL	FI	AT	IR	ES	PT	GR	IT
Overall sample period *from 05/09/2008 to 31/01/2012*											
Mean	127	79	47	56	40	99	366	198	384	970	191
Median	115	69	41	46	33	85	255	188	266	688	162
Maximum	406	250	119	140	91	269	1192	491	1527	5047	592
Minimum	21	12	8	11	11	11	11	39	39	52	41
Std.Dev	84	54	24	29	19	48	270	115	366	1086	128
Skewness	0.99	1.35	1.10	1.04	1.03	1.27	0.46	0.55	1.03	1.54	1.54
Kurtosis	0.15	1.18	0.49	0.02	-0.07	1.40	-1.03	-0.83	-0.19	1.27	1.46
Q1	56	40	32	35	28	69	150	94	82	172	106
Q3	161	91	56	68	50	119	615	266	548	1040	199
Subprime crisis *from 05/09/2008 to 13/10/2009*											
Mean	67	42	38	59	41	107	140	89	81	160	113
Median	61	39	35	48	37	100	151	87	75	147	104
Maximum	157	98	91	129	90	269	386	169	161	298	199
Minimum	21	12	8	11	11	11	11	39	39	52	41
Std.Dev	33	20	19	31	20	56	111	29	29	62	45
Skewness	0.97	0.85	1.09	0.58	0.63	0.80	0.23	0.69	0.70	0.38	0.36
Kurtosis	0.21	0.34	1.12	-0.75	-0.32	0.92	-0.95	0.09	-0.34	-0.77	-1.11
Q1	39	26	24	34	25	72	11	68	57	118	75
Q3	80	55	46	86	58	138	219	100	97	212	158
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*											
Mean	156	96	52	55	39	95	474	250	529	1359	229
Median	139	79	44	46	31	82	555	242	445	925	180
Maximum	406	250	119	140	91	241	1192	491	1527	5047	592
Minimum	33	20	19	24	17	48	111	66	51	123	68
Std.Dev	86	56	24	28	18	43	256	105	364	1131	137
Skewness	0.61	1.03	1.03	1.33	1.25	1.58	0.01	0.12	0.57	1.12	1.16
Kurtosis	-0.51	0.13	-0.02	0.63	0.14	1.50	-1.24	-0.80	-0.90	-0.02	0.07
Q1	93	64	37	35	28	68	199	180	245	677	138
Q3	213	108	59	60	39	98	688	342	837	1751	248

Note: Entries correspond to Q1 (first quantile), Q3 (third quantile), BE (Belgium), FR (France), DE (Germany), NL (Netherlands), FI (Finland), AT (Austria), IR (Ireland), ES (Spain), PT (Portugal), GR (Greece), IT(Italy). Statistics are computed based on daily data and are expressed in basis points except for Skewness and Kurtosis. The total number of observations is 882 for the whole sample period , 288 for the first sub-period and 594 for the second.

Panel A shows the overall statistics for the full sample and reveals the obvious difference in the creditworthiness of the Euro member countries. Based on the CDS data[29], one might want to characterize certain countries as healthy countries with stable economic conditions and vulnerable

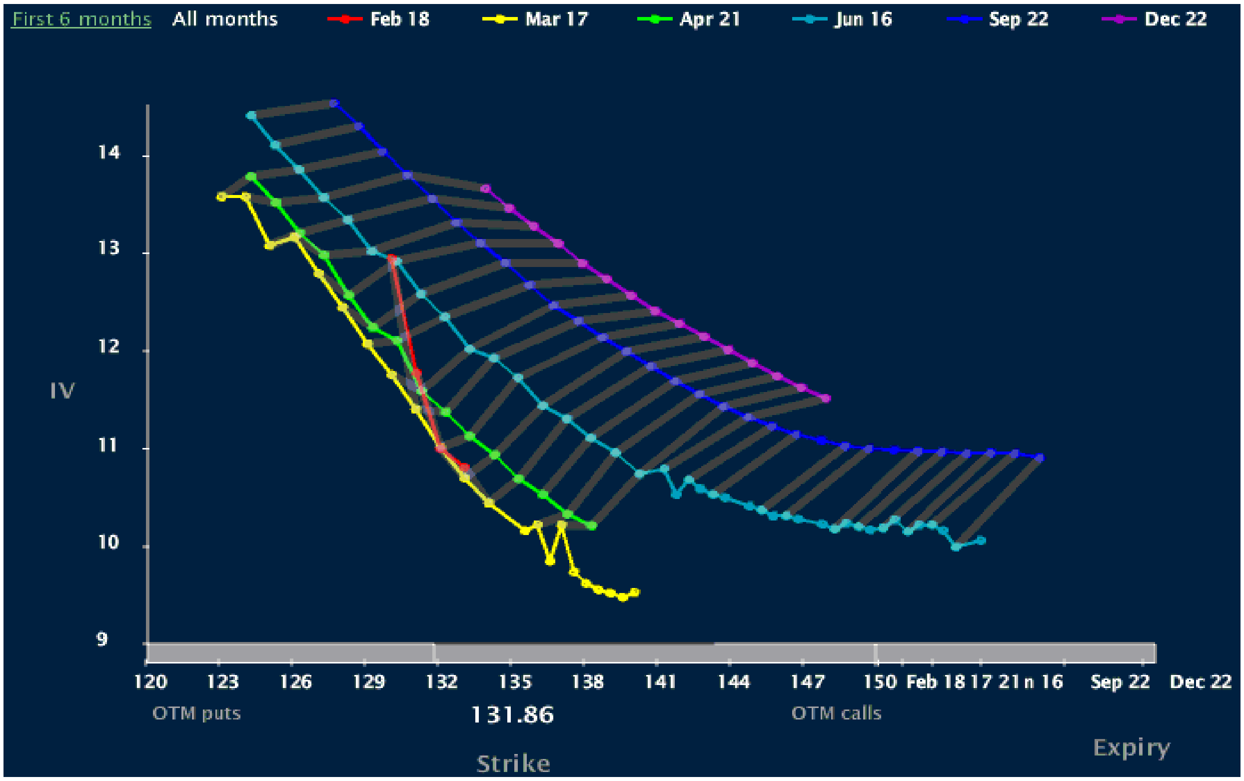
[29] We look at the average CDS for the entire sample period.

countries with fragile economic conditions. Following this logic, France, Germany, Netherlands, Finland and Austria would belong to the group of healthy countries. In contrast, Ireland, Spain, Portugal, Greece and Italy would belong to the group vulnerable country. We leave Belgium due to its political instability unclassified, while its CDS spread would suggest that it could be included in one of the groups. Panel B and Panel C allow us to compare the CDS spreads during the subprime crisis period and during the sovereign debt crisis. The summary statistics reveal substantial differences in the CDS spreads across countries. These differences are in particular pronounced during the sovereign debt crisis. While the average CDS spreads for the healthy countries shows only a slight increase during the subprime crisis, the increase in spreads was substantial for the vulnerable countries. As shown by panel C, the average value is 39bps for Finland and 1359 bps for Greece.

We also report in appendix (Table A.3 and A.4) summary statistics of the dollar-euro option prices quoted in terms of 10-delta and 25-delta implied-volatilities of calls and puts. The at-the-money options statistics are only reported once together with the put statistics. Summary statistics are presented for four different maturities. The statistics are computed over a sample period covering the subprime- and sovereign debt crisis period, ranging from September 5th 2008 until January 31st 2012. Overall, the implied volatilities for calls and puts increase with maturity and they are on average higher during the sub-prime crisis.

Figure 4.2 shows the dollar-euro option smile on February 14th 2012 for maturities of up to 9 months. The graph nicely characterizes the extreme shape of the smile, which characterizes the European sovereign debt crisis period. The smirk-type shape, typically observed for equity options, refers to the negative skewness in the risk-neutral distribution of the dollar-euro exchange rate and, therefore, proxies the crash risk of the euro.

Figure 4.2. Dollar-euro option smile on February 14th 2012 for various maturities



Source: www.fxoptions.com website

4.4 Methodology

It is industry practice to quote currency options in terms of implied volatilities at particular deltas. The Black-Scholes deltas of European-style call and put options are given by

$$\text{delta}_C = e^{-qT} N\left(\frac{\ln(Se^{(r-q)T} / K) + 0.5\sigma^2 T}{\sigma\sqrt{T}}\right) \tag{1}$$

$$\text{delta}_P = -e^{-qT}\left(1 - N\left(\frac{\ln(Se^{(r-q)T} / K) + 0.5\sigma^2 T}{\sigma\sqrt{T}}\right)\right) \tag{2}$$

where S is the dollar-euro exchange rate, K is the exercise, σ is the implied volatility of the option, r and q are the US and European risk-free interest rates corresponding to the time to maturity (T) of the option and N(.) is the cumulative normal distribution.

4.4.1 Estimating the implied volatility surface

For the empirical analysis, we first use a modification of the prominent ad-hoc Black-Scholes model of Dumas, Fleming and Whaley (1998) to estimate the implied volatility surface of our currency options. We use all available information content in currency option prices for different moneyness (deltas) and different maturities. The aim is to construct a time series of standardized measures (e.g. risk neutral volatility, skewness and kurtosis) that characterize the cross-section of prices and can be compared over time. Rather than averaging the two contracts that are closest to at-the-money or closest to one month maturity, we fit the modified ad-hoc Black-Scholes model to all option contracts on a given day and subsequently obtain the desired functional form of the implied volatility surface. This strategy successfully eliminates some of the noise from the data (see Christoffersen et al. (2010)). We allow each option to have its own Black-Scholes implied volatility depending on the options delta and time to maturity T. We use the following functional form for the options implied volatility:

$$IV_{i,j} = \alpha_0 + \alpha_1 \text{delta}_{C\,i,j} + \alpha_2 \text{delta}_{C\,i,j}^{2} + \alpha_3 T_j + \alpha_4 T_j^2 + \alpha_5 \text{delta}_{C\,i,j} T_j , \tag{3}$$

Where IV_{ij} denotes the observed implied volatility and $\text{delta}_{C,i,j}$, the delta of a call option for the i-th moneyness and j-th maturity, defined in Equation (1)[30]. T_j denotes the time to maturity of an option for the j-th maturity. It is common practice to estimate the parameters using standard OLS. For every call option delta (or put option delta) and maturity, we can compute the implied volatility and derive option prices using the Black-Scholes model. For example, the implied volatility for an at-the-money short term call option with three month maturity can be derived by setting delta equal to 0.5 and time to maturity T equal to 3/12.

[30] For put options, we use the corresponding put delta in the implied volatility regression.

4.4.2 Calculating the moments of the risk-neutral distribution

Having characterized the implied volatility surface of the dollar-euro exchange rate options, we calibrate the moments of the resulting risk-neutral distribution. Bakshi et al. (2003) derive a model-free measure of risk-neutral variance, skewness and kurtosis based on all options over the complete moneyness range for a particular time to maturity T.

Variance, skewness and kurtosis of the T-month risk-neutral distribution can be computed by

$$Variance_t(T) = e^{rT} V_t(T) - \mu^2$$

$$Skewness_t(T) = \frac{e^{rT} W_t(T) - 3\mu_t(T) e^{rT} V_t(T) + 2\mu_t(T)^3}{\left[e^{rT} V_t(T) - \mu_t(T)^2\right]^{\frac{3}{2}}} \tag{4}$$

$$Kurtosis_t(T) = \frac{e^{rT} X_t(T) - 4\mu_t(T) e^{rT} W_t(T) + 6 e^{rT} \mu_t(T)^2 V_t(T) - 3\mu_t(T)^4}{\left[e^{rT} V_t(T) - \mu_t(T)^2\right]^2}$$

where

$$\mu_t(T) = e^{rT} - 1 - \frac{e^{rT}}{2} V_t(T) - \frac{e^{rT}}{6} W_t(T) - \frac{e^{rT}}{24} X_t(T) \tag{5}$$

$$\mathrm{V}_t(T) = \int_{S_t^{-qT}}^{\infty} \frac{2(1 - \ln(K / S_t^{-qT}))}{K^2} c_t(T, K) dK + \int_0^{S_t^{-qT}} \frac{2(1 + \ln(S_t^{-qT} / K))}{K^2} p_t(T, K) dK$$

$$\mathrm{W}_t(T) = \int_{S_t^{-qT}}^{\infty} \frac{6 \ln(K / S_t^{-qT})) - 3\left(\ln(K / S_t^{-qT})\right)^2}{K^2} c_t(T, K) dK$$

$$- \int_0^{S_t^{-qT}} \frac{6 \ln(S_t^{-qT} / K)) - 3\left(\ln(S_t^{-qT} / K)\right)^2}{K^2} p_t(T, K) dK$$

$$X_t(T) = \int_{S_t^{-qT}}^{\infty} \frac{12\ln(K/S_t^{-qT})) - 4\left(\ln(K/S_t^{-qT})\right)^3}{K^2} c_t(T,K)dK$$

$$+ \int_0^{S_t^{-qT}} \frac{12\ln(S_t^{-qT}/K)) - 4\left(\ln(S_t^{-qT}/K)\right)^3}{K^2} p_t(T,K)dK \ .$$

The parameters correspond to the ones used in Equation (1) and (2). c and p refer to call and put prices. Again, rather than averaging the observed implied volatilities of all contracts that are closest to one particular maturity (e.g. 3 month), we derive the Bakshi et al. (2003) risk-neutral moments using the estimated implied volatility surface and the corresponding call and put prices. In the empirical analysis, we focus on the 3 months horizon and calculate the moments of the 3-months risk-neutral distribution.

4.4.3 Regression analysis

The first step in our analysis is to regress daily changes in credit default spreads of country i on contemporaneous and lagged changes in the various moments that we use to characterize the risk-neutral distribution as well as on lagged changes in credit default spreads in order to extract the residual component, hence, we estimate the following equations[31]

$$\Delta CDS_{i,t} = \omega^{Vol}{}_i + \sum_{k=0}^{5} \upsilon^{Vol}{}_{i,k} \Delta Vol_{t-k} + \sum_{k=1}^{5} \psi^{Vol}{}_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}^{CDS,Vol} \tag{6a}$$

$$\Delta CDS_{i,t} = \omega^{Skew}{}_i + \sum_{k=0}^{5} \upsilon^{Skew}{}_{i,k} \Delta Skew_{\ t-k} + \sum_{k=1}^{5} \psi^{Skew}{}_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}^{CDS,Skew} \tag{6b}$$

$$\Delta CDS_{i,t} = \omega^{Kurt}{}_i + \sum_{k=0}^{5} \upsilon^{Kurt}{}_{i,k} \Delta Kurt_{\ t-k} + \sum_{k=1}^{5} \psi^{Kurt}{}_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}^{CDS,Kurt} \tag{6c}$$

[31] We use log-changes for CDSs and simple changes for the other variables, which allow us to compare the results across countries.

We do this for up to five lags to absorb any contemporaneous information transmission and any lagged information transmission. In this way, we are able to identify the information arriving in the CDS market, which is not based on information that has been revealed in the dollar-euro options market. The resulting residuals ε_t can be interpreted as innovations in the CDS market relative to the risk-neutral moments that characterize the market conditions in the currency options market.

Subsequently, for each country i, we run a regression of changes in the moments of the risk-neutral distributions on lagged innovations in the CDS market and lagged changes in the variable itself, hence, we estimate

$$\Delta Vol_t = \tau^{Vol}{}_i + \sum_{k=1}^{5} \lambda^{Vol}{}_{i,k} \varepsilon^{CDS,Vol}_{i,t-k} + \sum_{k=1}^{5} \theta^{Vol}{}_{i,k} \Delta Vol_{t-k} + \mu^{Vol}{}_{i,t} \tag{7a}$$

$$\Delta Skew_t = \tau^{Skew}{}_i + \sum_{k=1}^{5} \lambda^{Skew}{}_{i,k} \varepsilon^{CDS,Skew}_{i,t-k} + \sum_{k=1}^{5} \theta^{Skew}{}_{i,k} \Delta Skew_{t-k} + \mu^{Skew}{}_{i,t} \tag{7b}$$

$$\Delta Kurt_t = \tau^{Skew}{}_i + \sum_{k=1}^{5} \lambda^{Kurt}{}_{i,k} \varepsilon^{CDS,Kurt}_{i,t-k} + \sum_{k=1}^{5} \theta^{Skew}{}_{i,k} \Delta Kurt_{t-k} + \mu^{Skew}{}_{i,t} \tag{7c}$$

For each of the risk-neutral moments, we examine $\beta^{Vol}{}_i = \sum_{k=1}^{5} \lambda^{Vol}{}_{i,k}$, $\beta^{Skew}{}_i = \sum_{k=1}^{5} \lambda^{Skew}{}_{i,k}$ and $\beta^{Kurt}{}_i = \sum_{k=1}^{5} \lambda^{Kurt}{}_{i,k}$ as measures of impact of countries' i credit risk on the risk-neutral moments of the dollar-euro exchange rate and, therefore, on the stability of the euro. A motivation and detailed discussion of the usefulness of this approach for testing transmission effects can be found in Acharya and Johnson (2007) and Berndt and Ostrovnaya (2008).

4.5 Empirical results

Figure 4.3 shows the annualized volatility of the daily 3-month risk–neutral distribution together with the dollar-euro exchange rate over the period from September 10th 2007 to January 31st 2012. Figure 4.4 shows the daily risk-neutral skewness and kurtosis of 3 month options calculated according to Bakshi et al. (2003). Interestingly, during the subprime crisis, the skewness is mainly positive and turns negative during the subsequent European sovereign debt crisis, with a turning point in October 2009, typically found to be the start of the sovereign debt crisis. Kurtosis was much higher and more volatile during the subprime crisis and reaches its peak in December 2008.

Figure 4.3. Dollar-euro exchange rate and annualized volatility of the 3-months risk-neutral distribution of options on the dollar-euro exchange rate

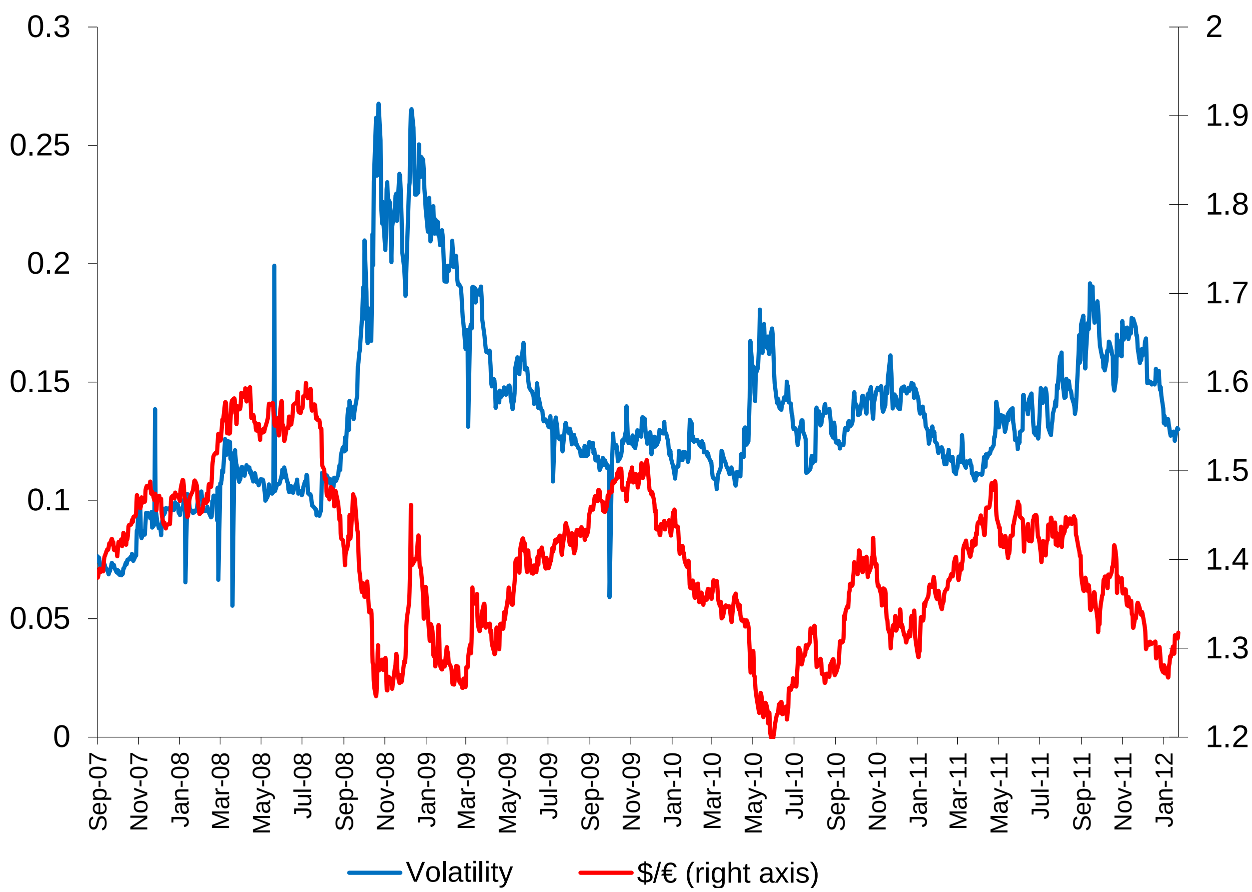
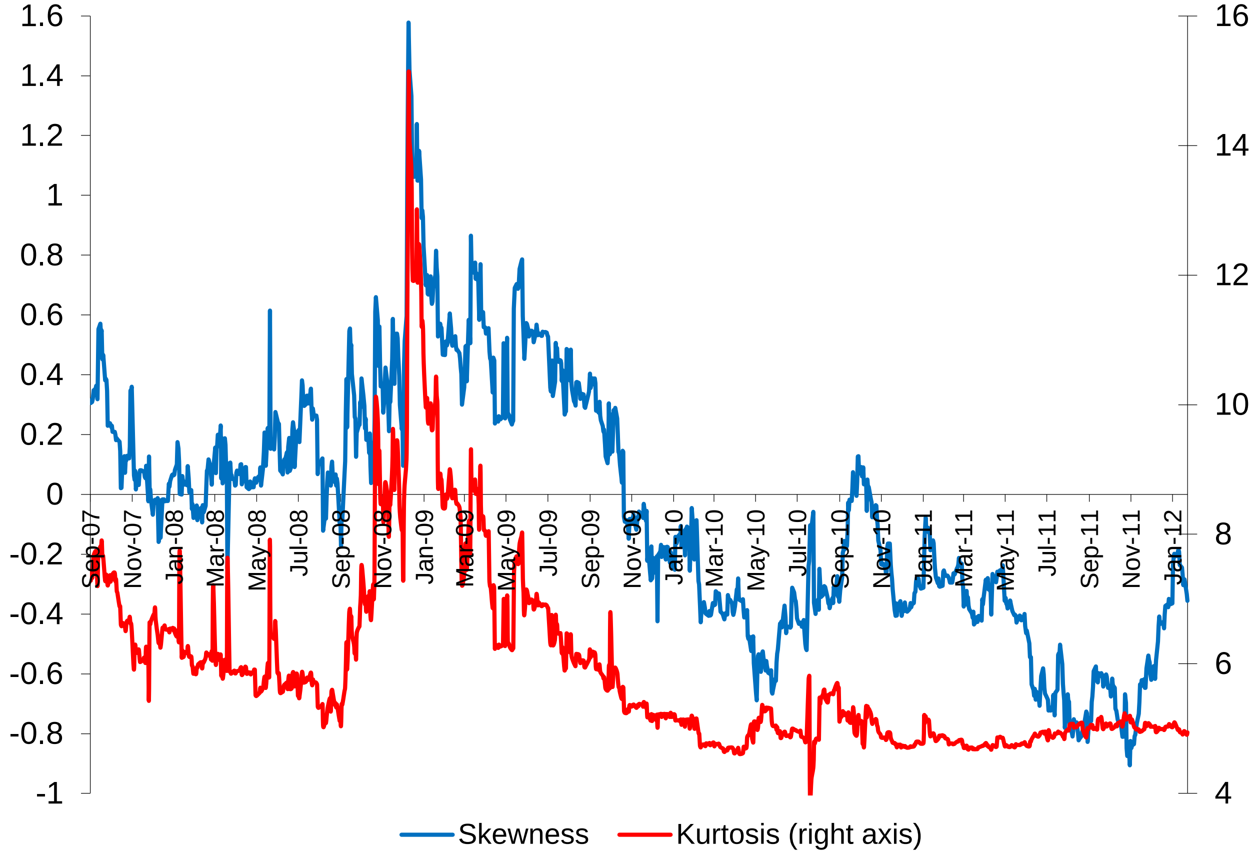


Figure 4.4. Skewness and kurtosis of the 3-months risk-neutral distribution of options on the dollar-euro exchange rate



Clearly, our risk neutral skewness measure is able to distinguish between turbulent times. During the subprime crisis, our measure is positive reflecting a possible depreciation (crash risk) of the Dollar. Towards mid-October 2009, the skewness measure turns negative, suggesting a change in the market expectations of the euro vis-à-vis the dollar. That is, markets expect the euro to depreciate, which translates into buying put options of the dollar-euro exchange rate. The lower kurtosis exhibited during the sovereign debt crisis is synonymous to "thinner" tails of the risk-neutral distribution of the dollar-euro exchange rate. Therefore, the tail risk of the two currencies seems to be priced in the US. The subprime crisis starting with the burst of the housing bubble in the US had a major impact on the US economy. Figure 4.4 shows that during the subprime crisis, not only the volatility of the dollar-euro exchange rate substantially increased, but the kurtosis of the risk-neutral distribution, our proxy for tail risk, increased as well. However, during the sovereign debt crisis period the volatility increased, but the tail risk of the two currencies is relatively stable at a low level.

Table 4.2. Summary statistics of risk-neutral moments and the dollar-euro exchange rate

	Exchange rate	risk-neutral Skewness	risk-neutral Kurtosis	risk-neutral Volatility
Subprime crisis *from 05/09/2008 to 13/10/2009*				
Mean	1.36	0.47	7.64	0.17
Median	1.36	0.45	7.06	0.16
Maximum	1.49	1.58	15.12	0.27
Minimum	1.25	-0.17	5.04	0.06
Std.Dev	0.07	0.25	1.75	0.04
Skewness	-0.07	1.06	1.34	0.41
Kurtosis	-1.22	2.57	2.05	-0.90
Q1	1.30	0.30	6.28	0.13
Q3	1.42	0.56	8.61	0.20
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*				
Mean	1.37	-0.37	4.99	0.14
Median	1.37	-0.36	4.96	0.13
Maximum	1.51	0.29	5.94	0.19
Minimum	1.19	-0.91	3.90	0.10
Std.Dev	0.07	0.23	0.25	0.02
Skewness	-0.16	-0.01	0.75	0.66
Kurtosis	-0.59	-0.22	1.62	-0.18
Q1	1.32	-0.54	4.78	0.12
Q3	1.42	-0.23	5.12	0.15

Notes: Statistics are computed based on daily data. The overall sample period spans from 05/09/2008 to 31/01/2012. The first sub-period (subprime crisis) is from 05/09/2008 to 13/10/2009 and the second sub-period (sovereign debt crisis) is from 14/10/2009 to 31/01/2012.Skew, Kurt and IV, respectively: Skewness, kurtosis and implied volatility are the independent variables.

Summary statistics of the dollar-euro exchange rate and the risk-neutral moments are displayed in Table 4.2[32]. The skewness measure is positive over the sub-prime crisis (0.47) but becomes negative during the sovereign debt crisis (-0.37) reflecting concerns of market participants about the stability of the euro. With respect to the kurtosis measure, the lower kurtosis exhibited during the sovereign debt crisis (5 versus 8 in the prior period) is synonymous to “thinner” tails of the risk-neutral distribution of the dollar-euro exchange rate and, therefore, lower tail risk

Table 4.3 summaries our regression analysis results. The reported betas refer to the sum of regression coefficients based on equations (7a) – (7c) and can be interpreted as a measures of impact of countries’ i credit risk on the risk-neutral moments of the dollar-euro exchange rate and,

[32] More detailed table in Appendix A.5

therefore, on the stability of the euro. For the complete sample period, the results suggest that member countries creditworthiness affects the volatility of the dollar-euro exchange rate. An increase in the CDS spreads, indicating worsening credit conditions, has a positive impact on the volatility of the exchange rate. However, the results for skewness and kurtosis are typically insignificant. Once we separate the period into a subprime crisis period and a sovereign debt crisis period, we observe significant differences over time. Looking at the subprime crisis period, our estimates have no statistical significance. The interpretation is that the credit risk of the euro-area member countries as measured by their CDS spreads does not affect the stability of the euro induced through the skewness (Skew) and kurtosis (Kurt) of the risk-neutral distribution of the dollar-euro exchange rate together with the risk-neutral volatility. In contrast, the results during the sovereign debt crisis period are quite pronounced. An increase in member countries' credit risk results in an increased risk-neutral volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. Furthermore, the impact for healthy countries is significantly not different to the impact for vulnerable countries. As result, both vulnerable and healthy countries have an impact on the stability of the euro in the way that higher levels of volatility are accompanied by lower levels of the exchange rate, and in turn, a weaker euro. However, we find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. Overall, the relationship is negative, suggesting that an increase in countries' credit risk has a negative impact on the stability of the euro.

With respect to the skewness measure, we find statistical significance only among countries belonging to the "vulnerable" group, namely: Ireland, Spain, Portugal and Italy. These coefficients are substantially negative, which entails that the struggling countries drive the euro crash risk. It can be shown that the betas for the healthy countries and the ones of the vulnerable countries are significantly different form each other at the 1% level. Additionally, we performed a principal component analysis on the CDS spreads changes of the healthy countries vis à vis the vulnerable countries. PCA_H refers to the first principal component of the first group and PCA_V refers to the first principal component of the second group. Results presented in Table 4.3 confirm previous findings and suggest that during the sovereign debt crisis period only the struggling countries drive the euro crash risk. Contrary to what one would expect, the creditworthiness of Greece does not seem to play a looming role in the stability of the common currency. This reflects the fact that currency option markets do not perceive the credit risk of Greece as a major determinant or risk factor for the stability of the euro.

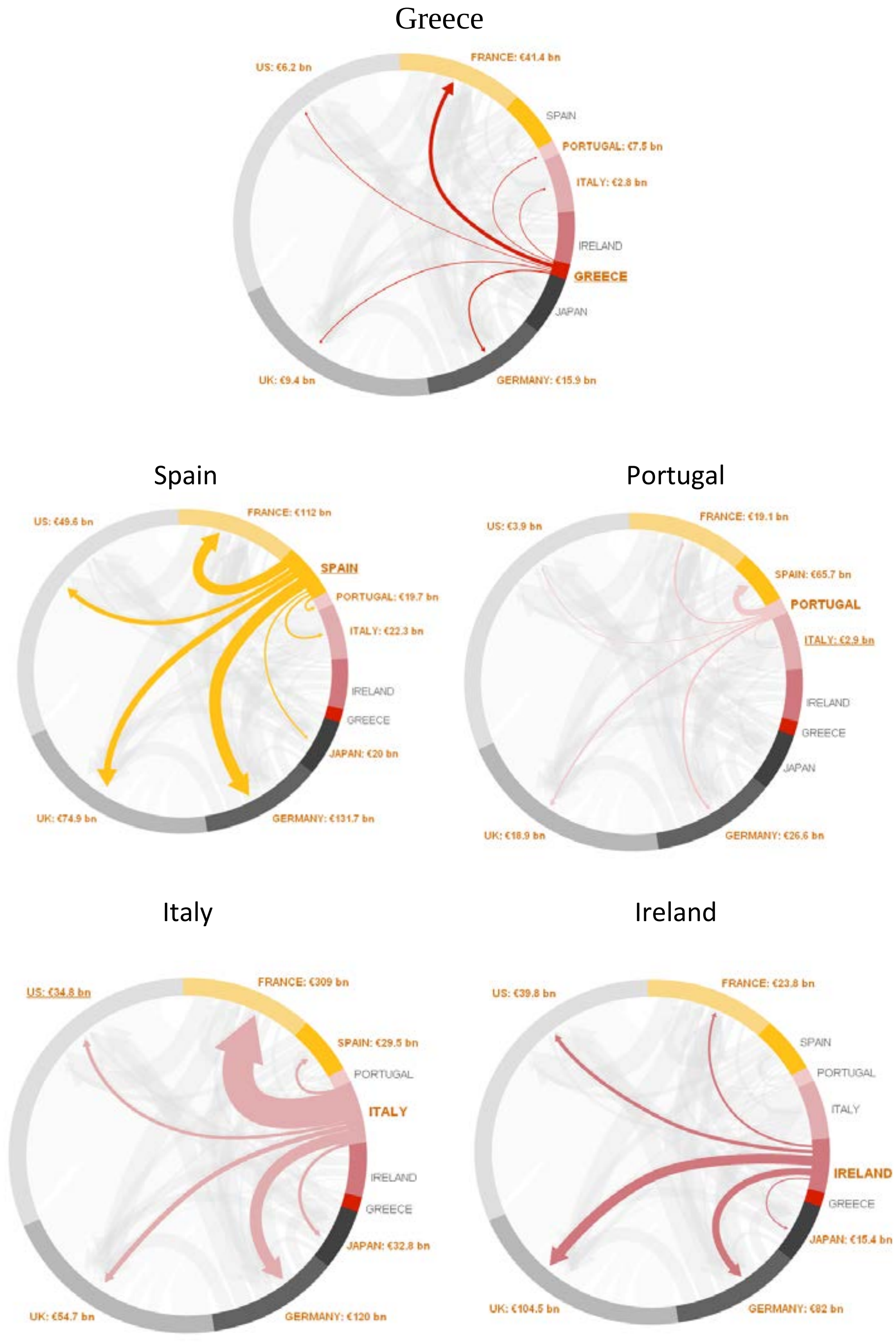
Table 4.3. Regression Results: Risk-Neutral Moments

	Skewness		Kurtosis		Volatility	
	Betas	T-stat	Betas	T-stat	Betas	T-stat
Overall sample period *from 05/09/2008 to 31/12/2012*						
Belgium	0.008	0.09	0.529	1.48	0.022***	2.37
France	-0.010	-0.11	0.634	1.69	0.029***	2.94
Germany	0.047	0.05	0.858**	2.20	0.024***	2.34
Netherlands	-0.020	-0.19	0.567	1.40	0.027***	2.64
Finland	-0.044	-0.39	0.423	0.94	0.024**	2.09
Austria	-0.001	-0.01	0.311	1.02	0.017**	2.14
Ireland	-0.082*	-1.84	-0.331*	-1.87	-0.003	-0.69
Spain	-0.074	-0.77	0.339	0.89	0.028***	2.82
Portugal	-0.049	-0.51	0.596	1.56	0.026***	2.66
Greece	-0.137	-1.45	0.135	0.36	0.013	1.37
Italy	-0.075	-0.75	0.608	1.53	0.033***	3.13
Subprime crisis *from 05/09/2008 to 13/10/2009*						
Belgium	0.089	0.54	0.569	0.76	0.016	0.93
France	0.082	0.43	0.774	0.89	0.034*	1.73
Germany	0.138	0.75	0.917	1.10	0.023	1.20
Netherlands	-0.005	-0.03	0.439	0.51	0.030	1.50
Finland	0.007	0.03	0.398	0.38	0.025	1.09
Austria	0.017	0.13	0.260	0.43	0.020	1.47
Ireland	-0.058	-0.86	-0.382	-1.26	-0.004	-0.63
Spain	-0.005	-0.02	0.272	0.26	0.028	1.16
Portugal	0.130	0.59	0.968	0.98	0.036	1.61
Greece	-0.100	-0.48	-0.120	-0.13	0.024	1.10
Italy	0.010	0.04	0.595	0.56	0.035	1.41
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*						
Belgium	-0.128	-1.26	0.538**	2.16	0.031***	2.81
France	-0.090	-0.99	0.420*	1.86	0.019*	1.94
Germany	-0.097	-0.92	0.698***	2.66	0.021*	1.80
Netherlands	-0.092	-0.85	0.657***	2.45	0.022*	1.84
Finland	-0.150	-1.37	0.481*	1.78	0.022*	1.89
Austria	-0.004	-0.04	0.421*	1.76	0.010	0.97
Ireland	-0.223**	-2.14	0.627***	2.43	0.016	1.40
Spain	-0.145*	-1.77	0.383*	1.89	0.024***	2.71
Portugal	-0.203**	-2.25	0.467**	2.10	0.018*	1.78
Greece	-0.134	-1.54	0.383*	1.80	0.008	0.87
Italy	-0.174**	-2.00	0.540***	2.51	0.030***	3.05
PCA_H	-0.045	-0.87	0.292**	2.25	0.011*	1.87
PCA_V	-0.099**	-2.14	0.275***	2.42	0.012***	2.34

It is interesting to confront these findings with figures published by the Bank for International Settlements (BIS). On a regular basis BIS publishes cross-border claims of BIS reporting European banks. The Eurozone member countries are interlinked throughout the foreign claims their national banks hold. Given this exposure, a default of one country would cause a spread of the crisis to the rest of the member countries. The speed and magnitude of those contagious effects depend on the amount of debt the defaulting country owes to the rest of Eurozone countries as well the way it is connected to their respective banks. Put another way, the higher the foreign exposure of a given country to the banks of other Eurozone countries, the stronger the potential contagion effects. Looking at the BIS figures for the third quarter of 2009, the onset of the sovereign debt crisis, the data suggest that other vulnerable countries like Ireland, Portugal, Spain and Italy account for nearly 16% of foreign claims in European banks[33], while Greece only accounts for a bit more than 1%. Interestingly, we find that the creditworthiness of countries like Ireland, Portugal, Spain and Italy have an impact on the stability of the euro, while the results for Greece are insignificant. Additionally, Figure 4.5 illustrates the Eurozone debt structure as of the end of June 2011.

[33] European banks refer to domestically owned banks of Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and the UK.

Figure 4.5. BBC Eurozone debt web: Who owes what to whom?



The circles above summarize data from the Bank for International Settlements and show the gross external, or foreign, debt of some of the main players in the eurozone as well as other big world economies. The arrows point from the debtor to the creditor and are proportional to the money owed as of the end of June 2011. The exposures, represented by the proportional arrows, shows what banks in one country are owed by debtors - both government and private - in another country. (Source: BBC website, http://www.bbc.co.uk/news/business-15748696)

Each cycle represents the foreign exposure of a given Eurozone country to other member countries as well as its exposure to major economies. The figure shows how a country would influence the rest in the event of a default. The countries of interest are: Greece, Spain, Portugal, Italy and Ireland. With 2tn euro of gross foreign debt, Italy has the highest exposure towards national banks of the Eurozone countries, and those of the U.S, Japan, and the UK. Spain comes second with 1.9tn, followed by Ireland 1.7tn and finally Portugal and Greece at the same indebtedness level of 0.4 tn. Given these amounts and the interlinkages of each country with national banks of the other countries, the creditworthiness of Italy, Ireland and Spain seem to be the main sources of worry regarding the common currency, which is in line with our empirical results. French and German banks together hold 429bn, 243.7bn, 105,8 bn of Italian, of Spanish and Irish debt respectively, whereas they only hold 57.3 of Greek claims. This lends further credence to our results which do not display significance for Greece. In the case of default, France and Germany would be in position to absorb the shock more easily than if Italy, Spain or Ireland were to default. Furthermore, while Portugal and Greece have similar levels of debt, Portugal proves more unsettling because it is more intimately linked to another struggling country like Spain.

A new indicator for currency stability

In the following, we combine the three risk neutral moments into one aggregated risk indicator that characterizes the complete risk-neutral distribution. This allows us to derive one single market-based indicator that measures currency stability from the cross-section of exchange rate options. During the sovereign debt crisis period, this indicator would measure the euro instability. However, the comovements of these three moments are supposed to have a nonlinear impact on the risk-neutral distribution as a whole. Some popular risk measures in risk management, such as Value at Risk (VaR) and Expected Shortfall (ES) constructed from this risk-neutral distribution are expected to be a good indicator of the euro stability. The Gram-Charlier and Cornish-Fisher expansions are tools often used to compute VaR and ES in the context of skewed and leptokurtic return distributions. These approximations use the higher moments of the unknown target distribution to compute an approximate distribution and quantile functions. Simonato (2011) compare these methods with the Johnson System of distributions which also uses the moments as main inputs but is capable of accommodating all possible skewness and kurtosis. In this study, we consider an alternative approach based on the Pearson System (Pearson (1895)), which can be used to model a wide scale of distributions with various skewness and kurtosis. The Pearson System is a family of probability density distributions which includes a unique distribution corresponding to every valid combination of the moments of a distribution. It is possible to find the distribution in the Pearson system that precisely matches the moments of the risk-neutral distribution and to generate a random sample. We calculate the VaR and ES for both lower tail and upper tail at the 1%-quantile from the generated random samples. We construct two euro stability indicators by relating the upper tail of the risk-neutral distribution to the lower tail, e.g. the absolute VaR of the upper 1%-quantile divided by the absolute VaR of the lower 1%-quantile. Clearly, these indicators nicely summarize the imbalances of extreme values of the risk-neutral distribution overall and can be considered to reflect currency stability. For example, a ratio below one indicates a fatter left tail of the distribution compared to the right tail and, therefore, suggests euro instability. Figure 4.6 shows the stability indicators for the complete period.

Figure 4.6. Euro stability indicators

Notes: Euro stability indicators based on the 3-months risk-neutral distribution of options on the dollar-euro exchange rate. VaR ratio refers to the indicator based on the Value-at-Risks measure and ES ratio refers to the indicator based on the expected shortfall measure.

We replicate the 2-step regression analysis outlined in Equations (6) and (7) by replacing e.g. the skewness measure by the different stability indicators. The resulting betas are shown in Table

4.4[34]. VaR ratio refers to the indicator based on the Value-at-Risks measure and ES ratio refers to the indicator based on the expected shortfall measure.

Table 4.4. Regression Results: Value-at-Risk and Expected Shortfall ratios

	VaR ratio		**ES ratio**	
	Betas	T-stat	Betas	T-stat
Subprime crisis *from 05/09/2008 to 13/10/2009*				
Belgium	0.03	0.365	0.00	-0.014
France	-0.02	-0.192	-0.02	-0.159
Germany	0.02	0.199	0.02	0.156
Netherlands	-0.03	-0.374	-0.05	-0.442
Finland	-0.05	-0.478	-0.08	-0.517
Austria	-0.02	-0.251	-0.04	-0.500
Ireland	-0.03	-0.864	-0.02	-0.462
Spain	-0.05	-0.416	-0.04	-0.272
Portugal	0.02	0.220	0.03	0.191
Greece	-0.01	-1.151	-0.03	-0.951
Italy	-0.08	-0.740	-0.07	-0.445
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*				
Belgium	-0.08	-1.518	-0.09	-1.359
France	-0.08	-1.573	-0.09	-1.423
Germany	-0.07	-1.298	-0.10	-1.404
Netherlands	-0.06	-1.078	-0.08	-1.119
Finland	-0.09	-1.554	-0.12	-1.674
Austria	-0.01	-0.274	-0.02	-0.269
Ireland	-0.12**	-2.195	-0.14**	-2.007
Spain	-0.08*	-1.925	-0.11**	-1.991
Portugal	-0.10**	-2.024	-0.12**	-2.006
Greece	-0.07	-1.571	-0.10	-1.464
Italy	-0.12***	-2.495	-0.15***	-2.530

Note: For each country, the dependent variables are the Value-at-Risk ratios and Expected Shortfall ratios of the daily moments of the 3-months risk-neutral distribution of dollar-euro exchange rate options (the variance is expressed in terms of annualized volatility). T-stats are computed based on the Wald test. . (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level.

The results suggest that our previous findings are robust to a change of measure for euro stability. Most of the coefficients are insignificant except the ones for the sovereign debt crisis sub sample. During that period, all coefficients are substantially negative, which entails that member countries credit risk have a negative impact on the stability of the euro. But again, during the sovereign debt crisis period the struggling countries drive the instability of the common currency. It can be shown that the betas for the healthy countries and the ones of the vulnerable countries are significantly

[34] More detailed table in appendix A.6

different form each other at the 5% level for both indicators. The principal component analysis again supports those conjectures. In line with previous findings and contrary to what one would expect, the creditworthiness of Greece does not seem to affect the stability of the common currency significantly.

4.6 Conclusions

In this paper, the recent Eurozone sovereign debt crisis is viewed through the twin lenses of sovereign credit swaps and currency option markets. We empirically investigate the impact of the credit risk of Eurozone member countries on the stability of the Euro. The credit risk of a country can be measured through its sovereign credit default swap (CDS). Market prices of CDS spreads reflect the perception of financial markets about the economic-political stability of a country, and thus about the creditworthiness of a given sovereign. The stability of the euro is examined by decomposing dollar-euro exchange rate options into the moments of the risk-neutral distribution. We document that changes in the creditworthiness of a member country on one day have a significant impact on the stability of the euro on the following day. On the one hand, an increase in member countries' credit risk results in an increase of the volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. On the other hand, we find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. We propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure and show that our results are robust to this change in measure. In line with previous research, these findings apply to the period of the sovereign debt crisis but not necessarily to the subprime crisis period. Noticeable is the fact the creditworthiness of countries with vulnerable fiscal positions is the main, but not the only risk-endangering factor of the euro-stability. While the creditworthiness of the latter countries has a significant impact on the skewness measure (i.e crash risk) and the stability indicators, healthier countries equally drive the relationship between the creditworthiness and the kurtosis (i.e tail risk). As one would expect, Ireland, Portugal, Spain and Italy play a prominent role. However, this does not seem to be the case for Greece, which can be partly explained by the only marginal foreign exposure of European banks to Greece.

Chapter Five

Does systemic risk affect credit ratings of sovereigns and banks?

5.1 Introduction

The financial crisis highlighted the implications of the ratings assigned to banks and sovereigns by the agencies that dominate the global credit rating industry: Moody's Investors Service, Standard and Poor's (S&P) and Fitch Ratings. Even though these agencies were blamed for helping to precipitate the crisis, they still play a major role in the financial markets. Ratings represent an estimation of the rating agency regarding the ability of an institution or a country to meet its obligations. In other words, ratings reflect the creditworthiness of the bond issuer, and signal improving and deteriorating fundamental credit quality. In this sense a rating issued by a credit rating agency is considered as a credit risk indicator and helps determines the funding costs for institutions and countries. The three agencies have different scales of ratings and different methods to assess credit quality. Given the role and implications of the ratings assigned by rating agencies, it is essential that they reflect properly the risk inherent in the entities they assess.

Recent events have demonstrated that any bank, even the mightiest, can suffer a rapid loss in market confidence which might even result in failure. Because of interconnection in the market, one bank failure could lead to a banking crisis with domestic and international consequences for financial markets and whole economies. The collapse of Lehman Brothers is a good example. In order to enhance financial stability, there has been an increased focus on systemic risk as a key aspect of macroprudential policy and surveillance (MPS). Government and financial regulators established government entities like the Financial Stability Oversight[35] Council in the U.S., the European Systemic Risk Board in the European Union (2013), and the Financial Stability Board (FSB) for the G20. The Bank for International Settlements (BIS) views systemic risk as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties". Systemic risk represents a critical part of global banking risk and has a big influence on an individual bank's and sovereign's financial profile, something that should be considered in their credit risk analysis. To the best of our knowledge there is no study that analyses the role of systemic risk in forecasting changes in credit rating which is the main contribution of the paper.

Previous research has documented that Distance to Default is informative for forecasting credit rating changes, Aggarwal et al. (2012); their study is based on Indian sample, Distinguin et al. (2012) focus on emerging markets while Gropp et al. (2002) uses European banks from 1991 to 2001. However, previous literature fails to address the link between banks' credit risk indicator and their sovereign rating. We try to mitigate this gap in the literature by making an original contribution with this paper. The aim of this study covering the financial crisis period from a European perspective is to investigate empirically the predictive power of banks' Distance to Default and systemic risk on banks' and sovereigns' credit ratings. For this purpose we consider a set of 39 banks from 14 European countries from 01/01/2007 to 01/08/2013. In this study we employ Panel Probit model, also, we estimate Distance to Default using a standard option pricing framework and the systemic risk indicator by an aggregation procedure (weight the individual Distance to Default by the implied value of asset) following the methodology used in the European Central Bank (ECB) report (2005). Regardless of our econometric specification, our results indicate that Distance to Default is a useful leading indicator, but systemic risk is more effective in predicting downgrades. The results show also that the three private agencies react differently to

[35] In July 2010, the U.S. Congress enacted the Dodd Frank Wall Street Reform and Consumer Protection Act (Dodd Frank Act), the most comprehensive financial reform bill since the 1930s. Among other things, the Dodd Frank Act created the Financial Stability Oversight Council (FSOC) and Office of Financial Research (OFR)

the deterioration in banks' credit risk proxies by Distance to Default and systemic risk. Regarding banks' ratings, among the three agencies, Moody's is the one that reacts least to an increase in banks' systemic risk and Distance to Default in comparison with its competitors S&P and Fitch. As to sovereign ratings, S&P is the agency that takes the banks' systemic risk factor most into account in its assessment of the sovereigns' risk profiles, with Fitch coming next.

The paper is organized as follows: section 5.2 presents the literature review. Section 5.3 describes our sample. Section 5.4 defines the methodology. Section 5.5 presents our results. Finally, section 5.6 concludes.

5.2 Literature review

A relatively large stream of literature focuses on the impact of sovereign credit rating on the financial market. Caporale et al. (2012) use a sample of S&P credit ratings for 86 countries over 2002–2008, and they show that bank ratings reflect banks' *financial position* and country of origin. A bank in a less developed economy appears to have a lower rating. Brooks et al. (2004) show that sovereign rating downgrades have a strong negative impact on *stock markets* but there is limited evidence of abnormal returns linked to upgrades. This result is supported by Alsakka and ap Gwilym (2012) who examine how abnormal returns by banks are affected by countries' rating changes during 2007-2011 (based on the European data set). Ismailescu and Kazemi (2010) analyze whether *emerging markets' CDS spreads* respond to countries' rating changes. They find that positive signals add new information to the markets, while negative news is anticipated and hence reflected in the CDS spreads. Kim and Wu (2008) examine whether S&P sovereign ratings help attract international capital in 51 emerging markets. Their results reveal significant domestic *bond market* developments after improvements in sovereign ratings. Alfonso et al. (2011) use the outlook of credit rating agencies and show that sovereign rating announcements have spillover effects on the European financial markets. First, they study the response of sovereign CDS spreads, banking stock indices, insurance stock indices and country stock indices. Then they focus on the response of government yield spreads. Either way, news about downgrades is found to have significant spillover effects.

Other literature studies the determinants of banks' and sovereigns' credit ratings. Shen et al. (2012) show that banks with higher ratios of profitability, liquidity and capital adequacy, and better ratios of efficiency (cost-to-income) and asset quality (loan loss provisions to net interest revenues) tend to be assigned higher ratings. One of the first empirical studies on the determinants of sovereign credit ratings was carried out by Cantor and Packer (1996), who focus on an examination of both the criteria underlying ratings and their impact on countries' borrowing costs. They found that ratings can be explained by per capita income, GDP growth, inflation, external debt, level of economic development, and default history. Alsakka and ap Gwilym (2009) examine the dynamics of ratings in emerging economies, including the watch status. They find that countries placed on the watch list have a higher probability of a rating change in the direction specified by the watch status within the subsequent year.

But below-mentioned papers are the most closely related to our study. They examine the impact of the Distance to Default or of the default probability as a measure of credit quality in institutions' ratings. Using the scoring and mapping method on emerging market data, Christophe J. Godlewski (2007) studies the consistency of banks' ratings with their default probabilities. Aggarwal et al. (2012) suggest that the change in the Distance to Default is informative in predicting a change in the credit rating using the Probit model. Their sample includes the top 500 listed firms in India from 2000 to 2011. Distinguin et al. (2012) test whether annual changes in the Distance to Default and in the Z-score are good indicators to estimate changes in credit ratings of Asian banks. In their paper, Gropp et al. (2002) show that the distance-to default and the subordinate bond spread are complete indicators of a bank's fragility in the sense that they reflect the three major determinants of default risk (earnings expectations, leverage and asset risk) and are unbiased in the sense that they reflect these risks correctly. Gropp et al. (2004, 2006) study the predictive performance of the Distance to Default indicator applying logit estimations. They show that the DD is a direct indicator of a bank's fragility that outperforms other indicators of risk in predicting bank defaults in Europe 6, 12 and 18 months prior to the event. Their data set consists of monthly observations of 83 European banks from 1991 to 2001. But the above mentioned studies do not link banks' credit risk indicator to sovereigns' credit ratings. In our study we investigate empirically the predictive power of the banks' Distance to Default and the systemic risk on banks' and sovereigns' credit rating covering the recent financial crisis, which started in 2007.

5.3 Data

Our study spans from January 2007 to August 2013, and thus covers the subprime and the sovereign debt crises. We work on a large sample of European banks. The initial sample covers 92 banks from the European Banking Authority stress test. After matching the rating data to all variables needed to estimate the Distance to Default (DD) we obtain a sample from 14 European countries, which consists of 39 banks for Fitch, and 34 banks for both S&P and Moody's[36].

The bank ratings data are from the Interactive Data Credit Ratings International database and they are at a monthly frequency from January 2007 to December 2013. The sovereign ratings, watch and Outlook status are obtained from the CRA's publications, and they have daily frequency from 03/07/2006 to 27/09/2013. We collect the data for the three credit rating agencies: S&P, Moody's and Fitch.

Rating changes are calculated according to the mapped 20-point numerical ratings (AAA/Aaa = 20, AA+/Aa1 = 19, AA/Aa2 = 18 …CCC- /Caa3 = 2, CC/Ca, SD-S/C = 1). As for the countries, we use the previous 20-point numerical ratings, but also a 58-point numerical ratings scale, which incorporates ratings, credit outlook and watch lists as follows: AAA/Aaa = 58, AA+/Aa1 = 55, AA/Aa2 = 52 …CCC-/Caa3 = 4, CC/Ca, SD-D/C = 1, and we add '+2' for positive watch, '+1' for positive outlook, '-1' for negative outlook, '- 2' for negative watch, and '0' for stable outlook and no watch/outlook assignments.

The default risk indicator DDs is estimated monthly based on the Merton model. For this purpose, we extract daily local currency stock prices and market *capitalization data* from *Thomson* Reuters' Datastream from January 2006 to December 2013. The stock prices of Swiss, Norwegian, Danish, Polish and Swedish banks are converted to euros using the exchange rates from Bloomberg. The stock returns and the historical volatility can therefore be calculated[37]. Quarterly long- & short-term debt[38], as well as daily 3-month German government bond yields (proxy for the risk-free rate), and S&P 500 returns (proxy for the market return), are also retrieved from Bloomberg. Finally, we obtain the monthly market risk premium from the Damodaran website.

[36] The banks are listed in appendix A.7

[37] Stock return data started from 28/09/2005 one year before the other data in order the compute the first historical volatility used to estimate the implied volatility.

[38] We double checked the borrowing levels by comparing them to the one on bank scope. The definition of short & long term debt is in Appendix.

Summary statistics

Table 5.1 reports summary statistics for banks' and sovereigns' downgrades and upgrades registered at the end of each month by the three credit rating agencies for 39 banks (34 for S&P and Moody's) from January 2007 to September 2013. It can be seen that there are 117 (11) bank downgrades (upgrades) by S&P, 124 (30) by Fitch, and 110 (8) by Moody's. There are also 31 (3) sovereign downgrades (upgrades) by S&P, 27 (0) by Fitch, and 27 (3) by Moody's. These statistics reflect the strong trend for downgrades in the European banking system during the financial and the sovereign debt crises. Table 2 also summarizes the sovereign downgrades (upgrades) based on the 58-point numerical rating scale taking into account the watch and outlook status, and identifies 54 (13) downgrades (upgrades) by S&P, 47(2) downgrades (upgrades) by Fitch, and 43 (9) downgrades (upgrades) by Moody's. These figures highlight differences in the policies of the three credit rating agencies.

Table 5.1. Descriptive statistics of credit rating data sample

		S&P	Moody's	Fitch	Total
	Number of countries	14	14	14	-
	Number of banks	34	39	34	-
Banks	Upgrade by 1-notch	11	17	4	32
	Upgrade by >1-notch	0	13	4	17
	Total upgrades	**11**	**30**	**8**	**49**
	Downgrade by 1-notch	93	67	76	236
	Downgrade by > 1-notch	24	53	32	111
	Total Downgrades	**117**	**124**	**110**	**351**
	Number of Observations	**2 720**	**3 120**	**2 720**	-
Sovereigns (20)	Upgrade by 1-notch	1	0	1	2
	Upgrade by >1-notch	2	0	1	4
	Total upgrades	**3**	**0**	**3**	6
	Downgrade by 1-notch	17	12	14	43
	Downgrade by > 1-notch	14	15	13	42
	Total Downgrades	**31**	**27**	**27**	**85**
Sovereigns (58)	Upgrade by 1-notch	9	2	6	17
	Upgrade by >1-notch	4	0	3	7
	Total upgrades	**13**	**2**	**9**	24
	Downgrade by 1-notch	19	12	15	46
	Downgrade by > 1-notch	35	35	28	98
	Total Downgrades	**54**	**47**	**43**	**144**
	Number of Observations	**1 120**	**1 120**	**1 120**	-

Table 5.1 reports summary statistics for banks' and countries' downgrades and upgrades registered at the end of each month by the three credit rating agencies for 39 banks (34 for S&P and Moody's) from January 2007 to September 2013.

Table 5.2 presents summary statistics of the time series averages of all other variables used in the study during the period from 02 January 2006 to 27 September 2013. It can be seen that, on average, firms in the sample have performed poorly, with an average daily stock return of -0.08% and a minimum time series average return of -0.30% for the British bank TSB. Only three banks among 41 in our sample have positive time series average returns: 0.01% for SHBA, 0.17% for PKO and 0.18% for Barkley. The standard deviation of average stock returns is 0.09% showing more or less homogeneity between various banks' performances.

Table 5.2. Summary Statistics of variables related to the Distance to Default

	Mean	STDEV	Min	Max	Q1	Q3	Median	Skew	Kurto
Equity value	**38 576.14**	50 054.86	994.08	258 344.44	6 171.77	43 611.22	16 996.29	2.52	8.36
Stock returns	**-0.08%**	0.09%	-0.30%	0.02%	-0.13%	-0.01%	-0.04%	-1.23	0.40
S T Debt	**88 446.55**	145 592.13	11.17	691 983.23	13 594.84	111 699.47	28 918.24	2.87	8.70
L T Debt	**87 835.95**	108 367.57	39.71	443 975.16	8 127.26	149 338.10	41 296.54	1.86	3.91
Equity Hvol annual	**0.47**	0.17	0.21	1.09	0.37	0.53	0.43	1.54	3.31
Market cap'	2.44%	3.23%	0.06%	16.76%	0.39%	2.75%	1.00%	2.59	8.79
leverage	23.90	69.66	0.01	434.42	1.38	16.79	8.62	5.49	32.05
vstoxx	27.53	9.52	13.41	87.51	22.84	29.33	23.84	2.04	5.45
Default probability	**0.08**	0.10	0.00	0.42	0.00	0.10	0.03	1.77	2.78
Distance to Default	**5.15**	2.87	1.73	16.27	3.55	5.62	4.30	2.15	5.69
Distance to Default Index	**6.94**	0.16	6.05	7.16	6.94	6.99	6.95	-4.54	25.72
Distance to Default at country level	6.67	4.01	2.67	16.27	4.03	7.76	5.50	1.42	1.43
Distance to Default Index country	6.90	0.45	5.45	7.52	6.88	7.04	6.96	-2.72	9.66

For each variable, Table 5.2 reports the summary statistics of the time-series averages of the entire sample of banks. The sample period extends from 02/01/2006 to 27/09/2013. Firm Daily Stock Return is the daily average of firm continuously compounded stock returns. Long and short term debts are quarterly data extracted from Bloomberg and expressed in billion euros. Default probability, Distance to Default and implied volatility are monthly data, we estimate them based on Merton model.

The equity value varies from 994 billion euros for the Danish bank NORDJYSKE, to the largest in our sample, the Swedish banks Nordea (258 344), SHBA (123 740), Skan Enskilada (108 830) followed by British HSBC (107 250), Danish Danske (106 157) and Norwegian DNB (105 794). The median shows that half of our sample has an equity value above 16 996 billion euros. The standard deviation is quite high and reveals substantial differences in the size across banks in the database.

The average of short-term and long-term debt is quite similar over the period of study, 88 447 billion euros and 87 836 billion euros, respectively, although, according to the standard deviation, there is more heterogeneity in the short-term debt compared to the long-term debt. Credit Agricole has the highest level of long-term debt, with a value of 443 975 billion euros. As for the short-term debt, Erste Group has the lowest level of debt (11 billion euros). The French banks have the largest amount of debt: BNP Paribas (691 983), Société Generale (527 473) and Credit Agricole (431 463). However, their leverage is 21.39, 23.22 and 38.53, respectively, which is not too far from the average leverage of banks of 23.90. The standard deviation of leverage (69.66) indicates a big variation between banks' leverage with a maximum of 434 for Dexia and a minimum of 0.01 for Erste Group**.**

The European volatility index (VSTOXX index) does not vary a lot during the study period with a standard deviation of 9.52 and mean of 27.53. The implied volatility index was at its lowest (13.41) in February 2007 before the start of the credit crunch, while in October 2008, after the Lehman Brother collapse, it reaches its maximum of 87.5.

According to the default probability, TSB represents the riskiest bank with the highest default probability (0.43) followed by Bank of Ireland (0.31) and Dexia (0.29). The less risky banks according to the same indicator are Erste Group (1.31 E-11) Nordea (2.48 E-12) and PKO (1.30E-15). The second risk indicator, the Distance to Default, represents the number of standard deviations between the market value of the bank's assets and the default barrier. In accordance with the DP, the DD is highest for Erste Group (16.27) and Nordea (14.4), while the lowest value is for TSB. The Distance to Default Index is calculated by weighting individual DDs by their respective implied asset values, and it represents a systemic risk indicator. Less risky banks (i.e. banks with lower DP and higher DD) are those with the smallest DDI. Nordea has the lowest index (6.05) followed by SHBA (6.74), PKO (6.83), DNB (6.87) and Erste Group (6.90). These banks are the most systematically important banks in our sample. As for the three French banks, BNP Paribas, Societé Generale and Credit Agricole (ACA), they represent the lowest systemic risk in the sample with respectively 7.16; 7.11 and 7.10.

5.4 Methodology

5.4.1 Distance to Default estimation

Many studies have shown that market-based risk measures are good risk indicators for the financial stability of an institution (Tudela and Young (2003), Hillegeist et al. (2004) and Agarwal and Taffler (2008)). Based on a sample of European banks, Gropp et al. (2004, 2006) show that Distance-to-Default is a direct and powerful indicator of bank distress that outperforms other indicators of risk in predicting bank defaults. Also, Vassalou and Yuhang (2004) found that DD is a powerful measure to predict bankruptcy.

We estimate DDs based on Contingent Claim Analysis (CCA) of Merton (1974). CCA combines accounting and market information to obtain indicators of default risk through the application of option pricing theory. Other measures can be estimated based on CCA as probabilities of default, risk-neutral credit risk premia etc. In the CCA approach, liabilities are viewed as contingent claims against assets, and the firm equity becomes an implicit call option on the market value of assets with a strike price equal to the total book value of the debts that is also referred to as the 'distress barrier'. Assets distribution follows the following stochastic process with 'W' a standard Brownian

$$dV_A = \mu V_A dt + \sigma_A V_A dw \qquad (1)$$

The normalized distance between the market value of an asset and the default barrier is called Distance-to-Default and constitutes a financial risk indicator. The Distance to Default expresses the number of standard deviations between the market value of bank assets and the default barrier. A default occurs when the value of the firm's assets hits the default barrier.

According to the Black-Scholes model, the value of a call is given by this equation:

$$V_E = V_A\, N(d_1) - Be^{-rT} N(d_2)) \qquad (2)$$

V_E Represent the value of the firm equity

$$\left.\begin{aligned} d_1 &= \frac{\ln(\frac{V_A}{B}) + (r + \frac{\sigma_A^2}{2})(T-t)}{\sigma_A\sqrt{T-t}} \\ d_2 &= d_1 - \sigma_A\sqrt{T-t} \end{aligned}\right\} \qquad (3) \text{ and } (4)$$

where V_A is the value of the firm's assets, B is the distress barrier, which is defined following the Moody's KMV (Crosbie 1999) as Short Term Debt + 0.5 Long Term Debt, r is the risk-free interest rate and T -t the time to maturity of the debt.

The volatility of equity σ_E is given by this expression:

$$\sigma_E = N(d_1)\frac{V_A}{V_E}\sigma_A \qquad (5)$$

N represents the cumulative normal distribution.

The probability of the firm's default is then $DP = N(-DD)$

Where DD is defined as:

$$DD = \frac{\ln\left(\frac{V_A}{B}\right) + \left(r - \frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A\sqrt{T-t}} \qquad (6)$$

In this formula, the leverage ratio is standardized by the expected return and scaled by the volatility.

Figure 5.1 shows the evolution of the time-series averages of individual Distance to Default of 41 banks over the period 01 January 2007 to 01 August 2013. As mentioned before, the Distance to Default indices are monthly and are estimated based on the Merton model. It can be seen that around September 2007 the DDs reached their maximum. Due to the spread of the crisis to the European financial system (for instance, Northern Rock, one of the UK's largest mortgage lenders was bailed out by the Bank of England on September 13th 2007, the Swiss bank UBS announced a $3.4 billion loss from a subprime-related investment on October 1st of the same year) the DDs dropped drastically until they reached their lowest point between the end of 2008 and the beginning of 2009. During that period the graph exhibits a negative value, indicating a default of a number of banks in our sample: Dexia (bailout by the Belgian, French and Luxembourgish governments pumping 6.4 billion euros into the group on 30 September 2008); the Bank of Ireland (bailout of 3.5 billion euros on 11 February 2009); on October 2008, the UK government pumped £37 billion into three UK banks RBS, TBS and HBOS; and finally, Commerzbank (on November 2008 the German government injected 8.2 billion euros). Towards mid-October 2009, after all government interventions, the value of the DDs was rising until early 2011, before dropping again. Also, the figure clearly shows that some banks have a negative value. These values correspond to the Greek banks: Agricultural Bank of Greece, Alpha Bank, AE Piraeus Bank and Ergasias.

Figure 5.1. Individual Distance to Default

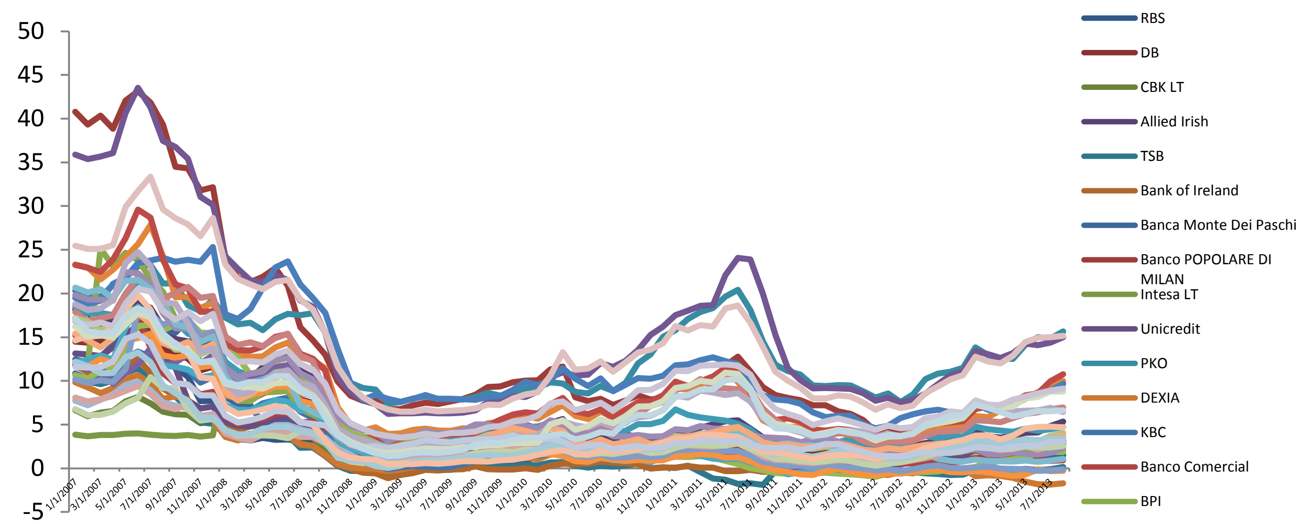


Figure 5.1 shows the evolution of individual Distance to Default time-series averages of the entire sample of banks (41 banks) over the period **01 January 2007 to 01 August 2013**; Individual Distance to Default indices are monthly, they are calculated using Merton model.

5.4.2 Systemic risk proxy

There is no consensus about the definition of systemic risk. Several definitions are proposed in the literature. However, there are qualitative and quantitative definitions.

The BIS views systemic risk as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties". Acharya and Yorulmazer (2007, 2008) define systemic risk as the risk of default of the banking system considered as a whole. According to DeBandt and Hartmann (2000) systemic risk can be rather an external effect hitting one institution, market or system which spreads to others, or wide systematic shocks, which badly affect many institutions or markets at the same time. Another strand of literature proposes a larger definition. Borio et al. (2001), Perotti and Suarez (2009) view the systemic risk as a propagation risk, where shock effects go beyond their direct impact causing disorder in the real economy. According to Borio et al. (2001) financial system turmoil can rarely raise from failure of a unique financial institution due to an idiosyncratic shock. But problems in the financial system are due to financial institutions underestimating their exposure to a common factor, most notably to the financial business cycle in the economy as a whole.

These definition above show that the concept of a systemic risk is not yet clearly defined, which makes its measurement challenging. Furthermore, the estimation should include the complex nature of the financial system (cross-section dimension as well as the time dimension). Many possible ways to classify different measures of a systemic risk are proposed in the literature. Hattori et al. (2014) propose a classification according to the channels through which systemic risk materializes.

In the first group of measures, the risk materializes from interconnectedness between financial institutions. In this case, the financial system is considered as a whole. Adrian and Brunnermeier (2011) estimate the risk that a shock of an individual financial institution spills over to the entire financial sector using "CoVaR[39]". Acharya *et al*. (2010), Huang et al.(2009, 2010, 2011) and Brownlees and Engle (2012) suggest quantifying the contribution of an individual financial institution to the risk of a financial sector-wide shock. They do this by estimating the "marginal expected shortfall" (MES[40]). Huang Segoviano and Goodhart (2009) suggest the "joint probability of distress" (JPoD)[41].

Other studies have proposed systemic risk measures based on interdependence between the financial sector and the real economy. In this context, Giesecke and Kim (2011) propose the "default intensity model" using the number of defaults or downgrades. Alternatively, De Nicolò and Lucchetta (2010) propose "GDP at risk" which models the interdependence between real GDP growth and the rate of return of a banking sector stock index. The literature also proposes measures of risk materializing from interdependence between the financial and public sectors. Jobst and Gray (2013) develop a measure of risk caused by an increase in the bailout cost incurred by the government, which they term "systemic contingent claims analysis". Finally, the "systemic

[39] The CoVaR is a measure indicating how the banking sector stock index falls when an individual bank stock price declines.

[40] This measure indicates which banks contribute to financial sector-wide risks when risk materializes, and the magnitude of these contributions.

[41] In Segoviano and Goodhart (2009), who suggest JPoD, three risk measures are introduced. The first is the JPoD, the probability that all sampled financial institutions default at the same time. The second is the "Banking Stability Index," the expected number of defaulting financial institutions conditional on the default of at least one financial institution in the sample. The third is the probability of a "cascade" of defaults, the probability that a specific financial institution defaults conditional on the default of another particular financial institution in the sample.

liquidity risk index” suggested by Severo (2012) measures risk materializing from malfunctions in the financial market in this context.Then the “volatility spillover index” is proposed by Diebold and Yilmaz (2009, 2014).

We estimate the systemic risk exposure of a banking system following the methodology used in the European Central Bank (ECB) report (2005), we aggregate individual banks’ risk indicators (DD) by their respective estimated implied asset value (from the Merton model). More specifically, to obtain the Distance to Default index (DDI) for each bank, we calculate the weighted average of remaining banks in the sample[42]. A number of studies and reports used this aggregated series of Distance to Default as an indicator of stability of the system. For instance, the International Monetary Fund (2011) reports that aggregated Distance-to-Default series computed for the US banking system did well in forecasting systemic extreme events and in detecting early turning points near systemic events. In the study based on the US banking system Carlson et al. (2008) find that the DD index properly captures the evolution of systemic risk over a period of three decades. However, a simple aggregation of DD presents shortcomings. Duggar and Mitra (2007) argue that it implicitly ignores the joint distributions.

Figure 5.2 shows the evolution of time-series averages of individual Distance to Default indices. Like the papers by Jin and Nadal De Simone (2011a) and Black et al. (2013), which uses different measures based on the PDs[43] and the distance to distress for European banking groups, this chart shows the same movement of systemic risk indicators. By the end of 2007, our systemic risk indicator started to decline till it tumbles to its minimum in 2008-2009 due to the spillover effects of the US financial crisis, which was caused by the failure of Lehman Brothers. During this period, the stress was mostly due to amplified risk aversion and liquidity issues in the global financial market.

[42] Index for each bank represents the weighted average assigning a weight of zero to one specific bank and considering only the remaining ones.

[43] For example, Delianedis and Geske (2003) compound option-based structural credit risk model to estimate implied neutral PDs.

Figure 5.2. Individual Distance to Default Indices

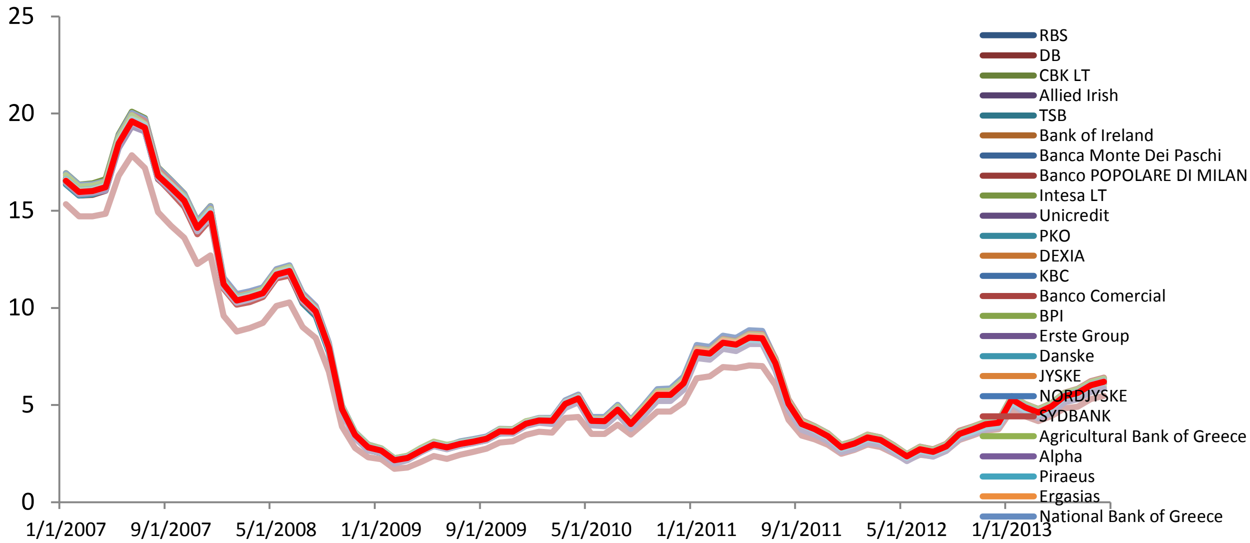


Figure 5.2 shows the evolution of individual Distance to Default indices time-series averages of the entire sample of banks (41 banks) over the period **01 January 2007 to 01 August 2013**; Individual Distance to Default indices are monthly, they are calculated by weighting Distance to Default by implicit asset value, both are estimated based on Merton model.

In order to analyze the impact of Distance to Default and systemic shocks on the probability of a downgrade at a sovereign level, we cluster the two indicators. In other words, we consider all banks in one sovereign as a subsystem. Therefore, the DD_S of this subsystem is the weighted average of individual banks' DD's of that given sovereign. Similarly, we estimate the DDI_S for each sovereign as a weighted average of all banks' Distance to Default in the sample excluding the banks of that sovereign.

5.4.3 Regression analysis

In order to analyze the impact of changes in the banks' credit risk ΔDD_i (ΔDD_S) and systemic risk ΔDDI_i(Δ DDI_S) on the banks' and sovereigns' ratings, we employ the Panel probit model. It is most appropriate to use the probit model is to represent the nature of the credit ratings data (discrete and ordinal). After running a Husman test on different specifications, we select the random effect over the fixed effect[44]. This stipulates that bank and country specific errors are not correlated with the explanatory variables $E(ai|X_{it},Z_i)=0$. Besides, in his paper, Alfonso (2011) explains why it's

[44] We run a Haussmann test on logit estimation and do not reject the null hypothesis that the efficient random effects estimators are the same as the consistent fixed effect estimators (significant p-value > 0.05).Greene (2002) addresses the shortcomings of non-linear fixed effect estimation. The first obstacle relates to the difficulty of estimating non-linear models with possibly a very large number of dummy variable coefficients. The other issue is methodological and concerns incidental parameters, which raises questions about inconsistency of estimators.

not appropriate to employ fixed effects. According to him, the dummies included in the regression capture the average rating because of the small variation of ratings over time; however, the other variables in the regression only capture movements in the ratings across time. So, even if it was statistically correct, a fixed effect regression does not make too much sense.

We estimate a model including only downgrades, because both downgrades and upgrades are driven by different factors (e.g. Williams et al., 2013). We do not estimate a model for upgrades because of the small number of observations in our sample potentially leading to biased results.

The rating changes are identified by notches (0 and 1 or more) using the 20-point rating scale for banks. As for sovereigns we use 20-point and 58-point rating scale. First, we focus only on the S&P credit rating agency. We introduce separately each ΔDD_i (ΔDD_S) and ΔDDI_i (ΔDDI_S) and we estimate a random Probit on 3 months[45] horizon through the following panel regression (equation 7).

Models:

$$\Delta Y^*_{i,a} = \alpha + \beta_1 \Delta DD_{i,-3} + \beta_2 \Delta IDD_{i,-3} + C_i + \varepsilon_i \quad (7)$$

where:

$\Delta DD_{i,-3}$ Monthly change in bank "i" Distance to Default 3 months prior to the rating change announcement;

$\Delta IDD_{i,-3}$ Monthly change in bank "i" systemic risk 3 months prior to the rating change announcement;

i = 1,…., 34

ε_i follows a normal distribution with the parameters zero and one (mean and variance)

$Y^*_{i,a}$ is an unobserved latent variable linked to the observed ordinal response categories :

$$Y_{i,a} = \begin{cases} 0 & \text{if } Y_{i,a} \leq \mu_1 \text{ (no rating change)} \\ 1 & \text{if } Y_{i,a} > \mu_1 \text{ (rating downgrade of 1 or more notches)} \end{cases}$$

[45] We controlled for the results above using a maturity of 6 months and the results remain robust.

μ_1 represents threshold. μ_1 and the parameters α and β are estimated using the Maximum Likelihood Estimation (MLE).

Also, we select a set of four market-based measures as control variables that we include in our specifications. The three first variables are the main inputs of the Merton model used to estimate both DD and DDI. In addition to this, we consider the risk appetite of the European financial market.

1. Bank size relative to the size of all banks in the sample measured by dividing the market cap of a bank i by the total of the market cap of all the banks;
2. Leverage measured as the ratio of total debt of bank "i" on its equity value;
3. Historical volatility of the equity prices over the past year;
4. Vstoxx index, which represents the European volatility index as a measure of the risk appetite of the financial markets.

After estimating the previous specification for banks ratings, we then make another estimation for the change in the downgrade for countries with 20-point and 58-point rating scale. In this case, the independent variables will be $\Delta DD_{S,-3}$ and $\Delta DDI_{S,-3}$ which represent monthly changes in Distance to Default and systemic shock of banks that are part of country "S" 3 months prior to the rating change announcement (S = 1,…., 14).

The expected relationship between changes in systemic risk indicator and changes in credit ratings

We expect a negative relationship between changes in Distance to Default and changes in credit ratings. DD, our risk default indicator, illustrates how far is the stock value from the default barrier. Thus, the smaller DD is, the closer we are to that barrier. Therefore, a negative change in DD should translate into an increase in the probability of a downgrade. The same logic applies to DDI_i, given that systemic risk of one bank represents the weighted average of remaining banks' default risk (Distance to Default) in the sample. It means that one bank is more systemically important than another when its DDI is lower (closer to default barrier). Thus, a negative change in DDI_i implies a higher systemic risk for that bank and should translate into an increase in the probability of downgrade.

Comparison across credit rating agencies

In order to confirm the predictive power of Distance to Default and systemic risk on the downgrade of banks and sovereign, and also to compare the impact of DD and systemic risk across agencies, we perform extra regressions using data from the three rating agencies. First, we incorporate lag value of DD_i (DDI_i) for different horizons: 1, 3, 6 and 12 months simultaneously (model 8). Afterwards, inspired by Aggarwal et al. (2012), we run the model (9) with one year non-overlapping changes in DD_{i-T} (DDI_{i-T}). Besides, we incorporate the control variables defined above.

$$\Delta Y^{*}_{i,a} = \alpha + \beta \Delta Risk_{i,-T} + C_i + \varepsilon_i \qquad (8)$$

$$\Delta Y^{*}_{i,a} = \alpha + \beta \Delta Risk_{t-1M} + \beta_1 \Delta Risk_{-(3M-1M)} + \beta_2 \Delta Risk_{-(6M-3M)} + \beta_3 \Delta Risk_{-(9M-6M)} + C_i + \varepsilon_i \qquad (9)$$

Equations (8) and (9) are estimated separately for the risk measure *"Risk"*

$\Delta Risk_{i,-T}$ Represent monthly changes in our risk measures (DD and DDI) 'T' months prior to the rating change announcement.

$\Delta Risk_{-(3M-1M)}$ Represent the change in the risk measures (DD and DDI) between the three month period prior to the rating change and one month prior to the rating change.

i = 1,…., 34 banks for S&P and Moody's; i = 1,…., 39 for Fitch

'a' represent the three CRAs: Moody's, S&P and Fitch.

Once we have estimated the two specifications above, we repeat the exercise using changes in the downgrade of sovereigns as dependent variable (20-point and 58-point rating scale) and DD_S (DDI_S) as an independent variable.

Furthermore, we run the regression using the logit model. We reported the results only for credit downgrades of the banks in appendix (A.20 and A.21). Also, we test for fixed versus random effect by performing a Husman test. In almost all cases the random effect is the selected model. The results are unchanged overall; they are reported in the appendix. Finally, we control the results by estimating pooled Probit with dummies for banks and years[46].

5.5 Empirical results

As already outlined in the introduction, we aim to investigate whether banks' Distance to Default and systemic shocks are able to predict changes in a credit rating. As mentioned before, previous studies by Distinguin et al. (2012), Aggarwal et al.(2012) and Gropp et al. (2002, 2006) focus on predictive performance of the Distance-to-Default indicator on changes in financial and non-financial institutions. The studies mentioned above find that the Distance to Default is a significant indicator of a credit rating change. However, Distinguin et al. (2012), who consider an annual change in the Distance to Default, find that the signs of the coefficient are not as would be expected.

Table 5.3 reports the results from estimating probit model of equation (7) for S&P at bank level. We report the coefficient estimates, Z-statistics and log-likelihood. Since the coefficient levels cannot be interpreted directly, we report marginal effects in percentage. Models are compared based on their log likelihood and R-squared. We estimate McFadden (1974)[47] pseudo R-squared, which captures the performance of the estimated model over the model with only the intercept. The coefficients associated with the change in both indicators are negative, which is consistent with the expected relationship, meaning that a positive (negative) change in the Distance to Default and Distance to Default index of a bank 3 months prior to the event will decrease (increase) the likelihood of a downgrade.

[46] The pooled estimator ignoring the correlation across periods generally leads to underestimating standard errors.

[47] Here are the details. Logistic regression is, of course, estimated by maximizing the likelihood function. Let L_0 be the value of the likelihood function for a model with only the intercept, and let L_F be the likelihood for the model with predictors. McFadden's R^2 is defined as $R^2 = 1 - (\ln(L_F) / \ln(L_0))$

Table 5.3. Probit estimations of the effect of monthly changes in 3 months lagged DD and DDI on S&P bank ratings over the entire sample

	Bank			
	M1	M2	M3	M4
ΔDD_{-3M}	**-0.26***** (-3.87)		**-0.14*** (-1.90)	**-0.13***** (-1.78)
Marginal effect	*-0.15%*		*-0.10%*	*-0.10%*
ΔDDI_{-3M}		**-0.44***** (-7.72)	**-0.54***** (-7.26)	**-0.49***** (-6.45)
Marginal effect		*-0.26%*	*-0.32%*	*-0.30%*
Volatility				0.04 (0.38)
Relative size				**-8.26***** (-4.54)
leverage				0.00 (1.64)
vstoxx				**0.01***** (4.12)
Constant	**-2.90***** (-69.27)	**-2.92***** (-68.63)	**-2.90***** (-69.47)	**-3.08***** (-29.99)
Log L	-833.60	-819.10	-817.58	-793.16
Pseudo-R^2	1,13%	2,85%	3,03%	5,93%

Notes: Table 5.3 reports coefficients and z statistics (in parentheses) of random probit estimations. The independent variables are monthly changes in 3 months lag of DD and DDI and the dependent variable is change in banks' downgrade for S&P. The model 1 includes only changes in DD and model 2 changes in IDD. Model 3 has both variables DD and IDD. Model 4 additionally contains the other four market-based measures capturing relative bank size, Leverage, Historical volatility of the equity prices and Vstoxx index. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The sample period extends from 01/01/2007 to 01/08/2013

In the first two models, we introduce separately DD and DDI as explanatory variables. The coefficients are significant at the 1 percent level. However, the marginal effect of DDI is higher than that of DD (0.26% vs. 0.15%) meaning that a change in one unit of DDI (DD) of a given bank will have as a consequence a change in the probability of a downgrade by 0.26% (0.15%). In other words, a change in the systemic risk of a bank has a bigger impact on its credit rating compared to a change in its credit risk indicator. Besides, if we compare the pseudo R-squared of the model including DD and the one with DDI, we find that the explanatory power of the model increases substantially together with the maximum log likelihood.

In the third column of the table, we estimate simultaneously DD and DDI. Both coefficients are still significant, but the coefficient related to DD is significant at 10% the level and its marginal effect decreases from 0.15% to 0.10%, while the coefficient of DDI remains highly significant and its marginal effect increases to 0.32%. Once we introduce market-based measures of banks, our results stay significant. The pseudo R-squared and the log likelihood indicate that this last model is the "best" one. Among the four control variables, only relative size and VSTOXX variables are significant at 1% level. The negative sign of the relative size coefficient indicates that the smaller the bank, the higher the probability that this bank will be downgraded. As to VSTOXX, the coefficient is positive, which suggests that high implied volatility for the European equity markets leads to a higher likelihood of a downgrade. One explanation for the fact that volatility and leverage are not significant is that these variables are main inputs in the Merton Model (used to estimate DD and DDI) and their effect was already captured by these two risk indicators.

Table 5.4 shows the estimate coefficients of change in the downgrade of countries. The first four models are based on the 20-point rating scale, while we use the 58-point rating scale in the four others. It can be seen that the coefficients are also all negative, as expected. Note that in this case, interpretation is quite different: a positive (negative) change in the Distance to Default and systemic shock of banks of a given country 3 months prior to the event will decrease (increase) the likelihood of a downgrade of that country. The pseudo R-squared and log likelihood indicate that model 2 including DDI is better than the one with DD. Moreover, the marginal effect of DDI (0.09%) is higher than the marginal effect of DD (0.02%). The results remain unchanged in model 3 and 4 with the two indicators and controls. With regards to the 58-point rating scale, looking at the first three models, the marginal effect of DD is higher or equal to the marginal effect of DDI. However, in model 4 the best specification according to R-squared and log likelihood is when DD and DDI are estimated jointly; the coefficient relative to DD becomes insignificant, meaning that systemic risk goes beyond DD in explaining changes in the downgrade of a sovereign. In addition, the coefficient of historical volatility is positive and significant, meaning that, higher is the volatility, bigger will be the probability of the bank downgrades.

Table 5.4. Probit estimations of the effect of monthly changes in 3 months lagged DD and DDI on S&P sovereign ratings over the entire sample

	Sovereign (20)				Sovereign (58)			
	M1	M2	M3	M4	M1	M2	M3	M4
$\Delta DD_{S\text{-}3M}$	**-0.07***** (-2.88)		**-0.04*** (-1.88)	**-0.11**** (-2.42)	**-0.05***** (-3.51)		**-0.04*** (-1.69)	-0.04 (-1.50)
Marginal effect	*-0.02%*		*-0.02%*	*-0.03%*	*-0.03%*		*-0.02%*	*-0.02%*
$\Delta DDI_{S\text{-}3M}$		**-0.14***** (-2.36)	**-0.12**** (-1.93)	**-0.17**** (-2.21)		**-0.05***** (-3.37)	**-0.02*** (-1.93)	**-0.06**** (-2.45)
Marginal effect		*-0.09%*	*-0.08%*	*-0.05%*		*-0.03%*	*-0.01%*	*-0.04%*
Volatility				0.89 (1.03)				**1.63**** (2.01)
Relative size				**-12.72*** (-1.79)				**-13.87***** (-3.04)
leverage				-0.68 (-0.77)				-0.39 (-0.53)
vstoxx				0.01 (0.17)				**0.01***** (2.33)
Constant	**-2.87***** (-17.30)	**-2.99***** (-16.00)	**-3.06***** (-17.60)	**-1.57***** (-3.24)	**-2.68***** (-23.14)	**-2.68***** (-19.76)	**-2.85***** (-23.78)	**-1.81***** (-5.58)
Log L	-223.80	-220.39	-220.73	-212.35	-364.39	-362.50	-361.67	-345.16
Pseudo-R^2	2,20%	3,54%	3,69%	7,20%	2,27%	3,00%	2,77%	7,42%

Notes: Table 5.4 reports coefficients and z statistics (in parentheses) of random probit estimations. The independent variables are monthly changes in 3 months lag of DD and DDI, and the dependent variable changes countries' downgrade for S&P using the 20-point and 58-point rating scales. Model 1 includes only changes in DD and model 2 changes in IDD. Model 3 has both variables DD and IDD. Model 4, additionally, contains the other four market-based measures capturing relative bank size, leverage, historical volatility of the equity prices and Vstoxx index. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The sample period extends from 01/01/2007 to 01/08/2013

Comparing the marginal effect of DD and DDI on the bank sample with that of the country sample, we notice that the effect of DDI is much higher for banks. In other words, changes in Distance to Default and systemic shock for banks will have a bigger impact on banks' rating than on countries' ratings, a finding which is quite intuitive.

Besides, Gropp et al. (2002) find that the Distance to Default is not a significant variable three months before a downgrade. They suggest that "many eventually downgraded banks exhibit a lowering in the equity volatility just before the downgrading, which causes the derived asset volatility measure to decrease as well, reducing the (-DD) value." But the time period they consider is from 1991 to 2001, during which the financial market was much more stable compared to the period we are studying. Overall, our results indicate that systemic risk goes beyond Distance to Default in explaining a downgrade of banks and countries.

Comparison across rating agencies

To check the predictive power of the Distance to Default and the systemic risk on banks' and sovereigns' propensity to be downgraded, and also to compare the impact of DD and systemic risk across agencies we incorporate the lag value of the DD (DDI) for different horizons: 1, 3, 6 and 12 months simultaneously and one year non-overlapping changes in both indicators for each credit rating agency: S&P, Fitch and Moody's. The results of these specifications are reported in the table 5.5.

Model 1 of each agency includes changes in the banks' DD over different horizons: 1, 3, 6 and 12 months before the rating change announcement. It can be seen that the coefficient related to the first three fixed horizons are negative and significant for S&P and Fitch, while only 1-month and 3-month lags are significant for Moody's indicating that a change in the DD of one bank 1, 3 and 6 months prior to the event has an impact on S&P and Fitch ratings. By introducing control variables, the results remain unchanged and the performance of the model increases subsequently according to the pseudo R-squared and the log likelihood (the results are reported in appendix A.8). In addition, if we compare the marginal effect of different horizons, we notice that the Moody's ratings react strongly to a 1-month DD change (0.19%) and much less to a 3-month DD change (0.11%), while the Fitch' ratings react more to a 3-month change in the DD (0.17%) and S&P' to a 6-month change (0.16%) meaning that Moody's incorporates the information more quickly compare to S&P and Fitch.

Models 2 in table 5.5 display the results of changes in banks' DD over the entire year before the rating change event. For S&P and Moody's, the coefficient of the first window is the only significant one, suggesting the deterioration of credit rating of a bank is driven by changes in DD between three and one month prior to the rating change: While the Fitch credit rating is determined by changes in DD between six and one month prior to the rating change (is significant at the 10% level). By comparing the two models (M1 and M2) we can state that there is no improvement in the performance between the different lag horizons and that with one year non-overlapping change, the pseudo-R^2 and the log Likelihood are unchanged.

In addition, the results show a difference across the three agencies. S&P downgrades are the ones that react most to the deterioration in credit risk quality of banks proxied by DD, followed by Fitch.

Table 5.5. ***Probit estimations*** **of the effect of monthly changes in lagged DD for different horizons on bank ratings over the entire sample**

	S&P				Fitch				Moody's			
	M1	**Marginal effects**	**M2**	**Marginal effects**	**M1**	**Marginal effects**	**M2**	**Marginal effects**	**M1**	**Marginal effects**	**M2**	**Marginal effects**
ΔDD_{-1M}	**-0.17**** (-2.10)	-0.11%	**-0.63***** (-4.03)	-0.41%	**-0.17*** (-1.95)	-0.08%	**-0.76***** (-5.29)	-0.39%	**-0.26***** (-3.49)	-0.19%	**-0.57***** (-3.51)	-0.42%
ΔDD_{-3M}	**-0.24***** (-3.27)	-0.16%			**-0.33***** (-5.33)	-0.17%			**-0.15*** (-1.66)	-0.11%		
ΔDD_{-6M}	**-0.24***** (-3.58)	-0.16%			**-0.24 ***** (-3.44)	-0.12%			-0.10 (-0.97)	-0.07%		
ΔDD_{-12M}	0.03 (0.27)	0.02%			-0.03 (-0.24)	-0.01%			-0.06 (-0.61)	-0.05%		
$\Delta DD_{-(3M-1M)}$			**-0.45***** (-3.01)	-0.30%			**-0.59***** (-4.25)	-0.30%			**-0.31*** (-1.92)	-0.23%
$\Delta DD_{-(6M-3M)}$			-0.21 (-1.64)	-0.14%			**-0.26**** (-2.14)	-0.13%			-0.16 (-1.21)	-0.12%
$\Delta DD_{-(12M-6M)}$			0.03 (0.27)	0.02%			-0.03 (-0.24)	-0.01%			-0.06 (-0.61)	-0.05%
Constant	**-2.88***** (-65.74)		**-2.88***** (-65.74)		**-2.98***** (-58.42)		**-2.98***** (-58.42)		**-2.84***** (-94.67)		**-2.84***** (-94.67)	
Log L	-812.67		-812.67		-776.49		-776.49		-830.49		-830.49	
Pseudo-R^2	3,61%		3,61%		4,33%		4,33%		6,54%		6,54%	

Notes: Table 5.5 reports coefficients, z statistics (in parentheses) and marginal effects (in percentage) of random probit estimations. In model 1 of each rating agency, the independent variables are lag value of DD for different horizons: 1, 3, 6 and 12 months. In Model 2, the independent variables are one year non-overlapping changes in DD. The dependent variable is change in banks' downgrade for S&P, Fitch and Moody's. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The sample period extends from 01/01/2007 to 01/08/2013

Table 5.6 reports the results of the effect of the DDI on changes in banks' credit downgrade over different horizons for the three credit rating agencies. All coefficients have the expected signs. As for the DD, a change in a banks' downgrade is driven by a change in the DDI 1 month and 3 months prior to the event for Moody's, 1, 3 and 6 months for S&P. As for Fitch, in addition to the first three lags, the one-year lag value of the DDI is also significant at 10% level with a relatively small marginal effect (0.09%). Model 2 of the three agencies shows that the first window $DDI_{-(3M-1M)}$ is informative for the three agencies, in addition, $DDI_{-(6M-3M)}$ is also informative for S&P and Fitch, furthermore $DDI_{-(12M-6M)}$ is significant for Fitch .

Marginal effects indicate that the Moody's ratings are more sensitive to changes in the DDI 1 month before the event (0.22%), while the S&P ratings react more to the 3-month change in the DDI (0.27%) and Fitch to the 6-month change (0.19%) meaning that Fitch reacts slowly to the changes in banks' DDI. However, Moody's responds quickly to changes in the DDI (which was also the case for DD).

By comparing marginal effects of the DD (table 5.5) and those of the DDI (table 5.6) for the three rating agencies and across different horizons, it is obvious that the DDI has a stronger impact than the DD on changes in banks' credit ratings. This finding only confirms that a systemic shock is more informative than the Distance to Default.

The results here also display differences across the agencies. Among the three agencies, Moody's is the one that reacts least to an increase in banks' systemic risk in comparison with its competitors, S&P and Fitch.

Table 5.6 *Probit estimations* of the effect of monthly changes in lagged DDI for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	Marginal effects	M2	Marginal effects	M1	Marginal effects	M2	Marginal effects	M1	Marginal effects	M2	Marginal effects
ΔDDI_{-1M}	**-0.23*****	-0.15%	**-0.92*****	-0.60%	**-0.20*****	-0.10%	**-0.90*****	-0.54%	**-0.30*****	-0.22%	**-0.43***	-0.31%
	(-3.03)		(-5.67)		(-2.42)		(-5.93)		(-4.16)		(-1.89)	
ΔDDI_{-3M}	**-0.41*****	-0.27%			**-0.38*****	-0.17%			**-0.22****	-0.16%		
	(-6.61)				(-5.80)				(-2.51)			
ΔDDI_{-6M}	**-0.29*****	-0.19%			**-0.37*****	-0.19%			0.18	0.13%		
	(-3.82)				(-6.06)				(1.05)			
ΔDDI_{-12M}	0.00	0.00%			**-0.17***	-0.08%			-0.10	-0.07%		
	(0.02)				(-1.94)				(-0.79)			
$\Delta DDI_{-(3M-1M)}$			**-0.70*****	-0.45%			**-0.92*****	-0.44%			-0.13	-0.09%
			(-4.37)				(-7.39)				(-0.55)	
$\Delta DDI_{-(6M-3M)}$			**-0.28****	-0.19%			**-0.54*****	-0.27%			-0.09	-0.06%
			(-2.00)				(-5.25)				(0.42)	
$\Delta DDI_{-(12M-6M)}$			0.00	0.00%			**-0.17***	-0.08%			-0.10	-0.07%
			(0.02)				(-1.94)				(-0.79)	
Constant	**-2.90*****		**-2.90*****		**-2.99*****		**-2.99*****		**-2.84*****		**-2.84*****	
	(-65.90)		(-65.90)		(-58.08)		(-58.08)		(-94.07)		(-94.07)	
Log L	-795.51		-795.51		-766.29		-766.29		-826.01		-826.01	
Pseudo-R^2	5,65%		5,65%		5,59%		5,59%		7,04%		7,04%	

Notes: Table 5.6 reports coefficients, z statistics (in parentheses) and marginal effects (in percentage) of random probit estimations. In model 1 of each rating agency, the independent variables are lag value of DDI for different horizons: 1, 3, 6 and 12 months. In Model 2 the independent variables are one year non-overlapping changes in DDI. The dependent variable is change in banks' downgrade for S&P, Fitch and Moody's. (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level. The sample period extends from 01/01/2007 to 01/08/2013

As already explained in the methodology, to analyze the impact of the Distance to Default and the systemic shocks on the probability of a downgrade at the sovereign level, we cluster the two indicators. In other words, we consider all banks in one country as a subsystem. Therefore, the DD_S of this subsystem is the weighted average of individual banks' DD's of that given sovereign. Similarly, we estimate the DDI_S for each sovereign as a weighted average of all banks' Distance to Default in the sample excluding the banks of that sovereign.

Tables below exhibit probit estimation of monthly DD (table 5.7) and DDI (table 5.8) for different horizons on a 20-point and a 58-point sovereign rating scale. The results of the estimation models including the one-year non overlapping windows and the market controls, are reported in appendix (Tables: A.12 to A.19). All the significant coefficients here have the expected sign. Comparing the marginal effect of DD and DDI, once again, DDI is more able to predict the future movement in countries' credit rating for both the 20-point and the 58-point sovereign rating scale. In addition, the results reveal that the two indicators are less informative for sovereign' ratings than banks' ratings. Looking at the first table, it can be seen that the S&P downgrade based on the 20-point rating scale is driven by change in DD 3 and 6 months before the event and the Moody's downgrade is driven only by a 1-month change in DD. However, the coefficients related to Fitch are not statistically significant indicating that a change in DD does not affect the probability of a downgrade by Fitch. The second table shows that the S&P downgrade reacts to changes in banks' systemic risk 3, 6 and 12 months afterwards. The other two agencies respond well to changes in the systemic risk after 1 year.

Looking at the 58-point rating scale for countries, changes in 3-, 6- and 12-month DD and DDI prior to the event, increase the probability of a downgrade by S&P. Fitch and Moody's downgrades do not react to the changes in DD. Nevertheless, the Fitch rating responds to the change in DDI 3, 6 and 12 months after the event, while the Moody's downgrade is driven only by the change in one year DDI lag value. These results indicate that of the three private agencies, S&P is more reactive to changes in the Distance to Default and the systemic risk of banks in assessing countries' credit ratings. Besides, the results are stronger for the 58-point ratings, which consider watch and outlook status compared to the 20-point ratings for S&P and Fitch. These results are robust after controlling for market-based indicators.

Table 5.7. ***Probit estimations*** **of the effect of monthly changes in lag of DD for different horizons on sovereign ratings over the entire sample**

	S&P				Fitch				Moody's			
	20-point scale	Marginal effects	58-point scale	Marginal effects	20-point scale	Marginal effects	58-point scale	Marginal effects	20-point scale	Marginal effects	58-point scale	Marginal effects
$\Delta DD_{S\text{-}1M}$	0.05	0. 01%	-0.02	-0. 01 %	-0.10	-0.03%	0.02	0.01%	-0.15*	-0.05%	-0.06	-0.03%
	(0.65)		(-0.46)		(-1.30)		(0.27)		(-1.66)		(-0.97)	
$\Delta DD_{S\text{-}3M}$	-0.17*	-0.04%	-0.10*	-0. 06%	-0.05	-0.02%	-0.09	-0.04%	-0.16	-0.05%	-0.02	-0.01%
	(-1.67)		(-1.67)		(0.76)		(-0.93)		(-1.39)		(-0.26)	
$\Delta DD_{S\text{-}6M}$	-0.09*	-0. 05%	-0.11***	-0. 07%	-0.03	-0.01%	-0.03	-0.02%	-0.09	-0.03%	0.04	0.02%
	(-1.79)		(-3.40)		(-0.92)		(-0.57)		(-1.16)		(0.86)	
$\Delta DD_{S\text{-}12M}$	-0.04	-0. 01%	-0.05**	-0. 03 %	-0.04	-0.01%	-0.02	-0. 01%	-0.02	-0.01%	-0.03	-0.02%
	(-1.44)		(-2.50)		(-1.19)		(-1.09)		(-0.81)		(-1.32)	
Constant	-2.69***		-2.55***		-2.73***		-2.71***		-2.73***		-2.64***	
	(-29.78)		(-36.18)		(-16.95)		(-19.43)		(-17.13)		(-20.11)	
Log L	-218.15		-353.61		-198.16		-293.88		-193.75		-315.95	
Pseudo-R^2	4,67%		5,16%		3,09%		4,10%		5,65%		4,40%	

Table 5.8. ***Probit estimations*** **of the effect of monthly changes in lag of DDI for different horizons on sovereign ratings over the entire sample**

	S&P				Fitch				Moody's			
	20-point scale	Marginal effects	58-point scale	Marginal effects	20-point scale	Marginal effects	58-point scale	Marginal effects	20-point scale	Marginal effects	58-point scale	Marginal effects
$\Delta DDI_{S\text{-}1M}$	0.10	0.02%	-0.06	0.04%	-0.06	-0. 00%	0.05	-0.02%	-0.02	-0.00%	-0.02	-0. 01 %
	(1.56)		(-1.49)		(-0.87)		(0.96)		(-0.32)		(-0.36)	
$\Delta DDI_{S\text{-}3M}$	-0.20**	-0.06%	-0.22***	-0. 12%	-0.03	-0. 01%	-0.12*	-0.05%	-0.08	-0.02%	-0.03	0. 01 %
	(-2.38)		(-3.50)		(-0.33)		(-1.87)		(-1.02)		(-0.40)	
$\Delta DDI_{S\text{-}6M}$	-0.13***	-0.03%	-0.17***	-0.09%	-0.02	-0. 01%	-0.08**	-0.03%	-0.04	-0.01%	-0.00	0.00 %
	(-2.95)		(-5.22)		(-0.44)		(-2.24)		(-0.76)		(-0.02)	
$\Delta DDI_{S\text{-}12M}$	-0.06**	-0.01%	-0.07***	-0.04%	-0.05**	-0. 01%	-0.04**	-0.02%	-0.04*	-0.01%	-0.03**	-0. 02 %
	(-2.47)		(-3.46)		(-1.98)		(-2.06)		(-1.74)		(-2.07)	
Constant	-3.06***		-2.64***		-2.87***		-2.68***		-2.91***		-2.67***	
	(-14.54)		(-24.08)		(-12.61)		(-22.61)		(-18.92)		(-22.07)	
Log L	217,22		-345.73		198,95		-303.64		-202.21		-319.10	
Pseudo-R^2	5,07%		7,27%		2,65%		4,15%		1,53%		3,45%	

5.6 Conclusion

In this paper, we demonstrate the crucial role played by systemic shocks in the forecasting of changes in a credit rating downgrade. Based on European data covering the financial crisis, we analyse empirically the impact of both Distance to Default and systemic risk on changes in the credit ratings of banks and sovereigns.

In line with previous research by Aggarwal et al.(2012) and Gropp et al. (2002, 2006), our empirical results show that Distance to Default is able to predict future changes in a credit rating. Furthermore, the main finding of this paper is that the proxy of systemic risk (DDI) appears to have better predictive properties about the likelihood of a downgrade compared to credit risk measured by Distance to Default. In other words, the DD of a bank is an early warning of the change in a bank's and a sovereign's credit rating, but DDI provides marginally more additional information. The two indicators taken together have more discriminatory power in predicting defaults than individually. Also, as expected, the marginal effect of DD and DDI is much higher for banks than for sovereigns.

On the whole, at the level of a bank, we find robust predictive performances for the Distance-to-Default and systemic risk indicator, with this being between 1 to 6 months in advance of S&P and Fitch and from 1 to 3 months ahead for Moody's. However, this finding differs for sovereigns' ratings. The 20-point rating scale for sovereigns is more influenced by changes in DD close to default (3 and 6 months for S&P and 1 month for Moody's), while for the predictive properties of DDI is good for longer maturities. Yet, DDI represent an early signal of the 58-point rating for countries, showing up 3 to 12 months before the announcement by S&P and Fitch and 12 months before for Moody's, However, DD is an early signal of the 58-point rating for sovereigns only for S&P. Finally, both indicators have more predictive power on the 58-point rating scale for sovereigns, meaning that watch and Outlook status are important and should be considered.

These results show that the three rating agencies react differently to the deterioration in banks' credit risk proxies: Distance to Default and systemic risk. Regarding banks' ratings, Moody's is the agency that reacts least (compared to its competitors S&P and Fitch) to an increase in banks' systemic risk and Distance to Default. As regards sovereign ratings, S&P is the agency that takes banks' systemic risk factors more into account in its assessment of the sovereigns risk profile. Fitch comes next.

Systemic risk represents a critical part of global banking risk, and has a big influence on an individual bank's and a sovereign's financial profile. Despite our examination demonstrating that this component is considered by credit rating agencies, they ought to take it more into consideration when they evaluate default risk.

In future research, we would like to use another systemic risk measure that estimates precisely the correlations between different banks, and we would also like to expand the sample being studied.

Chapter Six

General conclusion

Given the major role of credit risk in the recent financial crisis and its impact on financial stability, in this thesis we have analysed credit risk in Europe during the financial crisis, using different perspectives. We considered different markets: Credit Default Swap (CDS), options on equities and exchange rates, and finally, equities. We also looked at a range of different entities: corporates, banks and sovereigns, with a focus on banks. This dissertation contributes to the literature in several ways and we draw the following conclusions:

In **Chapter 2** we investigated empirically the relative informational efficiency of stock, options and credit default swaps. A lead-lag relation is found between the CDS market and other markets, in which changes in CDS spreads forecast changes in stock prices and equity options' implied volatilities. Moreover, in contrast to results of US studies, the stock market is found to forecast changes in the other two markets. Therefore, the findings suggest the existence of two different groups of investors: the most sophisticated will consider entering the CDS market, with the least sophisticated tending to prefer more traditional capital markets of which they have greater knowledge. Interestingly, these patterns have only emerged during the recent financial crisis, while before the crisis, the option market was found to be of major importance in the price discovery process. Additionally, we find those relationships being substantially stronger for financial firms relative to non-financial firms. This is as a result of the increased importance of financial firms in market participants' investment decisions during the crisis periods.

In **Chapter 3** we exploit the theoretical link between CDS spreads and put options to derive an indicator of credit deterioration (“the default arrival rate”) in a novel way. Altogether, our results indicate that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks (systematically important banks). They can also serve, at times, as early warning signals. Furthermore, our findings suggest that higher financial guarantees from sovereigns lead to lower default risk and hence a lower CDS spread along with a lower estimated default arrival rate. Ultimately, the government guarantee explains the differences in the level of estimated default arrival rates across banks, as well as the observed differences between estimated (i.e derived from Carr&Wu ‘s model) and historical (CDS spreads scaled by (1-recovery rate)) default arrival rates.

In **Chapter 4** we analysed the impact of Eurozone member countries’ credit risk on the stability of the euro, and we proposed two indicators for measuring currency stability. The credit risk of a country can be measured through its sovereign credit default swap (CDS). The stability of the euro is examined by decomposing dollar-euro exchange rate options into the moments of the risk-neutral distribution. We pointed out that the changes in the creditworthiness of a member country on one day have a significant impact on the stability of the euro on the following day. On the one hand, an increase in member countries’ credit risk results in an increase of the volatility of the dollar-euro exchange rate. There is also a strong increase in tail risk induced through the risk-neutral kurtosis. On the other hand, we find that member countries’ credit risk is a major determinant of the euro’s crash risk, as measured by the risk-neutral skewness. We propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure, and then we show that our results are robust to this change in measure. In line with previous research, these findings apply to the period of the sovereign debt crisis, but not necessarily to the subprime crisis period.

In **Chapter 5** we analysed the impact of Distance to Default and systemic risk on the probability of downgrading banks and sovereigns. We estimate Distance to Default using a standard option pricing framework. The systemic risk indicator is estimated by an aggregation procedure which is the standard practice in financial stability publications. The results show that both indicators impact the downgrade probability of banks and countries. However, systemic risk goes beyond Distance to Default to explain the deterioration of the financial stability of banks and sovereigns.

In addition, the results indicate that the marginal effect of DD and DDI is much higher for banks than for sovereigns. The results show also that the three main credit rating agencies react differently to the deterioration in banks' credit risk proxies by Distance to Default and systemic risk. As regards banks' ratings, Moody's is the credit rating agency that reacts least (in comparison to its competitors S&P and Fitch) to an increase in banks' systemic risk and Distance to Default. As for sovereign ratings, S&P is the agency that takes more into account banks systemic risk in its assessment of the sovereigns' risk profiles. Fitch is second, in this regard.

These results suggest that in order to ensure the financial stability of the whole system, it is important to regulate the CDS market. This is because it influences other financial markets and has an impact on the euro. In addition, systemic risk represents a critical part of global banking risk, and has a big influence on individual bank's and sovereign's financial profiles. Despite our examination demonstrating that this component is considered by credit rating agencies, they ought to take it more into consideration when they evaluate default risk.

Overall, our results have implications for risk management and they contribute to better understanding, estimation, management and forecast for credit risk by practitioners, as well as policymakers.

Future work

Our conclusions and research work opened avenues for further research:

In the second chapter we have shown that price discovery dynamics across three markets (stock, options and credit default swaps) changed during the financial crisis compared to the pre-crisis period. It would be insightful to look at a finer division of the sub-periods in order to have a better understanding of the dynamics across the three markets. In addition, our study does not fully cover the sovereign debt crisis period, hence it would be interesting to conduct similar work for that period.

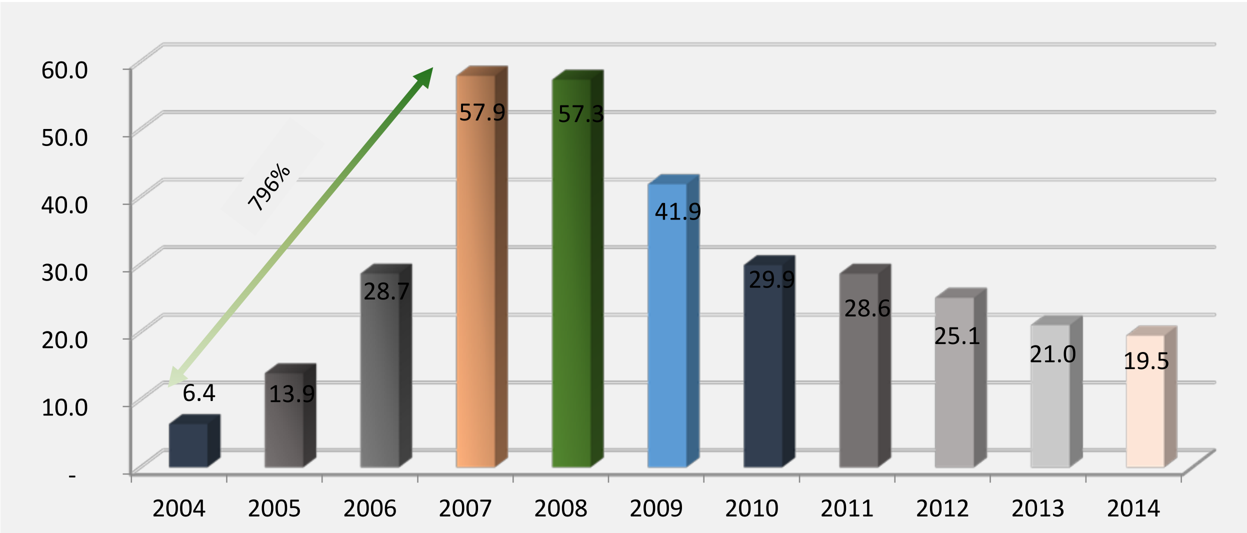
Furthermore, in chapter four, we analyze the impact of Eurozone member countries' credit risk on euro stability. When looking at currency stability we only consider the dollar, so future work could include a panel of other currencies.

Moreover, in chapter five, we consider only one measure of systemic risk that arises from the interconnectedness between financial institutions. In future work, one could estimate the systemic risk based on the interdependence between the financial sector and the real economy. This would capture shock effects that go beyond their direct impact and so causing disorder in the real economy. Finally, in this research we look only at the precise moment the impact of systemic risk on the banks' and countries' credit ratings. It could be revealing to examine the evolution of this impact in recent years. We think that this relationship had become stronger after the financial crisis 2007-2008. Rating agencies have realized the importance of systemic risk and the necessity of incorporating such factors in their risk assessment.

Appendixes

Chapter One

Figure A.1 Global Credit Default Swap Outstanding (trillions of dollars)



Source: Bank for International Settlements

Chapter Three

Table A.1 List of Banks

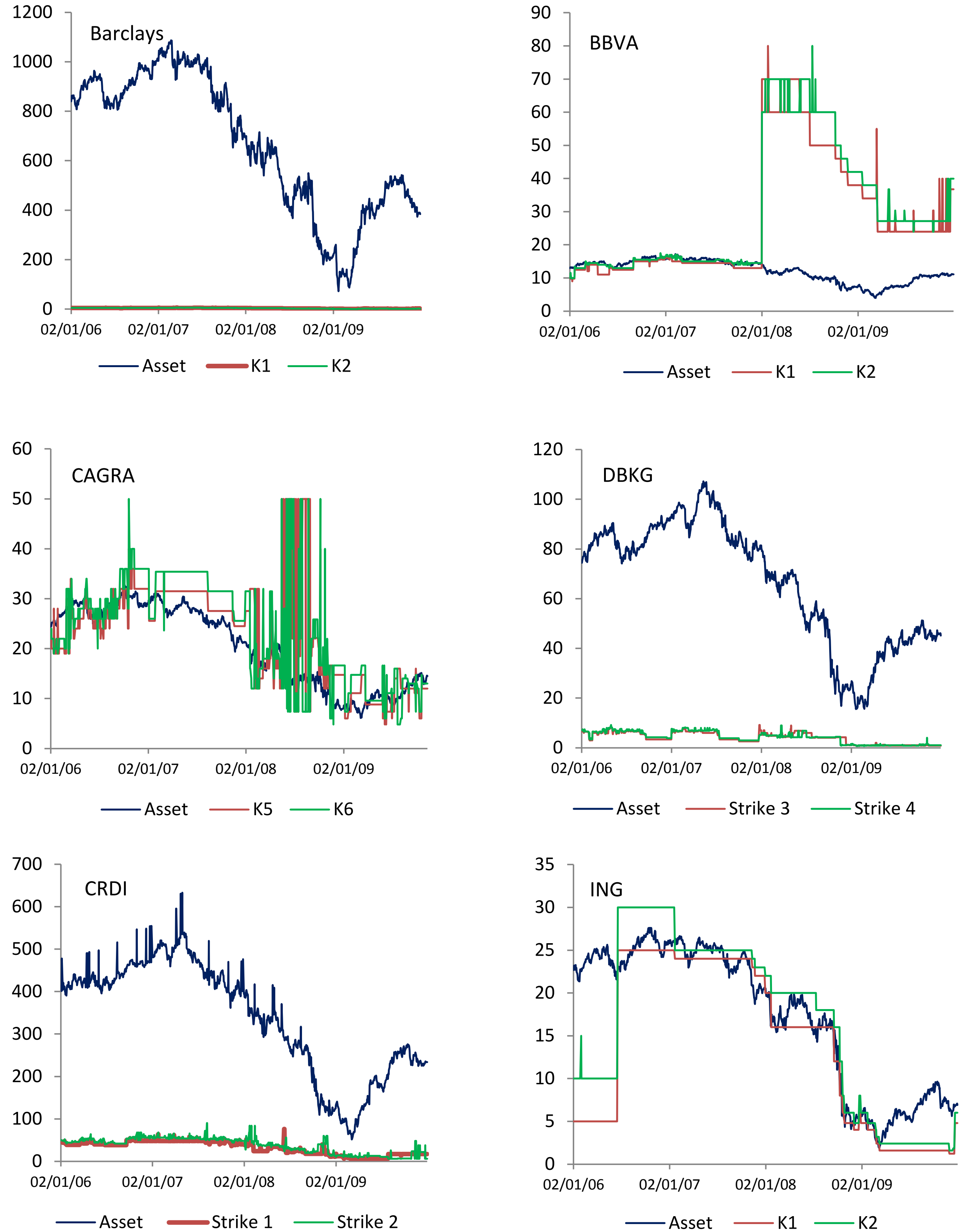
Bank Code	Bank Name	Ticker
BARC	Barclays	BARC:LN
BBVA	Banco Bilbao Vizcaya Argentaria	BBVA:SM
PNPPA	BNP Paribas	BNP:FP
CAGRA	Credit Agricole	ACA:FP
CBKG	COMMERZBANK	CBK:GR
CRDI	UniCredit SpA	UCG:IM
CSGN	Credit Suisse Group AG	CSGN:VX
DBKGn	Deutsche *Bank*	DBK:GR
DEXI	DEXIA	DEXB:BB
ERST	ERSTE Bank Group	EBS:AV
ING	*ING DIRECT*	INGA:NA
KBC	KBC Bank	KBC:BB
RBS	*Royal Bank of Scotland* (*RBS*)	RBS:LN
STAN	Standard Chartered *Bank*	STAN:LN
UBSN	UBS	UBSN:VX

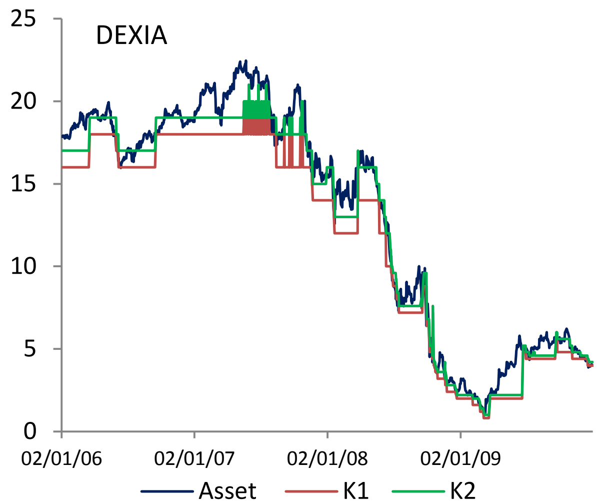
Table A.2 Summary statistics of Strikes prices and Stocks Prices

	Mean	Median	STDEV	Min	Max	Q1	Q3	Skew	Kurto
Barclays									
K1	3,30	4,20	1,48	0,48	6,4	1,70	4,20	-0,47	-1,19
K2	3,61	4,20	1,56		6,5	2,30	4,60	-0,47	-1,15
S	667,53	688,49	277,90	72,32	1086,74	439,19	926,48	-0,32	-1,16
BBVA									
K1	27,37	17,00	17,70	9	80	14,50	38,00	1,07	-0,17
K2	29,82	17,50	19,33	9,75	80	15,00	42,00	0,97	-0,51
S	12,18	13,01	3,30	4	17,16	10,02	14,95	-0,57	-0,82
CAGRA									
K1	23,17	24,50	10,13	4,8	50	14,76	31,48	0,30	-0,10
K2	23,77	25,84	10,49	4,8	50	14,76	32,00	0,04	-0,94
S	20,37	21,35	8,00	6,11	32,71	12,85	27,99	-0,20	-1,53
CBKG									
K1	1,13	1,40	0,66	0,13	2,79	0,48	1,60	-0,18	-1,19
K2	1,24	1,59	0,75	0,13	2,39	0,36	1,80	-0,28	-1,37
S	123,56	149,50	64,90	13,51	223,38	44,49	175,13	-0,38	-1,35
CRDI									
K1	32,22	38,00	15,66	6,4	76	17,00	48,00	-0,26	-1,24
K2	37,99	44,00	18,46	6,4	90	20,00	54,00	-0,37	-1,04
S	337,72	390,23	133,00	51,61	632,81	235,58	443,68	-0,43	-1,02
DBKG									
K1	4,15	4,00	2,28	0,74	9,2	1,20	6,00	-0,11	-1,31
K2	4,02	4,20	2,36	0,72	9,2	1,20	6,60	-0,07	-1,27
S	66,25	75,10	24,62	15,535	107,162	44,94	86,09	-0,41	-1,06
DEXIA									
K1	11,61	14,00	6,30	0,8	20	4,40	18,00	-0,43	-1,49
K2	12,48	16,00	6,67	1	21	4,80	19,00	-0,46	-1,50
S	13,08	16,08	6,84	1,03	22,46	5,31	18,94	-0,40	-1,49
ING									
K1	16,31	16,00	9,55	1,23	25	4,80	24,00	-0,09	-1,72
K2	13,81	20,00	10,11	1,6	30	6,00	25,00	-0,16	-1,50
S	17,30	19,79	8,17	1,91	27,61	7,40	24,60	-0,49	-1,37
KBC									
K1	41,80	44,00	28,55	4,4	88	10,00	72,00	0,09	-1,67
K2	45,15	41,00	30,44	4,8	92	11,00	76,00	0,05	-1,70
S	102,51	89,50	69,04	5,5	223,38	32,20	168,12	0,18	-1,43
RBS									
K1	10,20	13,50	5,36	1,67	17	4,00	14,00	-0,68	-1,30
K2	10,67	13,50	5,44	1,83	18	4,83	14,50	-0,72	-1,25
S	4430,91	4908,72	2940,02	145,49	8512,39	754,64	7144,26	-0,25	-1,59
UBS									
K1	11,12	5,80	7,80	1,6	44,82	4,40	18,68	0,47	-0,66
K2	13,55	6,40	10,51	1,6	85,91	4,80	22,41	0,87	1,55
S	37,98	30,36	22,02	8,57	71,147	16,52	62,37	0,24	-1,67
BNP									
K1	42,20	48,00	13,59	12	76	36,00	49,61	-0,63	-0,23
K2	47,52	54,57	15,22	14	90	40,00	54,57	-0,35	0,06
S	64,12	68,08	16,37	20,77	91,60	54,56	76,25	-0,71	-0,22
CSGN									
K1	39,89	59,69	37,75	3,8	119,38	4,60	59,69	0,50	-1,02
K2	41,70	43,77	34,13	4	139,28	5,20	67,65	0,28	-1,09
S	38,11	38,54	10,19	14,81	55,86	31,15	46,30	-0,26	-0,81
ERSTE									
K1	3,30	3,20	2,04	1	9,5	1,60	4,80	0,88	0,12
K2	3,48	3,40	2,09	1	9,5	1,70	5,00	0,88	0,04
S	38,18	41,99	14,07	6,59	57,93	28,73	49,51	-0,60	-0,78
STAN									
K1	11,51	11,50	0,98	10	17	11,00	12,00	0,99	3,57
K2	11,93	12,00	1,16	10	17,5	11,00	13,00	0,62	1,54
S	1263,52	1247,23	123,80	1024,6	1652,85	1176,39	1339,15	0,66	0,23

Table reports summary statistics of the DOOM put options strikes K1, K2 along with the underlying stock price S for each bank over the period of January 2006 to December 2009.

Figure A.2 Plots of daily strikes prices and the underlying asset for each banks




DEXIA
25
20
15
10
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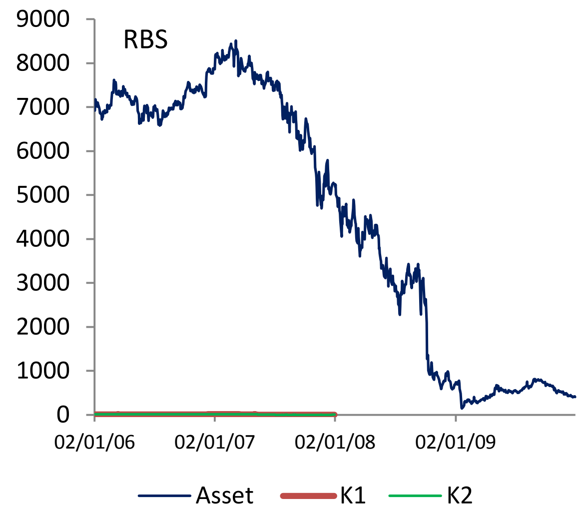
02/01/06
02/01/07
02/01/08
02/01/09
Asset
K1
K2


RBS
9000
8000
7000
6000
5000
4000
3000
2000
1000
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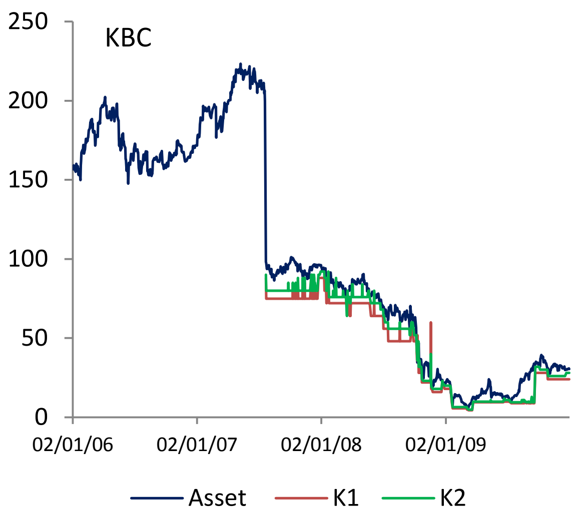
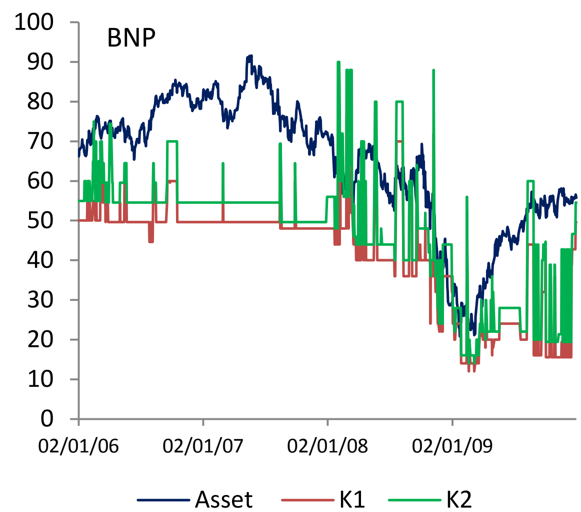
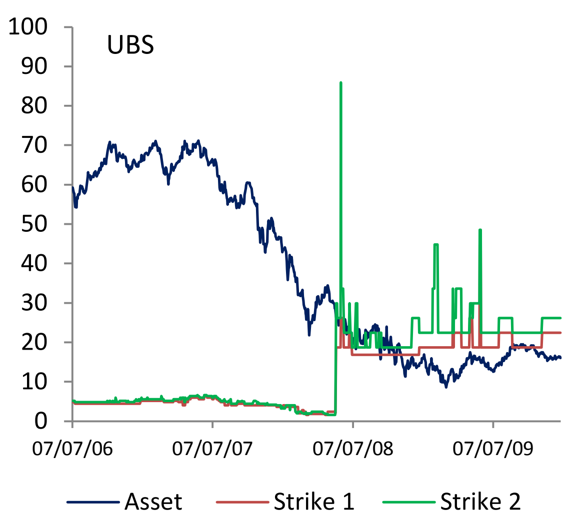
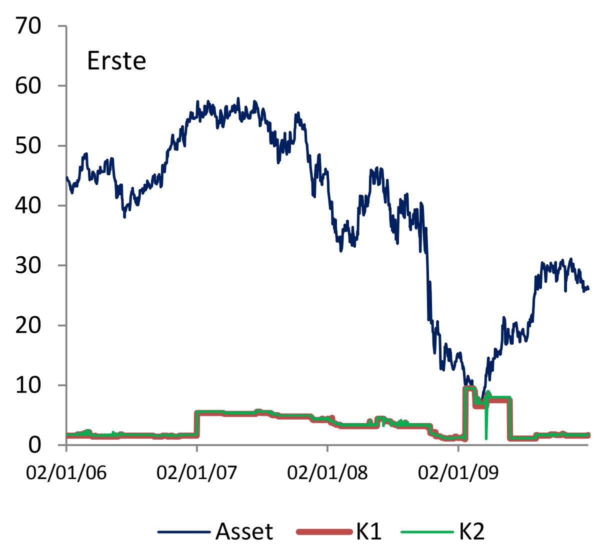
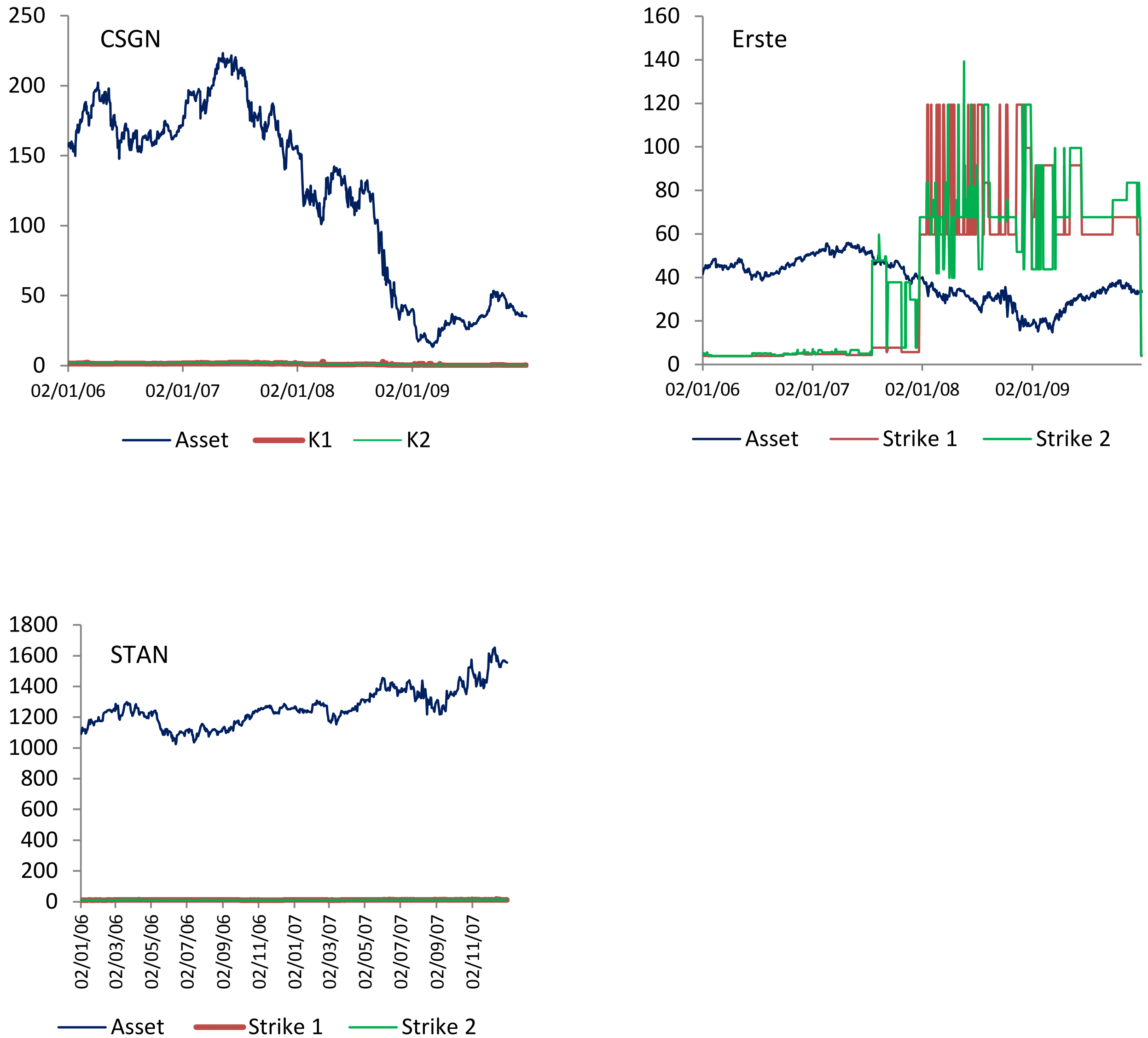
Asset
K1
K2


KBC
250
200
150
100
50
0
02/01/06
02/01/07
02/01/08
02/01/09
Asset
K1
K2


BNP
100
90
80
70
60
50
40
30
20
10
0
02/01/06
02/01/07
02/01/08
02/01/09
Asset
K1
K2


UBS
100
90
80
70
60
50
40
30
20
10
0
07/07/06
07/07/07
07/07/08
07/07/09
Asset
Strike 1
Strike 2


Erste
70
60
50
40
30
20
10
0
02/01/06
02/01/07
02/01/08
02/01/09
Asset
K1
K2



Plots of daily strikes prices, K1, K2 and the underlying asset for each banks. The strikes prices K1, K2 are comprised in the ‘default corridor’ described by the model, which the asset prices should never enter. For certain banks of our sample, this assumption is not materialized throughout the whole period of study.

Table A.3 Summary Statistics: Implied Volatilities for puts

PUT	10 Delta				25 Delta				At the Money			
	1M	3M	6M	9M	1M	3M	6M	9M	1M	3M	6M	9M
Overall sample period *from 05/09/2008 to 31/01/2012*												
Mean	15.42	16.44	17.00	17.24	14.23	14.78	15.04	15.16	13.40	13.67	13.82	13.88
Median	14.34	15.35	16.19	16.53	13.45	14.01	14.47	14.62	12.55	12.93	13.25	13.35
Maximum	33.60	28.65	25.55	24.33	31.05	25.70	22.49	20.95	29.00	24.25	21.70	20.15
Minimum	9.75	6.10	6.40	12.59	9.10	5.28	5.35	11.41	8.95	5.00	5.00	10.63
Std.Dev	4.15	3.46	2.93	2.66	3.64	2.94	2.39	2.12	3.48	2.79	2.23	1.94
Skewness	1.27	1.02	0.67	0.60	1.36	1.12	0.74	0.73	1.48	1.37	1.07	1.11
Kurtosis	1.36	0.48	-0.19	-0.67	1.91	1.03	0.41	-0.31	2.18	1.74	1.30	0.67
Q1	12.20	13.80	14.80	15.26	11.45	12.58	13.25	13.55	10.80	11.70	12.25	12.49
Q3	17.56	18.43	18.93	19.25	15.93	16.28	16.53	16.56	14.80	14.80	14.70	14.72
Subprime crisis *from 05/09/2008 to 13/10/2009*												
Mean	17.49	17.74	17.65	17.70	16.34	16.18	15.88	15.80	15.95	15.66	15.22	15.11
Median	15.76	16.06	16.34	16.54	14.88	15.05	15.03	15.00	14.85	14.80	14.68	14.53
Maximum	33.60	28.65	25.55	24.33	31.05	25.70	22.49	20.95	29.00	24.25	21.70	20.15
Minimum	9.75	6.10	6.40	12.59	9.10	5.28	5.35	11.41	9.00	5.00	5.00	10.63
Std.Dev	5.51	4.64	3.92	3.45	4.81	3.94	3.23	2.80	4.46	3.60	2.96	2.51
Skewness	0.56	0.44	0.22	0.21	0.57	0.42	0.13	0.22	0.51	0.37	0.05	0.19
Kurtosis	-0.72	-1.05	-1.15	-1.47	-0.54	-0.87	-0.79	-1.37	-0.61	-0.77	-0.54	-1.22
Q1	12.59	13.56	13.98	14.45	12.22	12.68	13.06	13.33	12.03	12.60	12.79	13.10
Q3	22.11	22.13	21.50	21.20	20.14	19.68	18.71	18.45	19.40	18.71	17.75	17.41
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*												
Mean	14.42	15.81	16.69	17.01	13.21	14.10	14.64	14.85	12.17	12.71	13.13	13.28
Median	13.83	15.23	16.16	16.50	12.95	13.73	14.27	14.48	11.85	12.38	12.90	13.06
Maximum	22.45	23.13	22.94	22.83	19.88	20.05	19.60	19.47	18.10	17.55	17.05	16.88
Minimum	10.23	11.49	12.19	12.62	9.50	10.83	11.75	12.15	8.95	9.95	10.70	11.07
Std.Dev	2.80	2.49	2.24	2.15	2.29	1.97	1.72	1.62	1.91	1.56	1.30	1.20
Skewness	0.85	0.77	0.78	0.78	0.71	0.65	0.72	0.75	0.65	0.61	0.62	0.69
Kurtosis	-0.13	-0.28	-0.24	-0.21	-0.22	-0.29	-0.19	-0.09	-0.28	-0.33	-0.16	0.00
Q1	12.89	14.48	15.64	16.03	11.30	12.52	13.30	13.61	10.60	11.50	12.10	12.34
Q3	15.78	17.19	17.87	18.11	14.45	15.24	15.58	15.72	13.34	13.79	13.95	13.99

Note: OTC European quotes at fixed maturities 1, 3, 6 , 9 months of out-of-the-money put (10-20-delta) and at-the-money-options (50-delta). The quotes are in terms of delta-implied-volatilities of Black-Scholes. Statistics are computed based on daily data. The overall sample period spans from 05/09/2008 to 31/01/2012. The first sub-period (subprime crisis) is from 05/09/2008 to 13/10/2009 and the second sub-period (sovereign debt crisis) is from 14/10/2009 to 31/01/2012.

Table A.4 Summary Statistics: Implied Volatilities for calls

Call	10 Delta				25 Delta			
	1M	3M	6M	9M	1M	3M	6M	9M
Overall sample period *from 05/09/2008 to 31/01/2012*								
Mean	13.22	13.76	14.16	14.39	13.01	13.28	13.46	13.57
Median	11.95	12.80	13.38	13.62	12.03	12.50	12.89	13.06
Maximum	28.68	27.55	24.83	23.95	28.05	25.08	22.35	21.00
Minimum	8.38	6.30	6.70	10.74	8.43	5.13	5.45	10.64
Std.Dev	3.96	3.44	2.99	2.76	3.58	2.95	2.43	2.14
Skewness	1.61	1.61	1.44	1.42	1.57	1.54	1.37	1.41
Kurtosis	2.18	2.09	1.44	1.31	2.33	2.17	1.69	1.47
Q1	10.60	11.63	12.16	12.46	10.50	11.40	11.85	12.14
Q3	14.20	14.30	14.78	15.25	14.06	13.95	14.03	14.07
Subprime crisis *from 05/09/2008 to 13/10/2009*								
Mean	16.98	17.24	17.26	17.38	16.06	15.89	15.64	15.57
Median	16.24	16.50	16.64	16.89	15.19	15.21	15.15	15.01
Maximum	28.68	27.55	24.83	23.95	28.05	25.08	22.35	21.00
Minimum	9.65	6.30	6.70	11.43	9.10	5.13	5.45	10.64
Std.Dev	4.69	3.92	3.30	2.88	4.43	3.62	2.97	2.50
Skewness	0.41	0.38	0.08	0.21	0.47	0.36	0.04	0.22
Kurtosis	-0.80	-0.73	-0.62	-0.82	-0.69	-0.71	-0.46	-1.00
Q1	12.75	14.07	14.68	15.25	12.10	12.98	13.23	13.74
Q3	20.34	20.39	20.05	19.83	19.38	18.76	18.13	17.72
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*								
Mean	11.40	12.08	12.65	12.95	11.52	12.02	12.41	12.60
Median	11.20	12.08	12.65	12.91	11.43	11.90	12.35	12.52
Maximum	16.75	15.63	15.41	15.24	16.88	15.95	15.55	15.36
Minimum	8.38	9.63	10.41	10.74	8.43	9.43	10.25	10.68
Std.Dev	1.57	1.20	1.02	0.94	1.67	1.30	1.04	0.93
Skewness	0.47	0.10	0.05	0.11	0.44	0.27	0.27	0.29
Kurtosis	-0.27	-0.55	-0.86	-0.86	-0.38	-0.50	-0.47	-0.40
Q1	10.62	11.15	11.81	12.08	10.18	11.03	11.58	11.86
Q3	12.46	12.98	13.50	13.71	12.52	13.00	13.22	13.30

Note: OTC European quotes at fixed maturities 1, 3, 6 and, 9 months of out-of-the-money call (10-20-delta) options. The quotes are in terms of delta-implied-volatilities of Black-Scholes

Table A.5 Summary statistics of risk-neutral moments and the dollar-euro exchange rate

	Exchange rate	risk-neutral Skewness	risk-neutral Kurtosis	risk-neutral Volatility
Overall sample period *from 05/09/2008 to 31/01/2012*				
Mean	1.37	-0.10	5.85	0.15
Median	1.37	-0.24	5.12	0.14
Maximum	1.51	1.58	15.12	0.27
Minimum	1.19	-0.91	3.90	0.06
Std.Dev	0.07	0.46	1.61	0.03
Skewness	-0.13	0.60	2.16	1.41
Kurtosis	-0.75	-0.34	5.22	1.75
Q1	1.31	-0.41	4.88	0.12
Q3	1.42	0.29	6.25	0.16
Subprime crisis *from 05/09/2008 to 13/10/2009*				
Mean	1.36	0.47	7.64	0.17
Median	1.36	0.45	7.06	0.16
Maximum	1.49	1.58	15.12	0.27
Minimum	1.25	-0.17	5.04	0.06
Std.Dev	0.07	0.25	1.75	0.04
Skewness	-0.07	1.06	1.34	0.41
Kurtosis	-1.22	2.57	2.05	-0.90
Q1	1.30	0.30	6.28	0.13
Q3	1.42	0.56	8.61	0.20
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*				
Mean	1.37	-0.37	4.99	0.14
Median	1.37	-0.36	4.96	0.13
Maximum	1.51	0.29	5.94	0.19
Minimum	1.19	-0.91	3.90	0.10
Std.Dev	0.07	0.23	0.25	0.02
Skewness	-0.16	-0.01	0.75	0.66
Kurtosis	-0.59	-0.22	1.62	-0.18
Q1	1.32	-0.54	4.78	0.12
Q3	1.42	-0.23	5.12	0.15

Note: Statistics are computed based on daily data. The overall sample period spans from 05/09/2008 to 31/01/2012. The first sub-period (subprime crisis) is from 05/09/2008 to 13/10/2009 and the second sub-period (sovereign debt crisis) is from 14/10/2009 to 31/01/2012.Skew, Kurt and IV, respectively: Skewness, kurtosis and implied volatility are the independent variables.

Table A.6 Regression Results: Value-at-Risk and Expected Shortfall ratios

	VaR ratio		ES ratio	
	Betas	T-stat	Betas	T-stat
Overall sample period *from 05/09/2008 to 31/12/2012*				
Belgium	-0.01	-0.315	-0.03	-0.585
France	-0.05	-1.114	-0.06	-1.000
Germany	-0.01	-0.282	-0.02	-0.392
Netherlands	-0.04	-0.771	-0.06	-0.853
Finland	-0.07	-1.202	-0.09	-1.264
Austria	-0.02	-0.621	-0.04	-0.876
Ireland	-0.04	-1.925	-0.04	-1.411
Spain	-0.07	-1.404	-0.08	-1.290
Portugal	-0.05	-1.100	-0.06	-1.010
Greece	-0.06	-1.123	-0.06	-1.292
Italy	-0.09*	-1.750	-0.10	-1.503
Subprime crisis *from 05/09/2008 to 13/10/2009*				
Belgium	0.03	0.365	0.00	-0.014
France	-0.02	-0.192	-0.02	-0.159
Germany	0.02	0.199	0.02	0.156
Netherlands	-0.03	-0.374	-0.05	-0.442
Finland	-0.05	-0.478	-0.08	-0.517
Austria	-0.02	-0.251	-0.04	-0.500
Ireland	-0.03	-0.864	-0.02	-0.462
Spain	-0.05	-0.416	-0.04	-0.272
Portugal	0.02	0.220	0.03	0.191
Greece	-0.01	-1.151	-0.03	-0.951
Italy	-0.08	-0.740	-0.07	-0.445
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*				
Belgium	-0.08	-1.518	-0.09	-1.359
France	-0.08	-1.573	-0.09	-1.423
Germany	-0.07	-1.298	-0.10	-1.404
Netherlands	-0.06	-1.078	-0.08	-1.119
Finland	-0.09	-1.554	-0.12	-1.674
Austria	-0.01	-0.274	-0.02	-0.269
Ireland	-0.12**	-2.195	-0.14**	-2.007
Spain	-0.08*	-1.925	-0.11**	-1.991
Portugal	-0.10**	-2.024	-0.12**	-2.006
Greece	-0.07	-1.371	-0.10	-1.364
Italy	-0.12***	-2.495	-0.15***	-2.530
PCA_H	-0.034	-1.21	-0.043	-1.23
PCA_V	-0.055**	-2.26	-0.069**	-2.27

Note: For each country, the dependent variables are the Value-at-Risk ratios and Expected Shortfall ratios of the daily moments of the 3-months risk-neutral distribution of dollar-euro exchange rate options (the variance is expressed in terms of annualized volatility). T-stats are computed based on the Wald test. . (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level.

Chapter Five

Bloomberg definition of short and long term debt:

ST debt (BS047): Includes bank overdrafts, short-term debts and borrowings, repurchase agreements (repos), short-term portion of long-term borrowings and current obligations under capital(finance) leases Due to other banks (including central bank) or any other financial institutions. Includes call money, bills discounted. Includes federal funds purchased. Includes securities sold, not yet purchased.

LT Debt (BS051): All interest-bearing financial obligations that are not current. Includes convertible debentures, bonds, loans, mortgage debts, sinking funds, long-term bank overdrafts and capital (finance) lease obligations. Excludes short-term portion of long term debt, pension obligations, deferred tax liabilities and preferred equity. Includes subordinated capital notes. Includes mandatory redeemable preferred and trust preferred securities in accordance with FASB 150 effective June 2003

Figure A.4 Implicit asset value

Figure A.4 shows the evolution of individual implicit asset value time-series averages of the entire sample banks (41 banks) over the period **01 January 2007 to 01 August 2013**. Implicit asset value are estimated based on Merton model.

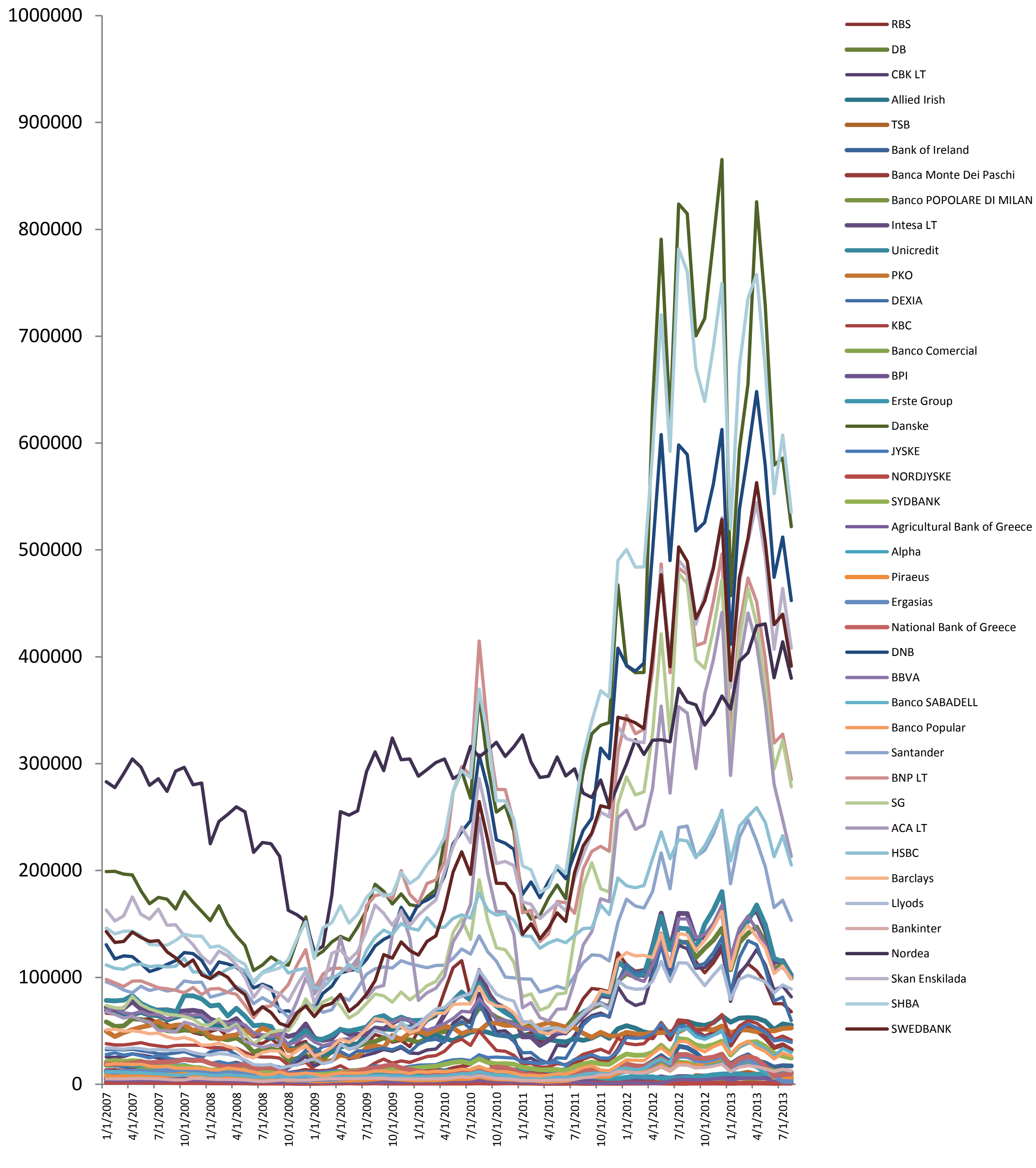


Table A.7 Final List of banks

The table below is the final list of banks extracted from the European Banking Authority stress test. Our sample consist on 41 banks from 14 European countries: Austria (1), Belgium (2), Denmark (4), France (3), Greece (6), Germany (2), Italy (4), Ireland (2),Norway (1), Poland (1), Portugal (2), Spain (4), Sweden (4), UK (5).

Banks	Sovereigns	Banks	Sovereigns
Erste Group Bank AG	Austria	Bank of Ireland	Ireland
Dexia	Belgium	Allied Irish Banks plc	Ireland
KBC Group	Belgium	DNB Bank ASA	Norway
Danske Bank A/S	Denmark	PKO Bank Polski	Poland
JYSKE	Denmark	Banco BPI SA Portugal	Portugal
Nordjyske Bank A/S	Denmark	BPI	Portugal
Sydbank A/S Denmark	Denmark	Banco Bilbao Vizcaya Argentaria SA	Spain
BNP Paribas	France	Banco de Sabadell SA Spain	Spain
Société Générale	France	Banco Popular	Spain
Crédit Agricole Group	France	Bankinter SA	Spain
Agricultural Bank of Greece SA	Greece	Banco Santander SA	Greece
Alpha Bank AE	Greece	Nordea Bank AB (publ)	Sweden
Piraeus Bank	Greece	Skan Enskilada SEB	Sweden
Ergasias	Greece	SHBA	Sweden
National Bank of Greece	Greece	Swedbank AB	Sweden
Deutsche Bank AG	Germany	Royal Bank of Scotland (RBS)	UK
Commerzbank AG (CBK)	Germany	TSB Bank plc	UK
Banca Monte Dei Paschi	Italy	HSBC	UK
Gruppo Banco Popolare de Milan	Italy	Barclay	UK
Intesa Sanpaolo[48] Sanpaolo	Italy	LLyods	UK
Gruppo UniCredit	Italy		

[48] Gruppo Bancario Intesa

Table A.8 Probit estimations of the effect of monthly changes in lagged DD for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDD_{-1M}	**-0.17****	**-0.63*****	**-0.19****	**-0.59*****	**-0.17***	**-0.76*****	**-0.17****	**-0.73*****	**-0.26*****	**-0.57*****	**-0.27*****	**-0.59*****
	(-2.10)	(-4.03)	(-2.23)	(-3.90)	(-1.95)	(-5.29)	(-2.01)	(-5.15)	(-3.49)	(-3.51)	(-3.54)	(-3.61)
ΔDD_{-3M}	**-0.24*****		**-0.20*****		**-0.33*****		**-0.31*****		**-0.15***		**-0.15***	
	(-3.27)		(-2.66)		(-5.33)		(-4.90)		(-1.66)		(-1.68)	
ΔDD_{-6M}	**-0.24*****		**-0.24*****		**-0.24 *****		**-0.23*****		-0.10		-0.11	
	(-3.58)		(-3.35)		(-3.44)		(-3.26)		(-0.97)		(-1.10)	
ΔDD_{-12M}	0.03		0.04		-0.03		-0.02		-0.06		-0.06	
	(0.27)		(0.37)		(-0.24)		(-0.16)		(-0.61)		(-0.56)	
$\Delta DD_{-(3M-1M)}$		**-0.45*****		**-0.40*****		**-0.59*****		**-0.55*****		**-0.31***		**-0.33****
		(-3.01)		(-2.77)		(-4.25)		(-4.06)		(-1.92)		(-1.98)
$\Delta DD_{-(6M-3M)}$		-0.21		-0.20		**-0.26****		**-0.24****		-0.16		-0.17
		(-1.64)		(-1.62)		(-2.14)		(-2.06)		(-1.21)		(-1.27)
$\Delta DD_{-(12M-6M)}$		0.03		0.04		-0.03		-0.02		-0.06		-0.06
		(0.27)		(0.37)		(-0.24)		(-0.16)		(-0.61)		(-0.56)
Volatility			-0.04	-0.04			-0.20	-0.20			0.11	0.11
			(-0.40)	(-0.40)			(-1.63)	(-1.63)			(1.21)	(1.21)
Relative size			**-8.34*****	**-8.34*****			**-10.74 *****	**-10.74*****			**-2.84****	**-2.84*****
			(-4.63)	(-4.63)			(-4.47)	(-4.47)			(-2.56)	(-2.56)
leverage			0.00	0.00			0.00	0.00			-0.00	-0.00
			(1.62)	(1.62)			(1.56)	(1.56)			(-0.32)	(-0.32)
vstoxx			**0.01*****	**0.01*****			**0.01****	**0.01****			0.00	0.00
			(3.77)	(3.77)			(2.45)	(2.45)			(0.31)	(0.31)
Constant	**-2.88*****	**-2.88*****	**-2.98*****	**-2.98*****	**-2.98*****	**-2.98*****	**-2.87 *****	**-2.87*****	**-2.84*****	**-2.84*****	**-2.85*****	**-2.85*****
	(-65.74)	(-65.74)	(-27.23)	(-27.23)	(-58.42)	(-58.42)	(-23.09)	(-23.09)	(-94.67)	(-94.67)	(-25.25)	(-25.25)
Log L	-812.67	-812.67	-790.16	-790.16	-776.49	-776.49	-757.48	-757.48	-830.49	-830.49	-825.08	-825.08
Pseudo-R^2	3,61%	3,61%	6,28%	6,28%	4,33%	4,33%	6,67%	6,67%	6,54%	6,54%	7,15%	7,15%

Table A.9 Marginal effect of probit estimations of the effect of monthly changes in lagged DD for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	M3	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDD_{-1M}	-0.11%	-0.41%	-0.13%	-0.41%	-0.08%	-0.39%	-0.10%	-0.41%	-0.19%	-0.42%	-0.19%	-0.43%
ΔDD_{-3M}	-0.16%		-0.14%		-0.17%		-0.17%		-0.11%		-0.11%	
ΔDD_{-6M}	-0.16%		-0.17%		-0.12%		-0.13%		-0.07%		-0.08%	
ΔDD_{-12M}	0.02%		0.03%		-0.01%		-0.01%		-0.05%		-0.04%	
$\Delta DD_{-(3M-1M)}$		-0.30%		-0.28%		-0.30%		-0.31%		-0.23%		-0.24%
$\Delta DD_{-(6M-3M)}$		-0.14%		-0.14%		-0.13%		-0.14%		-0.12%		-0.13%
$\Delta DD_{-(12M-6M)}$		0.02%		0.03%		-0.01%		-0.01%		-0.05%		-0.04%
Volatility			-0.03%	-0.03%			-0.11%	-0.00%			0.08%	0.08%
Relative size			-5.87%	-5.87%			-6.00%	-6.06%			-2.08%	-2.08%
leverage			0.00%	0.00%			0.00%	0.00%			0.00%	0.00%
vstoxx			0.01%	0.01%			0.00%	0.00%			0.00%	0.00%

Table A.10 Probit estimations of the effect of monthly changes in lagged DDI for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI_{-1M}	**-0.23*****	**-0.92*****	**-0.24*****	**-0.89*****	**-0.20*****	**-0.90*****	**-0.19****	**-0.86*****	**-0.30*****	**-0.43***	**-0.31*****	**-0.45***
	(-3.03)	(-5.67)	(-3.10)	(-5.60)	(-2.42)	(-5.93)	(-2.42)	(-5.52)	(-4.16)	(-1.89)	(-4.22)	(-1.94)
ΔDDI_{-3M}	**-0.41*****		**-0.38*****		**-0.38*****		**-0.35*****		**-0.22****		**-0.22****	
	(-6.61)		(-5.75)		(-5.80)		(-5.26)		(-2.51)		(-2.54)	
ΔDDI_{-6M}	**-0.29*****		**-0.28*****		**-0.37*****		**-0.36*****		0.18		0.18	
	(-3.82)		(-3.63)		(-6.06)		(-5.82)		(1.05)		(0.99)	
ΔDDI_{-12M}	0.00		-0.00		**-0.17***		**-0.17***		-0.10		-0.09	
	(0.02)		(-0.03)		(-1.94)		(-1.92)		(-0.79)		(-0.75)	
$\Delta DDI_{-(3M-1M)}$		**-0.70*****		**-0.66*****		**-0.92*****		**-0.88*****		-0.13		-0.14
		(-4.37)		(-4.28)		(-7.39)		(-7.00)		(-0.55)		(-0.59)
$\Delta DDI_{-(6M-3M)}$		**-0.28****		**-0.28 ****		**-0.54*****		**-0.53*****		-0.09		-0.08
		(-2.00)		(-2.10)		(-5.25)		(-5.16)		(0.42)		(0.40)
$\Delta DDI_{-(12M-6M)}$		0.00		-0.00		**-0.17***		**-0.17***		-0.10		-0.09
		(0.02)		(-0.03)		(-1.94)		(-1.92)		(-0.79)		(-0.75)
Volatility			-0.04	-0.04			-0.24	-0.24			0.11	0.11
			(-0.37)	(-0.37)			(1.00)	(1.00)			(1.27)	(1.27)
Relative size			**-8.49*****	**-8.49*****			**-11.04*****	**-11.04*****			**-2.79****	**-2.79****
			(-4.61)	(-4.61)			(-4.50)	(-4.50)			(-2.50)	(-2.50)
leverage			**0.00***	**0.00***			**0.00***	**0.00***			0.00	0.00
			(1.69)	(1.69)			(1.73)	(1.73)			(0.35)	(0.35)
vstoxx			**0.01*****	**0.01*****			**0.00***	**0.00***			0.00	0.00
			(2.80)	(2.80)			(1.65)	(1.65)			(0.02)	(0.02)
Constant	**-2.90*****	**-2.90*****	**-2.93*****	**-2.93*****	**-2.99*****	**-2.99*****	**-2.80*****	**-2.80*****	**-2.84*****	**-2.84*****	**-2.83 *****	**-2.84*****
	(-65.90)	(-65.90)	(-26.28)	(-26.28)	(-58.08)	(-58.08)	(-22.27)	(-22.27)	(-94.07)	(-94.07)	-(24.71)	(-24.71)
Log L	-795.51	-795.51	-775.46	-775.46	-766.29	-766.29	-748.23	-748.23	-826.01	-826.01	-820.74	-820.73
Pseudo-R^2	5,65%	5,65%	8,02%	8,02%	5,59%	5,59%	7,81%	7,81%	7,04%	7,04%	7,64%	7,64%

Table A.11 Marginal effect of probit estimations of the effect of monthly changes in lagged DDI for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	M3	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI_{-1M}	-0.15%	-0.60%	-0.16%	-0.62%	-0.10%	-0.54%	-0.11%	-0.57%	-0.22%	-0.31%	-0.23%	-0.33%
ΔDDI_{-3M}	-0.27%		-0.26%		-0.17%		-0.18%		-0.16%		-0.16%	
ΔDDI_{-6M}	-0.19%		-0.19%		-0.19%		-0.20%		0.13%		0.13%	
ΔDDI_{-12M}	0.00%		-0.00%		-0.08%		-0.09%		-0.07%		-0.07%	
$\Delta DDI_{-(3M-1M)}$		-0.45%		-0.46%		-0.44%		-0.47%		-0.09%		-0.10%
$\Delta DDI_{-(6M-3M)}$		-0.19%		-0.20%		-0.27%		-0.29%		-0.06%		-0.06%
$\Delta DDI_{-(12M-6M)}$		0.00%		-0.00%		-0.08%		-0.09%		-0.07%		-0.07%
Volatility			-0.03%	-0.03%			-0.12%	-0.12%			0.08%	0.08%
Relative size			-5.88%	-5.88%			-6.15%	-6.15%			-2.03%	-2.03%
leverage			0.00%	0.00%			0.00%	0.00%			0.00%	0.00%
vstoxx			0.01%	0.01%			0.00%	0.00%			0.00%	0.00%

Table A.12 Probit estimations of the effect of monthly changes in lagged DD for different horizons on sovereign ratings (20-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
ΔDD$_{-1M}$	0.05 (0.65)	**-0.06**** (-2.27)	0.11 (1.10)	**-0.06**** (-2.27)	-0.10 (-1.30)	**-0.10***** (-2.65)	-0.07 (-0.51)	**-0.10**** (-2.02)	**-0.15*** (-1.66)	**-0.10***** (-2.71)	**-0.19**** (-2.45)	**-0.20***** (-2.81)
ΔDD$_{-3M}$	**-0.17*** (-1.67)		**-0.22**** (-1.97)		-0.05 (0.76)		-0.03 (-0.22)		-0.16 (-1.39)		-0.19 (-1.34)	
ΔDD$_{-6M}$	**-0.09*** (-1.79)		-0.03 (-0.56)		-0.03 (-0.92)		-0.05 (-0.60)		-0.09 (-1.16)		-0.24 (-1.04)	
ΔDD$_{-12M}$	-0.04 (-1.44)		-0.02 (-0.59)		-0.04 (-1.19)		-0.02 (-0.56)		-0.02 (-0.81)		-0.04 (-1.03)	
ΔDD$_{-(3M-1M)}$		-0.13 (-1.56)		**-0.21**** (-2.06)		-0.00 (-0.06)		-0.04 (-0.36)		-0.05 (-0.63)		-0.01 (-0.09)
ΔDD$_{-(6M-3M)}$		-0.05 (-0.26)		-0.02 (-0.33)		-0.05 (-0.79)		-0.07 (-0.98)		**-0.12*** (-1.66)		**-0.21*** (-1.94)
ΔDD$_{-(12M-6M)}$		-0.04 (-1.47)		-0.02 (-0.59)		-0.05 (-1.39)		-0.02 (-0.54)		-0.02 (-0.18)		-0.04 (-1.03)
Volatility			-9.83 (-0.92)	-9.83 (-0.92)			-9.85 (-0.00)	-9.94 (-0.00)			-8.10 (-0.01)	-8.10 (-0.01)
Relative size			**-13.27*** (-1.85)	**-13.27*** (-1.85)			**-11.29 *** (-1.75)	**-11.20*** (-1.73)			-8.19 (-1.19)	-8.19 (-1.19)
leverage			-0.57 (-0.61)	-0.57 (-0.61)			8.88 (0.00)	8.97 (0.00)			5.80 (0.00)	5.80 (0.00)
vstoxx			0.00 (0.36)	0.00 (0.36)			0.00 (-0.17)	0.00 (-0.21)			-0.01 (-0.77)	-0.01 (-0.77)
Constant	**-2.69***** (-29.78)	**-2.89***** (-16.03)	**-1.87***** (-3.91)	**-1.87***** (-3.91)	**-2.73***** (-16.95)	**-2.74***** (-16.96)	**-1.92***** (-4.00)	**-1.90***** (-3.96)	**-2.73***** (-17.13)	**-2.73***** (-16.95)	**-1.87***** (-3.91)	**-0.94***** (-3.91)
Log L	-218.15	-218.15	-211.37	-211.37	-198.16	-193.06	-188.49	-188.19	-193.75	-193.06	-184.61	-184.61
Pseudo-R^2	4,67%	4,67%	7,63%	7,63%	3,09%	5,53%	7,77%	7,91%	5,65%	5,98%	10,10%	10,10%

Table A.13 Marginal effect Probit estimations of the effect of monthly changes in lagged DD for different horizons on sovereign ratings (20-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	**M3**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
ΔDD_{-1M}	0. 01%	-0.02%	0.04%	-0.04%	-0.03%	-0.03%	-0.02%	-0.04%	-0.05%	-0.03%	-0.06%	-0.07%
ΔDD_{-3M}	-0.04%		-0.08%		-0.02%		-0.01%		-0.05%		-0.06%	
ΔDD_{-6M}	-0. 05%		-0.01%		-0.01%		-0.02%		-0.03%		-0.08%	
ΔDD_{-12M}	-0. 01%		-0.01%		-0.01%		-0.01%		-0.01%		-0.01%	
$\Delta DD_{-(3M-1M)}$		-0.04%		-0.07%		-0.00%		-0.01%		-0.01%		0.00%
$\Delta DD_{-(6M-3M)}$		-0.01%		-0.01%		-0.01%		-0.03%		-0.04%		-0.07%
$\Delta DD_{-(12M-6M)}$		-0.01%		-0.01%		-0.01%		-0.01%		-0.01%		-0.01%
Volatility			-0.28%	-0.28%			-3.44%	-3.47%			-2.71%	-2.71%
Relative size			-4.52%	-4.52%			-3.94%	-3.91%			-2.74%	-2.74%
leverage			-0.19%	-0.19%			3.10%	3.13%			1.94%	1.94%
vstoxx			0.00%	0.00%			0.00%	0.00%			0.00%	0.00%

%

Table A.14 Probit estimations of the effect of monthly changes in lagged DDI for different horizons on sovereign ratings (20-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI_{-1M}	0.10	-0.03	0.12	-0.04	-0.06	**-0.06***	-0.10	**-0.12****	-0.02	-0.02	-0.02	-0.06
	(1.56)	(-1.21)	(1.51)	(-1.33)	(-0.87)	(-1.67)	(-1.07)	(-2.43)	(-0.32)	(-0.69)	(-0.18)	(-1.54)
ΔDDI_{-3M}	**-0.20****		**-0.21 ****		-0.03		-0.04		-0.08		-0.06	
	(-2.38)		(-2.48)		(-0.33)		(-0.52)		(-1.02)		(-0.74)	
ΔDDI_{-6M}	**-0.13*****		**-0.09***		-0.02		-0.02		-0.04		-0.08	
	(-2.95)		(-1.89)		(-0.44)		(-0.00)		(-0.76)		(-1.27)	
ΔDDI_{-12M}	**-0.06****		**-0.05***		**-0.05****		**-0.04****		**-0.04***		**-0.02***	
	(-2.47)		(-1.93)		(-1.98)		(-1.77)		(-1.74)		(-1.70)	
$\Delta DDI_{-(3M-1M)}$		**-0.13****		**-0.17****		-0.00		-0.07		-0.01		-0.03
		(-2.07)		(-2.23)		(-0.06)		(1.09)		(-0.15)		(-0.49)
$\Delta DDI_{-(6M-3M)}$		**-0.07****		-0.04		-0.03		-0.01		-0.07		-0.10
		(-2.18)		(-1.18)		(-0.74)		(-0.27)		(-1.49)		(-1.86)
$\Delta DDI_{-(12M-6M)}$		**-0.06****		**-0.05***		**-0.05****		-0.04		**-0.04****		**-0.04****
		(-2.47)		(-1.93)		(-1.98)		(-1.47)		(-1.75)		(-1.86)
Volatility			-1.42	-1.42			-15.87	-15.87			-16.03	-16.04
			(-1.29)	(-1.29)			(-0.00)	(-0.00)			(-0.00)	(-0.00)
Relative size			**-16.65 ****	**-16.65****			**-16.25 ****	**-16.25 ****			**-15.56 *****	**-15.60 *****
			(-2.42)	(-2.42)			(-2.74)	(-2.78)			(-2.65)	(-2.65)
leverage			0.71	0.71			15.18	15.18			14.90	14.90
			(0.71)	(0.71)			(0.00)	(0.00)			(0.00)	(0.00)
vstoxx			0.01	0.01			-0.01	0.01			0.01	0.01
			(0.54)	(0.54)			(-0.52)	(-2.00)			(0.03)	(0.03)
Constant	**-3.06*****	**-3.06*****	**-2.35*****	**-2.35*****	**-2.87*****	**-2.87*****	**-1.68*****	**-1.68*****	**-2.91*****	**-3.05*****	**-1.84*****	**-1.80*****
	(-14.54)	(-14.54)	(-4.11)	(-4.11)	(-12.61)	(-12.61)	(-2.89)	(-2.89)	(-18.92)	(-14.42)	(-3.08)	(-3.08)
Log L	217,22	217,22	210,29	210,29	198,95	192,21	187,27	187,27	-202.21	-196.95	-189.55	-189.43
Pseudo-R^2	5,07%	5,07%	8,10%	8,10%	2,65%	5,95%	8,37%	8,37%	1,53%	4,09%	7,69%	7,75%

Table A.15 Marginal effect Probit estimations of the effect of monthly changes in lagged DDI for different horizons on sovereign ratings (20-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	M3	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI_{-1M}	0.02%	-0.01%	0.04%	-0.01%	-0. 00%	-0.02%	-0.06%	-0.05%	-0.00%	-0.00%	-0.01%	-0.02%
ΔDDI_{-3M}	-0.06%		-0.07%		-0. 01%		-0.03%		-0.02%		-0.02%	
ΔDDI_{-6M}	-0.03%		-0.03%		-0. 01%		-0.01%		-0.01%		-0.03%	
ΔDDI_{-12M}	-0.01%		-0.02%		-0. 01%		-0.01%		-0.01%		-0.01%	
$\Delta DDI_{-(3M-1M)}$		-0.03%		-0.06%		-0.00%		-0.03%		-0.00%		-0.01%
$\Delta DDI_{-(6M-3M)}$		-0.02%		0.01%		-0.01%		-0.00%		-0.02%		-0.04%
$\Delta DDI_{-(12M-6M)}$		-0.01%		-0.02%		-0.01%		-0.01%		-0.01%		-0.01%
Volatility			-0.47%	-0.47%			-5.43%	-5.43%			-5.57%	-5.57%
Relative size			-5.47%	-5.47%			-5.54%	-5.54%			-5.40%	-5.42%
leverage			0.23%	0.23%			5.20%	5.20%			5.18%	5.18%
vstoxx			0.00%	0.00%			-0.01%	-0.01%			0.00%	0.00%

Table A.16 Probit estimations of the effect of monthly changes in lagged DD for different horizons on sovereign ratings (58-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDD_{-1M}	-0.02	**-0.06*****	-0.08	**-0.05****	0.02	**-0.06*****	**-0.09***	**-0.08***	-0.06	**-0.08*****	-0.09	**-0.13*****
	(-0.46)	(-2.92)	(-1.32)	(-2.26)	(0.27)	(-2.58)	(1.66)	(2.40)	(-0.97)	(-2.99)	(1.06)	(3.43)
ΔDD_{-3M}	**-0.10***		**-0.16****		-0.09		**-0.16***		-0.02		-0.03	
	(-1.67)		(-2.36)		(-0.93)		(-1.72)		(-0.26)		(-0.35)	
ΔDD_{-6M}	**-0.11*****		**-0.08****		-0.03		-0.06		0.04		-0.02	
	(-3.40)		(-2.00)		(-0.57)		(-0.96)		(0.86)		(-0.47)	
ΔDD_{-12M}	**-0.05****		**-0.05****		-0.02		-0.00		-0.03		0.01	
	(-2.50)		(-2.04)		(-1.09)		(-0.13)		(-1.32)		(0.53)	
$\Delta DD_{-(3M-1M)}$		-0.04		**-0.13****		-0.08		**-0.23****		-0.01		-0.04
		(-0.94)		(-2.28)		(-1.28)		(-2.54)		(-0.24)		(-0.52)
$\Delta DD_{-(6M-3M)}$		**0.06****		0.03		-0.01		-0.06		0.01		-0.01
		(2.41)		(1.00)		(1.65)		(-1.24)		(0.17)		(-0.24)
$\Delta DD_{-(12M-6M)}$		**-0.05****		**-0.05****		-0.02		-0.00		-0.03		-0.01
		(-2.49)		(-2.04)		(-1.23)		(-0.13)		(-1.32)		(-0.53)
Volatility			-0.90	-0.90			-10.77	-10.77			-1.44	-1.44
			(-1.13)	(-1.13)			(-0.01)	(-0.01)			(-1.53)	(-1.53)
Relative size			**-12.22*****	**-12.22*****			**-13.27****	**-13.27****			**-12.73****	**-12.73****
			(-2.65)	(-2.65)			(-2.33)	(-2.33)			(-2.19)	(-2.19)
leverage			0.24	0.24			9.36	9.36			0.34	0.34
			(0.30)	(0.30)			(0.01)	(0.01)			(0.36)	(0.36)
vstoxx			**0.01****	**0.01****			0.01	0.01			0.01	0.01
			(2.33)	(2.33)			(1.58)	(1.58)			(1.30)	(1.30)
Constant	**-2.55*****	**-2.67*****	**-2.45*****	**-2.45*****	**-2.71*****	**-2.71*****	**-1.97*****	**-1.97*****	**-2.64*****	**-2.64*****	**-1.03****	**-1.03****
	(-36.18)	(-21.11)	(-7.73)	(-7.73)	(-19.43)	(-19.43)	(-4.89)	(-4.89)	(-20.11)	(-20.11)	(-2.34)	(-2.34)
Log L	-353.61	-353.32	-344.19	-344.19	-293.88	-293.69	-282.88	-281.88	-315.95	-315.95	-302.68	-302.68
Pseudo-R^2	5,16%	5,23%	7,68%	7,68%	4,10%	4,16%	7,69%	8,01%	4,40%	4,40%	8,42%	8,42%

Table A.17 Marginal effect Probit estimations of the effect of monthly changes in lagged DD for different horizons on sovereign ratings (58-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	M3	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDD_{-1M}	-0. 01 %	-0.03%	-0.05%	-0.04%	0.01%	-0.03%	-0.06%	-0.05%	-0.03%	-0.04%	-0.06%	-0.08%
ΔDD_{-3M}	-0. 06%		-0.11%		-0.04%		-0.09%		-0.01%		-0.02%	
ΔDD_{-6M}	-0. 07 %		-0.05%		-0.02%		-0.03%		0.02%		-0.01%	
ΔDD_{-12M}	-0. 03 %		-0.03%		-0. 01%		-0.00%		-0.02%		0.01%	
$\Delta DD_{-(3M-1M)}$		-0.03%		-0.09%		-0.04%		-0.12%		-0.01%		-0.02%
$\Delta DD_{-(6M-3M)}$		0.04%		0.02%		-0.00%		-0.03%		0.00%		-0.01%
$\Delta DD_{-(12M-6M)}$		-0.03%		-0.03%		-0.01%		0.00%		-0.02%		-0.01%
Volatility			-0.61%	-0.61%			-5.92%	-5.92%			-0.89%	-0.89%
Relative size			-8.25%	-8.25%			-7.29%	-7.29%			-7.84%	-7.84%
leverage			0.16%	0.16%			5.15%	5.15%			0.21%	0.21%
vstoxx			0.01%	0.01%			0.01%	0.01%			0.01%	0.01%

Table A.18 Probit estimations of the effect of monthly changes in lagged DDI for different horizons on sovereign ratings (58-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI$_{-1M}$	-0.06	-0.05**	-0.17	-0.04	0.05	-0.07*	-0.09**	-0.09**	-0.02	-0.09*	-0.03	-0.18***
	(-1.49)	(-2.30)	(-1.11)	(-1.51)	(0.96)	(-1.79)	(-1.97)	(-2.23)	(-0.36)	(-1.69)	(-0.52)	(-2.69)
ΔDDI$_{-3M}$	-0.22***		-0.28***		-0.12*		-0.17**		-0.03		-0.02	
	(-3.50)		(-4.09)		(-1.87)		(-2.15)		(-0.40)		(-0.36)	
ΔDDI$_{-6M}$	-0.17***		-0.12***		-0.08**		-0.03		-0.00		-0.06	
	(-5.22)		(-3.27)		(-2.24)		(-0.65)		(-0.02)		(-1.17)	
ΔDDI$_{-12M}$	-0.07***		-0.06***		-0.04**		-0.03		-0.03**		-0.02	
	(-3.46)		(-2.95)		(-2.06)		(-1.32)		(-2.07)		(-0.86)	
ΔDDI$_{-(3M-1M)}$		-0.12**		-0.22***		-0.09*		-0.25**		-0.01		-0.04
		(-2.51)		(-3.46)		(-1.74)		(-2.35)		(-0.23)		(-0.72)
ΔDDI$_{-(6M-3M)}$		-0.10***		-0.06**		-0.04		-0.00		-0.03		-0.07
		(-4.39)		(-2.13)		(-1.45)		(0.02)		(-0.95)		(-1.61)
ΔDDI$_{-(12M-6M)}$		-0.07***		-0.06***		-0.04**		-0.03**		-0.04**		-0.02
		(-3.46)		(-2.95)		(-2.19)		(-2.32)		(-2.09)		(-0.86)
Volatility			-1.58***	-1.58***			-16.31	-16.31			-3.46***	-3.45***
			(-1.79)	(-1.79)			(-0.01)	(-0.01)			(-2.61)	(-2.60)
Relative size			-14.35***	-14.35***			-16.81***	-16.81***			-18.94***	-18.92***
			(-3.18)	(-3.18)			(-3.10)	(-3.10)			(-3.38)	(-3.37)
leverage			1.12	1.12			15.23	15.23			2.02*	2.02*
			(1.40)	(1.40)			(0.01)	(0.01)			(1.69)	(1.69)
vstoxx			-0.02***	-0.02**			-0.01	-0.01			-0.00	-0.00
			(2.22)	(-2.22)			(0.35)	(0.35)			(-0.18)	(-0.18)
Constant	-2.64***	-2.75***	-2.69***	-2.69***	-2.68***	-2.82***	-1.89***	-1.89***	-2.67***	-2.78***	-1.27***	-1.27***
	(-24.08)	(-17.52)	(-6.16)	(-6.16)	(-22.61)	(-15.75)	(-3.85)	(-3.85)	(-22.07)	(-16.01)	(-2.63)	(-2.63)
Log L	-345.73	-345.74	-348.47	-336.53	-303.64	-293.71	-282.34	-282.34	-319.10	-318.67	-305.15	-300.22
Pseudo-R^2	7,27%	7,27%	6,54%	9,74%	4,15%	4,15%	7,86%	7,86%	3,45%	3,58%	7,67%	8,56%

Table A.19 Marginal effect Probit estimations of the effect of monthly changes in lagged DDI for different horizons on sovereign ratings (58-point rating scale) over the entire sample

	S&P				Fitch				Moody's			
	M1	M3	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI_{-1M}	0.04%	-0.02%	0.11%	-0.03%	-0.02%	-0.04%	-0.05%	-0.07%	-0. 01 %	-0.06%	-0.02%	-0.10%
ΔDDI_{-3M}	-0. 12 %		-0.18%		-0.05%		-0.09%		0. 01 %		0.01%	
ΔDDI_{-6M}	-0.09 %		0.08%		0.03%		0.01%		0.00 %		-0.03%	
ΔDDI_{-12M}	-0.04 %		-0.04%		-0.02%		-0.01%		-0. 02 %		-0.01%	
$\Delta DDI_{-(3M-1M)}$		-0.06%		-0.14%		-0.03%		-0.14%		0.00%		-0.02%
$\Delta DDI_{-(6M-3M)}$		0.05%		0.04%		0.02%		0.00%		-0.01%		-0.04%
$\Delta DDI_{-(12M-6M)}$		-0.04%		-0.04%		-0.02%		-0.01%		-0.02%		-0.01%
Volatility			-1.02%	-1.02%			-8.86%	-8.86%			-2.08%	-2.07%
Relative size			-9.28%	-9.28%			-9.13%	-9.13%			-11.38%	-11.36%
leverage			0.72%	0.72%			8.27%	8.27%			1.21%	1.21%
vstoxx			0.01%	0.01%			0.01%	0.01%			0.00%	0.00%

Table A.20 Logit estimations of the effect of monthly changes in lagged DD for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDD_{-1M}	**-0.38***	**-1.45*****	**-0.40****	**-1.37*****	-0.57	**-1.05****	**-0.66***	**-0.82***	**-0.55*****	**-1.31*****	**-0.56*****	**-1.33 *****
	(-1.88)	(-3.69)	(-1.98)	(-3.87)	(-1.62)	(-2.23)	(-1.90)	(-1.77)	(-3.06)	(-3.11)	(-3.09)	(-3.13)
ΔDD_{-3M}	**-0.58*****		**-0.51*****		**-0.82*****		**-0.76*****		-0.35		-0.35	
	(-3.40)		(-2.98)		(-5.83)		(-5.31)		(-1.44)		(-1.43)	
ΔDD_{-6M}	**-0.61 *****		**-0.60*****		**-0.70*****		**-0.67*****		-0.27		-0.29	
	(-3.91)		(-3.80)		(-4.61)		(-4.38)		(-0.96)		(-1.02)	
ΔDD_{-12M}	0.13		0.15		-0.10		-0.04		-0.14		-0.12	
	(0.38)		(0.55)		(-0.38)		(-0.14)		(-0.46)		(-0.39)	
$\Delta DD_{-(3M-1M)}$		**-1.07*****		**-0.96*****		**-1.62*****		**-1.47*****		**-0.77***		**-0.77***
		(-2.67)		(-2.74)		(-4.99)		(-4.70)		(-1.69)		(-1.68)
$\Delta DD_{-(6M-3M)}$		-0.49		-0.45		**-0.80*****		**-0.71*****		-0.42		-0.41
		(-1.37)		(-1.49)		(-2.79)		(-2.60)		(-1.09)		(-1.08)
$\Delta DD_{-(12M-6M)}$		0.13		0.15		-0.10		-0.04		-0.14		-0.12
		(0.38)		(0.55)		(-0.38)		(-0.14)		(-0.46)		(-0.39)
Volatility			-0.16	-0.16			**-0.65***	**-0.65 ***			0.29	0.29
			(-0.51)	(-0.51)			(-1.67)	(-1.67)			(1.12)	(1.12)
Relative size			**-26.16*****	**-26.16*****			**-34.38*****	**-34.38*****			**-9.40****	**-9.40****
			(-4.47)	(-4.47)			(-4.38)	(-4.38)			(2.52)	(-2.52)
leverage			**0.00***	**0.00***			**0.00***	**0.00***			-0.00	-0.00
			(1.76)	(1.76)			(1.77)	(1.77)			(-0.32)	(-0.32)
vstoxx			**0.03*****	**0.03 *****			**0.02****	**0.02****			0.00	0.00
			(3.97)	(3.97)			(2.52)	(2.52)			(0.45)	(0.45)
Constant	**-6.20*****	**-6.20*****	**-6.46*****	**-6.46*****	**-6.51*****	**-6.51*****	**-6.14*****	**-6.14*****	**-6.07*****	**-6.07*****	**-6.13*****	**-6.13*****
	(-46.30)	(-46.30)	(-19.64)	(-19.64)	(-40.54)	(-40.54)	(-16.29)	(-16.29)	(-65.11)	(-65.11)	(-17.83)	(-17.83)
Log L	-814.46	-814.46	-791.58	-791.58	-779.30	-779.30	-760.08	-760.08	-832.15	-832.15	-826.75	-826.75
Pseudo-R^2	3,41%	3,41%	6,12%	6,12%	4,00%	4,00%	6,37%	6,37%	6,35%	6,35%	6,96%	6,96%

Table A.21 Logit estimations of the effect of monthly changes in lagged DD for different horizons on bank ratings over the entire sample

	S&P				Fitch				Moody's			
	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
ΔDDI_{-1M}	**-0.57*** **	**-2.19*** **	**-0.61*** **	**-2.16*** **	**-0.46** **	**-1.03*** **	**-0.48** **	**-0.95*** **	**-0.71*** **	-0.90	**-0.73*** **	-0.90
	(-3.15)	(-4.59)	(-3.24)	(-4.87)	(-2.27)	(-3.51)	(-2.30)	(-3.28)	(-4.02)	(-1.23)	(-4.10)	(-1.21)
ΔDDI_{-3M}	**-1.00*** **		**-0.90*** **		**-0.93*** **		**-0.85*** **		**-0.59*** **		**-0.60** **	
	(-7.21)		(-6.20)		(-5.79)		(-5.09)		(-2.56)		(-2.54)	
ΔDDI_{-6M}	**-0.83*** **		**-0.81*** **		**-1.06*** **		**-1.04*** **		0.63		0.64	
	(-4.68)		(-4.50)		(-7.72)		(-7.45)		(1.03)		(1.03)	
ΔDDI_{-12M}	0.22		0.16		-0.37		-0.32		-0.23		-0.21	
	(0.49)		(0.42)		(-1.60)		(-1.40)		(-0.62)		(-0.57)	
$\Delta DDI_{-(3M-1M)}$		**-1.62*** **		**-1.55*** **		**-0.98*** **		**-0.93*** **		-0.19		-0.17
		(-3.27)		(-3.50)		(-3.39)		(-3.41)		(-0.25)		(0.83)
$\Delta DDI_{-(6M-3M)}$		-0.62		-0.65		-0.30		-0.31		0.39		0.43
		(-1.32)		(-1.59)		(1.21)		(-1.33)		(0.56)		(0.55)
$\Delta DDI_{-(12M-6M)}$		0.22		0.16		0.31		0.28		-0.23		-0.21
		(0.49)		(0.42)		(1.53)		(1.47)		(-0.62)		(0.57)
Volatility			-0.11	-0.11			-0.57	-0.62			0.31	0.31
			(-0.35)	(-0.35)			(-1.50)	(-1.62)			(1.20)	(1.20)
Relative size			**-26.54*** **	**-26.54*** **			**-34.60*** **	**-35.08*** **			**-9.44** **	**-9.44*** **
			(-4.48)	(-4.48)			(-4.44)	(-4.41)			(-2.51)	(-2.51)
leverage			**0.00* **	**0.00* **			**0.00* **	**0.00*** **			-0.00	-0.00
			(1.67)	(1.67)			(1.74)	(1.71)			(-0.34)	(-0.34)
vstoxx			**0.02*** **	**0.02*** **			**0.02* **	**0.02*** **			0.00	0.00
			(3.14)	(3.14)			(1.85)	(2.64)			(0.28)	(0.28)
Constant	**-6.27*** **	**-6.27*** **	**-6.40*** **	**-6.40**** **	**-6.57*** **	**-6.50*** **	**-6.10*** **	**-6.17*** **	**-6.09*** **	**-6.09*** **	**-6.11*** **	**-6.11*** **
	(-46.63)	(-46.63)	(-19.23)	(-19.23)	(-41.28)	(-40.71)	(-16.29)	(-16.41)	(-64.55)	(-64.55)	(-17.67)	(-17.67)
Log L	-797.97	-797.97	-777.08	-777.08	-764.72	-777.59	-746.70	-757.96	-827.38	-827.38	-821.93	-821.93
Pseudo-R^2	5,36%	5,36%	7,84%	7,84%	5,80%	4,21%	8,02%	6,63%	6,89%	6,89%	7,50%	7,50%

References

Chapter one

Acharya, V., Yorulmazer, T ., 2007. Too Many to Fail - An Analysis of Time- inconsistency in Bank Closure Policies," Journal of Financial Intermediation, 16(1),1-31.

Acharya, V., Yorulmazer, T., 2008. Information Contagion and Bank Herding, Journal of Money, Credit and Banking, Vol.40, No.1, pp. 215-231.

Bank for International Settlement, 2010. International banking and financial market developments, BIS Quarterly Review December.

Blanco, R., Brennan, S., & Marsh, I. W., (2005). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. The Journal of Finance, vol. LX, No.6 , 2255-2281.

Borio, C., Furfine, C., Lowe, P., 2001. Procyclicality of the financial system and financial stability: issues and policy options. In: BIS Papers No. 1. Bank for International Settlements.

Calomiris, C, W., 2009. “The Subprime Turmoil: What’s Old, What’s New, and What’s Next,” Journal of Structured Finance, Vol. 15, No. 1, pp. 6-52.

Carr P., L., Wu., 2011, “A Simple Robust Link Between American Puts and Credit Protection”, Review of Financial Studies, 24 (2), 473-505.

Claessens, S., Kose, M, A., 2014. Financial Crises: Explanations, Types, and Implications, Working paper

Claessens, S., Kose, A., Laeven, L., Valencia, F., 2014. Financial Crises: Causes, Consequences, and Policy Responses, IMF, Washington, D.C. (also IMF Working Paper, 13/28).

De Bandt,O., Hartmann,P., 2000. Systemic Risk: A Survey . European Central Bank working paper

Drehmann, M., Tarashev, N., 2011. Systemic importance: some simple indicators.In: BIS Quarterly Review, March. Bank for International Settlements.

Duff, A., Einig, S., 2009. Understanding credit ratings quality: Evidence from UK debt market participants. The British Accounting Review, 41(2), 107-119

Eichengreen, B., 2010. Macroeconomic and Financial Policies Before and After the Crisis. University of California, Berkeley. Working paper. http://eml.berkeley.edu/~eichengr/macro_finan_policies_8-31-10.pdf.

European Central Bank, December 2009. The concept of systemic risk. FinancialStability Review, 134–142.

European commission. Tackling the financial crisis Europe’s response to the credit crunch.. http://ec.europa.eu/internal_market/publications/docs/financial-crisis_en.pdf

Ericsson, J., Jacobs, K., Oviedo-Helfenberger, R.(2009). The determinants of credit default swap premia. Journal of Financial and Quantitative Analysis 44, 109–132.

Giesecke, Kay, and Baeho Kim, “Systemic Risk: What Defaults Are Telling Us,” *Management Science*, 57 (8), 2011, pp. 1387–1405.

Lane P, R., 2012.The European Sovereign Debt Crisis. Journal of Economic Perspectives, Volume 26, Number 3, Pages 49–68

Longstaff, F., A., Mithal, S., & Neis, E., 2005. Corporate Yield Spreads: Default Risk or Liquidity? New Evidence From The Credit Deafult Swap Market. The Journal of Finance, vol.LX, No.5 , 2213-2253.

Pan, J., Singleton, K.J., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads, Journal of Finance 63 (5), 2345-2383.

Perotti, E., Suarez, J., 2009. Liquidity Risk Charges as a Macroprudential Tool. Mimeo-graph.

Reinhart, C.M., Rogoff, K.S., 2009. The aftermath of financial crises. National Bureau of Economic Research. Working Paper 14656.

Chapter Two

Acharya, V., T. Johnson, (2007). Insider Trading in Credit Derivatives. Journal of Financial Economics 84, 110–141.

Akaike, H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control, vol.19, 716-723.

Alexander, C., Kaeck, A., (2008). Regime dependent determinants of credit default swap spreads. Journal of Banking and Finance 32, 1008-1021.

Aunon-Nerin, D., Cossin, D., Hricko, T., & Huang, Z. (2002). Exploring for the Determinants of Credit Risk in Credit Default Swap Transation Data: Is Fixed-Income Markets' Information Sufficient to Evaluate Credit Risk? International Center for Financial Asset Management and Engineering, FAME Research Paper No 65 .

Avino, D., Lazar, E., Varotto, S., (2011). Which market drives credit spreads in tranquil and crisis periods? An analysis of the contribution to price discovery of bonds, CDS, stocks and options. ICMA Centre, University of Reading, United Kingdom . working paper.

Baba, N., Inada, M., (2009). Price discovery of subordinated credit spreads for Japanese mega-banks: Evidence from bond and credit default swap markets. Journal of International Financial Markets, Institutions and Money 19, 616-632.

Benkert, C. (2004). Explaining Credit Default Swap Premia. The Journal of Futures Markets, vol.24, No.1 , 71-92.

Berndt, A., Ostrovnaya, A., (2008). Do equity markets favour credit market news over option markets news? Carnegie Mellon University. Working Paper.

Black, F., (1976), “Studies of stock price volatility changes,” in *Proceedings of the 1976 Meetings of the American Statistical Association*, Business and Economics Section, pp. 177-181, Chicago, IL.

Blanco, R., Brennan, S., & Marsh, I. W., (2005). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. The Journal of Finance, vol. LX, No.6 , 2255-2281.

Bollerslev, T., Todorov V., Xu L., (2014), Tail Risk Premia and Return Predictability. Northwestern University. Duke University, US. Working Paper.

Byström, H.N.E. (2005). Credit default swaps and equity prices: The iTraxx CDS index market. Lund University, Sweden. Working Papers

Byström, H.N.E., (2006). CreditGrades and the iTraxx CDS index market. Financial Analysts Journal, 62 (6), 65–76.

Campbell, J. Y., & Taksler, G. B. (2003). Equity Volatility and Corporate Bond Yields. The Journal of Finance, vol 58, 2321–2350.

Cao, C., Chen, Z., & Griffin, J. (2005). Informational content of option volume prior to takeovers. Journal of Business 78 , 1073-1109.

Cao, C., Yu, F., & Zhong, Z. (2010). The Information Content of Option Implied Volatility for Credit Dafult Swap Valuation. Journal of Financial Markets, 13, 321-343.

Chen, Ren-Raw, Frank J. Fabozzi, and Ronald Sverdlove. (2010) "Corporate credit default swap liquidity and its implications for corporate bond spreads." *Journal of Fixed Income* 20.2: 31.

Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). The Determinants of Credit Spread Changes. The Journal of Finance, vol. LVI, No. 6 , 2177-2206.

Consigli, G. (2007). Credit Default Swaps And Equity Volatility: Theoretical Modelling and Market Evidence. Retrieved July 20, 2008, from Available at http://www.giorgioconsigli.it/download/1095343382.pdf.

Coudert, V., & Gex, M. (2010a). Contagion inside the CDS market: the case of GM and Ford crisis in 2005, Journal of International Markets, Money, Finance and Institutions, vol 20(2) 109-1034.

Coudert, V., & Gex, M. (2010b). Credit default swap and bond markets: which leads the other? Banque de France, Financial Stability Review, No. 14, 161-167.

Cosslett, S. R., Lee, L.-F. (1985). Serial correlation in discrete variable models. Journal of Econometrics, vol.27, 79–97.

Cremers, M., Driessen, J., Maenhout, P., & Weinbaum, D. (2008). Individual Stock-Option Prices and Credit Spreads. Journal of Banking and Finance, vol 32, 2706–2715.

Ericsson, J., Jacobs, K., Oviedo-Helfenberger, R.(2009). The determinants of credit default swap premia. Journal of Financial and Quantitative Analysis 44, 109–132.

Ericsson, J., Reneby, J., & Wang, H. (2005). Can Structural Models Price Default Risk? Evidence from Bond and Credit Derivative Market. McGill University,Canada and Stockholm School of Economics, Sweden. Working Paper.

Fan, J., Imerman, M.B., Dai, W., (2013), What Does the Volatility Risk Premium Say About Liquidity Provision and Demand for Hedging Tail Risk? SSRN Working Paper. Princeton University, US.

Forte, S., (2011). Calibrating structural models: A new methodology based on stock and credit default swap data. Quantitative Finance, vol. 11, Issue 12, 1745-1759

Forte, S., Peña, J.I., (2009). Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. Journal of Banking and Finance, Vol 33, 2013-2025.

Goldfeld, S. M., Quandt, R. E. (1973). A markov model for switching regressions. Journal of Econometrics, 1, 3–15.

Gonzalo, J., Granger., C.W. J, (1995). "Estimation of Common Long-Memory Components in Cointegrated Systems," Journal of Business & Economic Statistics, American Statistical Association, vol. 13(1), 27-35.

Hamilton, D. V., Ou, S., & Cantor, R. (2006). Default and Recovery Rates of Corporate Bond Issuers, 1920-2005. Moody's Investors Service, Global Credit Research. New York.

Hasbrouck, J., (1995). One Security, Many Markets: Determining the Contributions to Price Discovery," Journal of Finance, American Finance Association, vol. 50(4), 1175-99.

Hull, J., Predescu, M., & White, A. (2004). The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. Canada: Joseph L. Rotman School of Management, University of Toronto.

Leland, H.E., Toft K.B., (1996).Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads. The Journal of Finance. vol. LI, No. 3. 987-1019.

Longstaff, F., A., Mithal, S., & Neis, E. (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence From The Credit Deafult Swap Market. The Journal of Finance, vol.LX, No.5 , 2213-2253.

Meng, L., ap Gwilym, O., Varas, J., (2009). Volatility transmission among the CDS, equity, and bond markets. Journal of Fixed Income 18, 33-46.

Merton, R. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. The Journal of Finance, vol. 29, No. 2 , 449-470.

Neske, F. & Lehnert T. (2006). On the Relationship between Credit Rating Announcements and Credit Default Swap Spreads for European Reference Entities. Journal of Credit Risk, vol. 2, No. 2, 83-90.

Newey, W.K., West, K.,(1986). A simple, Positive-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.Econometrica, vol. 55, 703-708.

Nomura. (2004). Credit Default Swap Primer. New York: Nomura Fixed Income Research, Nomura Securities International.

Norden, L., & Weber, M. (2009). The Co-movement of Credit Default Swap, Bond and Stock Markets: An Empirical Analysis. Blackwell Publishing Ltd, European Financial Management, vol. 15, 529-562.

Pan, J., & Poteshman, A. (2006). The information in option volume for future stock prices. Review of Financial Studies, 19 , 871-908.

Wellink, N. (2008). Recent Market Turmoil - Implications for supervisors and risk managers. BIS Review 21/2008.

Zellner A. (1962). An Efficient Method of Estimating Seemingly Unrelated Regression Equations and Tests of Aggregation Bias, Journal of the American Statistical Association, Vol 57, Issue 298, 500-509.

Zhang, B.Y., Zhou, H., Zhu, H. (2009). Explaining credit default swap spreads with equity volatility and jump risks of individual firms. Review of Financial Studies, vo.22, 5099–5131.

Zhu, H., (2004). An empirical comparison of credit spreads between the bond market and the credit default swap market, Bank for International Settlements, working paper.

Chapter Three

Acharya, V., T. Johnson, 2007. Insider Trading in Credit Derivatives. Journal of Financial Economics 84, 110–141.

Alexander, C., Kaeck, A., (2008). Regime dependent determinants of credit default swap spreads. Journal of Banking and Finance 32, 1008-1021.

Amadori M., Bekkour L., Lehnert T., 2011, 'The Relative Informational Efficiency of Stocks, Options and Credit Default Swaps' working paper.

Anderson, R. W., and S. Sundaresan, 1996, "Design and Valuation of Debt Contracts," Review of Financial Studies, 9(1), 37–68.

Avino, D., Lazar, E., Varotto, S., 2011. Which market drives credit spreads in tranquil and crisis periods? An analysis of the contribution to price discovery of bonds, CDS, stocks and options. ICMA Centre, University of Reading. working paper.

Benkert, C. (2004). Explaining Credit Default Swap Premia. The Journal of Futures Markets, Vol.24, No.1 , 71-92.

Berndt, A., and A. Ostrovnaya, 2007, "Do Equity Market Favor Credit Market News Over Options MarketNews?," working paper, Carnegie Mellon University.

Berndt, A., Ostrovnaya, A., 2008. Do equity markets favour credit market news over option markets news? Carnegie Mellon University. Working Paper.

Bjerksund, P., G. Stensland, "Closed-Form Approximation of American Options," Scandivanian Journal of Management, 9, 1993, pp. 87-99.

Bjerksund, P., G. Stensland, "Closed-Form Valuation of American Options," Working paper NHH, 2002

Broadie, M., M. Chernov, and S. Sundaresan, 2007, "Optimal Debt and Equity Values in the Presence of Chapter 7 and Chapter 11," Journal of Finance, 62(3), 1341–1377.

Campbell, J. Y., & Taksler, G. B. (2003). Equity Volatility and Corporate Bond Yields. The Journal of Finance, vol 58, 2321–2350.

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

Carr P., L., Wu., 2011, "A Simple Robust Link Between American Puts and Credit Protection", Review of Financial Studies, 24 (2), 473-505.

Carr and Wu., 2010: Stock Option and Credit Default Swaps: A Joint Framework for Valuation and Estimation, Journal of Financial Econometrics,Vol 8, Issue 4, 409-449.

Gray, D. F., Jobst, A. A., 2011 Modelling systemic financial sector and sovereign risk sveriges riks bank economic review.

Gray, Dale F., and Samuel Malone.,2008, Macrofinancial Risk Analysis (New York: John Wiley & Sons). Book.

Gray, D. F., Malone, S., 2012, "Sovereign and Financial Sector Risk: Measurement and Interactions," Annual Review of Financial Economics, Vol. 4, No. 9, pp. 297–312.

Gray, D. F., Merton, R.C, and Bodie, Z., 2008, "A New Framework for Measuring and Managing Macrofinancial Risk and Financial Stability," Harvard Business School Working Paper No. 09-015 (Cambridge, Massachusetts: Harvard University).

Hull, J., I. Nelken, and A. White, 2004, "Mertons Model, Credit Risk and Volatility Skews," *Journal of Credit Risk*, 1(1), 8–23.

International Monetary Fund (IMF), 2014, Moving from Liquidity- to Growth-Driven Markets in Global Financial Stability Report (Washington).

Leland, H. E., Toft, K. B, 1996, "Optimal Capital Structure, Endogenous Bankruptcy and the Term Structure of Credit Spreads" Journal of Finance, 51(3), 987–1019.

Mella-Barral, P., Perraudin, W., 1997, "Strategic Debt Service" Journal of Finance, 52(2), 531–566.

Merton, R. C., 1973, "Theory of Rational Option Pricing," Bell Journal of Economics and Management Science, 4, 141–183.

Merton, R. C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," Journal of Finance, 29(1), 449–470.

Merton, R. C., 1976, "Option Pricing When Underlying Stock Returns Are Discontinuous," Journal of Financial Economics, 3(1), 125–144.

Chapter Four

Acharya, V., Johnson, T., 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84 (1), 110-141.

Afonso, A., Fureci, D., Gomes, P., 2011. Sovereign credit ratings and financial markets linkages: application to European data, *ECB Working Paper Series No 1347.*

Azerki, R., Candelon, B., Sy, A.-N.R., 2011, Sovereign rating News and Financial Markets Spillovers: Evidence from the European debt crisis, *International Monetary Fund WP/11/68*.

Bakshi, G., Kapadia, N. Madan, D., 2003, Stock Return Characteristics, Skew Laws, and Differential Pricing of Individual Equity Options, *Review of Financial Studies* 16, 101-143.

Bams, D., Lehnert, T., Wolff, C., 2009. Loss Functions in Option Valuation: A Framework for Selection. *Management Science* 55 **(**5), 853-862.

Berndt, A., Ostrovnaya, A., (2008). Do equity markets favour credit market news over options market news*?* Carnegie Mellon University. Working Paper.

Brunnermeier, M.K., Nagel, S., Pedersen, L.H., 2009. Carry trades and currency crashes, *NBER Macroeconomics Annual* 2008.

Burnside, C., Eichenbaum, M., Kleshchelski, I., Rebelo, S., 2011, Do peso problems explain the returns to the cary trade?, *Review of financial Studies* 24 (3), 853-891.

Calice, G., Chen, J., Williams, J.,2011. Liquidity spillovers in sovereign bond and CDS markets: An analysis of the Eurozone sovereign debt crisis.*Working Paper*.

Cao, C., Yu, F., Zhong, Z., 2012. The information content of option-implied volatility for credit default swap valuation, *Journal of Financial Markets* 13(3), 321-343.

Carr, P., Wu, L., 2007. Theory and evidence on the dynamic interactions between sovereign credit default swaps and currency options, *Journal of Banking and Finance* 31 (8), 2383-2403.

Christoffersen, P., Heston, S., Jacobs, K., 2010. Option Anomalies and the Pricing Kernel. Working Paper.

Cochrane, J.H., 2005, Asset Pricing, Princeton University Press, New Jersey.

Dumas, B., Fleming J., Whaley, R.E., 1998, Implied Volatility Functions: Empirical Tests, *The Journal of Finance* 53, 2059-2106.

Eichengreen, B., Rose, A.K., Wyplosz, C., 1996. Exchange market mayhem: the antecedents and aftermath of speculative attacks, *Economic Policy* 21, 249-312.

Fahri, E., Fraiberger, S.P., Gabaix, X., Ranciere, R., Verdlhan, A., 2009. Crash Risk in Currency Markets, *Working Paper* 15062, NBER.

Frankel, J., Rose, A., 1996. Currency crashes in emerging markets: am empirical treatment, *Journal of International Economics* 41 (3-4), 351-366.

Gapen, M., D.F. Gray, C. H. Lim and Y. Xiao (2005) Measuring and Analyzing Sovereign Risk with Contingent Claims. IMF Working Paper 2005/155.

Gray, D. and S. Malone, 2008, Macrofinancial Risk Analysis, (Wiley Finance Book).

Garleanu N., Pedersen L.H., Poteshman A.M., 2009.Demand-Based Option Pricing, Review of Financial Studies Volume 22, Issue 10 Pp. 4259-4299

Jurek, J.W., 2009. Crash-neutral currency trades, *Working Paper*, Princeton University.

Jylha, P., Suominen, M., 2010 Speculattive Capital And Currency Carry Trades, *Working Paper*, SSRN

Hui, C.-H, Chung, T.-H., 2011. Crash Risk of the Euro in the Sovereign Debt Crisis of 2009-2009, *Journal of Banking and Finance* 35: 2945-55

Hui, C.-H, Fong T., 2011, Information flow between sovereign CDS and Dollar-Yen currency option markets in the sovereign debt crisis of 2009-2011, *HKIMR Working Paper* No.40/2011.

Kaminsky, G., Lizondo, S., Reinhart, C.M., 1998. Leading indicators of currency crises, *International Monetary Fund Staff Papers* 45, 1-48

Neumann M. and G. Skiadopoulos, 2012. Predictable Dynamics in Higher Order Risk-Neutral Moments: Evidence from the S&P 500 Options, forthcoming*: Journal of Financial and Quantitative Analysis.*

Pan, J., Singleton, K.J., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads, *Journal of Finance* 63 (5), 2345-2383.

Pearson, K. (1895) "Contributions to the Mathematical Theory of Evolution. II. Skew Variation in Homogeneous Material", Philosophical Transactions of the Royal Society A, 186, 343-414.

Simonato, Jean-Guy (2011), "The Performance of Johnson Distributions for Computing Value at Risk and Expected Shortfall", *Journal of Derivatives*.

Wolff, C., 1987, Forward Foreign Exchange Rates, Expected Spot Rates and Premia: A Signal-Extraction Approach, *Journal of Finance*, Vol. 42, no. 2, pp. 395-406.

Chapter Five

Acharya, V.V., Yorulmazer, T., 2007. Too many too fail – an analysis of time inconsistency in bank closure policies, Journal of Financial Intermediation, vol. 16, p.1-31

Acharya, V.V.,Yorulmazer, T., 2008. Information contagion and bank herding, Journal of Money, Credit and Banking, vol. 40, p.215-231

Acharya, V.V., Pedersen, L.H., Philippon T., Richardson M., 2010. Measuring systemic risk. Unpublished working paper.

Aggarwal, N., Singh, M., Thomas, S ., 2012. Do changes in distance-to-default anticipate changes in the credit rating? Indira Gandhi Institute of Development Research, Mumbai.

Afonso, A., Gomes,P., Rother,P.,2011. Short- and Long-run Determinants of Sovereign Debt Credit Ratings. International Journal of Finance and Economics. 16: 1–15

Alsakka, R., ap Gwilym, O., 2009. Heterogeneity of sovereign rating migrations in emerging countries. Emerging Markets Review 10, 151–165.

Alsakka, R., ap Gwilym, O., 2012. Foreign exchange market reactions to sovereign credit news. Journal of International Money and Finance 31, 845-864.

Alsakka, R., ap Gwilym, O., 2013. Rating agencies' signals during the European sovereign debt crisis: Market impact and spillovers, Journal of Economic Behavior and Organization, 85, 144-162.

Arezki,R., Candelon,B., N. R. Sy,A., 2011. Sovereign Rating News and Financial Markets Spillovers: Evidence from the European Debt Crisis. IMF working paper

Borio, C., Furfine, C., Lowe, P., 2001. Procyclicality of the financial system and financial stability: issues and policy options. In: BIS Papers No. 1. Bank for International Settlements.

Brooks, R., Faff, R., Hillier, D., Hillier, J., 2004. The national market impact of sovereign rating changes. Journal of Banking and Finance 28, 233–250.

Brownlees, C.T., Engle, R., 2012. Volatility, Correlation and Tails for Systemic Risk Measurement, working paper

Caporale, G., Matousek, R., Stewart, C., 2012. Ratings assignments: lessons from international banks. Journal of International Money and Finance 31, 1593–1606

De Bandt, O., Hartmann, P., 2000. Systemic Risk: A Survey. European Central Bank working paper

De Nicolò, G., and Lucchetta, M., 2010. Systemic Risks and the Macroeconomy," IMF Working Paper No. 10/29, International Monetary Fund,

Diebold, F, X., and Yilmaz, K., 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets, The Economic Journal, 119 (534), pp. 158–171.

Distinguin, I., Hasan, I., Tarazi, A., 2012. Predicting rating changes for banks: How accurate are accounting and stock market indicators? Bank of Finland Research Discussion Paper No. 15/2012.

Giesecke, K., Baeho, K., 2011. Systemic Risk: What Defaults Are Telling Us, *Management Science*, 57 (8), pp. 1387–1405.

Gropp, R., Moerman, G., 2004. Measurement of contagion in bank equity prices, Journal of International Money and Finance, vol. 23, p.405-459

Gropp, R., Vesala, J., Vulpes, G., 2002. Equity and Bond Market Signals as Leading Indicators of Bank Fragility. European Central Bank Working Paper

Gropp, R., Vesala, J., Vulpes, G., 2006. Equity and Bond Market Signals as Leading Indicators of Bank Fragility. Journal of Money, Credit and Banking, 399–428

Godlewski, C., 2007. Are the ratings consistent with Default Probabilities? Empirical Evidence on Banks in Emerging Market Economies. Emerging Market Finance & Trade, Vol. 43, No. 4, 5-23

Greene, W., 2004. The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. Econometrics Journal (2004), volume 7, pp. 98–119.

Hattori, A., Kikuchi, K., Niwa, F., Uchida,Y., 2014. A Survey of Systemic Risk Measures: Methodology and Application to the Japanese Market, working paper

Huang, X., Zhou, H., Zhu, H., 2009. A Framework for Assessing the Systemic Risk of Major Financial Institutions, Journal of Banking and Finance, Volume 33, Issue 11, pp 2036-2049

Jobst A., Gray, F.D., 2013. Systemic Contingent Claims Analysis—Estimating Market-Implied Systemic Risk, IMF Working Paper No. 13/54, International Monetary Fund

Ismailescu, I., Kazemi, H., 2010. The reaction of emerging market credit default swap spreads to sovereign credit rating changes. Journal of Banking and Finance 34, 2861–2873.

McFadden, D. 1974. Conditional logit analysis of qualitative choice behavior." Pp. 105-142 in P. Zarembka (ed.), *Frontiers in Econometrics*. Academic Press.

Perotti, E., Suarez, J., 2009. Liquidity Risk Charges as a Macroprudential Tool. Mimeo-graph.

Segoviano, Miguel and Charles Goodhart, 2009. Banking Stability Measures, IMF Working Paper 09/04 (Washington: International Monetary Fund).

Severo, T., 2012. Measuring Systemic Liquidity Risk and the Cost of Liquidity Insurance, IMF Working Paper No. 12/194, International Monetary Fund,

Shen, C.-H., Huang, Y.-L., Hasan, I., 2012. Asymmetric benchmarking in bank credit rating. Journal of International Financial Markets, Institutions & Money 22, 171–193.

Tudela, M., Young, G., 2003. Predicting Default Among U.K. Companies: A Merton Approach,Bank of England Financial Stability Review, June, pp. 104–114.

Williams, G., Alsakka, R., ap Gwilym, O., 2013. The impact of sovereign rating actions on bank ratings in emerging markets. Journal of Banking and Finance 37, 563-577