CDS Spreads and the Euro Crisis

Masterproef voorgedragen tot het bekomen van de graad van
Master of Science in de Economische Wetenschappen

Frederik Mergaerts
onder leiding van
Prof. Dr. Rudi Vander Vennet
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PERMISSION

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Frederik Mergaerts
Preface

In writing a master thesis a student is expected to demonstrate the knowledge and understanding he has acquired in the chosen field of study. Over the last three years the professors, lecturers and research assistants of the departments of general, social and financial economics have consistently prepared me for this task and have succeeded effortlessly in conveying their enthusiasm. Having completed the present thesis to obtain the degree of Master of Science in Economics, my gratitude goes out to all of them.

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Frederik Mergaerts
Ghent, June 2012
Dutch Summary (Nederlandstalige samenvatting)

De recente financiële crisis sloeg toe in de meeste ontwikkelde economieën. Beleidsacties, gericht op de stabiliteit van het financiële systeem en het vermijden van schade aan de brede economie, leidden ertoe dat banken en overheden nauw met elkaar verbonden werden. Dit gebeurde voornamelijk in Europa, waar enkele landen zelfs volledig afgesloten werden van private schuldmarkten. Het is voor verdere beleidsacties absoluut noodzakelijk om goed te begrijpen welke factoren een rol spelen in de marktevaluatie van het kredietrisico van banken. Deze masterproef tracht daarom een verklaring te formuleren voor het kredietrisico van banken gedurende verschillende fases van de recente financiële crisis. Door de ontwikkelingen op markten voor overheidsschuld is het bovendien cruciaal om de band tussen banken en overheden te onderzoeken.

Om dit probleem te benaderen kiezen we voor een panelregressie van credit default swap (CDS) spreads. Los van de argumentatie ter ondersteuning van deze benadering, geven we een praktische beschrijving van de karakteristieken van deze kredietinstrumenten. Hierna voorzien we een bondig overzicht van de effecten van de financiële crisis en beleidsreacties in Europa om de groeiende verbondenheid van overheden en banken te verklaren. We gaan bovendien in op de mogelijke transmissiekanalen die deze band bestendigd hebben.

Vervolgens beginnen we aan ons empirisch onderzoek dat bestaat uit drie delen. In een eerste deel geven we toelichting over de gebruikte variabelen. We geven niet alleen een praktisch overzicht, maar maken ook onze eigen verwachtingen kenbaar met betrekking tot de effecten van elke variabele. Deze verwachtingen worden telkens ondersteund door een literatuuroverzicht. Daarna bespreken we de methodologische problemen die gepaard gaan met een panelstudie over CDS spreads. Deze complicaties zijn het gevolg van de niet-stationariteit van CDS spreads en de aanwending van een dynamisch panelmodel. Om deze obstakels te vermijden, gebruiken we een stationaire transformatie van CDS gegevens. We kiezen bovendien de Arellano-Bond (1991) GMM (generalised method of moments) schatter die, rekening houdende met technische beperkingen en beperkingen van alternatieve methodes, optimaal lijkt.

Onze schattingen leidden tot verschillende resultaten. Ten eerste werd de noodzaak van een dynamische benadering bevestigd. De vertraagde afhankelijke variabele toonde zeer significante resultaten in elke fase van de crisis. Ten tweede bleken variabelen die afgeleid werden uit structurele kredietmodellen (cfr. Merton 1974) relatief succesvol ter verklaring van
CDS spreads. Variabelen, die rechtstreeks afgeleid werden van de balansen van banken, leidden daarentegen tot zeer teleurstellende resultaten. Kredietrisico van overheden bleek, ten derde, een grote rol te spelen in de marktevaluatie van het kredietrisico van banken. Dit is voornamelijk het geval in de laatste subperiode, die begon in januari 2009 en eindigde in juni 2011. Dit resultaat ondersteunt eerder onderzoek. Ten slotte vonden we dat verschillende variabelen niet-lineaire effecten hadden. Dit wil zeggen dat hun invloed op de afhankelijke variabele niet stabiel was over de tijd. Onze keuze om de tijdreeksen op te delen in subperiodes moest dit ten dele opvangen, maar deze opdeling is gebaseerd op specifieke gebeurtenissen en is daarom in wezen arbitrair. Om hiervoor te corrigeren voerden we een rolling regression uit; dit is een reeks regressies waarbij we de schattingsperiode steeds een maand opschuiven. Onze eerdere resultaten werden echter grotendeels bevestigd.

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1. Introduction

The euro crisis, or sovereign debt crisis as it is also known, refers to the latest phase of the financial crisis in a broad number of European countries. The financial crisis, which started in the summer of 2007 in the US subprime mortgage market, undermined the whole financial system and led to an economic downturn in most advanced economies. Governments, poised to safeguard financial stability and economic activity, intervened on a large scale. They took monetary and fiscal action to support the financial sector and used expansionary fiscal policies to avoid or contain recession. This of course inflated sovereign debt ratios, which in turn led to doubts about governments’ ability to timely repay their debts. As a result, several countries’ credit ratings plummeted, while a smaller group (Ireland, Greece and Portugal) lost access to private debt markets altogether. Banks, which were already in a fragile state, were also affected by this as they relied on governments’ implicit and explicit guarantees in order to fund themselves. Most banks had, moreover, built up large exposures to the sovereign sector on their balances (CGFS 2011).

This master thesis will try to elucidate the relationship of bank default risk, as captured by credit default swap (CDS) spreads, with a number of possible drivers. We will dedicate special attention to the role of sovereign credit risk in the markets’ evaluation of default risk of financial institutions. We, however, limit ourselves to the effects of governments’ credit risk on their domestic banks. We justify this by the scarcity of the necessary balance sheet data. Sovereign exposures of European banks’ balance sheets were reported in July 2010 and May 2011 by the European Banking Authority in the context of stress testing. These data are, however, only available at two points in time and are therefore not suited for this analysis. We refer to Acharya, Drechsler and Schnabl (2011) for an empirical approach that uses these data.

In addition to a study of the effects of sovereign credit risk, we will also test the validity of two possible sets of drivers. The first group is a set of variables based on the structural credit spread model that was first developed by Robert Merton (1974). The second group uses fundamental variables instead, i.e. variables that are immediately based on banks’ balance sheet data. To accomplish this we conduct an empirical examination of the importance of different drivers. Our sample includes 35 European banks from 14 countries and covers a period that starts in January 2005 and ends in June 2011. Knowledge about the
drivers of bank credit risk are essential in guiding policy actions, because it is necessary to assess possible market reactions to new measures beforehand.

As such, this master thesis is situated on the crossroads of three strands of research. First of all, it is related to the empirical literature on credit risk and specifically to research that tries to explain corporate CDS spreads. Secondly, as a consequence of our focus on banks, this thesis also relies on the literature on bank risk. This literature is very broad and certainly not confined to banks’ credit risk. Finally, this paper also makes a modest attempt at contributing to the literature that examines the interlinkages of sovereigns and banks. Empirical research in this area is still rather recent and therefore limited in size.

After this introduction we will first discuss the concept of credit default swaps. Apart from an explanation of the practical nature of these credit derivatives, we will elaborate on different methods to approximate and model credit risk. We will also offer arguments to support our view that an empirical examination of bank CDS spreads is optimal in this respect. The second part of this master thesis is dedicated to the connections between the financial and the sovereign sector. We offer a brief overview of the financial crisis in Europe and subsequent policy actions. We also discuss transmission channels between the banking and sovereign sector that are brought forward in the literature.

In the third part we will present a thorough description of our sample, as well as of all the variables that are employed in our empirical models. This part of course provides all practical information about the retrieval and construction of the data, but it will also supply earlier findings of the literature on the influence of each variable.

The fourth and fifth part encompass our empirical research. We will first address several methodological issues in the fourth section, as an empirical study of bank CDS spreads is fraught with econometrical challenges. An accurate examination and deliberation of different possible methods, of which we assess the validity and properties, is therefore indispensable. The fifth and most important part of this thesis offers the results of our empirical study. For each model we discuss the validity and results. The sixth and final part presents our conclusion.
2. Credit Default Swaps

2.1. What is a credit default swap?

A credit default swap is a derivative financial instrument that allows market parties to hedge against the default risk of a reference entity (such as financial firms or sovereigns). It is a bilateral agreement that is traded over the counter (OTC), rather than through exchanges. This offers the ability to make these contracts highly customised. In this way, a CDS closely resembles an insurance contract: the buyer of the contract can effectively hedge against credit risk because the protection seller will compensate him in case of a credit event. Should the reference entity default during the life-time of the respective CDS contract, the protection seller must compensate the CDS buyer for his losses through a settlement procedure. Credit events that can trigger CDS payouts can include failure to pay, bankruptcy, debt restructuring, sovereign debt repudiation or moratoria and, less often, obligation acceleration and obligation default (ISDA 2012). What exactly constitutes a credit event, is always determined at the initiation of the CDS contract. The protection buyer in turn has to pay a periodic premium (much like a classic insurance premium). This fee is calculated as a fraction of the notional value of the insured debt. This percentage, expressed in basis points, is the CDS spread.

Although a CDS contract resembles a standard insurance, there is one key difference: one can hold protection against a reference entity’s default without actually being exposed to it. This has fuelled concerns of wrong incentives during the financial crisis and the possibility to ban *naked CDS trades* has been discussed widely (e.g. Litan 2010; Jarrow 2011). There are, however, clear advantages linked with the ability to take speculative positions in this market. The most important are that speculators are a necessary counterparty to hedgers (Litan 2010) and that restrictions on *naked CDS trades* would distort prices by moving them away from fundamental values (Jarrow 2011).

We will expand on this second point by explaining how the naked selling of CDS contracts allows to effectively short sell the reference entity’s debt. If a certain market party sells a CDS contract, its revenues from this deal would consist of the CDS spread, i.e. the periodic insurance premium. Should the reference entity, however, default on its debt, losses would amount to the notional value of the reference entity’s debt. This situation is equivalent to buying the reference entity’s debt, while shorting a risk-free bond with identical characteristics, as the spread between the yield of them should theoretically equal the CDS spread (Jarrow 2011). Therefore CDS contracts can be used to short sell debt, without
incurring the high costs that are usually related with this, due to the illiquidity and short maturities of repo markets (Di Cesare & Guazzarotti 2010). Restricting the ability to short sell has, for example, been linked with assets’ propensity for speculative bubbles as it hinders the incorporation of adverse information in prices (Jarrow 2011).

Chart 1 shows the evolution of the total notional amount of outstanding CDS contracts. This amount approximates the market size of CDS contracts. We remark that, as CDS contracts are not standardised and traded over the counter, data can differ, dependent on the source and methodology used to obtain the data. The Bank for International Settlements (BIS) data measure the total exposure to CDS contracts of banks and major dealers from the G10 countries and Switzerland. We must also remark that the drop in the outstanding notional amount from 2008 on has been primarily a consequence of portfolio compression, i.e. the netting of short and long positions of a single institution to the same reference entity. This reduces notional amounts, while at the same time ensuring an unchanged risk profile of the CDS portfolio (ISDA 2012). Chart 2 presents the constitution of the total outstanding notional amount of CDS contracts at the end of June 2012.

Chart 1: Total notional amounts of outstanding CDS contracts in trillions of US dollars over the period from July 2004 to end-of-June 2011. For CDS contracts the notional amount is defined as “gross nominal or notional value of all deals concluded and not yet settled on the reporting date” (BIS 2011). Source: BIS 2011.
2.2. Different approaches to approximate credit risk

In this master thesis we shall, as noted earlier, use CDS spreads as a measure for default risk. It must, however, be remarked that in the literature other market variables have been used to approximate credit risk, most notably the bond spread (also referred to as corporate bond spread or yield spread), i.e. the spread between the yield of a risky bond and a risk-free investment. We shall therefore present arguments here to support our choice of CDS spreads to approximate credit risk.

The bond spread was used particularly in the literature prior to 2000, as CDS contracts either did not yet exist or data on them was scarce and less reliable. It was calculated as the spread of the yield on bonds of a certain type, of a certain issuer, at a certain point in time over a risk-free interest rate. There are, however, a number of problems related with this default risk measure, which can be properly addressed by using CDS spreads instead.

The first and most obvious advantage of using CDS spreads is that they can be directly observed. Bond spreads, on the other hand, need several calculations to construct and are therefore more likely to become contaminated. Bonds have certain characteristics, such as maturity and coupon payments, that can differ among issuers or within issuers. To correct for

![Chart 2: Total notional amounts of outstanding CDS contracts by sector in trillions of US dollars at the end of June 2011. Securitised products and multiple sectors include, inter alia, CDSs written on ABSs, MBSs and CDOs. These derivatives accounted together for approximately 1.1 trillion US dollars. Source: BIS 2011.](image)
these idiosyncrasies, one has to use a method to construct a zero-coupon yield curve (Ötker-Robe & Podpiera 2010). A CDS spread circumvents this need because there is no cash flow at the initiation of the contract and maturities are most often fixed at five years; therefore “dealing with CDS quotes is comparable to having a sample of corporate bonds that trade at par on each and every day” (Benkert 2004: 76). As a CDS spread, moreover, is immediately quoted as a spread, no contamination can occur through the specific choice of the risk-free rate. Houweling and Vorst (2005), for example, find evidence that commonly used approximations for the risk-free interest rate, such as government bond yields, are not used by markets as risk-free benchmarks. The choice of the risk-free interest rate can therefore influence bond spreads and hence empirical results.

A second problem with bond spreads is the fact that they are sensitive to tax and liquidity effects, as found by Elton, Gruber, Agrawal and Mann (2001) in the case of tax treatment. As we use data from many different European countries, each with different tax rates, a serious bias could arise in the results, particularly when we include sovereign default risk, because government bonds enjoy different tax treatment. The importance of tax effects has further been illustrated by Driessen (2005). The role of liquidity effects on bond spreads is related to the fact that different bonds may not have the same liquidity, even if issued by the same debtor. It has been shown that these differences in liquidity might affect bond yields (Chen, Lesmond & Wei 2007; Driessen 2005). While tax effects can probably be ignored when using CDS spreads, it is not clear that this is also the case for liquidity effects. Bongaerts, De Jong and Driessen (2009) find evidence for liquidity premiums in the pricing of derivative products. We will expand on the role of liquidity premiums in CDS pricing in the section in which we discuss the explanatory variables (see section 4.3.2).

A final advantage of using CDS spreads rather than bond spreads, is that the former appear to lead the latter in the price discovery process of credit risk (Blanco, Brennan & Marsh 2005). The explanation for this observation is related to our earlier discussion on the nature of the CDS, particularly that it is quasi-equivalent to short selling debt without incurring high costs. This makes CDS contracts a very liquid way to trade credit risk. While bond and CDS spreads both reflect credit risk, the leading relationship appears to persist, and is seemingly not subject to arbitrage. This is linked with the difficulties that arise in other strategies to trade credit risk, e.g. repo costs of short selling a bond are often high. Moreover, CDS spreads are found to react not only faster, but also more strongly to new information (Blanco et al. 2005). As such, the CDS spread is an upper bound for credit risk.
2.3. Different approaches to model credit risk

In the literature on credit risk different modelling approaches have been put forward. In line with Benkert (2004) we argue that an empirical panel regression analysis is a good alternative to explain credit risk and particularly CDS spreads. This avoids the various problems of the theoretical models while maintaining an economic grounding. Panel regressions are, moreover, robust to missing data, which can be a particular problem when working with CDS spread data, as there are frequent interruptions in time series data. We will, however, briefly discuss the two main theoretical approaches to credit risk, i.e. the structural approach and the reduced-form approach, as well as their drawbacks.

The structural approach is based on the model proposed by Robert Merton (1974). It models default risk by making a set of assumptions about a firm’s debt, capital and asset value dynamics. In its most basic form this model assumes that a firm issues a zero-coupon bond with face value $K$ and maturity $T$ at time $0$. Default occurs when at time $T$ the firm is unable to repay its debtors, i.e. as the value of its assets at time $T$, $V_T$, is lower than the nominal value of outstanding debt, $K$. In case of a default, the bond holders take control over the assets and receive the total value of the remaining assets ($V_T$). If no default occurs, on the other hand, the creditors receive the face value of their debt at the time of maturity, while the residual value of the assets, $V_T - K$, is paid out to the equity holders.

Buying a firm’s risky debt is therefore equivalent to buying a risk-free zero-coupon bond with notional value $K$ and maturity $T$ and writing a put option on the firm’s assets to the equity holders. This option is of the European type with maturity $T$, as default can only occur at the maturity of the bond. The strike price of this option is $K$. The required compensation for creditors to write this put option for the equity holders equals the spread between the yield on the firm’s bond and the risk-free bond, i.e. the credit spread. As such, the probability of a default, and thus the required spread, depends completely on the dynamics of the value of the firm’s assets. These dynamics are assumed to be determined by a risk-free interest rate (the drift in the asset value), a volatility measure and a probabilistic motion, usually a geometric Brownian motion (Di Cesare & Guazzarotti 2010; Giesecke 2004).

These insights allowed Merton (1974) to use option valuation methods to determine the level of the credit spread. This model was subsequently ameliorated by relaxing some of the stringent assumptions of the original model, e.g. that firms can only default at the time of maturity of the zero-coupon bond. A discussion on these different structural models is,
however, beyond the scope of this master thesis and we refer to Giesecke (2004) for a more complete review.

The main problem with the structural approach is the fact that asset value and volatility cannot be observed. Using market variables to approximate or estimate these factors of the structural model, as in Di Cesare and Guazzarotti (2010), can become difficult for firms with less liquid securities or more complicated capital structures (Benkert 2004). It is furthermore apparent that structural variables offer only a limited explanation for credit spreads. This problem is dubbed the credit spread puzzle. Di Cesare and Guazzarotti (2010), for example, use a theoretical spread, calculated with the structural model, in a panel regression. Their analysis finds that it only explains about 25% of the variation of CDS spread changes during the period from January 2002 to June 2007. From July 2007 to March 2009, the crisis period in their sample, this number drops even further to a mere 7%. We conclude that, although the structural model has its merits and is economically well founded, it is not enough to adequately explain observed credit spreads.

The reduced-form approach makes no assumptions about the firm’s structure. Default happens randomly. In contrast, the structural approach clearly defines how a default occurs. A default is thus a stochastic event of which the probability is directly determined by an exogenous intensity process. These models are therefore also called intensity based models. A standard reduced-form model uses a Poisson process to model the default probability, although other processes, e.g. with time-varying intensities, are also possible; again, we refer to Giesecke (2004) for an overview of this type of models.

After the stochastic process has been modelled, it is calibrated based on market data. The reliance on market data calibration is both the strength and the weakness of these models. While they lack the economic footing of the structural approach, they fit the market by definition. The problem with reduced-form models, on the other hand, is the fact that CDS spread data, which as explained earlier is the best way to approximate credit risk, are often too scarce or too stale for reliable calibration (Benkert 2004).

We conclude that a panel regression analysis is therefore a valid alternative to explain CDS spreads. It preserves the economic underpinning of the structural model, while broadening it with other market variables. Panel data analysis is also robust to the specific problems concerning CDS spread data (e.g. frequent data gaps).
3. Bank and sovereign risk in Europe and transmission channels

The current financial crisis is, particularly in the euro area, characterised by the enormous strains in the sovereign sector. Such problems are, however, certainly not unique to this specific period or geographic area. Reinhart and Rogoff (2011) find compelling historical evidence that banking crises often precede or accompany sovereign debt crises, by using a data set that stretches over seventy countries and two centuries. They show how, historically, private debts commonly became public debt in the event of a banking crisis. They furthermore argue that government debt almost doubles in the three years after the start of a systemic financial crisis, even when not considering the fiscal effects of financial sector bail-outs. This in turn leads to doubts about the sovereign’s solvency. It is therefore safe to say that it is certainly no unique event that a banking and sovereign crisis unhappily coincide.

More specifically, during the current crisis it is customary to make a distinction between the financial or subprime crisis on the one hand and the sovereign debt crisis on the other. This is done to discriminate a first phase, when governments’ ability to repay their debts was not questioned, from a second phase, when particularly in Europe worries over sovereign default risk enveloped the financial markets. Although the exact time at which this second phase commenced is still a point of discussion (e.g. Mody & Sandri 2011), it is clear that policy makers’, as well as markets’, attention has been increasingly shifting towards the financial health of sovereigns. The most extensive and difficult problem in this respect is the interconnectedness of the financial health of governments and the European banking sector and specifically their respective domestic banking sectors. The latter commonly exhibit a high degree of home bias, i.e. the tendency to build up large exposures to the country they are based in. In the following sections we will first discuss the events specific to this crisis period and to Europe. We will then give an overview of the transmission channels that exist from banks to sovereign entities and vice versa. These channels are supplementary to the reciprocal relations of governments, e.g. through the financing structure of the EFSF1, and the interconnectedness of banks.

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1 The European Financial Stability Facility was created in May 2010 in order to provide financial assistance to troubled euro area countries. It funds its operations through the issuance of debt instruments that are guaranteed by all euro area countries.
3.1. The financial crisis in Europe

The credit boom that preceded the current crisis had a very positive impact on the condition of governments’ fiscal positions. This proved an incentive for many policymakers to reduce tax rates and increase long-term spending (Caruana 2011). This development made sure that as the crisis was finally triggered, governments had only limited power to address it. This was, moreover, just one episode in a legacy of fiscal irresponsibility for some countries (IMF 2011). The pre-crisis credit boom therefore made it easier for governments to postpone fiscal consolidation and policies to improve competitiveness. The lack of these policies before the crisis have seriously added to the sovereign stress European nations currently endure (Mody & Sandri 2011).

Apart from sovereigns’ fiscal conditions, financial markets had seen a sharp compression in risk premiums and a strong increase in the demand for riskier assets offering higher yields. The risks of these products were, however, very opaque. Many banks, moreover, failed to build up sufficient capital and relied heavily on short-term funding. This made them more susceptible to stress when these risks eventually materialised (Caruana 2011). This build-up of risk in the end led to a full-blown systemic financial crisis, triggered by unexpectedly high default rates on subprime mortgages (OECD 2008). This shock propagated rapidly throughout the international financial system as a consequence of the high interconnectedness of the banking sector and contagion within diversified banking groups (OECD 2009).

Governments of course reacted to this rise in financial stress in order to guarantee stability. The measures undertaken to support the banking sector can be divided into three categories. First, governments directly injected capital in some banks to avoid the deleveraging that could ensue after huge losses and raising risk-weights of assets. This type of support was primarily implemented by buying preferred shares, which do not distort ownership structures and ascertained the priority of public claims. There are, however, cases in which the government completely nationalised banks, e.g. the Irish nationalisation of Anglo Irish Bank² (Stolz & Wedow 2010).

Furthermore, schemes were introduced to guarantee bank liabilities in order to assure that banks retained access to private funding. During certain episodes of the crisis even viable banks’ funding sources all but dried up (OECD 2010). In practice, these guarantees were

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² This large Irish commercial bank was heavily involved in property lending. As a consequence of collapsing property prices it suffered huge losses. It was eventually nationalised in January 2009.
implemented by raising the amounts covered by deposit insurance programs and direct guarantees on bond issuance, in return for a fee. In Europe, however, take-up rates of bond guarantees were rather limited due to pricing practices, which disadvantaged weak banks from weak countries, i.e. those most in need of funding sources (Stolz & Wedow 2010). These measures to quench banks’ thirst for funding, were of course supplemented by extraordinary monetary policy initiatives.

Asset support schemes, finally, were used to counter market uncertainty about the value of the assets on banks’ balance sheets. In doing this, governments tried to oppose the risk of fire sales and extreme write-downs, which could push the whole financial sector in a negative spiral of ever-falling asset values. This would have negatively affected credit growth and economic activity further. This type of support came in three varieties: (1) asset removal schemes, i.e. the establishment of a bad bank, (2) asset guarantee schemes and (3) hybrid schemes, which used a combination of the previous two (Stolz & Wedow 2010).

Chart 3 shows the constitution of these measures for each country in our sample. It is clear that in a majority of countries liability guarantees were the most important parts of government programs. The degree to which different countries introduced support, however, varies widely, with a staggering maximum of over 300% of 2008 GDP in Ireland. These measures obviously put stress on the, often already weak, fiscal positions of several countries.

**Chart 3:** Constitution of cumulative government support to financial institutions over the period ranging from October 2008 to May 2010. Numbers in parentheses are the committed amounts of government support in terms of 2008 GDP. In case the actual amount spent exceeded the commitment or no explicit commitment was available, actual amounts are used. Other schemes include government support measures that were undertaken directly, without the introduction of a formal and national plan (e.g. local government support or direct government purchases). Source: Stolz and Wedow 2010.
Subsequently, credit ratings of some peripheral European countries have plummeted from 2009 on. As a consequence these countries have often lost access to debt markets themselves. This in turn called for broader European action. Thus far, Greece, Ireland and Portugal have each received support packages from the EU and the IMF in May 2010, November 2010 and May 2011 respectively. In May 2010 EU authorities, moreover, decided to establish the European Financial Stabilisation Facility (EFSF) to respond in a less ad-hoc manner to sovereign troubles. In return, bailed-out countries were expected to implement serious fiscal consolidation policies. Despite the expansion of existing policies, e.g. increases in the firepower of the EFSF, and the introduction of new ones, most notably private sector involvement (PSI), the sovereign debt crisis still dominates public debate.

3.2. Transmission from the banking sector to the sovereign sector

Reinhart and Rogoff (2011) find that banking crises have historically very often preceded sovereign crises. The question therefore is how the financial sector influences sovereign risk perceptions. The answer is in fact a combination of many channels and a series of negative feedback loops.

As is often the case, economic crises are often preceded by a period of high growth. In this respect, the current crisis is not different from many of its predecessors. As already mentioned before, this boom period weakened underlying fiscal positions for many countries as well as their resolve for fiscal consolidation and competitiveness policies. The plethora of unsustainable revenues linked to the pre-crisis credit boom enabled countries to effectively live beyond their means (Caruana 2011). Mody and Sandry (2011) show empirically that countries with worse fiscal positions or lower competitiveness at the start of the crisis suffered significantly more. The pre-crisis credit boom thus limited many countries’ policy options during the crisis.

As the crisis began and banks saw capital ratios melt away due to a combination of taking losses and increases in the risk weights of their assets, they curtailed private borrowing and investment. This brought the economy to a state of deep recession, combined with huge financial sector volatility. To preserve stability, governments often intervened in this sector, apart from already applying stimulus programs to the economy.

The recession following the credit crunch brought down government revenues as unsustainable ones disappeared almost overnight and unemployment rose. Furthermore the
recession caused a drop in the quality of borrowers, which induced further credit rationing, distorting capital allocation and deepening the recession. As such, the financial sector created a negative feedback loop, pushing economic activity ever further down (Caruana 2011). The banking crisis thus caused government revenues to drop and expenditures to rise sharply. The fall in GDP, accompanied by the increase in government debt, in turn damaged the sovereign debt ratio. The combination of very high budgetary deficits and high debt ratios severely impacted on sovereigns’ perceived creditworthiness (Caruana 2011; Stolz & Wedow 2010).

The worsening of certain countries’ credit conditions was, however, not immediate, but happened gradually. Mody and Sandri (2011) distinguish two turning points during the crisis. They show how in a first phase of the crisis (until March 2008) increased sovereign riskiness (calculated as the country’s sovereign bond spread over Germany’s) could be explained by the rise in global risk. After the Bear Stearns event\(^3\), however, domestic banking sector stress became the most significant factor, albeit lagged. The second turning point was the Irish nationalisation of Anglo Irish Bank in January 2009. From this point on, domestic banking sector stress influenced sovereign stress contemporaneously, indicating instantaneous transmission. They explain the lagged transmission prior to this event as learning effects.

### 3.3. Transmission from the sovereign sector to the banking sector

The transmission channels of the banking sector to the sovereign were ultimately quite straightforward and could be summarised as the banking sector affecting the real economy, which in turn impacted on governments’ balance sheets and undermined sovereign creditworthiness. The transmission channels of the sovereign sector to the banks is, however, less evident.

The first and most direct channel is the impact on bank risk through the sovereign debt holdings on their balance sheets. It is customary in accounting to make a distinction between trading book assets, assets available for sale and assets held to maturity. These categories are relevant from an accounting point of view as asset values are calculated in different ways (e.g. IMF 2011). As such, losses on sovereign exposures are recorded in different ways, according to the category they were placed in. This could lead to the underestimation of ultimate losses. Creditors, however, recognise this fact and appear to be more interested in total exposures

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\(^3\) This large US investment bank encountered severe problems during the subprime crisis. It was eventually sold at a steep discount to JP Morgan Chase, one of the largest US banks, in March 2008.
(CGFS 2011). Sovereign risk can therefore strongly affect asset values and increase default risk for banks. Note that this channel works across national borders. Although banks are generally most exposed to their respective countries (home bias), holdings of foreign sovereigns’ debt are in some cases non-negligible, e.g. the French banking sector (CGFS 2011).

A second channel through which sovereign risk affects banks is caused by the widespread use of sovereign debt as collateral for funding operations. As government debt is perceived as increasingly risky the value of this collateral drops and banks can obtain less funding for the same collateral pool. Government bond haircuts are, moreover, used as benchmarks for other securities and further diminish banks’ access to funding. Note that, in order to counter this channel, the European Central Bank has changed collateral rules (CGFS 2011). Government-guaranteed bonds could also be used as collateral in liquidity operations with the ECB (Stolz & Wedow 2010).

A third distinctive channel is the link between sovereign and bank ratings. It has been shown that sovereign and bank ratings interacted closely, because a sovereign downgrade reflects its decreased ability to guarantee financial sector stability (CGFS 2011). It has, however, been shown that increases in perceived credit risk (measured as CDS spreads) lead downgrade announcements, effective downgrades and negative outlooks (Hull, Predescu & White 2004). The impact of the downgrade itself on access to funding can therefore be questioned as markets have anticipated them with already raised credit spreads. On the other hand, a downgrade could force a number of institutional investors, which account for about a fifth of bank funding (IMF 2010), to sell off their exposures, thereby decreasing the market value of bank debt.

A final important channel is the effect of higher sovereign default risk on the value of explicit, as well as implicit, guarantees since banks rely on explicit liability guarantees to retain access to private funding. Levy and Zaghini (2010) show that government-guaranteed bond yields primarily reflected sovereign default risk, instead of the default risk of the issuing bank. In practice this means that banks from safe countries can significantly reduce borrowing costs by issuing guaranteed debt, whereas the difference is much smaller for banks from risky sovereigns. This is indeed the case (CGFS 2011).

In an attempt to quantify the spillovers from sovereigns to banks, the IMF (2011) found that they are largest for banks based in risky sovereigns, with the exception of Cyprus where the banking sector is heavily exposed to Greece.
4. Data description

4.1. Bank CDS spread data

The regressand in our model is the monthly change of the natural logarithm of CDS spreads. With this variable we try to approximate the proportional change of credit default risk of the underlying names of the included CDS contracts. Our sample consists out of 35 European financial institutions and covers the period from January 2005 to June 2011. In table 1 we present a summary of the included banks. The inclusion of each bank is grounded on three basic criteria. The first and most important criterion is the availability of daily CDS spread data on the Bloomberg database. Secondly, market information has to be available, i.e. the bank has to be listed. Finally we have excluded banks that did not exist throughout the whole sample period (e.g. as a result of mergers).

We chose data on single-name CDS contracts with maturities of five years. The choice for this particular market segment is dictated by the fact that it is by far the most liquid (cfr. Fabozzi, Cheng & Chen 2007, British Bankers’ Association 2006). These data were extracted from the Bloomberg database. For a comprehensive explanation of Bloomberg’s method of CDS data collection we refer to Völz and Wedow (2009).

| 1) Allied Irish Banks plc | 19) Bank of Ireland |
| 2) Alpha Bank | 20) HSBC Holdings plc |
| 3) Banco Monte dei Paschi di Siena S.p.A. (MPS) | 21) IKB Deutsche Industriebank |
| 4) Banco Bilbao Vizcaya Argentaria S.A. (BBVA) | 22) ING Bank NV |
| 5) (Millenium) Banco Comercial Português S.A. | 23) Intesa Sanpaolo S.p.A. |
| 6) Banco de Sabadell, S.A. | 24) Lloyds Banking Group plc |
| 8) Banco Popolare – SC | 26) Natixis |
| 9) Banco Santander S.A. | 27) Nordea Bank AB (PUBL) |
| 10) Barclays plc | 28) Raiffeisen Zentralbank Österreich AG |
| 11) BNP Paribas | 29) Royal Bank of Scotland Group plc |
| 12) Commerzbank AG | 30) Skandinaviska Enskilda Banken AB (PUBL) (SEB) |
| 13) Crédit Agricole | 31) Société Générale |
| 14) Danske Bank | 32) Standard Chartered plc |
| 15) Deutsche Bank AG | 33) Svenska Handelsbanken AB (PUBL) |
| 16) Dexia | 34) Unicredit S.p.A. |
| 17) DNB NOR Bank ASA | 35) Unione di Banche Italiane SCPA (UBI Banca) |

Table 1: This table contains all banks for which CDS spread data and market information were retrieved. Bank names in bold italics indicate the banks for which no quarterly balance sheet data were available.
Daily CDS spread data are, through their OTC nature not always completely reliable. Staleness of daily observations has been noted before as a possible problem (e.g. Di Cesare & Guazzarotti 2010). To evade this issue we drop daily quotations that did not change compared to the previous weekday. With the remaining observations we subsequently calculated an arithmetic average of the daily spreads for each month. If less than five ‘non-stale’, daily observations were available in the course of a month for a specific bank, the respective observation was dropped from our data set.

In table 2 we present the distribution of the banks and monthly CDS observations over the included countries. Most included banks are based in euro area countries, with France and Italy as the biggest contributors to our data set. We also included banks from Denmark, Sweden, Norway and the United Kingdom. In total we have 2258 monthly CDS observations for the sample with 35 banks and 1863 for the sample of 29 banks.

<table>
<thead>
<tr>
<th>Country</th>
<th>Number of banks</th>
<th>Number of CDS observations</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>2</td>
<td>96</td>
<td>4.25% (5.15%)</td>
</tr>
<tr>
<td>Belgium</td>
<td>1</td>
<td>37</td>
<td>1.64% (1.99%)</td>
</tr>
<tr>
<td>Denmark</td>
<td>1</td>
<td>61</td>
<td>2.70% (3.27%)</td>
</tr>
<tr>
<td>France</td>
<td>4</td>
<td>275</td>
<td>12.18% (14.76%)</td>
</tr>
<tr>
<td>Germany</td>
<td>3 (2)</td>
<td>193 (156)</td>
<td>8.55% (8.37%)</td>
</tr>
<tr>
<td>Greece</td>
<td>1</td>
<td>29</td>
<td>1.28% (1.56%)</td>
</tr>
<tr>
<td>Ireland</td>
<td>2 (0)</td>
<td>137 (0)</td>
<td>6.07% (-)</td>
</tr>
<tr>
<td>Italy</td>
<td>6 (5)</td>
<td>415 (338)</td>
<td>18.38% (18.14%)</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1 (0)</td>
<td>78 (0)</td>
<td>3.45% (-)</td>
</tr>
<tr>
<td>Norway</td>
<td>1</td>
<td>44</td>
<td>1.95% (2.36%)</td>
</tr>
<tr>
<td>Portugal</td>
<td>2</td>
<td>156</td>
<td>6.91% (8.37%)</td>
</tr>
<tr>
<td>Spain</td>
<td>3 (2)</td>
<td>222 (156)</td>
<td>9.83% (8.37%)</td>
</tr>
<tr>
<td>Sweden</td>
<td>3</td>
<td>125</td>
<td>5.54% (6.71%)</td>
</tr>
<tr>
<td>UK</td>
<td>5</td>
<td>390</td>
<td>17.27% (20.93%)</td>
</tr>
<tr>
<td>Total</td>
<td>35 (29)</td>
<td>2258 (1863)</td>
<td>100% (100%)</td>
</tr>
</tbody>
</table>

Table 2: The number of banks from each country used in this sample, the number of monthly CDS observations and the percentage of CDS observations of each country in the whole sample. These numbers are valid for the period of January 2005 to June 2011. Numbers in parentheses represent the statistics for the 29 banks for which quarterly balance sheet data were available.

In chart 4 we show the evolution of monthly CDS spread levels. It is clear that bank CDS spreads varied widely over time. Until the summer of 2007 they were close to zero and did not change much. From then onwards, however, bank CDS spreads rose markedly and became much more volatile. After a period of declining spreads and volatility that started in the second quarter of 2009, they again rose sharply from March 2010 on. There is, moreover,
a large cross-sectional variation. While the spread between the 0.1 and 0.9 deciles was only 6 basis points in April 2007, it reached 756 basis points at the end of our sample. As such, the financial crisis created a divergence between the creditworthiness of different banks.

We also need to offer some explanation on the specific choice of our regressand. We use the first difference of the logarithms of CDS spread levels in basis points. Absolute changes (expressed as a specific number of basis points) can offer only a small amount of information during the crisis period. During this period we noticed a huge divergence of absolute levels of CDS spreads over our cross-section units. Changes expressed in basis points are therefore no longer perfectly comparable over financial firms and are more susceptible to outliers (see also, for instance, Acharya et al. 2011). The CDS spread level is, however, not stationary. To test this, we will conduct a simple ADF panel unit root test later on (see section 5.1).

4.2. Explanatory Variables

4.2.1. Variables from the structural model

The variables introduced in this section are derived from the structural model and should capture firm-specific credit risk. Although a firm’s probability of default is a nonlinear function in this model, we choose to insert these structural variables in a linear fashion, as is
usually the case in regression models (e.g. Byström 2005, Annaert, De Ceuster, Van Roy & Vespro 2010). We refer to Di Cesare and Guazzarotti (2010) for a model that includes the nonlinear relationship of these variables with the dependent variable. While these variables perform rather well in most studies, Chen, Fabozzi, Pan and Sverlove (2006) note that structural models are most suited for estimating CDS spreads for firms that are deemed safe.

Our first explanatory variable is the monthly change of the **risk-free interest rate** (expressed in percentage points). This variable has both a firm-specific and a market-wide effect. In the Merton (1974) model the risk-free rate accounts for the drift in the value of the firms’ assets in a risk neutral world (Di Cesare & Guazzarotti 2010). A higher risk-free interest rate, moreover, also affects the present value of future cash flows. A higher rate decreases the value of expected future losses and therefore lowers the price of the hypothetical put option in the structural model (Raunig & Scheider 2009). On these grounds we expect a negative sign for this variable.

Völz and Wedow (2009), on the other hand, offer evidence supporting an opposite effect. They explain this by referring to banks characteristic reliance on debt rather than equity as a source of funding. As the risk-free rate rises, this also raises banks’ funding costs and therefore their probability of default. It is also possible, however, that banks are able to adequately hedge against interest rate risk and that financial markets recognise this ability. If this is indeed the case, the effects on banks’ asset values and funding costs would cancel out each other. Changes in the risk-free interest rate consequently do not affect bank credit risk.

Apart from the firm-specific effect, the risk-free rate can also be interpreted as an approximation for the state of the business cycle. A higher (lower) risk-free interest rate is in most cases connected to a period of higher (lower) growth. During recessions default probabilities and investors’ risk aversion rise (e.g. Nickell, Perraudin & Varotto 2000). Therefore a higher compensation is needed to take on credit default risk. This line of reasoning leads to an identical expectation as the first argument, i.e. a negative effect of the risk-free interest rate on the cost of credit default insurance.

In this thesis we approximate the risk-free rate with the five-year swap rate of the specific country in which the respective bank is based (retrieved from the Datastream database). Note that the euro area counts as a single country in this case. Houweling and Vorst (2005) show that the CDS market uses these swap rates (as opposed to treasury rates) to approximate the risk-free interest rate. We choose five-year maturities in accordance with the maturities of the CDS contracts for which we collected data. The daily rates are averaged for each month and subsequently first differences are calculated.
The second explanatory variable is the bank’s monthly logarithmic **stock return**. This variable is calculated as the logarithmic return at the end of each month, compared to the last day of the previous month. Stock prices were found on the Datastream database.

In the structural model the default probability of a specific firm is a function of, among others, the market value of the firm. This value is not directly observable, but this is not necessary. A positive stock return implies an increase in the market value of the respective firm and, hence, a lower probability of default (Di Cesare & Guazzarotti 2010; Byström 2005). We therefore expect a negative effect of stock returns on credit spreads.

A more intuitive approach to this relation can be found in the interpretation of stock prices. If stock prices increase, this reflects investors’ positive expectations about future earnings. A more profitable firm will be better able to repay its debts (Norden & Weber 2004). This expected negative relation has also been found in earlier empirical work on the effect of stock returns on credit spreads (e.g. Byström 2005).

Thirdly, we also take **equity volatility** into account. As explained earlier, a default on debt payments is caused by the transgression of a certain threshold asset value in the structural model. If a firm’s total asset value is lower than the value of its debt, the hypothetical put option will be used. The more volatile the asset value of a firm, the bigger the chance that the default boundary condition is met (Campbell & Taksler 2003; Benkert 2004; Di Cesare & Guazzarotti 2010). This means that we expect a positive effect of equity volatility on CDS spreads.

Analogous with stock returns, we can also explain the impact of equity volatility on credit risk more intuitively. If market returns are more volatile, this implies a higher degree of uncertainty about future earnings. The (future) profitability of the respective firm is thus in question and hence its ability to timely repay its debt (Ötker-Robe & Podpiera 2010).

We approximate the volatility of the respective firm’s assets with the historical volatility of its daily stock returns. We define historical volatility as the monthly standard deviation of the daily returns of the bank’s stock. In our regressions we will use the proportional (logarithmic) change of the monthly historical volatility measures. We choose not to use the absolute first differences for the same reasons we will not use these for CDS spreads. To check the robustness of our results, we will also use a measure for asset volatility that is calculated over a longer horizon, namely 26 weeks instead of one month.
4.2.2. Sovereign CDS spreads

In section 3 of this master thesis we already discussed the importance of sovereign credit risk in the explanation of bank CDS spreads. We gave an overview of the transmission channels that exist between these two sectors and how such a tight connection came about in practice. We therefore expect that sovereign credit risk will positively affect banks’ default probabilities and hence bank CDS spreads. We also expect that this effect will be nonlinear, i.e. that it will not be a significant influence on bank CDS spreads as long as sovereign risk is deemed low. Note that we are not trying to measure the importance of each separate channel, but rather the total influence of the sovereign sector on its domestic banks. As such, the effects of sovereign credit risk on foreign banks are outside the scope of this paper. We refer to Acharya et al. (2011) for an empirical study of the effects of sovereigns on foreign banks.

![Chart 5: Evolution of sovereign CDS spreads of different European countries. Each line represents the arithmetic average of the CDS spreads of the three respective countries. Source: Bloomberg; author’s calculations.](image)

In line with banks, credit risk of sovereign entities is approximated with CDS spreads, of which we retrieved daily observations from the Bloomberg database. The treatment of this data set is identical to that of our explanatory variable. We changed the frequency of the observations from daily to monthly and subsequently calculated logarithmic differences. This transformed variable is then used to estimate our model. Chart 5 shows the evolution of sovereign CDS spreads for different groups of countries. This figure clearly shows that sovereign credit risk diverged strongly between European countries from the second half of 2009 on.
4.2.3. Liquidity

We also include a variable in our model to account for the liquidity of CDS contracts. Bongaerts et al. (2009) showed that derivative securities also need liquidity premiums. The influence of liquidity on CDS spreads is, however, not completely clear and the literature offers contradictory evidence on this subject.

A first line of research found a positive impact of CDS liquidity on spreads (Chen, Cheng & Wu 2005, Fabozzi et al. 2007). This counterintuitive relation can be explained by the different economic characteristics of a bond as opposed to a credit default swap: a CDS contract demands the periodic payment of credit risk premiums, whereas a bond demands the complete credit risk payment upfront. We refer to Fabozzi et al. (2007) for a more detailed discussion.

A second, important part of the literature finds a significantly negative relation between the liquidity and the spreads of CDS contracts (e.g. Tang & Yan 2007). This result was furthermore confirmed by Bongaerts et al. (2009). They tested their aforementioned theory empirically on CDS spreads and found that a large part of CDS spread variation can be explained by liquidity. Pires, Pereira and Martins (2010) furthermore show how findings of a positive relation between liquidity and CDS spreads are probably the result of methodological mistakes.

We approximate the liquidity of the respective CDS contracts by dividing the number of non-stale CDS quotes in each month by the total number of trading days in the respective month. Consequently, our liquidity measure varies between zero and one. In our regression we use the first difference of this variable.

4.2.4. Market-wide variables

The inclusion of market-wide factors is necessary, as previous empirical studies on corporate bond and CDS spreads have found that, even after correcting for variables brought forward by the structural model, there still exists a lot of common variation in the residuals. Collin-Dufresne, Goldstein and Martin (2001), for example, concluded from a principal component analysis that, after correcting for credit risk variables and liquidity, over 75% of the remaining residual variation was caused by one common factor. They therefore argue that credit spread changes are also due to a single large and systematic factor that was not present in the structural model. Borio, Furfine and Lowe (2001) warned against using only the Merton (1974) type variables to assess credit risk. They argue that firms’ equity prices can be biased
due to underestimation (overestimation) of risk during booms (busts). This invalid assessment of risk therefore influences the implied default probabilities found through the structural credit risk model. It could also wrongfully decrease the observed default correlations. An obvious candidate to account for the common variation is the financial or business cycle. Different channels through which the economic environment can affect credit spreads of specific firms have been brought forward in the literature. Annaert et al. (2010) discuss two of these channels.

The first channel is a collection of effects that the business cycle itself has on credit risk. Generally, default probabilities vary over the business cycle (Nickell et al. 2000), as does the risk aversion of investors (Berndt et al. 2005). The business cycle is furthermore negatively correlated with the share of non-performing loans on banks’ balance sheets and positively correlated with recovery rates (Ötker-Robe & Podpiera 2010). The strong connection between default probabilities and recovery rates has also been highlighted by Altman, Brooks, Resti and Sironi (2005). The value of a bank’s assets and therefore its probability of default is thus closely related to macroeconomic conditions. This problem is made worse for banks by the absence of procyclical buffers and provisions (Borio et al. 2001).

The second channel is linked with capital market frictions. In a frictionless world risk premiums that are deemed too high attract more protection sellers. The rise in the supply of credit insurance will then bring premiums down to more normal levels. Annaert et al (2010) argue that in uncertain times frictions rise and take longer to disappear as protection sellers are less willing to increase their supply. The uncertainty of future earnings, moreover, increases during more volatile economic times. This also has a positive effect on credit spreads.

The first variable in this category is the return on a broad market index. This variable should account for the general business climate (e.g. Collin-Dufresne et al. 2001; Campbell & Taksler 2003). A higher return should signal an improvement of the business cycle. We therefore expect a negative relation with the CDS spread changes.

Di Cesare and Guazzarotti (2010), on the other hand, note that a positive sign for this variable is nonetheless possible if firms’ individual stock returns are also included in the regression. In the case of very high market returns, it is possible that the individual firm performs rather badly compared to the rest of the market. A positive impact of market returns on CDS spread changes could then be expected.
To approximate a market return for our geographic area, we use the Datastream broad European market index. Returns are calculated as the logarithmic return on the last day of the month, compared to the last day of the previous month.

A second market-wide factor is the slope of the yield curve. The term structure is often used as a measure of market expectations about the future business climate. A strongly positive slope implies that future short term interest rates are expected to be higher than the current, which can be interpreted as an improvement of the business cycle. A negative or flat slope, on the other hand, indicates that market expectations of the economy are more pessimistic (Fama & French 1989). As an improving business cycle (an increase in the slope of the yield curve) implies lower probabilities of default, higher recovery rates, less non-performing loans and therefore less credit risk, a negative relation with CDS spread changes is expected.

A positive relation is, on the other hand, also a possibility. Higher risk-free interest rates might diminish the number of available projects that generate profits for a firm. Second, a steepening of the yield curve could also be driven by drops in the current short term interest rates. This is often the case in recessions, as monetary policymakers decrease interest rates to stimulate the economy. In this way, a steeper yield curve could also be a symptom of a deeper recession (Di Cesare & Guazzarotti 2010).

We define the slope of the yield curve as the difference between the five- and two-year swap rates of the respective countries. Note that this implies that yield curves are identical for every euro area country. The choice for this measure might seem problematic as we used the five-year swap rate as our risk-free interest rate measure. As such, this variable could be correlated with the risk-free return and cause multicollinearity problems. To account for this problem we also estimate our model with another measure for the term structure, i.e. the difference between the ten- and two-year swap rates. We used the Datastream database to find daily swap rates. With these rates we calculated daily data on the slope of the yield curve. Subsequently, we averaged the daily term structure data for each month.

The choice of the terms from which the slope of the yield curve is calculated is in line with Annaert et al. (2010). We choose swap rates, rather than bond rates, following Raunig and Schneider (2009) and Houweling and Vorst (2005). Other measures, which are often used to calculate the slope of the term structure were furthermore heavily contaminated. Government bond yield data, which are used by several studies (e.g. Avramov, Jostova & Philipov 2007, Blanco et al. 2005), cannot be used for many of the included euro area countries as their bond yields were clearly driven by default risk and sovereign bond market
illiquidity (Sgherri & Zoli 2009). The three-month interbank offered rate can also not be used to approximate the short term risk-free interest rate as interbank markets suffered from prolonged strains of illiquidity from the summer of 2007 on. This was of course caused by the enormous uncertainty in this market and the subsequent counterparty risk (Taylor & Williams 2008).

The third market-wide factor we include in our model is a measure of market volatility. We already discussed how an increase in the uncertainty about the situation of the general economy affects credit risk pricing. We use market-wide volatility, as captured by the VStoxx index, to control for these effects. We used Datastream to obtain daily VStoxx quotations, which we subsequently averaged over the respective months. In our regression we use the logarithmic monthly change of these averages. The arguments for using logarithmic rather than absolute first differences have already been outlined earlier in the sections on CDS spread and equity volatility data.

The VStoxx index measures the implied volatility across all options of the EuroStoxx 50 index. It can therefore be interpreted as an approximation of market-wide, implied volatility. For a more detailed discussion on the concept, calculation and interpretation of the VStoxx index, we refer to Stoxx® (2011). Because of the reasons mentioned earlier, we expect a positive impact of the changes in the VStoxx index on CDS spread changes.

A market volatility index is used very often in the literature to approximate the uncertainty of the market (e.g. Alexander & Kaeck 2008; Ötker-Robe & Podpiera 2010). Pan and Singleton (2008) furthermore show that this measure is also closely related to investors’ risk appetite by comparing the risk premium component of the VIX index with a standardised VIX index series.

The final market-wide factor we introduce in our model is the spread between the interbank offered rate and the benchmark policy rate of the country in which the respective bank is based. From 9 August 2007 on, large increases in these spreads were legion. While in normal times this spread is constant and negligibly small (below 10 basis points), the recent financial crisis was - and is, in fact, still - characterised by unusually strained money market conditions (Taylor & Williams 2008). In September 2008, the spread of the Euribor rate, the rate at which prime euro area banks are willing to lend funds to each

\[4 \text{ VIX is essentially the same as the VStoxx index, except that it is calculated from the S&P500 index, rather than from the European EuroStoxx 50 index.}
\[5 \text{ In the remainder of this master thesis we will refer to this variable simply as the interbank spread.}
other, over the Eurepo rate spiked above 200 basis points, expressing the huge stress in the financial system.

The interbank spread is a good approximation of general financial sector stress. It signals not only increased borrowers’ default probabilities, but also lenders’ credit risk. A lending institution would raise its prices if it expects a liquidity shock itself prior to repayment and/or if it thinks that funding costs will rise sharply in the case of such an event (Eisenschmidt and Tapking 2009). These fears are of course closely related to the financial stress of the lender and of the whole funding market. We therefore expect a positive relation between the changes of interbank and CDS spreads.

We must, however, remark that there might be a few complications when using this measure for bank stress. In periods of uncertainty, for example, data on interbank offered rates (fixings) become less representative of banks’ true funding costs. Fixings are constructed by calculating a trimmed average of banks’ estimates of their own funding costs. In volatile times the dispersion of the reported rates increases because of uncertainty or incentives for banks to engage in strategic behaviour by underreporting their own funding costs (Gyntelberg & Woolridge 2008).

We obtained all necessary data from Datastream with a daily frequency. Table 3 summarises the data used to construct this variable. Monthly observations are then calculated by first deducting the risk-free rates from the interbank offered rates and subsequently averaging these spreads over each month.

<table>
<thead>
<tr>
<th>Country</th>
<th>Interbank offered rate</th>
<th>Benchmark Policy Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denmark</td>
<td>Cibor (3m)</td>
<td>Danish repo rate (3m)</td>
</tr>
<tr>
<td>Sweden</td>
<td>Stibor (3m)</td>
<td>Swedish OIS rate (3m)</td>
</tr>
<tr>
<td>Norway</td>
<td>Nibor (3m)</td>
<td>Norwegian National Bank’s key policy rate</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>Libor (3m)</td>
<td>UK repo rate (3m)</td>
</tr>
<tr>
<td>Euro area</td>
<td>Euribor (3m)</td>
<td>Eurepo rate (3m)</td>
</tr>
</tbody>
</table>

Table 3: Data used to construct the interbank spreads.

---

6 “[This] is the rate at which, at 11.00 a.m. Brussels time, one bank offers, in the euro-zone and worldwide, funds in euro to another bank if in exchange the former receives from the latter the best collateral within the most actively traded European repo market” (European Banking Federation 2012).
4.2.5. Balance sheet variables

In this section we present explanatory variables that are directly derived from banks’ balance sheets. We will use these variables in a second, alternative model. In line with Ötker-Robe and Podpiera (2010) we use the CAMELS framework for bank rating. CAMELS is an acronym for capital adequacy, asset quality, management quality, earnings potential, liquidity and sensitivity to market risk. We choose this framework because it offers a clear system to use banks’ balance sheet data to approximate a varied list of bank fundamentals. This framework is, moreover, commonly used by supervisors to analyse the financial health of banks. We also add a simple size measure to account for the too-big-to-fail phenomenon.

We obtained quarterly balance sheet data from Worldscope for 29 banks. These quarterly data are then interpolated in a linear fashion to acquire monthly statistics. The quarterly observation is used as the observation for the last month of the respective quarter (e.g. Q1 equals March). We refrain, however, from interpolation if information about a specific quarter is missing. This has the advantage of minimal distortion of the data, but has the inconvenient consequence of strongly reducing the number of observations. Banks that, for instance, only report a certain variable semi-annually only have two monthly observations for each year.

We first determine a measure for capital adequacy. The amount of capital available to a bank, in relation to its assets, conveys how much unexpected losses it can absorb before defaulting on its debt. Regulatory capital ratios are calculated by banks and supervisors as the ratio of its capital to its risk-weighted assets. The specific weights for each asset or asset type are internationally determined by the Bank for International Settlements and are subsequently implemented by national prudential authorities. During the recent financial crisis, however, this ratio became less relevant to measure capital adequacy due to banks’ huge exposure to structured financial products (e.g. CDOs), which were formerly regarded as having triple-A status. By 2008, however, the majority of these products was downgraded, increasing the required capital to hold these products, while inflicting heavy losses (Coval, Jurek & Stafford 2009). The same can be said of banks’ sovereign debt holdings: consecutive downgrades of European countries’ debt affected their risk weights on banks’ balance sheets. The rating of Ireland, for example, was still very high at the beginning of 2009 and therefore had a risk weight of 0% (Caruana 2011; CGFS 2011).

Based on these arguments we conclude that risk-weighted assets did not account for the true risk of a bank. We choose a simple inverted leverage ratio instead to assess a bank’s capital adequacy. This ratio is calculated by dividing the total book value of the common (and
therefore truly loss-absorbing) equity by the book value of the bank’s assets. We expect that this ratio, which is directly related to the level of capitalisation, will negatively affect CDS spreads. Demirgüç-Kunt and Huizinga (2010), on the other hand, argue that a positive relationship is also possible due to the fact that highly leveraged banks enjoy higher implicit subsidies from the financial safety net (e.g. deposit insurance).

Secondly, we introduce an indicator for asset quality. Lower asset quality, i.e. more impairments on banks’ assets, increases losses and therefore default risk. Similar to Ötker-Robe and Podpiera (2010) we measure asset quality as the share of loan loss provisions to total loans. This variable approximates the share of expected, rather than unexpected, losses on a bank’s loan book, compared to the total value of its loans.

We expect that this asset quality measure will positively affect CDS spreads. We must, however, remark that a negative correlation could also exist. Loan loss provisions cover expected losses. Lower provisions could therefore imply a lower buffer against losses. This in turn increases the probability of drops in the level of capitalisation, augmenting the risk of default (Fillat & Montoriol-Garriga 2010).

The third component of CAMELS, management quality, refers to efficiency as well as diversification. A commonly used indicator for efficiency is the cost-income ratio (e.g. Baele, De Jonghe & Vander Vennet 2010). This ratio is calculated by dividing the operational costs of a bank by its revenues. It ascertains whether a bank can remain profitable in adverse conditions. It is therefore expected that efficiency, in the shape of a lower cost-income ratio, will result in lower default risk. As with the variables discussed earlier, an opposite effect is nonetheless possible. As managers are risk-averse, they may spend resources in order to reduce exposure to risk. This would increase the cost-income ratio, while at the same time reducing the probability of default (Kwan & Eisenbeis 1997). The relevance of this variable can, however, be questioned on the ground that bank revenues came close to zero or even became negative during the financial crisis. This makes it impossible to interpret this ratio. Consequently, we do not include an efficiency measure in our model.

We use the share of non-interest income in total revenues as an indicator for diversification. In this light banks with high ratios can be considered as highly diversified, whereas low ratios signify a dominance of traditional retail activities. Although diversification of income sources can reduce idiosyncratic risk to a certain extent, it will increase systematic risk. Non-interest income is furthermore found to be much more volatile than interest revenues (Baele et al. 2007). More diversified banks are therefore expected to be regarded as riskier, certainly during a recession, which should positively affect CDS spreads.
The earnings potential of a bank is accounted for by including a profitability measure, i.e. the share of pre-tax income over total assets. A higher ratio indicates that the bank is more profitable, has better prospects for growth and is better able to withstand shocks (Ötker-Robe & Podpiera 2010). This variable is also closely connected to the structural credit risk model. A higher return on assets can be seen as an increasing asset value, which lowers the probability of becoming insolvent. On these grounds we expect a negative coefficient for this variable.

Fifth, we introduce an indicator for a bank’s liquidity. We already discussed the important role of money market conditions during the financial crisis. Banks lost access to a source of funding that had thus far proven to be very liquid. The inability to acquire funds of course inflated the risk that debts would not be repaid in time, however solvent the bank still was. This in turn induced fire sales of assets and plummeting asset values, increasing the probability of default. This further worsened the bank’s access to funds and cause further fire sales (Diamond & Rajan 2010). The spread of interbank offered rates over risk-free interest rates is, however, a market-wide factor and does, for example, not consider the differences between euro area banks. In a model based on banks’ balance sheet characteristics, we can account for this heterogeneity. We use the ratio of short-term debt over total debt to approximate the funding position of a bank. An increasing ratio would indicate that banks will have more trouble to roll over their maturing short term debt in case of a money market freeze, as witnessed during the financial crisis. We therefore expect that this variable will interact positively with CDS spreads.

Sixth, we have to include variables to account for a bank’s sensitivity to market risk. We have extensively discussed the importance of these variables in explaining credit risk earlier. In the respective section we have also introduced a range of market-wide factors that could affect CDS spreads. In the model based on banks’ balance sheet characteristics we will also include these variables to account for the condition of the business cycle and the general uncertainty affecting market parties. For a more detailed discussion about the construction and effects of these variables, we refer to their respective sections in this master thesis.

Finally, we also introduce a measure for bank size. The influence of this variable on banks’ creditworthiness is widely researched and has become a major topic for policymakers and financial supervisors (see e.g. Dermirgüç-Kunt & Huizinga 2010; Ötker-Robe, Narain, Ilyina & Surti 2011). The debate is primarily focussed on the facts that some banks have become too interconnected, too complex and too large to resolve safely. This problem grew especially in the years preceding the crisis as banks could inflate their balance sheets through
cheap short term funding (Dermirguc-Kunt & Huizinga 2010). Another contributing factor was the rising diversification of activities undertaken by a single bank (Ötker-Robe et al. 2011). As such, these banks became systemically important, i.e. their collapse could profoundly harm the financial system as a whole and the broader economy. This assured that they would be bailed out in the event of a crisis, effectively diminishing default risk. However, this also created moral hazard problems, as banks could take on more risk than was optimal because they were able to rely on the public safety net. As such, we expect bank size to negatively affect CDS spreads. A further and deeper discussion of this topic is, however, outside the scope of this master thesis, as it would take us too far. We refer to Ötker-Robe et al. (2011) for a more complete overview of the problem and an examination of policy options.

To account for the influence of bank size on CDS spreads we will use logarithmic changes in the value of banks’ total assets. Quarterly data of total assets were retrieved from the Worldscope database and were interpolated using the same method as for the other balance sheet data. Table 4 offers descriptive statistics of all the mentioned variables over our whole sample period.

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank CDS Spreads</td>
<td>2329</td>
<td>113.288</td>
<td>79.143</td>
<td>3.920</td>
<td>1402.162</td>
<td>153.764</td>
</tr>
<tr>
<td>Δ ln (CDS)</td>
<td>2190</td>
<td>0.036</td>
<td>-0.001</td>
<td>-0.709</td>
<td>1.234</td>
<td>0.218</td>
</tr>
<tr>
<td>Δ Risk-free Interest Rate</td>
<td>2695</td>
<td>-0.008</td>
<td>0.006</td>
<td>-0.817</td>
<td>0.561</td>
<td>0.193</td>
</tr>
<tr>
<td>Stock Return</td>
<td>2805</td>
<td>-0.010</td>
<td>0.000</td>
<td>-1.575</td>
<td>1.109</td>
<td>0.136</td>
</tr>
<tr>
<td>Stock Return – Market Return</td>
<td>2805</td>
<td>-0.015</td>
<td>-0.010</td>
<td>-1.416</td>
<td>1.077</td>
<td>0.112</td>
</tr>
<tr>
<td>Δ ln (Equity Volatility) [1 month]</td>
<td>2769</td>
<td>0.011</td>
<td>-0.012</td>
<td>-1.474</td>
<td>1.610</td>
<td>0.405</td>
</tr>
<tr>
<td>Δ ln (Equity Volatility) [26 weeks]</td>
<td>2763</td>
<td>0.010</td>
<td>0.007</td>
<td>-0.749</td>
<td>1.052</td>
<td>0.112</td>
</tr>
<tr>
<td>Δ ln (Sovereign CDS)</td>
<td>2159</td>
<td>0.045</td>
<td>0.008</td>
<td>-0.496</td>
<td>1.414</td>
<td>0.207</td>
</tr>
<tr>
<td>Δ Liquidity</td>
<td>2772</td>
<td>0.004</td>
<td>0.000</td>
<td>-0.857</td>
<td>0.957</td>
<td>0.120</td>
</tr>
<tr>
<td>Market Return</td>
<td>2772</td>
<td>-0.001</td>
<td>-0.006</td>
<td>-0.134</td>
<td>0.128</td>
<td>0.056</td>
</tr>
<tr>
<td>Δ ln (VStoxx)</td>
<td>2772</td>
<td>0.007</td>
<td>-0.021</td>
<td>-0.268</td>
<td>0.716</td>
<td>0.167</td>
</tr>
<tr>
<td>Δ Slope Yield Curve [5y – 2y]</td>
<td>2772</td>
<td>0.002</td>
<td>-0.012</td>
<td>-0.197</td>
<td>0.540</td>
<td>0.086</td>
</tr>
<tr>
<td>Δ Slope Yield Curve [10y – 2y]</td>
<td>2772</td>
<td>0.004</td>
<td>-0.019</td>
<td>-0.435</td>
<td>0.749</td>
<td>0.143</td>
</tr>
<tr>
<td>Δ Interbank Spread</td>
<td>2772</td>
<td>0.003</td>
<td>-0.001</td>
<td>-0.686</td>
<td>1.110</td>
<td>0.169</td>
</tr>
<tr>
<td>Δ Common Equity to Total Assets</td>
<td>1579</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.011</td>
<td>0.013</td>
<td>0.002</td>
</tr>
<tr>
<td>Δ Loan Loss Provisions to Total Loans</td>
<td>1414</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.003</td>
<td>0.003</td>
<td>0.000</td>
</tr>
<tr>
<td>Δ Non-interest Income to Total Income</td>
<td>1386</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.231</td>
<td>0.172</td>
<td>0.044</td>
</tr>
<tr>
<td>Δ Pre-tax Income to Total Assets</td>
<td>1576</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.003</td>
<td>0.004</td>
<td>0.001</td>
</tr>
<tr>
<td>Δ Short-term Debt to Total Debt</td>
<td>1458</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.251</td>
<td>0.268</td>
<td>0.088</td>
</tr>
<tr>
<td>Δ ln (Total Assets)</td>
<td>1579</td>
<td>0.008</td>
<td>0.005</td>
<td>-0.069</td>
<td>0.468</td>
<td>0.029</td>
</tr>
</tbody>
</table>

*Table 4:* Descriptive statistics of our variables (monthly frequency) over the whole sample period. Source: Bloomberg; Datastream, Worldscope, author’s calculations.
5. Econometrical Methodology

5.1. Test for a unit root in bank CDS spreads

If an overview were made of the empirical methodologies utilised in the literature on CDS spreads, it would become apparent that there are numerous problems. Before presenting our empirical results, it is therefore necessary to explain these issues coherently and discuss solutions to them.

The first and probably most important among these problems is the fact that CDS spreads are seemingly non-stationary, which means that they cannot be used in regression analysis as they will produce spurious results, i.e. the results lack any meaning and therefore economic interpretation. However, many empirical studies do not account for this statistical problem. Cremers, Driessen, Maenhout and Weinbaum (2008), for example, argue that credit spreads are ex ante expected return differentials and should therefore be stationary. They also mention a lack of econometric proof to support non-stationarity.

On the other hand, in this master thesis we will use (proportional) changes of bank CDS spreads as our dependent variable. To provide econometric evidence in support of non-stationarity we conduct a simple augmented Dickey-Fuller (ADF) panel unit root test. The results are presented in table 5. The null hypothesis of a unit root in CDS spread levels cannot be rejected at any reasonable significance level. A unit root in the first-differenced series can, on the other hand, be rejected at the 0.1% significance level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Test statistic</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS$_{i,t}$</td>
<td>24.3357</td>
<td>1.0000</td>
</tr>
<tr>
<td>Δln(CDS$_{i,t}$)</td>
<td>1661.67</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 5: Results of the ADF Fisher unit root test. Probabilities are computed using an asymptotic chi square distribution. The null hypothesis assumes a unit root.

This test, first proposed by Maddala and Wu (1999) and also called the Fisher test, has several advantages. As it estimates

$$\Delta y_{i,t} = \alpha_i + \pi_i y_{i,t-1} + \sum_{j=1}^{P} y_{i,j}\Delta y_{i,t-j} + \mu_{i,t}$$
it allows for heterogeneity in $\pi_t$, in contrast to earlier tests that assumed $\pi_t$ is identical for each cross-section unit. Furthermore it allows for a different number of lags of $\Delta y_{it}$ and even different unit root tests for every individual unit. The test statistic is calculated as:

$$ P = -2 \sum_{i=1}^{N} \ln (p_i) $$

where $p_i$ is the p-value of the unit root test of cross-section $i$. The null hypothesis assumes a unit root process. The test statistic is asymptotically (i.e. as the number of periods tends to infinity) chi square distributed with $2N$ degrees of freedom (Maddala & Wu 1999).

There are, however, severe problems when using this approach to test for a unit root. A first disadvantage is the fact that the distribution of the test statistic is only asymptotically chi square. This means that this test assumes that the time dimension of the data is large enough (Verbeek 2012). As our sample of bank CDS spreads covers a period of 78 months, we believe that this bias will not have a large influence on our results.

A second problem is practical in nature and concerns the number of lags for each individual unit root test and whether to include a specific trend. In our test we have assumed the absence of a trend. We have used the Schwarz information criterion to determine the number of lags for each individual test.

The most important problem of the Fisher ADF test is the fact that it assumes cross-sectional independence. Due to high degrees of global economic and, particularly, financial integration it is fair to say that this will not hold. As a consequence, the individual unit root tests will not be independent and the test statistic proposed by Maddala and Wu (1999) will not be asymptotically chi square distributed under the null of a unit root process (Verbeek 2012).

This final problem is amended by the so-called second generation panel unit root tests. Bai and Ng (2004) propose a new test that exploits the cross-sectional dependence as an asset rather than a problem. Broadly speaking it decomposes the data into an individual specific factor and a number of common factors. A series is then non-stationary if one or more of the common factors or the idiosyncratic error term is non-stationary. Thus one can determine the source of the non-stationarity. This test is, however, not available in our statistical software.

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7 We remark that from here on N will always denote the number of cross-section units in the sample and T the number of periods.
package\textsuperscript{8}, and is also problematic for our sample, due to the limited number of cross-section units. The approach of Bai and Ng (2004) needs a large value for $N$ to consistently estimate the common factors. As we will not apply second generation panel unit root tests, we will not explicitly discuss other methods that are less widely used. Instead we refer to Gegenbach, Palm and Urbain (2010) for an overview of different methodologies.

In conclusion, we accept the results of our panel unit root test with reservations, as the discussed problems with this test could affect results. However, we note that the intermediate ADF test results (not reported), i.e. the individual unit root tests, do not reject a unit root at any reasonable level of significance for the bank CDS spreads in levels. Similarly, a unit root is rejected for each and every cross-sectional unit for the proportional changes. In the remainder of this master thesis we will therefore treat bank CDS spreads as non-stationary variables and the proportional changes as stationary.

5.2. Dynamic Panel Estimation

In this thesis we will use dynamic panel estimation techniques to elucidate the relationship of bank CDS spreads and a set of explanatory variables. The number of time series observations is quite high for our whole sample (78 months) and we could in fact choose to estimate each cross-section unit separately, rather than in a panel framework. We opt, however, not to do this as the time dimensions of sub samples are rather small and estimates would turn out to be seriously biased. The division of our data set into different periods is, however, necessary to account for the fact that some factors may not have had identical effects during the different phases of the recent crisis. A panel regression offers further advantages, particularly robustness against missing observations, which is a serious problem in our data set. This type of analysis will thus help to produce better results. To assure comparability over different periods we will use the same estimation technique for the whole sample as for the sub samples.

Furthermore we will include the first lag of the proportional change in bank CDS spreads to allow for persistence in spread changes and possible under- or overshooting. This means that we correct for the fact that a change in a certain month due to some factor could affect bank CDS spread changes in the following month as markets understand that their

\textsuperscript{8} EViews 7.
initial reaction might have been too small (i.e. they undershot) or vice versa. Our regression model is thus given by:

$$y_{i,t} = \alpha_i + x_{i,t}^{'} \beta + \rho y_{i,t-1} + \mu_{i,t}$$ (1)

where $y_{i,t}$ is the proportional change of the CDS spread of bank $i$ at time $t$. The vector $x_{i,t}$ contains model-specific variables, while $\beta$ is the corresponding vector of factor loadings.

Now that we have argued why a dynamic panel regression analysis seems best to examine bank CDS spread changes, we must address a number of issues concerning estimation techniques, i.e. we have to determine which estimator we will use. This is primarily the consequence of the correlation between $\alpha_i$ and the lagged dependent variable. A first option to estimate our model, which would also be the most straightforward approach, is the use of a simple ordinary least squares (OLS) estimator. Due to the above mentioned correlation problem, however, OLS would become inconsistent and would overestimate $\rho$ in case it is positive. A random effects (RE) estimator would also be inconsistent because a prerequisite to its application is the absence of correlation between $\alpha_i$ and the explanatory variables. In a dynamic model this correlation is imposed by definition. As with the OLS estimator, the RE estimator would overestimate $\rho$, in case it is positive (Verbeek 2012).

The fixed effects (FE) estimator\textsuperscript{9}, on the other hand, does not require that $\alpha_i$ and the explanatory variables are uncorrelated. Nickell (1981), however, shows that this estimator is biased for fixed T. This bias will, moreover, not disappear as the number of cross-section units tends to infinity. It will, on the other hand, converge to zero as the time dimension of the data increases. In case $\rho$ is greater than zero, the FE estimator will underestimate the true autoregressive coefficient. As the time dimension of our whole sample is in fact quite large (78 months), we could assume the influence of this Nickell bias to be minimal. We do, however, remind the reader that we use sub samples in which the number of time periods is far lower than in the whole sample. The bias, furthermore, appears to be quite large and to persist even for a moderately high number of time periods. Judson and Owen (1999) find a bias between 3% and 20% from the true value of the parameter, even for T=30. We therefore choose not to use the FE estimator, not even for the whole sample, because this allows us to compare results.

\textsuperscript{9} This estimator is also called the within estimator and the least squares dummy variable (LSDV) estimator. We will use these terms as synonyms throughout this master thesis.
The question then is how we can remedy or avoid this bias. The literature offers, broadly speaking, two options. The first can be described as a transformation of the FE estimator to correct for the bias directly. This bias-corrected least squares dummy variable (LSDVC) estimator, however, has a major drawback in that it is not applicable in the presence of regressors, which are not strictly exogenous (Bruno 2005; Everaert & Pozzi 2007). We choose not to use this method for two particular reasons. First, we always have one or more endogenous explanatory variables in our model, as we investigate the relation of bank and sovereign CDS spreads. Second, our statistical software is unable to use this estimator.

A second approach is based on the elimination of the problematic individual effects $\alpha_t$ by differencing equation (1). This yields:

$$\Delta y_{i,t} = \Delta x_{i,t}^\prime \beta + \rho \Delta y_{i,t-1} + \Delta \mu_{i,t}$$  

This, however, creates a new problem as $y_{i,t-1}$ (in $\Delta y_{i,t-1}$) is by definition correlated with $\mu_{i,t-1}$ (in $\Delta \mu_{i,t}$). The lagged dependent variable $\Delta y_{i,t-1}$ is therefore endogenous and needs to be instrumented, either with an external instrument or, in the absence of such an instrument, with its own lagged values. It is easy to see that, under the assumption that the error term $\mu_{i,t}$ has no autocorrelation, $\Delta y_{i,t-2}$ is correlated with $\Delta y_{i,t-1}$ (through the common term $y_{i,t-2}$), but not with $\Delta \mu_{i,t}$ (Verbeek 2012). This approach was first proposed by Anderson and Hsiao (1981). Arellano and Bond (1991) further developed this method by exploiting the fact that instrumental variable (IV) estimators are actually a special case of generalised method of moments (GMM) estimators, i.e. IV estimators impose one moment condition. By using a GMM framework instead, one is able to increase the number of (valid) moment conditions and hence the efficiency of the estimator (Verbeek 2012). The estimator is then called the first-difference GMM or Arellano-Bond estimator.

Moreover these estimators are very well suited for analysis of samples with a small number of periods and a high amount of cross-section units (Roodman 2009). This means that these estimators are very well suited for our sub samples, which have quite a low number of periods. Our whole sample, on the other hand, does not suffer from this problem and the number of moment conditions increases as T rises. The first difference GMM estimator will nonetheless remain consistent, and will approach the FE estimator (Verbeek 2012). Although the FE estimator appears to be a better alternative in this case, we will still use the GMM estimator on the ground of retaining comparability of results.
In order to use the GMM estimator one has to make assumptions about the structure of the error term. This is the consequence of the fact that the calculation of this estimator relies on the choice of a weighting matrix. The structure of this matrix is in turn based on the variances and the covariances of the residuals. In practice this problem is resolved by estimating the coefficients and error terms in several stages. In a first step a minimally arbitrary matrix is used to approximate the optimal weighting matrix. This estimator will be consistent as long as the arbitrary matrix is positive definite and symmetric. The residuals from this one-step estimator are therefore also consistently estimated and can thus be used to construct an optimal weighting matrix. In a second step this optimal matrix is used. This will of course also yield consistent estimates. The two-step estimator is, moreover, efficient and by its construction robust to arbitrary patterns of heteroskedasticity and cross-correlation (Roodman 2009).

In a model, such as ours, with exogenous variables, these too can be used as instruments. We do not lose a lot of information if we apply the first-difference transformation on these variables, while this avoids inflating the number of rows in our instrument matrix. If these variables, however, are not strictly exogenous but predetermined, i.e. their current and past values are uncorrelated with the current error term, but their future values are not, we can only use lagged values of these variables as instruments (Verbeek 2012). Finally, endogenous explanatory variables must be treated much like the lagged dependent variable. They have to be instrumented with either an external variable or with an internal instrument, i.e. their own past values (Roodman 2009).

A final issue that needs to be addressed is the usefulness of first-difference GMM estimators for inference. First, the one-step estimator is based on an initial weighting matrix, the structure of which is dependent on assumptions about the variance of the error term. As we use the identity matrix, i.e. we assume the error term to be independent and identically distributed (i.i.d.), which will probably not hold, our assumptions are likely to be incorrect. In this case, the variance estimates of the parameters would become inconsistent and hence useless for inference (Roodman 2009). To remedy this problem it is possible to construct standard errors that are robust to heteroskedasticity and serial correlation by using the estimated error terms. For a formal representation of this procedure we refer to Roodman (2009).

Inference based on the two-step estimates of the variances of the parameters is also prone to problems. Windmeijer (2005) shows that coefficient standard error estimates produced by the two-step estimator may be downward biased in small samples, due to the
fact that it ignores the variation generated by the use of estimated parameters in the construction of the optimal weighting matrix. This could even render these estimates useless for inference\(^{10}\) (Arellano & Bond 1991). Traditionally, this has led researchers to also report one-step estimates, as they are asymptotically unbiased (e.g. Ötker-Robe & Podpiera 2010). To circumvent this problem, Windmeijer (2005) proposes a finite sample correction, which made the two-step estimates more accurate.

Roodman (2009: 99-100) distinguishes eight assumptions about the data-generating process that underlie the use of GMM estimators.

- “The process may be dynamic […].
- There may be arbitrarily distributed fixed individual effects. […]
- Some regressors are endogenous.
- The idiosyncratic disturbances […] may have individual-specific patterns of heteroskedasticity and serial correlation.
- The idiosyncratic disturbances are uncorrelated across individuals.
- Some regressors may be predetermined but not strictly exogenous. […]
- The number of time periods of available data, \(T\), may be small. […]
- The only available instruments are “internal” […].”

We already addressed the first four and the final three points. The fifth may be problematic in our case and will require attention. We will therefore discuss it in more detail in the following section.

5.3. Cross-Sectional Dependence

In an economic environment of globally integrated financial institutions and markets, it is not realistic to assume bank CDS spreads to be contemporaneously uncorrelated. The financial crisis has shown that banks and other financial market participants (e.g. insurers, pension funds, hedge funds, etc.) are in fact highly interconnected. We do not need to look further than the subprime mortgage crisis for evidence of this state of affairs. The trigger of this crisis was not located in a core market segment, but rather a peripheral one (see for instance OECD 2008). A shock in this market segment nevertheless propagated throughout the whole financial system with destructive power. It showed that banks (and other financial institutions, such as AIG\(^{11}\)) had built up enormous exposures to one another. It is therefore very clear that banks are highly interconnected and it would be a grave mistake to discard this influence. The

\(^{10}\) Note however that the coefficient estimates themselves remain consistent.

\(^{11}\) American International Group, a large American insurance corporation. It was bailed out by the Federal Reserve Bank in September 2008.
fact that the use of GMM estimators is based on the assumption that the error terms are uncorrelated across individual cross-section units is, as a consequence, problematic.

In order to resolve this problem it is first of all crucial to determine the effects of error cross-sectional correlation on the properties of the GMM estimator. These appear to be quite severe. Phillips and Sul (2003) show that the efficiency gains from pooling the data in a panel structure over estimating each cross-section unit separately may dissipate entirely if severe contemporaneous correlation is ignored. In our case this would mean that the advantages we hoped to achieve by using a panel framework to examine bank CDS spreads might in fact be negligible. Furthermore, Robertson and Sarafidis (2009) show that all IV and GMM estimators might become inconsistent as the number of cross-section units grows larger for fixed T. As these estimators are typically designed for such data sets, this poses a serious issue.

The effects of error cross-sectional correlation on our model are very likely to be quite onerous. The problem of inconsistent estimators might be of lesser interest to us as our number of individual cross-section units is of rather moderate size. The problems with the efficiency of the GMM estimator are, on the other hand, more threatening as they raise serious problems with our ability to make inferences and draw conclusions from our models. It is therefore necessary to take a look at possible solutions to avoid this problem.

In a previous section of this master thesis, in which we presented our market-wide variables, we already emphasised the need to account for common influences on bank CDS spreads. We discussed channels through which the business cycle could influence credit risk and the fact that bank credit spreads appear to be driven by large and important common factors. The inclusion of market-wide factors that are equal to all individual banks in a certain time period (i.e. the broad European market index from Datastream and the VStoxx index) therefore offers a first method for expunging cross-sectional dependence. It is, however, unlikely that we could find enough adequate and valid factors to account for all observed contemporaneous correlation, let alone that these two factors would suffice. We will test for this, of course, in the section in which we present our empirical results, but it would also be prudent to already discuss an alternative approach.

A widely used method to address contemporaneous correlation in the error terms is the use of fixed time effects, i.e. period specific dummy variables. Robertson and Sarafidis (2009) argue in favour of the implementation of fixed time effects. This is the consequence of the fact that the inclusion of common time effects has a positive outcome in the case of cross-sectional dependence. In the case that this correlation across individual units is absent, this
procedure will do no harm. Similarly, Roodman (2009) advises to include common time effects as they at least correct for one type of cross-sectional dependence and therefore make the crucial assumptions of the GMM estimator and various tests derived from it more likely to hold.

Robertson, Sarafidis and Yamagata (2009), however, warn that the inclusion of fixed time effects will only completely remedy cross-sectional dependence if it is identical for all pairs of individual units. Other methods to remedy cross-sectional dependence are, however, increasingly complex and lie outside the scope of this master thesis. We refer to Robertson and Sarafidis (2009) for an overview of econometric methods that aim to completely dispose of all cross-sectional dependence, rather than only the contemporaneous correlation that is shared by all individual units. These methods, moreover, have the disadvantage that they require a large time dimension, while some of them are not even applicable to GMM estimators.
6. Empirical Results

In the previous sections we discussed the assumptions and properties of the GMM estimator. This estimator appears to be the optimal methodology to examine the relationship of bank CDS spreads with a list of possible explanatory variables. First of all, our data has a panel structure and we want to use this in order to gain efficiency in our results. Secondly, we suspect that proportional changes in bank CDS spreads might be generated by a dynamic process. The inclusion of past values of the explanatory variable, however, induces a number of problems. The GMM estimator offers a solution for these issues. Thirdly, we assume some of our explanatory variables to be endogenous and others to be predetermined. This effectively rules out another method of dynamic panel estimation, the bias-corrected LSDV estimator. Fourth, some sub samples include only a small number of periods, which would make the standard LSDV estimator biased. Fifth, we assume that the residuals of our model suffer from autocorrelation and heteroskedasticity and that these patterns are specific to each separate bank. The GMM estimator is thus left as the only plausible methodology, as it can handle all the mentioned issues.

However we need to be very conscious that the estimation of parameters and their respective standard errors may be biased due to cross-sectional dependence in the error terms. We will actively try to lessen the extent of this problem by using two alternative strategies. The first is to estimate the model with suspected common factors, i.e. a broad market return and the VStoxx implied volatility index. The results of this first strategy will then be compared with those of a second, the use of period fixed effects. If the first method is not effective in eliminating cross-sectional dependence, then at least the second will account for contemporaneous correlation.

Within the class of all possible GMM estimators, we choose the one-step Arellano-Bond (1991) estimator. The choice for the one-step estimator, rather than the two-step alternative is not at all obvious. Windmeijer (2005), for example, reports from Monte Carlo experiments and empirical applications that gains can be made from using the two-step estimator with finite sample bias-corrected standard errors. By definition the two-step estimator should be more efficient, as it uses consistent estimates of the residuals to counter serial correlation and heteroskedasticity.

We nevertheless choose the one-step estimator, mainly due to technical issues. Our statistical software encounters problems when trying to estimate the two-step parameters and
standard errors. Moreover, it appears to be impossible to include period fixed effects when using the two-step estimator. If period fixed effects cannot be implemented in our model, it could become impossible to diminish the degree of error cross-sectional dependence. This would then cause several problems with the consistency and efficiency of said estimator. A model in which period fixed effects can be implemented, would therefore be preferable.

Secondly, the Windmeijer (2005) standard error corrections for the two-step estimator are not available to us. This would make it very time-consuming and nigh impossible to calculate corrected standard errors, even if it were possible to use the two-step estimator. This problem was traditionally resolved by reporting one-step estimates as well, because the parameter and standard error estimates are asymptotically unbiased. This makes it possible to consistently make inferences, while using the one-step estimator. Because we do not expect the residuals of our model to be i.i.d., we report standard errors that have been corrected for arbitrary and individual-specific serial correlation and heteroskedasticity.

Based on these arguments we prefer the one-step Arellano-Bond (1991) GMM estimator. We will avoid the problem of biased coefficient standard errors by correcting them in a straightforward way. We will try to resolve the expected problem of error cross-sectional correlation as much as possible by applying two different approaches. This estimator should then yield consistent results for the coefficients of the model as well as for their respective standard errors.

6.1. A model with structural variables

6.1.1. The model

Our first model regresses the proportional changes of bank CDS spreads on four groups of variables. The first set of variables is of particular interest here as it is based on the structural credit risk model of Robert Merton (1974). It includes the monthly change of the risk-free interest rate, the monthly return on the banks’ stocks and the proportional change of historical equity volatility. The risk-free interest rate changes are assumed to be strictly exogenous. The bank’s stock return, on the other hand, is included in our model as an endogenous variable. Byström (2005) finds evidence, suggesting that stock returns lead CDS spread changes. The results, however, are based on daily observations. It would be hard to believe that bank CDS spreads and stock returns do not simultaneously influence each other in the course of an entire month. This variable is therefore instrumented with GMM style regressors, i.e. its second and third lag. Finally, we assume changes in historical equity volatility are not endogenous, but
rather predetermined. In practice, this means that they are uncorrelated with current idiosyncratic disturbances, but not with past ones. A shock in bank CDS spreads at period $t$ may influence equity volatility in subsequent periods. We therefore instrument it with its first lag.

The second important explanatory variable is the proportional change of sovereign CDS spreads. We also assume this variable to be endogenous as the financial crisis solidified the connection between governments and big, domestic financial institutions (see, for example, Mody & Sandri 2011). It is therefore instrumented with GMM style regressors (second and third lag).

Thirdly, we also introduce our measure of bank CDS liquidity and a list of market-wide factors. The latter include the monthly change of the slope of the yield curve, the monthly change of our financial sector stress measure, the monthly market return and the monthly proportional change of market implied volatility. The first two are country-specific (note, however, that the euro area counts as only one country for these variables), whereas the latter two are identical for each cross-sectional unit. The market-wide factors are all included in our model as strictly exogenous, as they represent the whole market, or at least the whole financial sector.

Our first model of interest is thus given by:

$$\Delta \ln(CDS_{it}) = \alpha_i + \rho \Delta \ln(CDS_{i,t-1}) + \beta_1 \Delta \text{Policy rate}_{i,t} + \beta_2 \Delta \text{Stock return}_{i,t} + \beta_3 \Delta \ln(\text{Equity volatility}_{i,t})$$

$$+ \beta_4 \Delta \ln(\text{SCDS}_{i,t}) + \beta_5 \Delta \text{Liquidity}_{i,t} + \beta_6 \Delta \text{Slope yield curve}_{i,t}$$

$$+ \beta_7 \Delta \text{Interbank spread}_{i,t} + \beta_8 \Delta \text{Market return}_{i,t} + \beta_9 \Delta \ln(V_{stoxx_{i,t}}) + \mu_{i,t}$$

where $SCDS_{i,t}$ is the sovereign CDS spread at time $t$ of the country in which bank $i$ is based.

6.1.2. Explicit common factors and period fixed effects

Before we present the estimation of our first model, it is important to choose a strategy to minimise error cross-sectional correlation. The specification given by (3) implicitly assumes that the market return and implied volatility index changes will correct for all contemporaneous correlation. Another possible specification would include period fixed effects instead of these two variables. We therefore estimated these two alternative models with the one-step Arellano-Bond (1991) GMM estimator in order to compare the structure of the residuals and to decide which strategy is superior.
We present time series of the residuals of both models in chart 6. Simple eyeball-econometrics suffice to see that the two common factors are not effective at all in eliminating cross-sectional dependence in the error terms. On the contrary, a clear co-movement of the entire range of the cross-section residuals is noticeable. Throughout the entire sample period the 0.1 and 0.9 deciles both rise and fall with the median. We therefore think that the first strategy to eliminate cross-sectional dependence is not suitable at all.

The second strategy, i.e. the inclusion of period fixed effects yields much better results as seen on the right panel of chart 6. The median of the residuals is much more stable over time, while the 0.1 and 0.9 deciles fluctuate almost symmetrically around it. It thus appears, on sight, that the period fixed effects do a much better job at eliminating contemporaneous correlation of residuals. Therefore we choose this second strategy over the first: the assumption that residuals are uncorrelated across individuals is much more likely to hold if we implement period fixed effects. As explained earlier in this master thesis, this assumption is critical for the properties of the GMM estimator.

6.1.3. Validity of the model

Having determined the exact econometrical methodology and the strategy to counter error cross-sectional dependence, we continue by presenting the results of the estimation of our first model in table 6. We estimated our model for the whole sample period (January 2005 to
June 2011) as well as for three sub periods. Each of these sub periods represents a specific phase in the recent events of the European economy. The first period represents the pre-crisis period and ends in June 2007. During this phase markets saw a continued compression in risk premiums to, possibly, unreasonable lows (OECD 2008). The second starts in July 2007 as financial market tensions increased and is characterised by enormous troubles for banks, but, critically, not for governments. The final sub period starts in January 2009 and lasts until the end of our sample. The starting point of this phase is the Irish nationalisation of Anglo Irish

<table>
<thead>
<tr>
<th>Variable</th>
<th>Whole sample</th>
<th>Period I</th>
<th>Period II</th>
<th>Period III</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln (CDS_{t-1})$</td>
<td>-0.0038</td>
<td>0.1945 ***</td>
<td>-0.2442 ***</td>
<td>0.1356 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0388)</td>
<td>(0.072)</td>
<td>(0.0576)</td>
<td>(0.0332)</td>
</tr>
<tr>
<td>$\Delta$ Risk-free Interest Rate</td>
<td>-0.0929</td>
<td>1.5127 ***</td>
<td>-0.0013</td>
<td>0.0065</td>
</tr>
<tr>
<td></td>
<td>(0.0808)</td>
<td>(0.3505)</td>
<td>(0.2012)</td>
<td>(0.0461)</td>
</tr>
<tr>
<td>Stock Return</td>
<td>-0.1774 ***</td>
<td>-0.1038</td>
<td>-0.3005 ***</td>
<td>-0.0361</td>
</tr>
<tr>
<td></td>
<td>(0.0466)</td>
<td>(0.0908)</td>
<td>(0.0939)</td>
<td>(0.0458)</td>
</tr>
<tr>
<td>$\Delta \ln (\text{Equity Volatility})$</td>
<td>0.0398 ***</td>
<td>0.0007</td>
<td>0.0967 ***</td>
<td>0.0171 *</td>
</tr>
<tr>
<td></td>
<td>(0.0089)</td>
<td>(0.0083)</td>
<td>(0.0198)</td>
<td>(0.0095)</td>
</tr>
<tr>
<td>$\Delta \ln (\text{Sovereign CDS})$</td>
<td>0.124 ***</td>
<td>0.1609 ***</td>
<td>0.087</td>
<td>0.2168 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0392)</td>
<td>(0.0491)</td>
<td>(0.0681)</td>
<td>(0.0764)</td>
</tr>
<tr>
<td>$\Delta$ Liquidity</td>
<td>-0.0112</td>
<td>-0.0159</td>
<td>-0.0509</td>
<td>0.0091</td>
</tr>
<tr>
<td></td>
<td>(0.0179)</td>
<td>(0.0144)</td>
<td>(0.0519)</td>
<td>(0.0237)</td>
</tr>
<tr>
<td>$\Delta$ Slope Yield Curve $[5y - 2y]$</td>
<td>0.3844 ***</td>
<td>-2.94 ***</td>
<td>0.8304 ***</td>
<td>0.0514</td>
</tr>
<tr>
<td></td>
<td>(0.1216)</td>
<td>(0.5369)</td>
<td>(0.2262)</td>
<td>(0.0984)</td>
</tr>
<tr>
<td>$\Delta$ Interbank spread</td>
<td>-0.0874 *</td>
<td>0.0268</td>
<td>-0.2622 **</td>
<td>-0.021</td>
</tr>
<tr>
<td></td>
<td>(0.0446)</td>
<td>(0.0171)</td>
<td>(0.121)</td>
<td>(0.0447)</td>
</tr>
</tbody>
</table>

**Table 6:** Empirical results for our first model. These results are estimated with the one-step Arellano-Bond (1991) GMM estimator, using the first difference transformation and period fixed effects. Standard errors (in parentheses) are corrected for individual patterns of serial correlation and heteroskedasticity. Significance levels are presented with stars (1%: ***; 5%: **; 10%: *). The instruments used in this model are the GMM style regressors (second and third lag) of the lagged dependent variable, the stock return, the proportional changes of sovereign CDS spreads and the first lag of the proportional change of equity volatility. All other (strictly exogenous) variables are also transformed and included in the instrument matrix.

12 Note that due to the necessary use of past values as instruments, the whole sample and first sub period effectively start in April 2005.
Bank. Mody and Sandri (2011) show that this event was an important turning point of the financial crisis. In this phase national fiscal balances and the health of the domestic financial sector became increasingly intertwined.

Our model appears to be valid. The Sargan test of over-identifying restrictions, which tests whether too many instruments are being used, delivers a highly significant test statistic for the whole sample, as well as for each sub period. This would mean that not all our instruments are valid. Note, however, that we use the one-step GMM estimator and that the error terms are therefore not necessarily homoskedastic, which is a basic assumption of this test (Verbeek 2012). Roodman (2009) reports that it is common practice to instead present the Hansen test statistic from the two-step estimation. In our case, however, this is impossible for reasons explained earlier.

A second possible issue with our model may be the fact that idiosyncratic error terms are serially correlated. This could cause complications because typical GMM style regressors might become invalid, as they become endogenous if there is serial correlation in the idiosyncratic disturbances. Because the error terms also contain the individual specific effects, one must test the first-differenced residuals for autocorrelation to eliminate this source of correlation. First-order autocorrelation in the differenced error term is expected to be negative by definition and is therefore not informative. Second-order autocorrelation of the differenced error term, however, would invalidate second lags as instruments and it should therefore be close to zero (Roodman 2009). The theoretical expectation of high negative first-order autocorrelation is clearly confirmed for our model. We also see that second-order autocorrelation is indeed very low. Only in the first sub period it exceeds 0.1. A formal test of first- and second-order autocorrelation was proposed by Arellano and Bond (1991). This test is, however, not available to us and suffers from bias if the number of cross-sections is low. It is therefore not used in this master thesis.

Our results largely confirm the need to include a dynamic component in our model. Although the parameter of the lagged dependent variable is not significant over the whole sample period, it is significant for every sub period. Its sign, however, changes, which is probably the cause of its apparent insignificance over the whole sample period. These results suggest that before the crisis changes to bank CDS spreads happened gradually. In times of increased financial sector stress and risk re-evaluation, on the other hand, markets tended to overshoot, i.e. overreact to factor innovations. The significant and positive parameter for the final sub period can then be interpreted in two ways. First, it could indicate that financial stress was from then on handled by governments and monetary authorities, who stepped in
strongly after the fall of Lehman Brothers\textsuperscript{13} in September 2008. This would have made sudden \textit{free falls} in the financial sector less likely and would lessen the tendency of financial markets to overreact to news in volatile times. A second interpretation is that financial markets needed time to fully implement sovereign risk into bank risk. Although it might have been a combination of these two interpretations, we prefer the second, because the European financial sector remained highly unstable after December 2008. Finally note that the parameter estimates are all situated within a credible range and do not suggest a unit root or explosive process. If our dependent variable would have been generated by a unit root process, this would have caused our instruments (lags) to be of little practical use.

\textbf{6.1.4. Results}

The variables of interest in the first model, i.e. structural credit risk factors and sovereign CDS spread changes, perform rather well. Changes in the risk-free interest rate do not significantly influence bank CDS spreads over the whole sample, nor do they in the second and third sub period. We also used another measure for the slope of the yield curve to correct for possible effects on the coefficient of the changes in the risk-free interest rate. As table 7 (column C) shows, these effects do not qualitatively change our results. The insignificance of this variable’s parameter suggests that banks successfully hedge against interest rate risk and that markets recognise this ability. The significance of the parameter in the first sub period is, however, somewhat puzzling. One possible explanation could be found in the fact that risk premium compression during the pre-crisis period can be attributed to the \textit{search for yield} (e.g. OECD 2008). A rising risk-free interest rate could lessen the attractiveness of higher yielding risky assets, raising their credit spreads.

The other structural variables, i.e. bank stock returns and proportional changes in historical equity volatility also perform well. Their parameters are significant for the whole sample period and the second sub period. In all periods they furthermore show the expected sign. Table 7 (columns A and B) shows that changing the measures for stock returns and equity volatility does not influence our result qualitatively. Note, however, that the measure for equity volatility that is calculated over a longer time span (26 weeks) raises the value of the parameter. The t-statistic, however, remains about the same (4.02 instead of 4.47 in the baseline model), suggesting that the sensitivity of our dependent variable to equity volatility does not change by using different measures.

\textsuperscript{13} Until its demise, one of the biggest US investment banks.
Table 7: Robustness checks with deviations from our baseline model. These results are estimated with the one-step Arellano-Bond (1991) GMM estimator, using the first difference transformation and period fixed effects. Standard errors (in parentheses) are corrected for individual patterns of serial correlation and heteroskedasticity. Significance levels are presented with stars (1%: ***; 5%: **; 10%: *). The instruments used in this model are the GMM style regressors (second and third lag) of the lagged dependent variable, the stock return, the proportional changes of sovereign CDS spreads and the first lag of the proportional change of equity volatility. All other (strictly exogenous) variables are also transformed and included in the instrument matrix. Note that the variables, which were not included in the baseline model are treated the same as their baseline counterparts.

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln (\text{CDS}_{t,t-1})$</td>
<td>-0.0038</td>
<td>-0.0125</td>
<td>-0.0156</td>
<td>-0.0058</td>
</tr>
<tr>
<td></td>
<td>(0.0388)</td>
<td>(0.0393)</td>
<td>(0.0409)</td>
<td>(0.0398)</td>
</tr>
<tr>
<td>$\Delta \text{Risk-free Interest Rate}$</td>
<td>-0.0929</td>
<td>-0.0985</td>
<td>-0.1004</td>
<td>-0.062</td>
</tr>
<tr>
<td></td>
<td>(0.0808)</td>
<td>(0.0813)</td>
<td>(0.0839)</td>
<td>(0.0822)</td>
</tr>
<tr>
<td>Stock Return</td>
<td>-0.1774 ***</td>
<td>-0.1565 ***</td>
<td>-0.1758 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0466)</td>
<td>(0.0459)</td>
<td>(0.048)</td>
<td></td>
</tr>
<tr>
<td>Stock Return - Market Return</td>
<td>-0.1374 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0415)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln (\text{Equity Volatility})$</td>
<td>0.0398 ***</td>
<td>0.0395 ***</td>
<td>0.0403 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0089)</td>
<td>(0.0088)</td>
<td>(0.0087)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln (\text{Equity Volatility})$ [26 weeks]</td>
<td></td>
<td>0.162 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0403)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln (\text{Sovereign CDS})$</td>
<td>0.124 ***</td>
<td>0.1367 ***</td>
<td>0.1512 ***</td>
<td>0.1331 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0392)</td>
<td>(0.0392)</td>
<td>(0.0369)</td>
<td>(0.0384)</td>
</tr>
<tr>
<td>$\Delta \text{Liquidity}$</td>
<td>-0.0112</td>
<td>-0.0123</td>
<td>-0.0089</td>
<td>-0.0122</td>
</tr>
<tr>
<td></td>
<td>(0.0179)</td>
<td>(0.0183)</td>
<td>(0.02)</td>
<td>(0.0182)</td>
</tr>
<tr>
<td>$\Delta \text{Slope Yield Curve}$ [5y - 2y]</td>
<td>0.3844 ***</td>
<td>0.3856 ***</td>
<td>0.3916 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1216)</td>
<td>(0.1204)</td>
<td>(0.1259)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \text{Slope Yield Curve}$ [10y - 2y]</td>
<td></td>
<td></td>
<td>0.1705 *</td>
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<td></td>
<td></td>
<td></td>
<td>(0.0958)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \text{Interbank Spread}$</td>
<td>-0.0874 *</td>
<td>-0.0889 **</td>
<td>-0.0803 *</td>
<td>-0.0944 **</td>
</tr>
<tr>
<td></td>
<td>(0.0446)</td>
<td>(0.0452)</td>
<td>(0.0447)</td>
<td>(0.0471)</td>
</tr>
<tr>
<td>Cross-Sections</td>
<td>35</td>
<td>35</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td>Periods</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>75</td>
</tr>
<tr>
<td>Observations</td>
<td>1725</td>
<td>1725</td>
<td>1725</td>
<td>1725</td>
</tr>
<tr>
<td>Sargan J-statistic (df)</td>
<td>789.33 ***</td>
<td>802.36 ***</td>
<td>816.12 ***</td>
<td>797.07 ***</td>
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<tr>
<td></td>
<td>(519)</td>
<td>(519)</td>
<td>(519)</td>
<td>(519)</td>
</tr>
<tr>
<td>First-order serial corr.</td>
<td>-0.537</td>
<td>-0.532</td>
<td>-0.533</td>
<td>-0.537</td>
</tr>
<tr>
<td></td>
<td>-0.007</td>
<td>-0.011</td>
<td>-0.003</td>
<td>-0.005</td>
</tr>
</tbody>
</table>

Sovereign CDS spread changes also appear to be rather successful in explaining bank credit risk. The coefficient of this variable is significant for the whole sample period as well as for the first and third sub period. In contrast the results for our CDS liquidity measure are
disappointing. Its coefficient is not significantly different from zero in any considered period. This was, however, in line with expectations, because we used quite a rudimentary measure to approximate CDS liquidity. Finally, the market-wide factors present a mixed image. The influence of changes in the interbank spread is only weakly significant. Its parameter shows a different sign than expected, especially in the second period. The slope of the yield curve, on the other hand, performs better. In the first sub period its parameter is significantly negative, which indicates that this variable still reflected economic growth expectations. A positive change of this slope therefore lowered credit spreads. In the second sub-period the markets’ interpretation of the term structure changed, as it was primarily moving downwards at the short-term end. As such, the steepening of the yield curve reflected current financial and economic stress, hence the positive sign of its coefficient. The still positive (but no longer significant) parameter in the third period may signal a normalisation of sorts.

6.1.5. A familiar narrative

If we combine our results for the structural credit risk variables and the sovereign CDS spread changes, they support an expected narrative of the financial crisis. The first phase was characterised by risk premium compression. This was not only true for the financial, but also for the sovereign sector. In the pre-crisis period we see this confirmed by the fact that structural credit risk variables did not offer an explanation for bank CDS spread dynamics. This interpretation is supported by the significantly positive impact of risk-free interest rate changes on bank CDS spreads in the pre-crisis period and the positive relationship with sovereign CDS spreads. In the search for yield, risk premiums on financial as well as sovereign sector debt were compressed. A higher (lower) risk-free interest rate, on the other hand, tempered (aggravated) this effect.

In the second sub period, hidden risks materialised and risk premiums reflated. As shown earlier, markets tended to overreact to news during this phase. The search for yield, furthermore, was over and replaced by a flight to quality. This could have eradicated the influence of the risk-free interest rate on bank CDS spreads. It is, however, most interesting to see that the other structural factors mattered a great deal. It is not unrealistic to assume that markets adapted their behaviour in an environment of increased financial risk and that structural variables were therefore again able to explain bank CDS spreads. Note, furthermore, that sovereign CDS spreads did not affect bank credit risk during this period.
This indicates that sovereign risk did not immediately reflate and was not considered a relevant risk factor at that time.

The third and final period shows an inverted picture; while the effects of the structural factors lose a great deal of influence, the changes in sovereign CDS spreads become very important in the explanation of bank CDS spreads. This clearly indicates that financial markets now saw governments’ fiscal positions as the relevant risk factor. Against the new background of sovereign-bank interconnectedness, structural credit variables again lost their ability to explain bank CDS spreads, not unlike the way in which they had lost it prior to the crisis.

Before the crisis, bank CDS spreads and structural variables decoupled because risk premiums were unreasonably compressed across the whole market. In the stage in which governments and the financial sector became interconnected, the influence of structural variables was replaced by a new and more relevant factor: sovereign credit risk.

6.1.6. Non-linear behaviour of the coefficients

Our estimation results show that bank CDS spreads are influenced by different factors at different times. In other words, the factors affect bank credit risk in a non-linear fashion. The division of our whole sample in sub periods was meant to partially correct for this. This division may, however, seem arbitrary. In line with Annaert et al. (2010) we will therefore conduct a rolling regression of our baseline model. We present the results graphically in chart 7. We do not report results for the lagged dependent variable, nor for the liquidity measure and market-wide factors, due to the fact that they are of lesser interest in the context of this thesis. We estimated our parameters in windows of 24 months. In chart 7 a solid line denotes that the parameters are significant at the (two-sided) 95% level of confidence. We furthermore remark that changing the required level of confidence to 90% barely alters these results.

The results of the rolling regression confirm the need to divide our sample into three sub periods. In the first period the risk-free interest rate and the sovereign CDS spreads are the most significant influences. We already discussed the reasons for this. In a second period, these explanatory variables, however, no longer significantly influence bank CDS spreads. Instead, equity return and volatility are now the relevant risk factors. In the third sub period structural variables again lose their influence and sovereign credit risk becomes the only significant explanatory variable. As such, these results also support the suggested narrative of the financial crisis.
Finally, we must remark that the results of the rolling regression indicate that, while we can clearly discern three sub periods, the choice of their exact starting and end points might be controversial. The data, for instance, suggest that the third period only really began during the first quarter of 2010. A different division of the sample is therefore justifiable. An in-depth discussion on this topic is, however, outside the scope of this master thesis.
6.2. A model with balance sheet variables

6.2.1. The model

The set-up of our second model shows much resemblance to our first, save a few core differences. Although three types of variables, i.e. sovereign CDS spreads, CDS liquidity and market-wide factors, are also present in this model, the list of structural variables is replaced by balance-sheet variables. As explained earlier, these explanatory variables are all derived from the CAMELS structure. We also include our size measure in this model. All these variables are assumed to be strictly exogenous. The other variable groups have already been explained for our first model. The treatment of these variables does not change.

Furthermore, we conducted an identical analysis to determine whether to include explicit common factors or period fixed effects. The results of this second analysis are not reported, as they strongly corroborate the results for our first model. As such, we again prefer the implementation of period fixed effects, at the cost of losing our common factors, to minimise the effects of error cross-section dependence. The specification for the second model is thus given by:

$$\Delta \ln(CDS_{it}) = \alpha_t + \delta_i + \rho \Delta \ln(CDS_{it-1}) + \Delta \text{CAMEL}_{it} + \beta \Delta \ln(\text{Total Assets}_{it}) + \gamma_1 \Delta \ln(SCDS_{it})$$

$$+ \gamma_2 \Delta \text{Liquidity}_{it} + \gamma_3 \Delta \text{Slope yield curve}_{it} + \gamma_4 \Delta \text{Interbank spread}_{it} + \mu_{it}$$

where $SCDS_{it}$ is the sovereign CDS spread at time $t$ of the country bank $i$ is based in and $\Delta \text{CAMEL}_{it}$ is a vector of our balance sheet variables, which were introduced earlier.

6.2.2. Validity of the model

We present the results for our second model in table 8. In line with our first model we estimate the second for the whole sample period as well as for sub periods. A first problem, however, already surfaces. Due to data scarcity we cannot estimate this model for the first sub period. We can, on the other hand, estimate it for the second and third period, but the number of used observations is critically lower than in our first model, even when accounting for the decreased number of available cross-section units. Even for the whole sample period, about a fourth of available cross-sections is dropped due to the very high number of missing values. The estimated models, however, seem to be valid. The Sargan test again offers very high and very significant statistics. This would indicate that we have too many instruments.
<table>
<thead>
<tr>
<th></th>
<th>Whole sample</th>
<th>Period II</th>
<th>Period III</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \ln (CDS_{t-1}) )</td>
<td>0.1188 ***</td>
<td>-0.168 *</td>
<td>0.1532 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0408)</td>
<td>(0.0969)</td>
<td>(0.0303)</td>
</tr>
<tr>
<td>( \Delta ) Common Equity to Total Assets</td>
<td>3.7349</td>
<td>6.1096</td>
<td>3.9425</td>
</tr>
<tr>
<td></td>
<td>(2.621)</td>
<td>(13.3378)</td>
<td>(3.0293)</td>
</tr>
<tr>
<td>( \Delta ) Loan-loss Provisions to Total Loans</td>
<td>-5.7347</td>
<td>17.2795</td>
<td>11.5373</td>
</tr>
<tr>
<td></td>
<td>(11.6256)</td>
<td>(41.9529)</td>
<td>(9.3224)</td>
</tr>
<tr>
<td>( \Delta ) Non-interest Income to Total Income</td>
<td>0.0677</td>
<td>0.2197</td>
<td>-0.0933</td>
</tr>
<tr>
<td></td>
<td>(0.0581)</td>
<td>(0.137)</td>
<td>(0.1166)</td>
</tr>
<tr>
<td>( \Delta ) Pre-tax Income to Total Assets</td>
<td>-1.3431</td>
<td>-58.4192 *</td>
<td>25.4121</td>
</tr>
<tr>
<td></td>
<td>(10.3039)</td>
<td>(31.5537)</td>
<td>(15.7231)</td>
</tr>
<tr>
<td>( \Delta ) Short-term Debt to Total Debt</td>
<td>-0.0842 *</td>
<td>0.0272</td>
<td>-0.1134</td>
</tr>
<tr>
<td></td>
<td>(0.0464)</td>
<td>(0.1487)</td>
<td>(0.0748)</td>
</tr>
<tr>
<td>( \Delta ) ln (Total Assets)</td>
<td>-0.1398</td>
<td>-0.025</td>
<td>-0.2437</td>
</tr>
<tr>
<td></td>
<td>(0.1316)</td>
<td>(0.876)</td>
<td>(0.2188)</td>
</tr>
<tr>
<td>( \Delta ) ln (Sovereign CDS)</td>
<td>0.2706 ***</td>
<td>0.1312 *</td>
<td>0.4031 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0544)</td>
<td>(0.0734)</td>
<td>(0.0986)</td>
</tr>
<tr>
<td>( \Delta ) Liquidity</td>
<td>0</td>
<td>0.0154</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>(0.0297)</td>
<td>(0.0453)</td>
<td>(0.0395)</td>
</tr>
<tr>
<td>( \Delta ) Slope Yield Curve ([5y - 2y])</td>
<td>0.4748 **</td>
<td>1.1717 ***</td>
<td>0.1141</td>
</tr>
<tr>
<td></td>
<td>(0.2014)</td>
<td>(0.3068)</td>
<td>(0.1187)</td>
</tr>
<tr>
<td>( \Delta ) Interbank spread</td>
<td>-0.1493 ***</td>
<td>-0.5463 ***</td>
<td>-0.1451 ***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.0824)</td>
<td>(0.0556)</td>
</tr>
</tbody>
</table>

| Cross-Sections | 22 | 15 | 22 |
| Periodes       | 75 | 18 | 30 |
| Observations   | 806| 179| 493|
| Sargan J-statistic (df) | 357.59 *** (287) | 103.36 *** (70) | 221.56 *** (118) |
| First-order serial correlation | -0.568 | -0.559 | -0.558 |
| Second-order serial correlation | -0.018 | 0.146 | -0.001 |

Table 8: Empirical results for our second model. These results are estimated with the one-step Arellano-Bond (1991) GMM estimator, using the first difference transformation and period fixed effects. Standard errors (in parentheses) are corrected for individual patterns of serial correlation and heteroskedasticity. Significance levels are presented with stars (1%: ***; 5%: **; 10%: *). The instruments used in this model are the GMM style regressors (second and third lag) of the lagged dependent variable and the proportional changes of sovereign CDS spreads. All other (strictly exogenous) variables are also transformed and included in the instrument matrix.

We have, however, discussed issues with this test earlier and the same reasoning applies here: there is no reason to assume that error terms are homoskedastic. To test whether our instruments are indeed valid, it is therefore more useful to inspect the serial correlation of the differenced error terms. As in our first model the theoretically expected negative first-order autocorrelation is confirmed. Second-order serial correlation, on the other hand, appears to be
very limited for the whole sample period as well as for the two estimated sub periods. This supports the assumption that our instruments are valid.

The inclusion of the lagged dependent variable in our model is also confirmed to be necessary. Its parameter is significantly different from zero for the whole sample period and for the two sub periods. Note, however, that in our first model the lagged dependent variable did not seem to influence bank CDS spreads significantly over the whole sample period. We argued that this was probably the consequence of its changing sign over different periods. The same pattern for the sign of the lagged dependent variable can be observed in this model. As such, the instability of its coefficient over the different periods, makes this coefficient’s size and significance uninformative for the whole sample period. The interpretation of this parameter remains essentially the same as for our first model.

6.2.3. Results

The results for our balance sheet variables are very disappointing across the board. While all but a few parameters are insignificant, some also show puzzling signs (e.g. the ratio of common equity to total assets). Interpretation of these results is therefore impossible in practice.

On the other hand, the other explanatory variables, which were also present in the first model show results that are very similar to our first estimation. Sovereign CDS spreads affect bank credit risk only weakly in the first phase of the financial crisis (period II). The effects of this variable are, however, much stronger in the third sub period. Similar to our first model, its coefficient is also significant over the whole sample period.

The parameter of our CDS liquidity measure is again very close to zero, as could be expected from such a rudimentary approximation of liquidity. Finally, the market-wide factors also show a picture that is very similar to our first model. Note, however, that the parameter for the interbank spread changes appears to be very significant, notwithstanding the fact that it has an unexpected sign in all sub periods. The results from our first model, however, indicate that it becomes less significant in a different model. This suggests that this variable captures a number of effects and that, if we correct for these effects more directly, i.e. through the inclusion of the structural variables, its estimated influence declines. Its significance is therefore possibly attributable to the specification error of not including structural variables.
7. Conclusion

In this master thesis we have tried to offer an explanation for banks’ credit risk during different phases of the recent financial crisis. This crisis struck most advanced countries and seriously affected the ability of financial institutions to acquire funding. Subsequent policy reactions weakened governments’ fiscal positions, which were already fragile prior to the crisis in some countries. As a consequence several countries, most notably Ireland, Portugal and Greece, have also lost access to cheap sources of funding. This development further worsened prospects for ailing banks as the sovereign and banking sector were effectively connected through a number of channels.

To examine the behaviour of the markets’ evaluation of credit risk of financial institutions, we conducted an empirical analysis of bank CDS spreads over different phases of the financial crisis. We chose CDS spreads as an approximation of credit risk because other measures, such as the corporate bond spread, suffered from methodological problems, which were not present in CDS spreads. An empirical analysis in a panel regression framework furthermore appeared optimal as it enabled us to use a broad number of variables, while at the same time providing robustness to missing values.

In our empirical framework we wanted to test two different models. The first was based on the structural model, originally proposed by Robert Merton (1974). The second model, on the other hand, was based on the use of fundamental variables, i.e. variables retrieved from bank balance sheets. Both models were supplemented with three other types of variables: sovereign CDS spreads, CDS liquidity and market-wide factors. As the latest phase of the recent financial crisis is characterised by some European governments’ troubles in accessing private debt markets, a diligent study of the effects of sovereign entities’ credit risk on their domestic bank sector was an essential part of this thesis. CDS liquidity and market-wide factors were found to be necessary to capture a number of effects that the other variables could not account for.

Although the choice for a panel regression framework was quite straightforward, we encountered a number of methodological issues. These issues were mainly the consequence of four separate characteristics of our data set. First of all, we suspected that CDS spread changes were driven by a dynamic process. This obliged us to use a dynamic panel regression analysis. We were limited in our choice of estimators due to the fact that we chose to divide our sample into sub periods. An estimator would therefore only be adequate if it was able to
deal with samples with limited time dimensions. Secondly, some of our variables were not strictly exogenous. This further limited our choice of possible estimators. Thirdly, error terms were expected to be heteroskedastic, i.e. their variance is not stable over time. Finally, the interconnectedness of financial institutions and markets on a global scale posed a serious challenge, as this made improbable the assumption of cross-sectionally uncorrelated error terms. Considering these issues and the technical restrictions we faced, we chose to use the one-step Arellano-Bond (1991) GMM estimator with period fixed effects. We furthermore corrected the parameters’ standard errors for arbitrary and individual-specific serial correlation and heteroskedasticity.

Our estimations yielded several results. First of all, we were right to suspect a dynamic model, as the effects of the lagged dependent variable proved to be significant in each sub period. These effects were, however, non-linear, probably due to the fact that the financial crisis posed a serious problem for the evaluation of banks’ credit risk. Secondly, structural credit risk variables proved to be much more successful in explaining bank CDS spreads. The second model, which employed the fundamental balance sheet variables, on the other hand, yielded disappointing results. This is probably due to the paucity of balance sheet data. Apart from making the model easier to estimate, more readily available data could bring markets to make better use of such data in evaluating banks’ credit risk. Thirdly, the effects of governments’ credit risk on bank CDS spreads were found to be very significant, especially in the last sub period, which started in January 2009. This corroborated earlier research results, which found sovereign credit risk an important explanation of banks’ credit spreads during the later phases of the financial crisis. Most variables, finally, had non-linear effects, i.e. their impact on bank CDS spreads was not stable over time. This could signal that our choice of sub periods affects the results, as the choice of these sub periods was essentially arbitrary, although it was based on events. To account for this possibility we conducted a rolling regression of our first model. While this suggests that the latest phase of the financial crisis, characterised by sovereign credit stress, started only in the first quarter of 2010, it generally supports our results.

Broadly speaking, we can discern three phases. Prior to the crisis, bank CDS spreads were mainly driven by the risk-free interest rate. This can be explained by the search for yield in that period: with low risk-free interest rates, investors sought out riskier products with higher yields. This compressed credit spreads to sometimes unreasonable lows. After the summer of 2007 the effect of the risk-free interest rate is no longer significant. Instead bank CDS spreads are now driven by the other structural variables as creditors need to rely on a
different method to determine previously compressed credit spreads. Sovereign credit risk on the other hand is not a significant factor. In the third sub period, starting in January 2009, structural variables again lose their significance. In lieu, sovereign CDS spreads became the relevant factor to determine banks’ default risk. As such, these results confirm the standard narrative of the financial crisis in Europe.

There is obviously much variation in the explanation of banks’ default risk over the different phases of the recent financial crisis. The fact that bank CDS spreads are driven by different factors in different periods, could offer a useful tool to evaluate the market’s assessment of credit risk. Bank CDS spreads that are hard to explain reasonably might serve as a warning to supervisors and policymakers. As such, it is always important to understand what drives credit risk.

Fundamental balance sheet variables appear to have very limited ability in explaining bank credit risk across all time periods. A better availability of these data would, in our view, improve the value of this model. Not only would balance sheet data that are both accurate and more easily and frequently available enhance the precision of the estimation of empirical models, it would also enable financial markets to use this information in order to evaluate banks’ default risk more accurately.

With respect to further research, it would be interesting to expand the data set to also include the period after June 2011. In July 2011 a new initiative was discussed to regain control over Greece’s debt problems: private sector involvement (PSI). This measure was intended to let creditors voluntarily consent to a haircut on privately held Greek debt, thereby avoiding the triggering of CDS payouts. An analysis of the effects of PSI on sovereign and bank CDS spreads would certainly be interesting from a policymaker’s point of view.
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