

Credit risk in the Banking Sector:

**International evidence on CDS spread
determinants before and during the recent crisis**

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of the Degree of Doctor of Philosophy*

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Appendix A: Required statement of originality for inclusion in research degree theses

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Summary of the thesis

Credit Default Swaps (CDS) instruments - as an indicator of credit risk - were one of the most prominent innovations in financial engineering. Very limited literature existed on the drivers of CDS spreads before the financial crisis due to the opacity of this market and its lack of transparency.

First, this thesis investigates the drivers of CDS spread in the UK banking sector, by considering the role of the housing market, over the period of 2004-2011. I find that, in the long-run, house price dynamics were the main factor contributing to wider CDS spreads. In addition, I show that a rise in stock prices lead to higher availability of capital and therefore increased bank borrowing activities, which led to lower credit risk. Furthermore, findings show that with higher aggregate bank liquidity, banks tend to grant more loans to low-income consumers, thus increasing bank credit risk. In addition, in the short-run, I employ the Structural VAR by imposing short-run restrictions to identify the five shocks arising from the CDS spread, the house price index, the yield spread, the TED spread, and the FTSE100. The SVAR findings indicate that a positive shock to house prices significantly increases the CDS spread in the medium-term, in the UK banking sector. In addition, apart from its own shock, the house price shock explains a big part of the variance (nearly 20%) in CDS spread. These results remained robust even after changing the ordering of the variables in the Structural VAR.

Second, considering the bank-level factors across 30 countries and 115 banks, I find most significant bank-level drivers of the CDS spread were asset quality, liquidity and the operations income ratio. As such, banks with better asset quality, high levels of liquidity and operations income ratio were subject to lower CDS spreads and credit risk. Furthermore, larger banks were found to be more risky than smaller banks. We have conducted the U-test and our results indicate the presence of a U-shape relationship between bank size and bank CDS spread. It should be noted that in order to ensure that our results are robust, we used several estimation frameworks, including the FE, RE and alternative Generalized Method of Moments (GMM) approaches, which all prove the existence of a U-shape relationship between the CDS spread and bank size. In addition, we find a threshold

level of bank size, which shows that banks growing beyond this point are subject to wider CDS spreads.

Finally, I consider the difference in financial systems at country-level and regulatory structures at bank-level, in a panel setting, over the period of 2004-2011. At country-level, my findings directly link financial deepening to higher credit risk, reflecting a sign of credit bubble. Besides, at bank-level, I confirm my previous findings whereby asset quality, liquidity and operations income remain significant drivers of the CDS spread.

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Chapter 1

Introduction

1.1 Background of this thesis

In the middle of summer 2007, the world economy was hit by the drastic collapse of the housing market. The burst of the housing bubble generated a long lasting crisis, which subsequently led many economies across the world to experience the worse financial meltdown since the great depression of 1929. The recent crisis not only affected the banking sector but also the entire global economy, resulting in millions of people losing their jobs, houses, and trust in the financial system as a whole. Although the housing bubble primarily started in the US, the shock quickly transmitted to the UK, Ireland, France, Spain, Portugal, Iceland and many other countries around the globe. This predominantly shows the close linkage between banking systems across the world.

The CDS market was introduced in mid-90s, but started growing exponentially in early 2000s, during credit boom. It reached its highest market share during the financial crisis. Theoretically, a Credit Default Swap (CDS) is very similar to an insurance contract, whereby the protection buyer pays a premium to the protection seller. In exchange, in case of a negative credit event, the protection seller is bound to make a physical or cash settlement to the protection buyer. As such, CDS instruments were considered to be one of the most prominent innovations of financial engineering.

The demand for such derivatives was brought by banks and financial institutions as a way to hedge and diversify risk. Thus, the market share of CDS contracts grew as a result of an increased demand for low-cost instruments that allowed investors to take credit exposures. Furthermore, given that CDS contracts are standardized relative to the underlying cash market, it greatly contributed to enhancing liquidity in financial markets. The way CDS contracts are designed served both investors and banks as it helped offsetting credit risk and narrow the credit spread. In addition, it provided market depth and the ability for financial institutions to trade in high numbers without necessarily suffering from the price impact. Furthermore, CDS contracts provided resilience as it improved the speed at which the market absorbed high trades.

With all the advantages of CDS derivatives, soon following its introduction in the financial markets, both bankers as well as investors started misusing it. Instead of buying CDS contracts for hedging purposes, this instrument became more of a speculative toll. As such, investors started taking CDS contracts as an insurance on real estate they did not own (synthetic CDS contracts). This in turn created an issue of moral incentives, where investors were more interested in the underlying asset to default in order to get compensation from CDS protection. In addition, the CDS market suffered from a lack of transparency as it traded Over-the-Counter (OTC), where trades do not go through the clearing house.

While one of the advantages of the CDS market is its ability to enhance liquidity, as the crisis revealed, the misuse of this derivative can often translate into the exact opposite result, thus causing a market squeeze. This tends to happen when

agents have the ability to exploit advantageous information in the cash market, through the trades conducted in the derivative market. In fact, due to the anonymous nature of trades in the derivative market, it becomes very difficult to capture the underlying condition of the cash market, as perceived by informed market participants, who may have the incentive to distort prices in the cash market, for the sake of personal benefits. This causes the market to destabilize and undermine the benefits of CDS trading.

For a long time, financial regulators, central banks and governments ignored the importance and the significance of the CDS market. It is only with the beginning of the financial crisis, when a high number of investors and banks started defaulting on their obligations that both the importance and the danger embedded in the CDS trading came truly to light. In fact, with a staggering multi-trillion-market share, the financial system started fearing the worse.

Many factors led to the recent financial meltdown, both at bank and country levels. These include the ability of banks to expand their leverage intakes during the credit expansion of 2000s, escape regulatory requirements and hold insufficient capital buffers to cope with a negative credit event. In addition, reckless lending to low-income consumers and holding insufficient levels of liquidity also strongly contributed to fueling the levels of credit risk.

Furthermore, it is important to recognize the change in the structure of the banking system as a whole and the type of activities financial institutions started engaging in since the beginning of the credit boom. In fact, while in the past, most

banks used to specialize in either commercial or investment banking, the trend had reversed in the last decade as most banks became more driven to larger scale investments. This led to the creation of universal banking, where instead of focusing on a particular segment of banking, financial institutions were now conducting both commercial and investment banking. As a result, many small and mid-size banks started growing in size as they went through mergers and acquisitions.

On the one hand, the move to universal banking was perceived as positive move since financial institutions were expanding their business activities and granting more credit, which in turn boosted their revenues. Other advantages include banks' ability to reduce their costs through economies of scale. However, the major disadvantage of universal banking arose from banks growing to a worrying extent, well beyond their optimal size. This endangered the stability of the entire financial system. As such, bigger banks became heavily involved in financial engineering activities, which very often involved the use of CDS instruments. After the slicing and dicing of plain vanilla instruments, banks with the participation of the Special Purpose Vehicle (SPV) and credit rating agencies, repackaged these instruments, creating highly structured and risky derivatives.

Eight years have elapsed since the beginning of the chaotic crisis, yet policy makers, governments and central banks are still looking for answers and possible solutions to prevent defaults and another financial crisis to hit the system again.

1.2 Overview of the Credit Default Swap Market

Since early 2000, there has been a huge development and innovation in the credit derivative market instruments, most specifically in the Credit Default Swap market. A credit default swap (CDS) is a contract between two parties; where the investor purchasing the protection pays a premium to the party selling the CDS agreement, while in exchange, the protection seller pays compensation, which can be either a cash or physical settlement, to the policy holder, if a negative credit event occurs (Mengle (2007)). In most cases, the protection seller pays the buyer of the CDS contract the par value of the underlying asset such as a bond, while the protection buyer delivers the bond obligation to the seller. As such, it functions similarly to an insurance contract, where the premium represents a series of repayments, also referred to as the CDS spread (Lokken (2009)). The form of the redemption strictly depends on the terms and conditions stipulated in the original contract that both the holder and the seller of the CDS contract signed.

The International Swaps and Derivatives Association (ISDA) gives a clear outline of what constitutes a credit event that would lead to compensation of the CDS policy holder. These include the following: bankruptcy, restructuring, default in payments of the obligation, credit rating downgrade, repudiation or moratorium and obligation acceleration (Fabozzi (2009)). It should be noted that CDS contracts are typically traded as five-year contracts, although three seven and ten-year contracts can be also issued.

The creation of Credit Default Swaps is attributed to JP Morgan. In 1994, the bank extended a credit line of \$4.8 billion to Exxon, which was facing \$ 5billion

damage charges following the 1989 Valdez oil spill. For this deal, JP Morgan contracted with the European Bank of Reconstruction and Development (EBRD) (Lanchester (2009)). Regular payments were made to the EBRD in order to hedge the \$4.8 billion credit exposure. This meant that if a negative event occurred or Exxon defaulted, JP Morgan would get compensation from the EBRD (Lanchester (2009)). This first CDS deal benefited JP Morgan as it kept its long-time customer Exxon, without causing any damage to its credit lines (Tett (2009), (Lanchester (2009))).

The real development of the CDS market started throughout the 90s. In 1999, the International Swaps and Derivatives Association (ISDA) published a Standardized Master Agreement on CDS contracts. This was the first set of guidelines that was made available to banks and other financial participants on CDS trading practices. However, most of the initial rules outlined by ISDA were not very clear. As such, in 2003, the ISDA issued a more comprehensive version of the practices that primarily aimed at improving the understanding the definition of a credit derivative and its underlying rules. The new document outlined standardized practices that subsequently improved financial participants' ability to trade in the credit derivative market.

In the early 90s, trading in Credit Default Swaps was basic, involving single name CDS contracts. However, with the introduction of the CDS index in 2004, the CDS market started establishing itself, thus, becoming more complex. The development of the market was brought with the creation of the iTraxx index for the European region as a result of the merger of iBoxx and Trac-x indices (Bystrom

(2005)). In addition, another CDS index was also introduced focusing on the North America market. In case of default, single name CDS agreements and CDS index behaved differently. While simple CDS contracts end immediately, the CDS index contract does not terminate until the agreed expiry date; with only the reference entity that defaulted being removed (Calice and Ioannidis (2012)).

Thus, the CDS index trading offered many advantages to financial institutions, including banks and hedge funds, as it helped them reduce their credit risk exposure by taking positions on baskets of reference entities. With the characteristic of high market liquidity and low bid/ask spreads, the CDS index market allowed financial institutions to be more efficient (Stulz (2009)). In addition, it also benefited investors as they now had a better access to different sectors, which made hedging more straightforward, compared to trading through multiple single name CDS contracts. In addition, the CDS index market provided more transparency and clearer set of rules, with superior degree of standardization (European Central Bank (2009)).

According to ISDA, the CDS market grew dramatically from 2001, when the outstanding notional amount was \$631.5 billion, to the last quarter of 2007, when the outstanding amount peaked at \$62.2 trillion, an amount larger than world economic output of \$55.8 trillion (ISDA (2010)). By the end of 2008, as a result of the severe financial crisis, this had nearly halved to \$38.6 trillion (ISDA (2008)) and continued decreasing thereafter: at the end of the third quarter of 2009, the Depository Trust and Clearing Corporation (DTCC) estimated that the notional outstanding amount of CDS contracts averaged \$28 trillion (Squam Lake Working Group on Financial

Regulation (2009)). As of December 2011, the gross notional amount of all CDS contracts remained high at \$25.9 trillion, with the net notional amount for the same time period reaching \$2.7 trillion (ISDA (2014)).

Although the recent financial crisis caused dramatic distortions in the CDS market; after 2009, it still remained steady and positive. As such, over a seven year period, from 2001 to 2008, the CDS market generated approximately \$60 trillion; with an estimated growth of \$50 trillion. This implies that as of 2008, the CDS market outperformed the world economic output, which was \$55.8 trillion (ISDA (2008)). At the end of the third quarter of 2009, the Depository Trust and Clearing Corporation (DTCC) estimated that the notional outstanding amount of CDS contracts averaged \$28 trillion (Squam Lake Working Group on Financial Regulation (2009)).

Given that the CDS market represented a very high market share the global financial markets, the opaque structure and the complexity of its underlying reference entities raised high concerns across European Union countries as well as the US. In the light of the recent financial crisis, there was an imminent need to tighten the lax regulatory regime of the CDS market and an urge to enhance its transparency.

One of the arguments against CDS trading was related to the fact that it traded on the Over the Counter (OTC) market; which meant that it did not go through a clearing house. It was therefore very hard to know with certainty the number of contracts exchanged throughout a particular period. In addition, CDS

trading was highly criticized by financial market participants as it raised issues regarding moral incentives in financial markets. In fact, before the recent financial crisis, any investor had the right to take a CDS contract without owning the underlying reference entity; thus, most investors hoped for the underlying asset to default in order to get compensation. As a result, in 2012, EU regulators imposed a ban on outright speculation of naked sovereign CDS instruments in order to prevent speculators trading CDS contracts without even owning the underlying security.

1.2.1 Difference between a CDS and an Insurance Contract

First and foremost, the holder of a CDS contract is under no obligation to own the underlying asset in order to enter into a CDS contract. One form of a synthetic CDS is the naked CDS contract that allows investors to hold a CDS without owning the underlying debt. This implies that any investor can take an exposure in a CDS without having a real insurable interest. On the other hand, with an insurance contract, the buyer of the policy must have an insurable interest for the contract to be binding on both parties. Second, unlike insurance agreements, with a CDS contract, the seller does not have to be regulated by the regulatory authority (such as the Financial Services Authority (FSA) in the UK) or any other regulatory body. The third major distinction between a CDS and an insurance contract is that with a CDS contract, there is no obligation for the seller of the derivative to hold any capital reserves to guarantee the payment of the underlying claims. Furthermore, with a single name CDS contract, daily collateral must be posted in order to offset any fluctuations in the market-to-market value of the CDS. This is why CDS contracts are referred to as collateralized instruments. Thus, as the risk of default of the reference entity goes up, consequently the CDS spread widens and the seller of

the protection must post additional collateral in order to offset this increase in default risk. This in turn reduces counterparty credit risk, in case if a negative event occurs (Squam Lake Working Group on Financial Regulation (2009)).

With an insurance contract, the insurance company does not have to post additional collateral to offset an increase in default risk. Instead, it is typically required to hold a minimum amount of capital to be able to reimburse the insured party an indemnity. Furthermore, with a CDS contract, the holder of the protection can take a view not only on the specific event occurring, but also on the overall weakening or the improvement of a credit environment. This allows the investor to achieve a profit or eventually avoid a major loss without the occurrence of the negative credit event. As a result, any fluctuation in the credit default swap premia represents a source of income for the CDS holder. These are few of the many reasons that make credit default swap contracts more dynamic than insurance contracts that solely dependent on the occurrence /non-occurrence of a negative event (Squam Lake Working Group on Financial Regulation (2009)).

1.3 Aim of this thesis

The literature on CDS started developing in early 2000s, becoming popular only in the wake of the financial crisis. One of the reasons that explain limited previous research on CDS instruments is related to the unavailability of data, as it trades through the OTC market. In addition, CDS trading also lacked transparency. Therefore, previous research on this topic was very limited. In early 2000s, CDS spread was identified as the best proxy for credit risk. In fact, many researchers conducted comparative analysis between bond spread, equity spread and CDS

spreads and all concluded that the CDS spread proved to be the best indicator of credit risk (Houweling and Vorst (2005), Blanco et al. (2005), Hull et al. (2004), Zhu (2006), Norden and Weber (2004)).

A stream of previous literature focused on uncovering the theoretical determinants driving credit risk, finding that the risk free rate, yield spread, business cycle and inflation had strong power to affect credit spreads (Bevan and Garzarelli (2000), Estrella and Hardouvelis (1991), In et al. (2003), Freidman and Kuttner (1998), Minton (1997), Stokes and Neuburger (1998)). In addition, Duffie et al. (2007) also showed that industrial growth was another useful factor that could potentially affect changes in credit risk. Very limited literature considered the impact of the housing market on credit risk in the banking sector. Before 2004, there was limited information on CDS trading. Given that most CDS contracts were written on structured mortgage products, the role of the housing market became increasingly important in driving CDS premiums. This aspect was not recognized in the literature until the recent financial crisis. For this reason, there has been limited literature linking the housing market to credit risk. Thus, it is this research gap that this thesis aims to investigate.

The fourth chapter significantly contributes to the existing literature considering the housing market, among other factors as a driver of the CDS spread in the UK banking sector. Therefore, I focus on credit risk, by looking at different markets: the housing market, the money market and the stock market. The analysis cover the period of 2004-2011, which considers both the pre-crisis and crisis period. As such, I establish the transmission mechanism of the housing bubble that caused

the drastic increase in credit risk and unveil the close linkage that exists between these four different markets. I consider both the short-run and the long-run analysis employing various methodologies. Thus, the Johansen's Cointegration analysis was employed to derive the long-run determinants of the CDS spread. In addition, I used the SVAR analysis in order to uncover the drivers of the CDS spread in the short-run; by imposing specific shocks.

Besides the theoretical determinants of the CDS spread, another stream of literature focused on identifying the bank-level drivers of credit risk. Both Carling et al. (2007) and Tang and Yan (2010) found that macroeconomic and financial ratios were indicative of changes in credit risk levels. In addition, a number of researchers used bond spread as a proxy for credit risk to reflect on bank level factors (Campbell and Taksler (2003) and Cremers et al. (2004)). The authors showed that the yield spread and volatility played a significant role in explaining bond spreads. Furthermore, Collin-Dufresene (2001) uncovered the significance of leverage and volatility along the yield spread as important drivers of bond spreads, while Benkert (2004) on the other hand used the CDS spread as a measure of credit risk and showed that it was inversely related with volatility measures.

Previous literature also looked at the significance of leverage, amongst other bank level factors, affecting bond spreads and CDS spreads (Beltratti and Stulz (2011), Annaert et al. (2013) and Chiaramonte and Casu (2013)). Similarly, Christie (1982), Collin-Dufresne et al. (2001) and Alexander and Kaeck (2008) used bank stocks as a leverage indicator, and showed that higher leverage yields to increased level of credit risk. In addition, Aunon-Nerin et al. (2002) studied the determinants

of the CDS spread and found that stocks price fluctuations can be understood in two different ways; it can be either an indication of a business cycle, or alternatively a decrease in the stock price can also lead to higher levels of leverage; if it is assumed that changes in both the level and value of debt are lower than variations in the equity value.

Furthermore, previous literature also recognizes the importance of regulatory capital and liquidity as bank level drivers directly impact on credit risk (Antao and Lacerda (2011), Chiaramonte and Casu (2013), Saidenberg and Strahan, (1999) and Akhavein et al. (1997)). In addition, Fabozzi et al. (2007) and Hull et al. (2004) incorporated credit ratings to reflect on the importance of asset quality as a factor affecting credit risk. Other researchers used CAMEL indicators to address the importance of bank capital, asset quality, management, earnings and liquidity characteristics (Curry et al. (2001), Evanoff and Wall (2001), Gropp et al. (2004), Oshinsky and Olin (2006) and DeYoung et al. (2001)).

Although past literature looked at the bank-level determinants of credit risk, very limited literature investigated the impact of bank size on the CDS spread. As such, Völz and Wedow (2013) were amongst the very few authors that focused on bank size in the context of the CDS market, while exploring the factors affecting market discipline. In addition, Demirgüç-Kunt and Huizinga (2013) focused on the *too-big-to-save* or *too-big-to-fail* banks and found that large banks were more prone to risk. In an earlier research by Demsetz and Strahan (1997), the authors looked at bank size and the ability of bigger banks to reduce their default risk through diversification. Furthermore, Rime (2005) looked at banks size in the context of

credit ratings, while Soussa (2000) considered the importance of bank size on financial stability and market discipline.

Overall, the literature linking bank size to credit risk in the light of the recent financial crisis is still very limited, therefore in the fifth chapter of my thesis, I identify the drivers of the CDS spread, by considering not only bank-level factors (regulatory capital, leverage, bank liquidity, asset quality and operations income ratio) but I also incorporate a measure of bank size as a driver of credit risk. The data I employed in my thesis contributes to the previous research on CDS spread as it is extensive and unique in nature; allowing us to observe the behavior of both small and bigger banks, across 115 banks and 30 countries, over the period of 2004-2011. Using fixed effect, random effect (depending from the Hausman test) estimations and GMM analysis, I derive an optimal bank size. Thus, any bank exceeding that optimal threshold becomes risky and more prone to experience higher levels of CDS spread and vice versa.

Another significant gap in the existing literature is about linking both the bank-and-country level indicators of CDS spread. Very few authors looked at the impact of CDS spread on systemic stability except Huang et al. (2009), Cont and Minca (2010), Markose et al. (2012) and Rodríguez-Moreno and Peña (2013). In addition, no previous research linked financial profitability to other country level indicators of the CDS spread. More broadly, financial profitability was studied in the context of credit risk, financial distress and bank failure by Ötoker-Robe and Podpiera (2010), Chiaramonte and Casu (2013), Poghosyan and Cihak (2009), Kick and Koetter (2007) and Wheelock and Wilson (2000). Furthermore, although past

literature identified the factors contributing to the recent financial crisis, namely financial imbalances, large foreign funding inflows, lax monetary policy of low interest rates as well as financial innovation (Bernanke and Gertler (1999) and Taylor (2007, 2009), Jorda et al. (2011)), no previous research addressed how excessive credit supply led to higher CDS spread and the overall credit risk.

In the sixth chapter of this thesis, I uncover how the differences in regulatory structures and financial systems lead some countries to experience higher levels of CDS spread and credit risk relative to others. Thus, my research will help regulatory authorities to better mitigate credit risk and prevent systemic default in the future. My findings also shed light into the close linkage between various sectors and the most plausible way to prevent another financial crisis.

1.4 Research Questions

Research Question 1:

The first research question relates to ‘What are the factors driving credit risk in the UK banking sector’ with special reference to the housing market.

Research Question 2:

What are the bank-level drivers of CDS spreads? Do bigger banks face higher credit risk relative to smaller banks?

Research Question 3:

Does the difference in financial systems and regulatory structures matter in explaining cross-country bank CDS spreads?

1.5 Data and Methodology

1.5a Data

The data used in this thesis come from published secondary sources, mainly from: Thomson Reuters Datastream, Bankscope and the World Bank databases.

The fourth chapter of this thesis use CDS spread in the UK banking sector. The data sample considers the period over 2004-2011, using the 5-year CDS spread index (the most liquid type of instruments). In addition, all of the CDS determinants considered in the model (UK House price Index, the TED spread, the yield spread and the FTSE 100) are monthly data, ranging over the period of 2004-2011. All the data were obtained from Thomson Reuters Datastream.

The fifth chapter, of this thesis looks at 30 countries and 115 banks, over the period of 2004-2011. The data for the CDS spread for each bank represents a mid-spread. Furthermore, I use the 5-years bank CDS spread as it is the most liquid type of index. Individual CDS spread data for each bank was retrieved from Thomson Reuters Datastream. More details about the data are given in the data chapter. The aim of the fifth chapter is to reflect on the bank-level drivers of the CDS spread namely regulatory capital, leverage, liquidity, asset quality, operation income ratio and bank size. All the bank-level indicators are annual, ranging over the period of 2004-2011. The data was retrieved from Bankscope and published by BureauVan Dijkand.

In order to address the differences in financial systems, four additional country-level indicators are used in the panel analysis namely: financial stability,

financial deepening financial access and financial profitability. The panel analyses are conducted using annual frequency data. This dataset is compiled from the Global Financial Development Database (GDFD) available at the World Bank website: <http://go.worldbank.org/AWACYAMMM0>).

1.5b Methodology

In the fourth chapter of my thesis, I employ two distinct empirical methodologies in order to determine the drivers of the CDS spread in the UK banking sector, particularly focusing on the role played by the housing market. As such, for the long-run analysis, I use the Johansen's Cointegration analysis, while I conduct the Structural VAR approach by imposing specific shocks (i.e. housing bubble, among other shocks) in order to investigate the determinants of the CDS spread in the short-run.

In the fifth chapter, I look at the drivers of the CDS spread by considering the bank-level factors along the housing market. Thus, rather than focusing only on one country, I conduct cross-bank and cross-country analysis, over 30 countries and 115 banks, in a panel setting. As such, I employ fixed (FE) methodology in order to control for the unobserved heterogeneity across banks, and also I use the random effect (RE) in my analysis (depending from the outcome from the Hausman test). In addition, given that the number of banks in my sample is higher than the number of countries, I employ the GMM analysis in order to uncover the drivers of the CDS spread and to overcome any existing endogeneity between the variables employed in my analyses.

In the sixth chapter of my thesis, I look at both bank-level and country-level determinants of CDS spread, in a panel setting, over the period of 2004-2011. I employ the OLS, Fixed Effect and Random Effect methods. In addition, I also use the GMM method in order to overcome the issue of endogeneity between the variables used in the analysis. Another reason that makes the GMM model an appropriate method is related to the number of banks being higher than the number of countries in the data sample.

1.6 Findings

This thesis unveils a number of important findings related to the drivers of the CDS spread and credit risk over the period of 2004-2011, both at bank and country-levels.

The empirical findings from the fourth chapter show that the housing market is strongly related to the credit market. As such, I find that the housing bubble directly contributed to the drastic increase in the credit risk, which translated into wider CDS spreads. My results show evidence that before the financial crisis, as house prices were high, even if mortgage holders defaulted in their payments, banks had the ability to recover their initial loan value and even make a profit since over the period of 2004-2007, the real estate market was continuously booming. However, my findings also indicate that with the beginning of the recent financial crisis, this trend reversed because of the drastic fall in house prices. As such, as consumers started defaulting not being able to repay their mortgage obligations, when banks

tried to resell the properties in the secondary market, they were worth considerably less than before. Given the scale of the housing bubble, the situation deteriorated affecting not only bank risk but also the entire financial system.

The findings from the fifth chapter of this thesis unveil the bank-level drivers of the CDS spread and the credit risk variations across 30 countries and 115 banks. My results show that liquidity, asset quality and the level of operation income are important bank-level determinants of credit risk over the period of 2004-2011. In fact, I find that banks with higher liquidity levels were better able to cope with the recent financial crisis and avoid bank runs as they had enough liquidity to sustain cash shortages. Furthermore, banks that had better asset quality proved to be subject to less risk and narrower CDS spread, while banks that had higher level of bad loans suffered more in the wake of the recent crisis as they were unable to cope with the high level of defaults. Finally, banks with higher levels of operational income ratio have more revenue to withstand a negative credit event such as the recent financial crisis and therefore faced lower CDS spread as compared to banks with lower levels of operations income ratio that found themselves in a more vulnerable situation.

In addition, my results indicate the presence of a U-shape relationship between the CDS spread and bank size, which proves to be significant after using FE, RE and GMM estimations. As such, I find that smaller banks were subject to lower credit risk as compared to bigger banks that grew beyond their optimal size and experienced wider CDS spreads. In addition, I also derive an optimal bank size whereby any bank growing beyond that point becomes riskier and starts facing high credit risk.

In the sixth chapter, I look at both country and bank-level drivers of credit risk, over the period of 2004-2011, in a panel setting. At bank-level, I reassert my previous findings from the chapter five, confirming the significance of liquidity, asset quality and operations income as factors driving CDS spreads and credit risk. The most significant findings of the sixth chapter relates to the country-level indicators of credit risk. I find that excessive credit supply has directly caused the credit bubble that later translated into global financial crisis. I show that excessive credit supply enables banks to expand their lending activities to low-income consumers that were unable to repay their debts in the wake of the financial crisis. My findings also show that the financial system became unstable as a result of the recent financial crisis, which was largely due to greater level of financial deepening driving credit bubble and leading to higher credit risk.

1.7 Organization of this thesis

The remainder of this thesis is organized as follows:

In chapter 2, I will describe the data used in this thesis. As such, two types of data have been used in this thesis: the aggregate data used in the analysis for the UK banking sector and the bank-level data used for the analysis across 30 countries and 115 banks. The bank-level data consists of both bank-level characteristics and country-level characteristics.

In chapter 3, I will provide a detailed overview of the literature on the CDS spread and credit risk. More specifically I will start by looking at the literature that

focused on the theoretical determinants of the CDS spread. I will then analyse the literature that recognized the importance of bank-level determinants of the CDS spread. Moreover, I will analyse the previous research that looked at the phenomenon of the too-big-to-fail and the too-big too save. Finally, I will analyse the literature that considered the importance of the country-level determinants in driving credit risk. The literature review will also consider the more recent research that linked the CDS spread to the recent financial crisis.

In chapter 4, I focus on the aggregate macroeconomic drivers of the CDS spread in the UK banking sector, focusing on both the short and long-run factors affecting credit risk. The fourth chapter starts with an introduction, followed by section 4.2.1, where I conduct numerous unit root tests. In section, 4.2.1a, I explain the results from the unit root tests. In section 4.2.2, I conduct the cointegration test to establish the long-term drivers of the CDS spread in the UK banking sector. In section 4.3 I focus on the short-term analysis using the structural VAR model and by imposing specific shocks. In section 4.4, I present the conclusion.

In chapter 5, my research focuses on the drivers of the CDS spread, but now looking at the bank-level factors and the effect of bank size on credit risk. In the first section, I start by introducing the aim of conducting bank-level analysis on the CDS spread. In section 2, focus on explaining the methodology, while in section 3; I present the unit-root test for the panel analysis and explain the empirical results. I also conduct additional robustness checks to prove the strength of the obtained results. In addition, I establish the U-shape relationship between bank CDS spread

and bank-size and derive the optimal bank size. In section 4, I conclude with the most significant bank level drivers of the CDS spread and the effect of bank size on credit risk.

Chapter 6 focuses on the bank and country level drivers of the CDS spread. The chapter starts with an introduction in section 1. It is followed by the methodology in section 2. In section 3, I present the empirical results and conduct the necessary robustness checks. In section 4, I present the conclusion on the most important country and bank level drivers of the CDS spread.

Finally, chapter 7 of this thesis concludes reflecting the factors that have the strongest power in affecting CDS spreads, over the period of 2004-2011, considering both bank and country level indicators. In addition, I will highlight the important policy recommendations and some limitations of this research.

Chapter 2

Literature Review

The literature chapter of this thesis first looks at the fundamental determinants of credit risk and CDS spreads. Second, the literature discusses the bank level determinants of CDS spreads, with a particular focus on: leverage, liquidity, asset quality and profitability. In addition, I present the literature on bank size and credit risk, with specific emphasis on the phenomenon of the *too-big-to-fail* and the *too-big-to-save*, which will help understanding and investigating the impact of bank size on credit risk. Finally, this chapter reviews the country level determinants of CDS spread and credit risk.

2.0 Determinants of the CDS spread

In the wake of recent financial crisis, Credit Default Swaps (CDSs) attracted a lot of attention from governments, regulators and central banks due to its large market size and the subsequent impact it had on financial institutions such as the American International Group (AIG), Lehman Brothers and Bear Sterns, among others. Despite the very large and rapidly growing size of the CDS market, in the run up to the financial crisis, existing literature on this derivative was very limited. In fact, it was hindered by the limited amount of data available and the lack of transparency of the credit derivative market. As such, CDS contracts were mainly traded in the over the counter (OTC) market and not all trades are recorded.

Understanding the determinants of credit spreads is crucial for financial regulators, traders, and policy makers, given the high growth in the credit derivative

market over the last decade. A large body of literature has focused on analyzing credit defaults and investigating the reasons why the CDS spread is considered to be a better proxy for default risk compared to bond spreads. In fact, earlier research relied on bond spreads in order to get an approximation of the level of credit default risk. Authors including Duffie and Singleton (1999) and Hull et al. (2004) demonstrate that the CDS spreads are related to the credit spread implicit in bond prices. Bhanot (2001) highlights problems associated with bond spreads as indicators of corporate risk, discussing the lack of reliability of the Moody's index as a corporate default indicator.

There are a number of reasons that make the CDS spread a better proxy for default risk. Authors including Hull et al. (2004), Zhu (2006), Das and Hanouna (2006), and Ericsson et al. (2009) find that CDS premiums are a better measure of credit risk compared to bond spreads. One of the reasons is related to the fact that CDSs are directly quoted in premiums. One of the downsides of using bond spreads as a measure of credit risk is the assumption related to the risk free benchmark yield curve (Houweling et al. (2005)). In addition, Blanco et al. (2005) indicate that price discovery tends to occur in the CDS market ahead of the bond market. There are a number of factors that make the bond market less responsive to macroeconomic and financial factors. For example, Sarig and Warga (1989) and Chen et al (2007), find that bond spreads tend to react sharply to liquidity as well as credit risk. In addition, bond spreads tend to respond to changes in tax rates, time to maturity and the performance of alternative assets such as equities.

An attractive aspect of the CDS premium is the speed with which it reacts to changes in the credit quality and ratings of the underlying asset, see for example, Blanco et al. (2005), Hull et al. (2004) and Zhu (2006). Research conducted by Norden and Weber (2004), indicates that ratings of bonds with long maturities are typically affected by the changes in the CDS spread. Although the credit default swap premium can be affected by changes in bond spreads, studies conducted by Anderson and Anderson (2000), Delianedis and Geske (2001) and Huang (2003) show that expected default losses account for only a small fraction of observed credit spreads. In fact, Amato and Remolona (2003) refer to this phenomenon as the credit spread puzzle.

The literature on Credit Default Swap spread and its determinants is relatively new. In fact, it started developing only in early 2000s. One of the reasons that explain the limited research in the field relates to the lack of availability of data. As previously mentioned, CDS is an Over the Counter (OTC) instrument. This implies that it is less transparent than other instruments that are traded through the clearing houses. Nonetheless, CDS became very popular in the light of the credit boom of early 2000s as investors were using it as a result of the increased securitization activities. In addition, it became very topical in the light of the recent financial crisis as it was often used for speculative purposes.

In the next section we will look at the literature that focused on the theoretical determinants of the CDS spread.

2.1 Theoretical Determinants of the CDS spread

The pre-crisis literature focused mainly on the macroeconomic and financial determinants of the CDS spreads. As such, Anderson and Sundaresan (2000) Duffie and Singleton (1997), Duffee (1998), Lekkos and Milas (2001) and In et al. (2003) find that the risk free rates and their term structure are important determinants of the credit spread. In a similar vein, Estrella and Hardouvelis (1991), Friedman and Kuttner (1992), Longstaff and Schwartz (1995), Stokes and Neuburger (1998), Bevan and Garzarelli (2000), Neal et al. (2000), Fehle (2003) and In and Fang (2003), Carling et al. (2007) and Duffie and Singleton (2007) find that both the yield spread and the risk free rate are significant in explaining the CDS spread.

The literature on CDS spread determinants recognizes the significance of the theoretical variables. More specifically, authors including Fama (1984) and Estrella Hardouvelis (1991), Duffie and Singleton (1997), Duffee (1998), Lekkos and Milas (2001), In and Fang (2003), Bystrom (2008), Alexander and Kaeck (2008), Naifar (2010) find that both the risk free rate as well as the yield spread are important determinants of the CDS spread. Friedman and Kuttner (1992) find that interest rates are very important in predicting default risk. Furthermore, Longstaff and Schwartz (1995) show a negative relationship between the probability of default and the level of interest rates. The rationale behind this finding is that when interest rates rise, the risk neutral drift of firm tends to increase, resulting in a lower probability and a narrower spread. In addition, Neal et al. (2000) and Bevan and Garzarelli (2000) both confirm this negative relationship in the short-run. However, in the long-run, the authors argue that the relationship between the CDS spread and interest rates changes into a positive one.

Research by Estrella and Hardouvelis (1991), Fehle (2003) and In and Fang (2003) and Kobor et al. (2005) all find a negative relationship between the credit spread, interest rate and the yield curve. In fact, in times of economic recession, interest rates are typically low. An improvement in the state of the economy is usually associated with a steeper yield curve. Similarly, Friedman and Kuttner (1998) find that the business cycle impacts on the aggregate economy and investors' behavior, thus affecting the number of defaults and credit risk. Minton (1997) on the other hand finds that the yield curve has a positive relationship with the swap spread.

In addition, Stokes and Neuburger (1998) find that inflation is another factor that greatly affects credit default risk through its impact on input and output prices. This implies that if a firm is facing higher costs as a result of inflation, the firm might find it hard to carry on with its daily business obligations and achieve the targeted profit. If inflation reaches extreme levels, this may lead the company to default on its obligations, thus increasing default risk. Furthermore, in a research conducted by Duffie et al. (2007), the authors found that macroeconomic variables and industrial production growth tend to be good indicators for predicting and understanding the future fluctuations of credit risk.

Having analysed the literature that focuses on the theoretical determinants of the CDS spread, in the next section we will identify the literature that recognizes the importance of credit ratings, volatility and financial determinants as factors affecting the CDS spread.

2.2 Financial Determinants, Volatility and Credit Ratings as determinants of CDS spread

Past literature also incorporates financial ratios such as leverage and implied volatility and finds that these variables have a significant power in explaining CDS premiums (Collin-Dufresne et al. (2001), Campbell and Taksler (2003), Cremers et al (2004) and Benkert (2004)).

Different researchers highlight the importance of financial variables in explaining the credit risk. Collin-Dufresne et al. (2001) analysed bond spread as a measure of credit risk and found that financial leverage, volatility and the yield spread have significant power in explaining bond spread. Similarly, Carling et al. (2007) and Tang and Yang (2010) find that both financial ratios and macroeconomic factors help explain default risk. Furthermore, in a research conducted by Campbell and Taksler (2003), the authors used company bond spreads and find that volatility explains bond spreads. In a similar vein, Benkert (2004) use various volatility measures to analyze the CDS spread, and finds the presence of a negative relationship. Moreover, Cremers et al. (2004) also confirmed the importance of volatility in explaining bond spreads as a proxy for credit risk.

Another stream of research has focused on analyzing whether credit ratings matter in explaining CDS premiums. Research conducted by Hull et al. (2004), Cossin et al. (2002), Fabozzi et al. (2007) and Karagozoglou and Jacobs (2010) and Alper et al. (2012) have all confirmed the importance of credit ratings in explaining CDS premiums. In addition, credit rating proved to be important in the pricing for sovereign CDS spread (Alper et al. (2012)).

In the light of the above literature, for the UK banking sector, we investigate both the macroeconomic and financial determinants of CDS spread in the UK banking sector by considering house prices, the yield spread, TED (difference between the three-month UK T-Bill and the three-month LIBOR rates) and the FTSE 100 index.

In the next section, we will investigate the literature that recognized the importance of the bank-level determinants of the CDS spread.

2.3 Bank Level Determinants

Regulatory Capital

The recent financial crisis brought into light the inadequate regulatory structure and the lax supervisory regime under which banks were operating. Regulatory authorities and central banks agreed that there was an imminent need to take action and insure that banks had enough capital to sustain a negative credit event and avoid another crisis. Therefore, the previous Basel 2 Agreement was replaced by the more detailed and focused Basel 3 Accord, which provides a stricter definition of capital and en-globes both the micro-prudential and macro-prudential elements (Rossignolo et al. (2013)).

A number of authors investigated the impact of regulatory capital and capital buffers on credit risk (Antao and Lacerda (2011) and Chiaramonte and Casu (2013)). Previous literature states that traditionally banks held capital as a buffer against the risk of insolvency, and high level of liquid assets in order to protect themselves against unexpected, high volume bank withdrawals by depositors (Saidenberg and Strahan, (1999)). However, through the increased use of securitization in the years leading to the financial crisis, and the high reliance on the new techniques of risk

management, many financial institutions escaped such regulatory requirements by shifting their debt to off balance sheet items. This allowed them to hold less capital to increase their lending activities, at the same time complying with the necessary regulatory requirements (Gorton and Haubrich (1990)).

In a research conducted by Akhavein et al. (1997), findings indicate that systemically important banks were able to decrease their capital exposure and increase their lending operations after undergoing a merger. In addition, Demsetz and Strahan (1997) found that large banks have the capacity to engage in riskier lending activities, keeping at the same time a low level of capital. In a similar vein, Froot et al. (1993) and Froot and Stein (1998) analyzed lending practices for both financial and non-financial institutions and found that vigorous risk management enabled banks to conduct risky and illiquid investments and escape regulatory requirements; thus, holding insufficient capital buffers during an unexpected crisis.

Previous literature questioned whether banks were well capitalized before and after the financial crisis. Ambrose et al. (2005) argue that the level of capital held by banks that trade securitized derivatives was too high. The paper referred to the trading of mortgage-backed securities, which according to their findings, experienced lower levels of default when compared to loans kept in bank portfolios. The authors therefore suggested that regulation should be more “light touch”, with more relaxed capital requirements for structured derivative trading. However, since this research was conducted before the financial crisis, after the 2007-2009 financial crises, there has been a clear consensus to increase bank regulatory requirements.

In a more recent research, Roesch and Scheule (2012) analysed capital adequacy of US banks that conducted securitization. The authors found that before 2007, the level of regulatory capital held by banks was insufficient to secure all the underlying risks of structured derivative trading and sustain a shock such as the recent financial crisis. There is also evidence that suggests that the credit rating of these derivatives gave rise to capital arbitrage, which in turn helped banks to hold less regulatory capital and experience high levels of default. In a similar vein, Kretzschmar et al. (2010) also agreed that banks were undercapitalized before the financial crisis. The authors criticized the Basel 2 Capital Accord generally, and more specifically the Pillar 2 of the Accord, as it was deemed to be an insufficient capital buffer given the real risks faced by banks. In addition, Tian and al. (2013) also analyzed bank capital and the risk of contagion during bailouts and established that high levels of minimum regulatory capital did not necessarily imply that banks could avoid contagion. Instead the authors argue that financial institutions should hold a conservation capital buffer, as suggested in the Basel 3 Capital Accord, in order to reduce such risk.

Previous literature also looks at various advanced models that banks used in order to optimize their capital structure by responding to different types of pressures from shareholders, debt holders and price fluctuations in the market (Flannery (1994), Flannery and Sorescu (1996), and Myers and Rajan (1998)). However, the recent financial crisis proved that the previous Basel 1 and Basel 2 Capital Accords were strongly criticized as it did not ensure the soundness of the regulatory financial system (Antao and Lacerda (2011)). Thus, in 2013, Basel 3 was introduced to

strengthen the weak financial institutions' capital requirements, decreasing leverage intakes and raising liquidity levels.

Furthermore, a stream of literature analyzed the determinants of bank capital buffers and analyzed its relationship with business cycle. As such, Terhi and Milne (2008) focused on an unbalanced panel of 486 EU banks, using annual balance sheet data, between 1997 and 2004. They found that capital buffers of large banks as well as commercial and savings banks were negatively related to the business cycle. However, smaller banks and co-operative banks' capital buffer was found to be positively related to the business cycle. In a more recent research, Terhi and Milne (2011) analyzed US banks' capital buffers in relation to risk adjustment. Their results indicate that banks that are well capitalized adjust their capital buffer and risk positively, while this relationship proves to be negative for banks that have lower capital buffer.

Hypothesis: Strong capital buffers decrease credit risk and narrow the CDS spread.

The hypothesis is that regulatory capital is negatively related to the CDS spread. In fact, as banks have stronger capital buffers, in times of crisis, they are better equipped to sustain a shock, repay their outstanding liabilities and keep the bank in a stable condition, whereas a financial institution that has a low level of capital is very likely to go bankrupt if the financial system is hit by a crisis, especially with risk-averse investors losing confidence in the system and capital markets becoming reluctant to lend.

Leverage

Past literature acknowledges the importance of financial variables driving credit risk, including: leverage, regulatory capital, asset quality and liquidity. Leverage was at the epicenter of debates among regulators, being deemed as one of the main factors contributing to the recent crisis. A number of authors incorporated leverage among other bank level factors driving credit risk, using CDS spread and bond spread (Beltratti and Stulz (2011), Annaert et al. (2013) and Chiaramonte and Casu (2013)).

Before 2007, banks and other financial institutions heavily relied on borrowing from capital markets, beyond their real borrowing capacity, with debt to equity ratios exceeding 20 times their allowance for many large EU banks. These highly leveraged banks were granting loans to low income consumers. Therefore, in case of a bank run, there was a high likelihood of bankruptcy, with the situation potentially deteriorating and causing contagion, followed by a systemic collapse of the entire financial system (Antao and Lacerda (2011)). In the wake of summer 2007, most investors defaulted on their obligations, drastically increasing CDS spreads and credit risk (Kalemli-Ozcan et al. (2011)).

Recent literature examined the impact of common factors and found that leverage was a powerful driver of the CDS spread and credit risk (Aunon-Nerin et al. (2002), Ericsson et al. (2009)). In Ericsson et al. (2009), CDS spreads were used in both levels and first-differences and they demonstrate that their model was able to explain 23% of CDS spread fluctuations. When CDS spread was used in levels, the explanatory power augmented to 70%. The main variables that were found to drive

the CDS spread were leverage and volatility. Similarly, Aunon-Nerin et al. (2002) also incorporated leverage, and other variables, such as credit ratings, market capitalization and the price fluctuations in the stock market, with results indicating that all of these factors were strong determinants of credit spread. Furthermore, authors including Christie (1982), Collin-Dufresne et al. (2001) and Alexander and Kaeck (2008) used bank stocks as a proxy for leverage, and found that higher levels of debt was positively associated with credit risk.

More recently, Galil et al. (2013), looked at 718 US firms over the period of 2002-2013 and found that among other fundamental variables leverage (defined as the book value of debt divided by the sum of book value of debt and the market value of equity) significantly explained fluctuations in the CDS spread.

Similarly, Annaert et al. (2013) looked at 31 listed EU banks and showed that leverage strongly affects the CDS spread. In another research conducted by Eom et al. (2004), leverage also proved to have the ability to explain changes in credit spread, but with limitations. In fact, bonds (as a proxy for credit risk) that were considered less risky were underestimated by the structural models, while the risky bonds were overestimated. Other authors including Christie (1982), Collin-Dufresne et al. (2001) as well as Alexander and Kaeck (2008) proxied leverage using bank stock returns. Their findings indicate that negative stock returns have a positive impact on leverage. Thus, there is a positive relationship between leverage and credit spreads. In addition, recent literature proves that financial institutions in developing countries were more risk averse and had lower levels of debt. Therefore, developing

countries were found to be better able to resist the financial crisis when compared to developed countries (Beltratti and Stulz (2011)).

Another stream of literature linked leverage, pro-cyclicality and the risk it poses on global economy. In a research conducted by Bernanke and Gertler (1995), pro-cyclical leverage was found to have a strong power to amplify risk in the financial markets; thus negatively affecting the global economy. In addition, Fostel and Geanakoplos (2008) focused on emerging markets and showed that leverage cycles have the tendency to translate into contagion, causing a flight to collateral and creating volatility in financial markets.

In a similar vein, Adrian and Shin (2008, 2009, 2010) demonstrate from their findings that leverage is countercyclical for non-financial US institutions, and pro-cyclical for investment banks. Pro-cyclical leverage has the ability to negatively impact on the business cycle, thus causing systemic instability. Kalemli-Ozcan et al. (2011) show evidence that investment banks tremendously expended their leverage intakes through capital markets, and utilized their strong market power to attract additional funds. The presence of deposit insurance –played another significant role during the process

Hypothesis: Higher leveraged banks face increased credit risk and wider CDS spreads.

In this chapter, we assume that leverage and credit default risk are positively associated. As such, when a bank starts heavily borrowing, the level of capitalization becomes lower, while its leverage capacity starts exceeding its ability to repay

investors. In addition, the financial institution becomes vulnerable to shocks and may easily go bust if there is a crisis. Over the period of 2007-2008, many banks were downgraded due to their excessive leverage intakes, which further hampered their ability to attract additional external funding, finally resulting in their collapse.

Liquidity

The drastic squeeze in the liquidity levels that followed the 2007-2008 financial crisis led to a dramatic decrease in the bank lending activities in the developed economies. In the UK, Northern Rock was one of the first casualties of a bank run that required government intervention and bailout.

A stream of literature started developing in the last decade linking liquidity to credit risk. While certain researchers, including Longstaff et al. (2005) and Blanco et al. (2005), argued that the CDS spread reflected only credit risk, a new stream of literature argues that irrespective of market conditions, liquidity risk is more important in explaining the CDS spread than firm level credit risk (Corò et al. (2013)). Furthermore, Arakelyan et al. (2011) analyzed market-wide liquidity in credit default swap spreads and found that: 1) CDS spreads with a low-grade credit rating tend to be very sensitive to a shock in aggregate liquidity, when compared to good credit quality CDS spreads. 2) By employing a two-factor intensity model, there is evidence that the CDS spread incorporates an important liquidity risk premium. In a similar vein, Campbell and Taksler (2003) also considered aggregate liquidity in order to model credit spreads.

Moreover, Tang and Yan (2007) conducted a panel regression analysis and found evidence that liquidity had a significant power in explaining the variations in the CDS spread. Their results suggest that on average, both liquidity and liquidity risk account for approximately 20% of CDS spread fluctuations. Similarly, Bongaerts et al. (2011) emphasized the significance of liquidity effects for the pricing of CDS instruments. Other authors that also recognized the importance of liquidity as a driver of credit risk include Acharya and Johnson (2007), Pires et al. (2011) and Chen et al. (2007)). Furthermore, Chiaramonte and Casu (2013) found that liquidity was a significant driver of the CDS spread only during the recent financial crisis, while in the pre-crisis period, liquidity turned out to be insignificant. The relationship linking both the CDS spread and liquidity indicators is therefore time dependent. It can be positive if the bank experiences a shortage in liquidity; due limited number of deposits, the risk of default increases, pushing up the overall level of CDS spread. The CDS spread and liquidity can also be positively related when for a set level of deposits, the number of loans is relatively high. Thus, the market may react positively, especially commercial financial institutions which consider loan issuance as their main source of revenue (Chiaramonte and Casu (2013)). Furthermore, in a research conducted by Buhler and Trapp (2008), the authors looked at credit and liquidity risk in both bond and CDS markets, using a reduce form credit risk model. They uncover surprising findings which indicate that the CDS market is more liquid when the level of default risk is high.

Furthermore, Diamond and Rajan (2005) looked at liquidity shortages in the context of banking crises and shows that bank failures typically lower liquidity levels; thus reducing the already short liquidity reserves. This subsequently causes

the level of credit default risk to go up and resulted in a contagion and collapse of the entire financial system. The authors explained that banks go bankrupt either because they become insolvent or because they suffer from an aggregate shortage of liquidity, which in turn makes them insolvent. As such, illiquidity may cause the failure of systemically important banks, which in turn can lead to the collapse of the entire financial system.

In another research by Calice et al. (2009), the authors looked at liquidity spill-overs in sovereign bond and CDS markets and found that for EU countries; including Greece, Ireland and Portugal, liquidity of the sovereign CDS market have a strong time dependent impact on sovereign bond spreads. In a similar vein, De Socio (2013) looked at liquidity and credit risk in the Euro-interbank market. The author decomposed credit and liquidity components of the Euribor spread, by using CDS of various financial institutions. Their findings indicate that before August 2007 credit risk went up. In October 2008, the situation reversed with liquidity risk becoming the main driver of the Euribor spread.

Similarly, Qiu and Yu (2012) looked at the determinants of liquidity provisions in the OTC market for credit default swaps. Focusing on fluctuations of CDS liquidity across 732 firms, over the period of 2001-2008, the authors find that big companies and corporations near the investment-grade tend to have the highest liquidity levels. In addition, Berger and Bouwman (2010) related liquidity to monetary policy and show that during normal economic climate, there is a decrease

in liquidity created by small banks. Their findings also indicate that liquidity creation is high before financial crises.

Hypothesis: Higher liquidity decreases credit risk and CDS spread

We assume that liquidity and the CDS spread are negatively related. The higher the liquidity level, the better the bank's ability to deal with large withdrawals and possible bank runs. During the recent financial crisis, banks faced huge liquidity shortage, with frozen capital markets; this meant that there was no other source of liquidity to comply with investors' demand. Banks with stronger liquidity levels were able to sustain themselves, keeping at the same time their credit risk and CDS spread levels at moderate levels.

Asset Quality

Previous literature incorporated asset quality as a driver of credit risk using the CAMEL indicators approach. In a research conducted by Ötker-Robe and Podpiera (2010), the authors looked at the fundamental determinants of credit default risk for large and complex EU financial institutions. Three distinct ratios were used in order to reflect the quality of assets, namely: Loan-loss Provisions to Total Loans, Share of Non-performing Loans in Total Loans and Loan-Loss Reserves Ratio. Their findings show that asset quality did not make a substantial difference in the pricing of CDS instruments. The non-significance of asset quality was attributed to the period of analysis that covered only the beginning of the crisis. In addition, the authors argue that one of the measures of asset quality (such as: non-performing loans) referred to credit risk with a lag. Furthermore, Chiaramonte and Casu (2013)

also investigated the drivers of the CDS spread by incorporating asset quality among other bank level determinants. The authors used two ratios to reflect asset quality: the ratio of Loan Loss Reserve to Gross Loans and Unreserved Impaired Loans over Equity. Findings conclude that before the financial crisis, financial markets were not concerned with the low quality of bank assets. Similarly, Kick and Koetter (2007) also used the ratio of non-performing loans to total assets as an indicator of asset quality to determine the drivers of bank risk taking activities.

Asset quality can be also reflected using credit ratings of the underlying asset on which CDS contracts are written on. From the previous literature, a number of authors have identified credit ratings as an important driver of credit risk (Hull et al. (2004), Fabozzi et al. (2007) and Karagozoglu and Jacobs (2010)). As such, high credit ratings would be indicative of a better asset quality of the underlying instrument, while a lower credit rating would reflect a riskier asset. Before the financial crisis, securitization activities allowed banks to sell toxic instruments that had a high credit rating. With the bursting of the housing bubble and the beginning of the crisis, most of these securitized instruments on which CDS contracts were written on defaulted, increasing the CDS spread and credit risk.

Bank size effect and the notion of *too-big-to-fail* and *too-big-to-save*:

Before summer 2007, financial institutions and banks were expanding and growing in size, given the favorable economic climate. In fact, credit expansion occurred on the back of low interest rates and exceptionally low funding costs. This allowed bigger banks to benefit and make very high profits. In addition, high foreign funding inflow was another factor that greatly contributed to banks' incentive to

grow in size. In fact, many small banks in Europe and across the Atlantic drastically expanded. For instance, the Icelandic banking system liabilities surpassed its GDP level by 9 times in the last quarter of 2007 (Demirgüç-Kunt and Huizinga (2013)).

In a similar vein, the Swiss and the UK banking systems were also expanding beyond the recognized norm, surpassing the size of their GDP by 6.3 and 5.5 times, respectively (Demirgüç-Kunt and Huizinga (2013)). In addition, other banks in France, Denmark, Belgium, Ireland and Netherlands had liabilities ratios, twice the size of their country's GDP (Demirgüç-Kunt and Huizinga (2013)). According to Demirgüç-Kunt and Huizinga (2013), at least 30 banks across the world were identified to have liabilities being double their countries' GDP, with 12 banks having a liability of over \$1 trillion. These figures explicitly illustrate how banks and financial institutions were recklessly expanding before the recent financial crisis.

Bank size has been recently analyzed in the context of the CDS market (Völz and Wedow (2013)). The authors focused on investigating whether bank size reduces market discipline and found that on average market discipline exists in the CDS market. Nevertheless, the prices of CDS instruments were found to be affected in banks that were considered to be *too-big-to-fail*. In fact, a 1 percent rise in the bank size proved to narrow the CDS spread for the same bank by approximately 2 basis points. Although at a first glance this number may not appear substantial, banks that are already systemically important may merge, thus becoming ever bigger and narrowing the CDS spread on a much larger scale. This would automatically affect the overall banking system, as a narrower CDS spread would typically send the signal of a more stable bank when it is very likely that the CDS spread is narrower

because of the more substantial size of the bank itself. In addition, the authors looked at the *too-big-to-be-rescued* phenomenon and found that certain banks may attain a limit in their size where it becomes too hard for the government to intervene, in case of a negative credit event or crisis, and offer bailout packages due to the very high number of depositors that expect to be repaid and compensated.

Another stream of literature documented how bank size may impact on financial institutions' incentives to undertake risky investments and consequently affect its credit rating. In fact, both Sousa (2000) as well as Rime (2005) looked at banks' size and its credit rating and found that large banks, that reached the threshold of being considered *too-big-to-fail*, enjoyed a considerably better credit rating and could therefore benefit from a cheaper cost of funding compared to smaller banks. Similarly, Gómez-González and Kiefer (2009) also demonstrated that large banks have the tendency to experience less risk as they have the ability to diversify their assets in a more efficient way compared to smaller banks. They also have the capability to lower their costs through the economies of scale. In addition, large banks usually have more experience as they have been in business for a long time.

Similar conclusions were derived by Demsetz and Strahan (1997) that have also confirmed the ability of being bigger to better diversify their investments and therefore hedge their exposures and reduce the overall risk of default. The authors show from their research that large bank could increase their debt intakes and lend more to investors, keeping at the same time their risk record at moderate levels. Along the same vein, Mishkin (2006) focused in his research on the *too-big-to-fail* phenomenon and the reaction of large banks to the Federal Deposit Insurance

Corporation Act (FDICIA) that was introduced in the early 90s. He found that the issues associated with the *too-big-to-fail* significantly diminished after the introduction of FDICIA.

However, another stream of literature contradicts findings of Mishkin (2006). In fact, both Boyd and Gertler (1993) as well as Ennis and Malek (2005) argue that FDICIA gave large US banks more incentives to invest in risky projects as they had the safety net that the government will not let them down in case it faced financial difficulties, due to their potential impact on the overall systemic stability. In addition, banks that pursued the goal of joining the *too-big-to-fail* circle were found to go beyond their optimal size by taking over other smaller banks. This resulted in higher returns and narrower credit spreads, but at the same time, causing a bad allocation of resources (Penas and Unal (2004) and Kane (2000)).

Along the same lines, in a recent research conducted by Demirgüç-Kunt and Huizinga (2013), large banks were found to be more prone to risk. Looking at how bank size and government deficit may impact on the CDS spread and the value of banks' stock, the authors focused on whether the *too-big-to-save* or *too-big-to-fail* banks did exist in the real financial world. The CDS spread in this research was used as an indicator of the approximate credit losses on banks' liabilities. Their findings indicate that there is a negative relationship between both the absolute (log of assets) and the systemic bank size (liabilities to GDP) with their corresponding book-to-market value. This in turn implies that when the already systemically important bank further expends, it may become *too-large-to-be-rescued*; thus, exposing itself to more credit risk.

Furthermore, bank size has been recently analyzed in the context of capital buffers. García-Suaza et al. (2012) focused on a panel of Columbian banks over the period of 1996-2010, and found that large banks behaved differently from small banks. While large banks typically experience a better ability to obtain funding from capital markets, they have the tendency to keep their capital buffers low during credit booms, without necessarily exposing themselves to excessive risk. However, smaller banks were observed to have more barriers accessing financial markets, and were therefore facing increased costs when trying to rebuild their capital buffers. Moreover, Hakenes and Schnabel (2011) also analyzed bank size in relation to capital buffers and bank risk incentives. Looking at the Basel 2 Capital Accord, the authors show that smaller banks are subject to higher risk taking activities if they are allowed to choose between the IRB approach and the standardized approach to satisfy capital requirements. In fact, smaller financial institutions tend to compete with larger banks that have the advantages of increased competition in financial markets. This may result in higher aggregate risk-taking activities.

Moreover, in a research conducted by Brown and Dinç (2011), bank failure was analyzed in twenty-one emerging countries in the 90s. By designing a specific risk hazard model, the authors show that if there are high numbers of banks with excessive level of leverage, it is less likely that the government would let the problem bank collapse in case it required financial assistance to survive; this is also referred to as *too-many-too-fail*. In another paper by Steever (2005), bank size, credit as well as market risk were analyzed in the context of the equity market. After focusing on the relationship between firm size and equity risk for commercial banks, the authors found that smaller banks have the tendency to issue loans which are

deemed to be safer than the ones issued by bigger banks. However, because smaller banks are unable to diversify their risk exposures as efficiently as bigger banks, equity risk is almost the same for small and big banks.

Hypothesis: Bank size is positively associated with the CDS spread and credit risk.

In light of the recent financial crisis, the functioning of financial markets has dramatically shifted. As suggested by Demirgüç-Kunt and Huizinga (2013), big banks are now more prone to risk, given that they engage in bigger scale and riskier investments as compared to smaller banks. This chapter therefore assumes that before the financial crisis, larger banks faced reduced CDS spreads as they had the conviction to belong to the category of the too-big-to-fail banks. However, during the recent financial crisis, this phenomenon proved to be only limited to the very few big financial institutions that had the highest power to affect the public sector.

Having reviewed the literature that focuses on the bank-level determinants of the CDS spread, we will now investigate what are the country-level factors that drive credit risk.

2.4 Country Level Determinants

Financial Deepening

The period of early 2000s was marked by an economic boom with easy credit, high mortgage lending and excessive foreign funding inflow. Financial institutions made it very easy for low income borrowers to obtain loans and mortgages. Furthermore, capital markets were readily providing cash to banks. In summer 2007, the credit expansion era came to an end as the world economy entered

a long lasting and deep recession. Thus, the credit bubble, measured here by the level of financial deepening, probably made investors to default; pushing the CDS spread levels to historic high levels, as show in Figure 3.3.

Previous literature identified a number of factors that acted as a ground for the economic boom and helped the rise of easy credit provision. Among these factors there is: the policy of low interest rates, high foreign funding inflow, financial innovation and financial imbalances (Bernanke and Gertler (1999), Taylor (2007, 2009), Obstfeld and Rogoff (2009), Obstfeld (2010), Ferguson and Schularick (2011), King (2010)). Evidence suggests that credit supply is high during economic expansions and low during economic downturns (Bernanke and Gertler (1989), Holmström and Tirole (1997), Kiyotaki and Moore (1997), and Diamond and Rajan (2005)). As it was observed in the early 2000s, credit growth was elevated, while interest rates were depressed (Jorda et al. (2011)). Milcheva (2013) addresses in her research whether the house price appreciation was transmitted from the monetary channel or through the exogenous fluctuation in the supply chain of credit. She found that the rising level of credit was a contributing factor to the increased demand and rising house prices. In the wake of summer 2007, real estate prices crashed, while the level of defaults

In a similar vein, Peek and Rosengren (2003) analysed the effect of bank credit supply on the economy and found that during the Japanese crisis in the early 1990's, firms that were performing poorly were more likely to get additional bank loans. This is similar to the period before 2007 as weak banks were easily borrowing credit without having to demonstrate they were eligible for it. This significantly

contributed to the already high levels of default. Similarly, Rajkamal et al. (2013) looked at the effects of credit supply on the frozen EU interbank market. Using an extensive dataset on Portuguese loans, the authors showed that smaller banks experienced a higher reduction in the supply of credit. Since capital markets lend more to bigger banks as they are more established, smaller banks were therefore more exposed to default and credit risk.

Financial Stability

The imposing size of the CDS market and its opaque nature raised concerns among governments, regulators and central banks on the possible impact it may have on the stability of the overall financial system. As of June 2001, the outstanding notional amount of credit derivatives was slightly over \$631 billion. Over a 7 years period (2001-2008), the CDS market generated approximately \$60 trillion. This increase in the CDS market outperformed the world economic output, which averaged \$55.8 trillion (ISDA 2008 Report).

The significant size of the CDS market was not the only reason which raised fear about financial stability; there was also the misuse of such derivatives. Because of speculative CDS trading, the market was no longer able to reflect the real ongoing economic climate in financial markets. Thus, speculators took advantage of the situation by purchasing CDS contracts sold by weak banks, expecting them to default to get a repayment (Cont (2010)). As a precautionary measure, European regulators intervened and recently imposed a ban on outright speculation of naked sovereign CDS instruments.

Recent literature recognized the strong impact the CDS market has on financial fragility. According to Markosea et al. (2012), the size of both derivative and CDS markets was way too large to internalize the resulting failures from the deeply connected financial institutions. Similarly, Nijskens and Wagner (2011) blame banks and financial institutions that were involved in credit risk transfer for the recent financial crisis. The authors found that although individual banks that conduct credit risk transfer may appear to be less risky when considered individually, altogether they pose a greater risk to financial stability.

With the beginning of the financial crisis, many countries experienced excessively high levels of CDS spreads, which brought to light the danger of defaults, domino effect and contagion between countries (Cont (2010), Cont and Minca (2010)). In Greece, CDS spread figures grew from \$7.4 billion in 2009 to a remarkable 9.2 billion in 2010 (Cont (2010)). The state of panic and financial instability made it impossible for banks to borrow from the frozen capital markets (Terzi and Uluçay (2011)).

A new stream of literature developed, considering the CDS spread as a good proxy for systemic stability. Rodríguez-Moreno and Peña (2013) looked at the period before and during the financial crisis and find that at a macro level, the best measure of systemic risk is the first principal component of a portfolio of CDS spread. At individual bank level, the multivariate densities computed from the CDS spreads were the best indicator of systemic risk. Similarly, Huang et al. (2009) used CDS spreads and the equity prices to derive an indicator of systemic risk. Using 12 banks, the authors computed the probability of default from the CDS spread and the

subsequent asset return correlations. An analogous technique to estimate systemic risk using CDS spreads was employed by Chan-Lau and Gravelle (2005) and Avesani et al. (2006). The authors considered the system of banks as a portfolio, and used the default probability from the CDS and equity markets as an indicator of systemic risk. Similarly, Trapp and Wewel (2013) used 550 banks, including financials and non-financials to analyze systemic risk in both the EU and US regions and establish whether it arose from common shocks or contagion.

Financial Access

In the wake of the recent crisis, frozen capital markets lead to a reduced investors' and firms' ability to access banks and basic financial services. The extent to which financial systems channel savings to parties which have the best ability to maximize investment prospects is very important for economic recovery. Thus, a better access to financial institutions helps to ensure the borrowers' credit worthiness. This in turn minimizes the risk of default and reduces the overall credit risk.

Past literature indicates that a well-established financial system has a positive impact on economic development. Hence, there is a close connection between a developed financial system and the degree of financial access and outreach to banks. The benefits of a developed financial system with good access will reduce asymmetries and ensure the harmonization of markets. Other benefits include: transaction cost reduction, credit check controls and ensuring that both the lender and the borrower get the necessary protection when a contract is established (Levine (2005)). Similarly, Beck et al. (2008) state that the following basic services should

be provided to ensure good outreach: savings, payments, and risk-management instruments to participants, aim for financing positive growth projects. This is particularly important for smaller companies, start-ups and investors who have lucrative business ideas that require funding (Galor and Zeira (1993)). In a research conducted by Beck et al. (2007), financial outreach was analyzed using cross-country analysis to investigate the extent to which investors, households and firms were able to utilize banking services. By building indicators for financial penetration across 99 countries, the authors show that state owned firms have a lower outreach, unlike more concentrated financial institutions. In addition, countries with more ATMs, bank branches and loan services have fewer financing barriers.

In a more recent research by Beck et al. (2008), the authors focused on 209 banks in 62 countries and found that (a) account and loan balances, account fees and documentation requirements were all inversely related to financial access; (b) financial factors such as efficiency of credit information sharing, the rights of creditors and contract enforcements were all strongly correlated with financial access barriers. In addition, when competition is high in the financial system, market based supervisions is associated with better access. Thus, privately owned and foreign financial institutions offer more flexibility to depositors, which in turn improve the level of outreach.

Profitability

The existing literature linking banks' earnings to credit risk started developing only recently. In fact, most of the past literature used earning indicators in relation to bank failures rather than incorporating it as a driver of credit risk.

In a research conducted by Ötoker-Robe and Podpiera (2010), the authors analyzed 29 EU large financial institutions, over the period of 2004 to 2009 to uncover the drivers of CDS spreads. Using the CAMEL indicators (Capital, Asset Quality, Management Quality, Earnings Potential and Liquidity), it was found that riskier business activities raise the CDS spread, reduce operating costs, improve revenues and lower the ROA. More specifically, a 1% increase in the ROA ratio would lead to a 21.7 basis point reduction in the CDS spread. In the same vein, Chiamonte and Casu (2013) analysed whether the CDS spread can be considered as a good proxy for banks efficiency. Using pre-crisis, crisis and post crisis data, the authors found that the ROE tends to increase probability of default. In the same vein, Poghosyan and Cihak (2009) used CAMEL indicators in order to analyse European banks in distress over the period of early 1990s to 2008. Findings show that on average, banks that are in distress tend to experience lower levels of earnings. Thus, banks with a better capitalization are more likely to have greater earnings. This in turn reduces their overall lower level of default and narrows their CDS spreads. In addition, Kick and Koetter (2007) also incorporated earnings ratios among other CAMEL indicators to uncover the factors driving financial distress in the German banking system over the period of 1995 to 2004. They find that banks in distress have lower level of earnings. Similarly, Wheelock and Wilson (2000) found that banks that have lower profitability ratio are subject to higher probability of failure.

Although the literature on credit risk and the CDS spread has only started emerging in the early, its importance significantly grew in the financial markets, especially after the recent financial crisis where many researchers blamed it for

increasing speculation and endangering the entire financial system. Therefore, in the next section, we will investigate the literature that linked CDS instruments to the recent financial crisis.

2.5 Literature on CDS spreads in the light of recent financial crisis

A number of recent studies have focused on the impact of the recent financial crises as well as the sovereign crisis on CDS spread (Li et al (2010), Wang and Moore (2010), Chen et al (2011), Terzi and Ulucay (2011), Dionne et al. (2011), Eichengreen et al. (2012), Breitenfellner and Wagner (2012) and Arora et al. (2012)).

In a research conducted by Apergis and Mamatzakis (2014), the authors investigated dynamics of selected euro-area sovereign bonds by employing a factor augmenting vector autoregressive (FAVAR) model using five year CDS (Corporate CDS premium (iTraxx)). Their findings indicate that liquidity, credit risk and flight to quality drive both spreads and CDS of five years maturity over swaps for Greece and Ireland in recent years.

Among other recent authors that link the CDS spread to the financial crisis were Eichengreen et al. (2012), who focus on how the subprime crisis affected the CDS premium in the banking sector. Their research demonstrates the importance of common macroeconomic factors in determining the CDS premium in both normal and recessionary conditions. They also find that common macroeconomic factors, that have a strong influence on the CDS premium in normal times, tend to have less explanatory power during the credit crisis. The authors relate these findings to the change in investors' behavior. It appears that investors became more concerned with

the performance of sub-prime mortgage securities they had invested in than the risk of a general economic recession.

The research by Chen et al. (2011) analyses the behavior of the CDS indices in three different sectors: banking, financial services and insurance during normal and stress periods. The authors analyze whether the short and long run adjustments in the equilibrium of the CDS spread in these sectors was symmetric or asymmetric, in both tranquil and stress periods. They found that profitable arbitrage opportunities exist only in the banking CDS index, which is very responsive to credit events. In addition, their results indicate that arbitrage profit is more likely to be achieved following the occurrence of a negative shock. The authors find that in the long run, the insurance CDS index does not seem to adjust; while in the short run, all individual spreads in the insurance sector contribute to the equilibrium.

In a research conducted by Li and Mizrach (2010), the authors also analyze the CDS premium in the context of the recent financial crisis. Their research compares different models of Bear Sterns CDSs using a Markov Monte Carlo algorithm. The findings show that CKLS with GARCH volatility and exponential power distribution errors were the most appropriate model. Furthermore, the authors show evidence that level effects, volatility clustering as well as jumps were crucial elements of the credit default swap premiums. Their research unveils one very surprising finding, in the four months before the collapse of Bear Sterns, the CDS premium was almost equal to the risk free rate. As such, the CDS premiums did not signal the forthcoming bankruptcy or the global banking and financial crisis.

Moreover, Wang and Moore (2010) use the multivariate GARCH model to conduct a dynamic correlation analysis to establish how the credit default swap premiums of emerging markets are integrated with the US market during the financial crisis. Their results indicate that Lehman Brothers' shock significantly strengthened the integration especially in developed markets. The authors explain that the drastic fall in the US financial interest rates resulted in a high correlation between the US and developed countries markets; meaning that when the financial crisis reached its highest level, the CDS market was mainly affected by developments in the United States.

In addition, Breitenfellner and Wagner (2012) focused on aggregate credit default swap premiums. Their research uses the European ITraxx CDS index to analyze the factors that determine the premium. They found that prior to and following the outbreak of the financial crisis, the CDS premium was determined by stock returns and implied volatility of the S&P 500 stock index. In addition, before and during the recent crisis, global financial variables were also found to have an explanatory power. Another interesting observation was that liquidity factors only mattered for financial institutions, but were irrelevant to non-financial firms.

In a similar vein, Dionne et al. (2011) used a Markov-switching risk-free term structure model to investigate that factors that caused the yield spread and default risk to rise. They used default probabilities implied by credit default swap premiums for different classes of bond ratings, the risk-free rate, and risky zero-coupon bond yields. The authors used variables such as inflation, consumptions and the yields of risk free securities to calibrate their analysis. They find that

between the late 1980s and 2008 macroeconomic factors were the main determinants of the sudden jump in CDS premiums. The credit default swap market has also been analyzed in relation to counterparty credit risk. As such, Arora et al. (2012) show that counterparty credit risk is priced in the CDS market. Their results show that credit default swap premiums are more expensive when the credit risk of the protection seller is low.

Having reviewed the literature on CDS and credit risk, both at bank-level and country-level, in the next section we will focus on the first research question that this thesis addresses. More specifically, we will look at the determinants of UK bank CDS spread and investigate the role by the housing market, over the period of 2004-2011.

Chapter 3

Data

In chapter 3, I will explain the type and sources of data used in this thesis. As such, two types of data have been employed for the purpose of our analysis. I have first conducted the aggregate-level analysis for the UK Banking sector (time-series analysis). I have then used bank-level analysis across 30 countries and 115 banks (panel-analysis). It should be noted that two types of characteristics were used for the purpose of bank-level analysis, namely: bank-level characteristics which consist of bank accounting ratio and country-level characteristics. Let us first explain the aggregate analysis for the UK banking sector.

3.0 Aggregate analysis for the UK Banking sector

In this section of the thesis we will first start by presenting the dependent and the set of independent variables used for the time-series analysis, which focuses on the UK banking sector. These are defined as follows:

UK Bank CDS

The CDS spread represents the CDS Premium Mid for the entire UK banking sector. It should be noted that the sector indices is equally weighted and corresponds to the average of ‘CDS premium bid’ and ‘CDS premium offered’. The rate is expressed in basis points (bp). We use the monthly 5-Year Credit Default Swap (CDS) Index as a proxy for credit risk. The index includes the aggregate banking sector in the UK. We use log of CDS spread in our analysis. The data include indices with a five-year maturity because they are the most liquid type of CDS.

The data is monthly and covers the period ranging from January 2004 to April 2011. This time period is of great interest as it enables us to shed light on the behavior of the CDS spread before and during the financial crisis, including the period when the credit market was booming. CDS data were obtained from Thomson Reuters Datastream, the world's largest financial statistical database, and published by the Credit Market Analysis (CMA) Group. The CDS banking sector data were first launched by the CMA group in 2004.

For the purposes of the time series analysis, we examine the CDS premium for the UK banking sector against four financial explanatory variables. A number of authors have identified the importance of theoretical variables as drivers of credit risk (Fama (1984), Estrella and Hardouvelis (1991), Longstaff and Schwartz (1995), Duffie and Singleton (1997), Duffee (1998), Lekkos and Milas (2001), Fehle (2003), In and Fang (2003), Fang (2003). Kobor et al. (2005), Bystrom (2008), Alexander and Kaeck (2008), Das et al., (2009), Naifar (2010) and Dionne et al. (2011)). We therefore include both the *Yield Spread* and the *TED Spread* as theoretical determinants of the CDS spread. In addition, previous research identified the relevance of financial variables as drivers of credit risk (Collin-Dufresne et al. (2001), Campbell and Taksler (2003), and Benkert (2004)); we therefore incorporate the *FTSE100* to reflect the state of the UK financial market. Moreover, in order to reflect the underlying economic factors, we include the *UK House Price Index*.

Figure 1.2 shows that before July 2007 when the crisis began, the CDS spread was very low. The reason why the level of the CDS spread was not high prior to the financial crisis was due to the low perception of credit default risk in the

financial system. However, in July 2007, the CDS spread started to increase dramatically. This dramatic and sudden increase in the CDS spread was a reflection of the subprime mortgage crisis that affected the financial markets. In fact, the period between July 2007 and March 2009 was marked by the bankruptcy of large investment banks, including AIG, Lehman Brothers, and Bear Sterns among other major banks that threatened the stability of the overall financial system.

In February 2011, although the level of credit risk started to gradually decrease as a result of the slow economic recovery, its level was still high relative to the period preceding the financial crisis. This reflects the vulnerability of the financial system to external shocks.

The variables that have been identified in the literature in explaining CDS spread determinants are as follows:

UK House Price index

The UK house price Index is obtained from Datastream Thompson Reuters and published by Nationwide Anglia Building Society under the reference 'Nationwide House Price Index', which is a monthly average and denominated in British Pounds (£). It is seasonally adjusted and ranges from January 2004 to April 2011. Again we use a log transformation for the empirical tests. Given that houses are not similar, a simple average of all house prices in a specific sample would lead to misleading inferences. For this reason, Nationwide adopts a statistical method, which uses the constantly varying sample of mortgage approvals to produce a consistent index, capturing price fluctuations on a regular basis.

From figure 1.2, it can be clearly observed that during the period before October 2007, the UK house price index was gradually increasing. However, with the beginning of the subprime mortgage crisis, the house price index drastically fell. Although, the house price index started to marginally increase again, the index never came back to its previous peak level that was recorded before the financial crisis.

Before the financial crisis, consumers borrowed heavily due to the low interest rates that in turn were partly a result of foreign inflows. This created a massive credit expansion and easy borrowing to low-income consumers, leading to a housing boom in the economy. In fact, most of the borrowers had very low credit ratings and were still able to obtain mortgages. Furthermore, given the increased securitization activities in the financial system, banks were not very concerned about the quality of borrowers. Due to the sophisticated financial engineering practices and securitization activities, banks that were granting mortgages were repackaging these mortgage obligations into synthetic structured products such as Mortgage Backed Securities (MBS), Retail Mortgage Backed Securities (RMBS) or Collateralized Debt Obligations (CDOs) among other more complex structured products. The repackaging process of mortgages and other instruments were achieved with the help of credit rating agencies and Special Purpose Vehicles (SPV), which effectively trashed the MBS and RMBs, reselling them to other parties who were better equipped to handle risk. This has allowed a better risk diversification while resulting in low lending standards. Given the easy borrowing in the financial market, the demand for real estate purchases dramatically increased, pushing up house prices. As a result, borrowings increased and savings decreased. This has in turn led to a

housing boom, followed by a surplus of unsold houses driving the real estate prices down. This period corresponds to the beginning of the subprime mortgage crisis.

At the beginning of 2007, sub-prime mortgage borrowers started heavily defaulting on their mortgage obligations, and given that house prices were already decreasing, banks were no longer able to recover their loans by reselling the properties. It should be noted that financial institutions were not the only parties who suffered from the sub-prime mortgage crisis. Primary borrowers who defaulted were also in distress as a result of losing their primary residence. In addition, there was another class of borrowers who were taking mortgage loans to later resell it into the secondary market when real estate prices were higher, with the aim to achieve a profit (also referred to as re-mortgaging activities). Following the crisis, these borrowers were now holding negative equity. This has caused a further increase in the number of defaults and houses for sale. Thus, all securitized products were drastically falling in value, with most of the mezzanine tranches defaulting first. In addition, the CDS spread on Mortgage Backed Securities (MBS) was extremely high, leading to an overall increase in the CDS spread. The high CDS spread was a reflection of the rising default risk in the financial system. The transmission channel leading to the credit crisis is explained in a Flow Chart in Figure 1.1.

UK Yield Spread

The *UK 3-month Treasury Bill* is obtained from Datastream Thompson-Reuters database. It is the middle market-closing rate (i.e. the mean of bid and offer) as recorded by the Bank of England in the late afternoon. Also the *30-year UK*

Treasury bond yield has been obtained from Datastream. It represents the UK Government 30-year benchmark bid yield, denominated in the UK Sterling currency. The yield-spread variable is calculated as the yield of a 30-year UK Treasury bond minus 3-month UK Treasury bill. The data frequency for both variables is monthly, ranging from January 2004 to April 2011. The yield spread is defined as follows:

$$\text{Yield Spread} = 30 \text{ year UK Treasury bond} - 3 \text{ Month UK Treasury bill}$$

In Figure 1.2, the yield spread can be compared over two different time periods: the period preceding the financial crisis (January 2004 until August 2007), and the period following the financial crisis (August 2007 to April 2011). In the first period, before the crisis emerged, the yield curve was downward sloping, and progressively decreasing. However, from the beginning of the financial crisis, the direction of the yield curve has changed, becoming upward sloping. The yield spread can increase either as a result of higher yields being offered on long-term bonds (yield on the 30 year Treasury bond) or due to the decrease in short term yields (yield on 3-month Treasury bills).

The yield on the long-term bond can increase following perception of higher credit risk in the government sector resulting from a large fiscal deficit. The higher Sovereign credit risk can get transmitted to the private sector, given the government's borrowing requirement from financial markets. In addition, inflation rate is another factor that could influence the shape of the yield curve. A higher public sector borrowing requirement and inflation risk would lead to an increase in the yield of the long-term bond. Furthermore, it can be observed from figure 1.2 that

the yield curve steepened at the beginning of the credit crisis, while from March 2009 onwards, the yield curve started to flatten, reflecting the beginning of an economic recovery.

UK TED Spread

The liquidity spread is represented by TED. The acronym is formed from *T-Bill* and *ED* – the ticker symbol for the Eurodollar futures contract. Instead of the Eurodollar, we use the LIBOR rate. The series were obtained from Datastream. It is monthly, ranging from January 2004 to April 2011.

The *UKTED* spread is defined as follows:

$$TED = 3 \text{ Month LIBOR} - 3 \text{ Month UK Treasury Bill}$$

Figure 1.2 indicates the fluctuation of the liquidity spread over the period of January 2004 - April 2011, in the UK money market. Following the financial crisis, liquidity in the financial markets started to decline considerably. The dramatic collapse in liquidity was recorded around September 2008, when capital markets froze and investors started withdrawing their funds from financial institutions, eventually causing bank runs.

UK FTSE 100 Index

The *FTSE-100 index* was chosen as a benchmark for the UK stock prices. The *FTSE-100* is a share index of the 100 most highly capitalized UK companies listed on the London Stock Exchange. The data was obtained from Thompson Reuters Datastream, at monthly frequency, ranging from January 2004 to April 2011.

Before the recent financial crisis, the *FTSE-100 index* was gradually increasing, reflecting a constantly improving economic performance of the UK 100 most capitalized companies (see Figure 1.2). After August 2007, with the beginning of the financial crisis, the *FTSE-100 index* started to drastically fall, signaling deteriorating market conditions. Given that most of the financial institutions are interlinked, defaults in one financial institution may spill over to other banks, companies and sectors. This was exactly what happened in the recent financial crisis. With the beginning of the sub-prime mortgage crisis, major investment banks collapsed, and investors lost confidence in the financial system and started heavily withdrawing their funds. This has caused bank runs (for example, in the case of Northern Rock) and the drying up of liquidity in the financial sector. Many banks went bankrupt as they faced liquidity crisis and were unable to repay their debt obligations, resulting in a global financial crisis affecting not only the housing and financial sectors, but also causing distress in other sectors as reflected in rising unemployment rates.

Having explained our dependent and set of explanatory variables for the aggregate analysis of the UK banking sector, in the next section we will discuss the data used for the bank-level analysis.

3.1 Bank-level analysis across 30 countries

There are two types of data considered in the bank-level analysis of this thesis, namely: the bank-level characteristics and the country-level characteristics. The panel data is yearly, ranging across 30 countries and 115 banks, over the period of 2004-2011.

3.1.1 Bank-level Characteristics

We use annual data for a panel of 30 countries and 115 banks, over the period of 2004- 2011, for which a variety of bank characteristics is used. The list of banks and countries used in the analysis is presented at the end of this chapter in table 0.1 and table 0.2. In addition, table 2.1 outlines the summary of the source of the bank-level data as well as expected sign of the coefficients. Furthermore, table 2.2 summarises the hypothesis of the bank-level data.

Bank CDS spread: The index includes 115 banks in 30 countries, over the period of 2004-2011. The data was obtained from Thomson Reuters Datastream, and published by the Credit Market Analysis (CMA) Group. The CDS banking sector data were first launched by the CMA group in 2004. This dataset is unique as it allows us to uncover the behavior of CDS before and after the financial crisis, including the period of economic expansion. We use the yearly 5-Year Credit Default Swap (CDS) Index as a proxy for credit risk as it is considered to be the most liquid type of CDS index. We use log of CDS prices in our analysis. The CDS spread is expressed in basis points.

Graphes 2.1-2.6 shows the relationship of the CDS spread with respect to leverage, regulatory capital, asset quality, liquidity operations income ratio and bank size, over the period of 2004 to 2011, for the entire sample of 30 countries and 115 banks. Although the level of bank CDS spread varied across different countries, the trend of these fluctuations was similar. In fact, before 2007, bank CDS spread levels were very low, reflecting low the level of default and credit risk. This entire trend reversed with the beginning of the financial crisis. The pattern of low bank CDS spread before the crisis, which drastically increased after the crisis, was observed for the rest of developed and emerging countries across the sample.

All the bank-level explanatory variables used to reflect bank characteristics were retrieved from Bankscope and published by Bureau Van Dijk. As such, the set of bank-level explanatory variables, that reflect bank characteristics, simply represent accounting ratios that have been previously used in past literature as a proxy for CDS and credit spreads. We have followed the approach used by Ötker-Robe and Podpiera (2010), Chiaramonte and Casu (2013), Fabozzi et al. (2007), Hull et al. (2004), Collin Dufresne et al. (2001), Campbell and Taksler (2003) and Benkert (2004).

- **Leverage:** ratio of long-term debt to common equity. It is denominated in the local currency and expressed as a fraction.
- **Regulatory Capital:** Tier 2 Capital, which is computed as the difference between Total Capital and Tier 1 Capital.
- **Asset Quality:** ratio of Impaired Loans to Equity.

- **Bank Liquidity:** ratio of Liquid Assets to Total Deposits and Borrowings.
- **Operations Income Ratio:** EBITA / Average Assets
- **ln(Bank Size):** Natural Logarithm of Bank Total Assets
- **Bank Size Sq:** Squared term of the Natural Logarithm of Bank Total Assets

Having given the definition of each bank-level indicator used in the panel analysis, we will now describe in more detail the trends in each of the variables over the period of 2004-2011.

Leverage

The credit expansion in early 2000, securitization activities and the increased use of structured products allowed banks to increase their lending activities, which eventually translated into a credit bubble. Most importantly, banks were able to increase their lending to low-income consumers thanks to their ability to borrow more from other banks and capital markets. Abnormally high leverage ratios were already observed before the financial crisis. Regulators paid little attention to the level of debt, as banks were not disclosing their real leverage exposures. Instead, they used off-balance sheet securitization to escape regulatory requirements.

We observe that the highest leverage multipliers are usually associated with banks in developed countries, which were known to be less conservative with their financial regulatory approach. On the other hand, the more conservative banks in

emerging countries enjoyed considerably smaller levels of leverage, due to their more conservative approach to risk and tighter financial regulation.

Graph 2.1 shows that the long-term debt to common equity ratio and the CDS spread across a panel of 30 countries is positively correlated. This implies that the higher the leverage ratio, the higher the CDS spread, and the greater the overall credit risk.

Regulatory Capital

From graph 2.2, it can be observed that over the period of 2004 to 2011, regulatory capital and the bank CDS spread were inversely related. In fact, the Tier 2 capital varied across countries and institutions. Countries with tighter regulatory regimes requested banks and financial institutions to hold more capital aside as a cushion to absorb losses in case if there was a negative event. However, countries with more lax regulatory regimes allowed their banks to hold less capital aside. Banks typically preferred have lower capital buffers as it allowed them to undertake more investments. However, in the light of the crisis, banks in developed countries that were known to be more risky were faced with stricter regulatory rules. It should be noted that the higher the tier 2 capital, and the stricter is the regulatory capital regime, the narrower is the CDS spread and smaller is credit risk. Basel 3 was introduced on the 1st of January 2013 in response to the failure of the previous financial regulatory regime. Its main objective was to strengthen capital requirements, by lowering leverage, increasing liquidity levels and introducing a new minimum risk based capital ratios.

Asset Quality

Impaired Loans over Equity reflects the quality of assets, over the period of 2004-2011. A typical example of a bank that experienced a high level of bad loans was the UK bank Northern Rock which had to be rescued and bailed out by the Bank of England as it was on the verge of collapse, or the German IKB Deutsche Industrial Bank which experienced very high ratios of impaired loans to equity. As such, graph 2.3 clearly demonstrates that the higher the value of impaired loans over equity and the wider is the CDS spread. This implies a deteriorating quality of the underlying instrument and a rising credit risk.

Bank Liquidity

Bank liquidity is defined as the ratio of Liquid Assets / Deposits and Borrowings. The data was obtained Banckscope.

Over the period of 2004 to 2011, the liquidity ratio varied highly across banks. From our data sample, it appears that Russian and Malaysian banks had high levels of liquidity as compared to other banks in developed countries. The exception was few strong UK banks, such as Barclays and HSBC which despite the financial crisis, in 2007, still sustained high liquidity ratios.

Graph 2.4 points a negative relationship between the ratio of liquid assets to total deposits and borrowings and the CDS spread. Higher liquidity ratios signal a rather safe and stable bank, which is able to provide cash to its investors and sustain

itself in times of crisis and dry capital markets. This implies that high liquidity is expected to be negatively related to CDS spread and credit risk.

Operating Income Ratio

Operating income ratio is defined as the ratio of EBITA / Average Assets. The data was obtained from Bankscope. It is annual, covering 115 banks and 30 countries.

Graph 2.5 shows that there is a negative relationship between bank CDS spread and bank-level of operations, across a sample of 30 countries and 115 banks, over the period of 2004-2011. As such, there is an expectation that banks that achieve high level of revenue, gain higher income and therefore generate more return. Therefore, in times of financial crisis, they have more income to sustain themselves and avoid the high reliance on capital and money markets.

Bank Size

Graphs 2.6, 2.7 and 2.8 demonstrate the nature of the relationship linking bank size and the CDS spread over the sample period 2004-2011. In graph 2.6, on average, there appears to be a negative relationship between credit risk and bank size. Thus, as banks grow in size, the CDS spread narrows. Before the crisis, there was a fundamental belief amongst banks that the government will never let a big institution fail due to the possible contagion it may generate in the financial markets. However, it should be noted that graph 2.6 does not account for institutions that surpass the optimal size. As such, after conducting our analysis, we demonstrate in

graphs 2.7 and 2.8 that there is a U-shape relationship between bank size and credit risk. Therefore, bigger banks were subject to higher CDS spreads and increased credit risk, while smaller banks experienced relatively lower CDS spreads and were considered to be safer. Any financial institution growing beyond that threshold becomes subject to higher credit risk.

Having identified the bank-level characteristics, we will now proceed and identify the country-level characteristics used in our panel analysis.

3.1.2 Country-level characteristics

We use annual data for a panel of 30 countries, over the period of 2004- 2011, for which a variety of country-level characteristics is used. The list of the countries used in the analysis is presented at the end of this chapter. The variables used to reflect the country-level characteristics in a panel setting are explained as follows:

House Price Index: we use a log transformation of the house price index. The data is denominated in the local currency and expressed in basis points. The data is yearly, covering 30 countries, over the period of 2004-2011. It was retrieved from Thomson Reuters Datastream and published by Oxford Economics.

The housing market has fluctuated steadily over the period of 2004-2011, across the 30 countries. Some countries such as the UK and the US experienced

drastic changes in the housing market before and during the financial crisis. More specifically, it has been observed that the housing market goes through cycles of booms and busts. As such, during the credit boom we note that many developed economies experienced a high expansion in the housing market. Typically, after a peak, the housing market starts to drastically fall, bringing the rate of defaults to very high levels. Given the high reliability of developed economies on the mortgage-backed securitization, there is higher likelihood that such types of countries will be more affected by drastic changes in the housing market. Therefore, any changes in the real estate market, is very likely to affect the level of the CDS spread and credit risk.

The variables that are used in this thesis to reflect the financial system are all at aggregate level, and are represented by: *Financial Deepening*, *Financial Stability*, *Profitability* and *Financial Access*. These data were all retrieved from the Global Financial Development Database (GFDD) of the World Bank (available at: <http://go.worldbank.org/AWACYAMMM0>). However, the raw data used to compile the Global Financial Development Database came from different sources, which are outlined below for each variable as follows:

Financial Stability

The data was retrieved from the GFDD at the following World Bank website (available at: <http://go.worldbank.org/AWACYAMMM0>). Raw data came from two different sources: Bankscope and Bloomberg.

- ***Financial Stability 1:*** Bank Z-score: Ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio). The loan amount recorded as nonperforming includes the gross value of the loan as recorded on the balance sheet, not just the amount that is overdue. The source of the raw data is from Bankscope.
- ***Financial Stability 2:*** Volatility of stock price index: It is the 360-day standard deviation of the return on the national stock market index. The source of the raw data is from Bloomberg.

The Bank Z score is also referred to distance to default reflects the level of stability of a bank. Figure 3.1 illustrates a negative relationship between the CDS spread and the bank Z score, across the 30 countries considered in our sample, over the period of 2004-2011. This implies that a more stable financial institution would have a higher the Bank Z score, a lower probability of going insolvent, and a lower CDS spread. Thus, the Bank Z score is inversely related to the probability that the value of bank's assets becomes lower than the value of its debt. In fact, the Z score measures the number of standard deviations a return realization has to fall in order to deplete equity. Similarly, Financial Stability 2 (*Volatility of stock price index*), reflects the volatility of stock prices in each of the 30 countries considered in our sample. As such, we observe that many developed economies such as the UK, US, France, Spain and Italy experienced very high volatility levels since 2007, as a result of the financial crisis which eventually led to financial instability. The relationship linking Financial Stability with the CDS spread is expressed in figure 3.1.

Financial Deepening

The data was retrieved from the GFDD at the following World Bank website (available at: <http://go.worldbank.org/AWACYAMMM0>). Raw data came from three different sources: International Monetary Fund, International Financial Statistics, and World Bank GDP estimates.

- ***Financial Deepening 1:*** Deposit money bank assets to GDP (%): Total assets held by deposit money banks as a share of GDP. Assets include claims on domestic real non-financial sector, which includes central, state and local governments, nonfinancial public enterprises and private sector. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. The raw data came from the International Monetary Fund, International Financial Statistics, and World Bank GDP estimates.
- ***Financial Deepening 2:*** Financial system deposits to GDP (%): It represents demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP. The raw data came from the International Monetary Fund, International Financial Statistics, and World Bank GDP estimates.

The higher the ratio of deposit money bank assets and the better the banks' ability to generate credit (Financial Deepening 1). The same applies for the ratio of financial system deposits to GDP (%) (Financial Deepening 1). We observe that the period before the financial crisis was a period of high credit expansion, where low-income consumers were able to get loans and buy houses. The level of credit rose to drastic levels, leading to major credit imbalances in the financial system. This subsequently gave rise to a credit bubble, which later transformed into the global financial crisis. The relationship linking Financial Deepening with the CDS spread is demonstrated in graph 3.1.

Financial Access

The number of bank branches per 100,000 adults represents the number of commercial bank branches per 100,000 adults. The data is from commercial banks-bank survey and has been published by International Monetary Fund and the Financial Access Survey. For each country, it is calculated as: $(\text{the number of institutions} + \text{number of branches}) * 100,000 / \text{adult population in the reporting country}$. The data was retrieved from the GFDD at the following World Bank website (available at: <http://go.worldbank.org/AWACYAMMM0>).

As such, Financial Access reflects the extent to which investors and the public generally speaking can access banks. A financial system that functions efficiently would strive to enhance and ensure that investors have easy access to

financial institutions. The relationship linking Financial Stability with the CDS spread is expressed in figure 3.1.

Profitability

The country-level data was retrieved from the GFDD at the following World Bank website (available at: <http://go.worldbank.org/AWACYAMMM0>). In addition, raw data was retrieved from Bankscope and was calculated from underlying bank-by-bank unconsolidated data.

- **Profitability 1:** *Overhead costs to total assets (%)*: Operating expenses of a bank as a share of the value of all assets held. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax assets, discontinued operations and other assets. raw data was retrieved from Bankscope.
- **Profitability 2:** *Return on equity (%)*: Commercial banks' net income to yearly averaged equity. Both the numerator and denominator are first aggregated on the country level before division.

Figure 3.1 shows that the CDS spread and the level of profitability (country-level) are negatively related. When banks have a high level of return, it would

typically attract more investors as the bank enhances its marketability and positions itself as a strong financial institution in the markets. Thus, as long as a bank invests in safe assets, it would usually have a better availability of funds compared to other institutions; thus, it becomes financially stronger. Higher net interest margin would typically decrease the probability of default, narrow the CDS spread and decrease the level of credit risk.

Having explained all the data used in our analysis, we will now proceed to the next chapter and analyse the literature review and hypothesis developed in this thesis. In subsequent chapters, all the data related analysis will be undertaken.

Table 0.1: List of Banks

List of Banks
ABN Amro Bank
ABU DHABI COMR BK
AKBANK TURK ANONIM
ALFA-BANK (OJSC)
ALPHA BANK A.E.
AOZORA BANK, LTD
Alliance and Leicester Commercial Bank
BAWAG P.S.K
BAYERISCHE LANDESBK
BCP FINANCE BK
BNP Paribas
Banca Intesa
Banca Italese
Banca Monte Dei Paschi
Banca Nazionale del Lavoro
Banca Popolare Di Milano
Banco BPI
Banco Bilbao Vizcaya Argentaria SA
Banco Comr Portugues
Banco Espirito Santo SA
Banco Pastor SA
Banco Popolare Italiana
Banco Popular
Banco Santander SA
Banco de Sabadell SA
Bank of America Corporation
Bank of China Limited
Bank of India
Bank of Moscow
Bankinter
Barclays
CAIXA D'ESTL DE CATA
CAIXA PNOS DE BARCA
CATHAY UNITED BK CO LTD
CDA DE VLNCIA CASTLN
CDA DEL MEDITERRANEO
CDA Y MP DE MADRID
CIMB BANK BERHAD
CITIGROUP INC.
CREDIT LYONNAIS
CREDIT SUISSE GROUP
Caixa Geral De Depositos
Capital One Financial Corp
China Development Bank (China DEV Bank)
Commerzbank
Credit Agricole
DANSKE BANK A/S
DBS BANK LTD
DEV BK OF JAPAN INC
DNB NOR BANK ASA
DZ Bank

Deutsche Bank
Dexia
EFG Eurobank Ergas
EMIRATES NBD (PJSC)
ERSTE GROUP BANK AG
Export-Import Bank of China
Fortis Bank
GAZPROMBANK (OJSC)
HANA BANK
HBOS
HSBC Holdings PLC
ICICI Bank limited
IDBI Bank LTD
IKB Deutsche Industrial Bank
IND & COM BK OF CHIN
INDL BK OF KOREA
ING Bank
Irish Life and Permanent Plc
JP Morgan Chase & Co.
JSC BK CENTERCREDIT
KBC Group
KOOKMIN BANK
KOREA EXCHANGE BANK
LANDESBANK BERLIN AG
LB BADENWUERTTEMBERG
LB HESSTHRGN GIRO
Lloyds Banking Group PLC
MIZUHO CORP BANK LTD
MORGAN STANLEY
Malayan Banking Berhad
Mediobanca
NAT BK OF ABU DHABI
NAT BK OF GREECE SA
NATIONAL AUS BK
NORD-LB - GIRO
NORDEA BANK AB
Nationwide Building Society
Natixis
Northern Rock PLC
OS CHINESE BKG CORP LTD
RAIF ZNTRLBK OSTER AG
RHB Bank Berhad
Rabobank Nederland
Rosselkhosbank
SHINHAN BANK
SKANDINAVISKA ENSK BNKN
SNS Bank
Sberbank of Russia
Societe Generale
State Bank of India
THE BTMBI UFJ LTD
THE CO-OP BANK PLC
THE EXPT-IMPT BK OF KOA
THE GOLDMAN SACHS GP
THE KOREA DEV BANK

THE RBS GROUP PLC
TURKIYE IS BANKASI
UBS AG
Unicredito Italiano
Unione Di Banche Italia (UBI Banka)
VTB Bank
WESTLB AG
WESTPAC BANKING CORP
WOORI BANK

Table 0.2: List of countries

List of Countries
Australia
Austria
Belgium
Cayman Islands
China
Denmark
France
Germany
Greece
Hong Kong
India
Ireland
Italy
Japan
Kazakhstan
Malaysia
Netherlands
Norway
Portugal
Russia
Singapore
South Korea
Spain
Sweden
Switzerland
Taiwan
Turkey
UAE
UK
US

Chapter 4

Determinants of Bank Credit Default Swap Spreads: The role of the housing sector

Abstract

The fourth chapter of this thesis relates credit spreads (CDS prices) in the UK banking sector with the performance of the housing sector. Using data on banking sector CDS spreads for the period January 2004 to April 2011, we analyze the impact of the house price index, the liquidity premium (TED), the yield spread and the FTSE 100 index on CDS spreads. Each of these variables represents four different sectors, namely the credit market, the housing market, the money market and the stock market. We find evidence that house price dynamics and the yield spread are the key driving factors behind the increase in credit spreads as reflected in CDS prices. In addition, we employ a structural VAR model to investigate the short-run determinants of the CDS spread. The obtained results support our previous findings, suggesting that the CDS spread is highly affected by variations in the house price index, which is influenced by the yield spread and the liquidity premium. As such, a positive shock to the CDS spread reduces house prices, suggesting that an increase in the CDS premium causes financial institutions and banks to lend less, reducing the demand for housing and consequently putting downward pressure on house prices. Although, the remaining variables in the model did not have a direct impact on CDS, indirectly they influenced the CDS premium via their impact on house prices. By undertaking a variance decomposition analysis, we show that the house price shock explains nearly 20% of the long-run forecast-error variance of the CDS premium while shocks in the other variables each explain less than 10% of this forecast-error variance.

4.1 Introduction

A great deal has been written about the financial crisis that started in the summer of 2007. The credit crisis initially began with a housing bubble in the US, but because of contagion, it spread from the housing market to affect worldwide financial system. The growth of the credit default swap market coincided with the rapid growth of securitization activities in mortgage backed securities and collateralized debt obligations. During the period 2002-07, the US economy witnessed an economic expansion driven by low interest rates and a housing construction and price boom. Financial innovation enabled banking and other financial institutions to expand their lending capacities and offer mortgage contracts to low-income consumers who were ultimately unable to honor their debt obligations. As such, that period witnessed low quality underwriting standards and a higher than normal default rate on home mortgages (see Taylor (2009); Klomp (2010)). Banks transferred junk loans, subprime and other mortgages into Special Purpose Vehicles (SPVs) and then sold these assets as Residential Mortgage Backed Securities (RMBS) and Collateralized Debt Obligations (CDOs). In the case of CDOs, the senior, mezzanine and junior tranches had differing yields determined by the credit ratings.

Therefore, financial engineering as well as securitization allowed banks and other financial institutions to expand their lending while at the same time satisfying regulatory capital requirements. The subsequent mortgage crisis that commenced in the summer of 2007 led to turmoil in the mortgage markets. Large banking corporations and other financial institutions were obliged to write off losses on many of the structured derivatives and securitized assets on their balance sheet.

The fourth chapter of this dissertation studies the relationship between housing prices in the UK and credit spreads in the UK Banking sector. The sudden and sharp decline in the house prices in the aftermath of the crisis has direct implications for the credit default swap (hereafter CDS spread) of financial institutions. In fact, there are several reasons to believe that house prices have a direct impact on credit risk. Firstly, the recent financial crisis in large part resulted from the bursting of the housing bubble. During the period of credit expansion between 2000 and 2006, credit underwriting standards of mortgage securities were associated with lax supervision by financial authorities (Taylor et al. (2009)). With the continuous rise in house prices and the increasing securitization activities, mortgage lending expanded substantially. As long as the real estate prices increased, lending to lower quality borrowers did not pose a problem for financial institutions as they could always resell houses at a higher price in the secondary market. However, in summer 2007, when residential prices drastically plummeted and mortgage rates substantially increased, with borrowers' personal income growth reaching its lowest level, sub-prime mortgages fell in value and resulted in huge financial losses. This caused a rise in both the overall credit risk of the lending institutions and their CDS spread. In the UK, the CDS spread in the banking sector increased from an average of only 9 basis points in early July 2007 to over 220 basis points in March 2008. Given the close linkage between the housing market and the credit market, there is *a priori* strong evidence to suggest that changes house prices affected CDS premiums.

The CDS spread is usually interpreted as the price of the credit default risk of the underlying asset (Ötger-Robe and Podpiera (2010)). A CDS contract is similar to an insurance contract, meaning that the buyer of the contract, also referred to as the

protection buyer, makes a series of payments, i.e. the spread, to the protection seller of the CDS. In case a credit event occurs, such as a default, a restructuring or bankruptcy of the financial institution involved, the protection buyer is entitled to receive a pay-off from the protection seller. The payment is usually equal to the par value of the underlying asset, typically a bond. If no credit event occurs, the protection seller receives quarterly premium payments (also referred to as the CDS spread) from the protection buyer.

It should be noted that during the credit expansion, there was a large growth in Credit Default Swap (CDS) contracts that were used by banks and financial institutions as a form of insurance against the occurrence of a credit event. Hedging is not the only use of CDS instruments. Banks and hedge funds also use such contracts for speculative purposes. The holder of a CDS contract has no obligation to own the underlying instrument. This characteristic makes it different from insurance contracts in which the holder of the contract is required to have an “insurable interest”. In addition to mitigating the concentration of credit risk at banks and financial institutions, CDS contracts allow institutions providing credit to actively diversify their exposures and increase their lending capacities. Furthermore, CDS contracts helped financial institutions issuing debt to decrease their cost of capital by reducing the level of risk for investors holding bond instruments.

As a result, the CDS premium represents a reliable proxy for credit risk. It can be interpreted as the price of insuring against a credit event (e.g. default) in the underlying asset. The buyer of the CDS contract makes a series of premium payments to the protection seller. If there is a credit event such as a default,

restructuring or bankruptcy, the protection seller is bound by law to pay the holder of the CDS contract the par value of the underlying security upon receipt of the security from the protection buyer. If no credit event occurs, the protection seller receives quarterly premium payments from the protection buyer (1).

The literature on credit risk, more specifically the CDS spread, focuses on analyzing the key structural determinants of CDS spreads. These include the risk free rate and the yield spread, but not the underlying economic factors such as the housing market.¹ The risk-free rate and the yield spread are significant factors in explaining the CDS spread (Naifar (2010), Alexander and Kaeck (2008), Duffie and Singleton (1999), Bevan and Garzarelli (2000), Lekkos and Milas (2001), and In et al. (2003)). Other researchers including Collin-Dufresne et al. (2001), Campbell and Taksler (2003), and Benkert (2004) analyze the CDS spread by focusing on firm level data and incorporate financial variables and volatility. Recent research studies the impact of credit ratings on the CDS spreads and demonstrates that it is important in determining the spread at the firm-level (Hull et al. (2004), Fabozzi et al. (2007)).

With the financial crisis, it became clear that credit risk is not only related to interest rates, yield spread and financial leverage, but most defaults that occurred during the crisis were driven by an underlying factor that is closely related to the house prices. In the fourth chapter of this dissertation, we analyze the impact of the housing

¹ See for example Hammoudeh and Sari (2011) for sectoral CDS focusing on the financial sectors and examining the linkage of such sectoral CDS with interest rates and stock market only.

market on the CDS spread in the UK banking sector, along with other factors such as money market yield spreads and the stock market index in the UK.

This thesis employs the Johansen's method in order to establish the key determinants of the CDS spread in the long run. We then employ the structural VAR model in order to analyze the short-term determinants of the CDS spread. The findings suggest that the house price dynamics are a key-driving factor behind the recent collapse of corporate CDS market influencing credit risk. The Johansen's method indicates the presence of a negative relationship between house prices and the CDS spread. This finding implies that the banking sector, credit market and the housing market are strongly related. Thus, financial distress in the housing market is highly likely to get transmitted to the credit market and impact related markets. Furthermore, we find a negative relationship between the CDS spread and the yield spread in the long run, implying that as investors demand higher yield to compensate for bearing extra risk, it could reflect lower likelihood of credit default in future. These results remained unchanged and consistent even after changing the ordering of the variables in the VAR.

The remaining part of the fourth chapter of this dissertation is structured as follows. Section 4.2 divided into 2 subsections with section 4.2.1 focusing on the various unit root tests conducted on the time series analysis, while in 4.2.1a we discuss in detail the results obtained from the unit root test. In section 4.2.2, we conduct the cointegration analyses using the Johansen's method in order to establish the long-run relationship between our variables. In sector 4.3 we focus on the short

term effects by applying the structural VAR to analyze the short term impact of house prices on the credit default swap premium, and imposing specific shocks. Section 4.4 concludes the fourth chapter.

4.2 Methods and Results

4.2.1 Unit Root tests:

In this section, we discuss the methods used in both the short-run and long-run analysis on the drivers of the CDS in the UK banking sector as a whole. Our first objective is to establish if a long-run relationship exists between CDS spread, house price index, yield spread, TED and stock prices. Each of these variables represents different markets, namely the credit, housing, money and stock markets. In order to identify a long-run relation, it is essential to first test each of the variables for stationarity. Stationarity test is therefore used to assess whether a unit root exists in the series under consideration.

There are various tests that exist to identify the presence of a unit root, including the benchmark Augmented Dickey-Fuller (ADF) test. However, it should be noted that the sample period we are considering includes a highly sensitive period, as it covers both the period before the crisis and the crisis period (2004-2011). Therefore, it is essential to conduct robust stationarity tests that will account for the occurrence of the structural breaks as a result of the crisis.

Testing for the presence of a unit root in series is a crucial condition to establish whether there exists a cointegrating relationship between our variables.

Originally, the Augmented Dickey-Fuller (1979) test was considered to be the benchmark test for stationarity. However, Perron (1989) showed that failing to allow for an existing break may lead to wrong inferences and to a bias that may cause researchers to reject a false unit root null hypothesis. In order to overcome this issue, Perron (1997) offered a solution to allow for a known or exogenous structural break in the Augmented Dickey-Fuller (ADF) tests.

Following this development, several authors including, Zivot and Andrews (1992) and Perron (1997) proposed determining the break point in an endogenous manner from the data. As such, in a research conducted by Lumsdaine and Papell (1997), the authors extended the Zivot and Andrews (1992) model to allow for the occurrence of two structural breaks. However, it should also be noted that these endogenous tests were subject to criticism for the way they treated the existence of breaks under the null hypothesis. As such, given that in the previously mentioned models, the breaks were absent under the null hypothesis of unit root, there may be a tendency for these tests to suggest evidence of stationarity with breaks (Lee and Strazicich (2003)). Therefore, in a research conducted by Lee and Strazicich (2003), the authors came up with a test that proposed a two break minimum Lagrange Multiplier (LM) unit root test, where the alternative hypothesis explicitly implied that the series was trend stationary. In addition, in a research conducted by Ben-David et al (2003), the authors showed that not allowing for multiple breaks may lead to the non-rejection of the null of unit root by these tests that only allow for one break. Zivot and Andrews (1992) model developed a test that allows for one structural break, allowing for breaks in level and trend. In a later research by Lumsdaine and Papell (1997), the authors showed that having only one endogenous

break might prove to be insufficient as it could lead to loss of information. In addition, Maddala and Kim (2003) found that allowing for the possibility of two endogenous breaks gives additional evidence against the unit root hypothesis.

Other researchers that built tests with multiple breaks were Clemente, Montañés and Reyes (1998) who based their analysis on Perron and Vogelsang (1992), by allowing for two breaks. As such, both the Clemente-Montañés-Reyes and the Perron and Vogelsang unit root tests modeled the additive outlier (AO) scheme and the innovational outlier (IO) schemes. In addition, Ohara (1999) further extended the Zivot and Andrews approach by using sequential t-tests; thus examining the scenario of having m breaks along with an unknown break dates. The findings of these researches indicate that allowing for multiple trend breaks was crucial for the consistency of results. The particularity of these previously mentioned endogenous tests that allow for the occurrence of one or several breaks is that under the null hypothesis, the assumption states that there is no structural break. Therefore, the critical values are derived according to this assumption.

Another important unit root test that has been developed by Lee and Strazicich (2003), also referred to as the minimum Lagrange Multiplier (LM) unit root test, has addressed the issue of identifying the structural breaks in an endogenous way. This made a significant contribution to the existing literature on unit root test that allows for structural breaks, as it solved the issue of misinterpretation of results that could result in spurious regressions. It should be noted that the method proposed by Lee and Strazicich (2003) follows the approach

developed by Perron (1989) that allowed for the occurrence of exogenous structural breaks, with a subsequent change in both level and trend. The test developed by Lee and Strazicich (2003) allowed for two endogenous breaks under the null and alternative hypothesis. This solved the issue of incorrectly rejecting the null hypothesis of unit root.

Having discussed both the traditional unit root tests and the ones that allow for the occurrence of one or more, endogenous or exogenous, structural break, in the next section of this thesis, besides using the traditional unit root test (ADF and the Elliott-Rothenberg-Stock-DF-GLS, KPSS tests), we will also conduct different stationarity tests that allow for the presence of one or more structural breaks.

Figure 1.2 illustrates the fluctuations of the CDS, House Price Index, Yield Spread and the FTSE 100 index over the period of 2004-2011. Simply analyzing the figure is not a sufficient way to assess whether our data is stationary or not, i.e. whether all of the variables do or do not have a constant mean, a constant variance and constant auto-covariances for each given lag. Section 2.4 will look at the different stationarity tests, the traditional ones and the ones that allow for one or more structural breaks in the data.

4.2.1a Unit Root Tests results

In this chapter, seven unit root tests have been conducted on the CDS spread, house price index, yield curve, TED spread (liquidity index) and the FTSE100. We have used both standard unit root tests and additional tests that allow for the occurrence of one or more structural breaks. More specifically, these tests are: the

Augmented Dickey–Fuller test (ADF), the GLS, Phillips-Perron Test, Kwiatowski Phillips Schmidt Shin (KPSS), Zivot-Andrews, Lumsdaine-Papell, and the Lee-Strazicich tests. The results from these tests are summarized in table 1.1.

The ADF is a test of the unit root null hypothesis where the test regression contains a constant and no deterministic components. The DFGLS and KPSS tests are known as Dickey-Fuller test with Elliott-Rothenberg-Stock DFGLS detrending, and the Kwiatkowski, Phillips, Schmidt, and Shin tests respectively. It should be noted that the DFGLS test involves estimating the standard ADF test equation with the GLS de-trended data as opposed to the original series. In this chapter, all the stationarity tests contain a constant and no deterministic components. Moreover, we have conducted the KPSS test that differs from other unit root tests in the sense that the time series is assumed to be trend-stationary under the null. Furthermore, besides the traditional unit root tests, three additional stationarity tests have been used that allow for the occurrence of one or more structural breaks. These tests are: Zivot-Andrews (ZA) test that allows for structural break in both intercept and trend, Lumsdaine-Papell and Lee-Strazicich tests. It should be noted that the Zivot and Andrews unit root test is performed by allowing a break at an unknown point in either the intercept, the linear trend or in both. The test is based upon the recursive estimation of a test regression. The test statistic is interpreted as the minimum t-statistic of the coefficient of the lagged endogenous variable.

The second column of table 1.1 illustrates the outcome of the unit root test for [ln(CDS), ln(House Price Index), Yield Spread, TED and ln(FTSE 100)] using the

ADF test. The results indicate that at 1% level, all the variables [ln(CDS), ln(House Price Index), Yield Spread, TED and ln(FTSE 100)] contain a unit root and are therefore, according to this specific test (ADF test), non-stationary.

The third column of the table 1.1 shows the outcome of the Elliott-Rothenberg-Stock DF-GLS test – which is considered to be a more powerful test relative to the ADF test. The results confirm the existence of a unit root (or non-stationarity) in the variables. The fourth and fifth column of table 1.1 illustrates the results obtained from the Phillips Perron test, which similar to the previously conducted ADF and the DF GLS tests indicate that all of [ln(CDS), ln(House Price Index), Yield Spread, TED and ln(FTSE 100)] are non-stationary. In the fifth column of table 1.1, the Kwiatowski Phillips Schmidt Shin (KPSS) tests indicate that lnCDS spread and the yield spread are non-stationary, implying that these two variables contain a unit root, while the TED spread, lnFTSE100, and the house price index turn out to be all stationary. The mixed evidence in the stationarity results from the traditional unit root tests lead us to conduct the stronger and more reliable stationarity tests that allow for the occurrence of one structural break. Therefore, we employ the Zivot and Andrews test, the Lumsdaine and Papell, and the Lee-Strazicich test that allows for the occurrence of two structural breaks.

It should be noted that the Zivot and Andrews (1992) test reflects only one structural break in each variable. However, there is always a possibility that the series were subject to multiple structural breaks. This follows the recent events that

occurred in the global financial system. In fact, the severe financial crisis strongly affected not only the credit risk in the banking sector but also the housing market, by causing structural breaks in the data. At first, there was the housing bubble which later translated into global financial crisis. This means that considering only one endogenous break can turn out to be insufficient and it could therefore lead to a loss of information especially when there is more than one break.

In Ben-David et al (2003), the authors found that “just as failure to allow one break can cause non-rejection of the null of unit root by the Augmented Dickey – Fuller test, failure to allow for two breaks, if they exist, can cause non-rejection of the unit root null by the tests which only incorporate one break”. Thus, Lumsdaine and Papell (1997) introduced a test to capture two structural breaks. As such, the authors found that unit root test that take into consideration two structural breaks (if significant) tend to be more powerful than the tests that allow for only one structural break. Moreover, we also consider the minimum Lagrange Multiplier (LM) unit root test proposed by Lee and Strazicich (2003) which does not only determine endogenously the structural breaks but also avoids issues of bias and spurious rejections. In fact, Lee and Strazicich (2003) procedure is considered to be very reliable and powerful as it allows for two endogenous breaks both under the null and the alternative hypothesis. The results of the Zivot and Andrews, the Lumsdaine and Papell and the Lee-Strazicich tests are summarized in the last three columns of table 1.1.

The outcome from the Zivot and Andrews test is summarized in column 6 of table 1.1. As such, once we allow for a break in the variables, $\ln(\text{CDS})$, $\ln(\text{House price Index})$, and the Yield Spread turn out to be stationary. Both $\ln(\text{CDS})$ and the Yield Spread are significant at 1% level. It is therefore possible to reject the null hypothesis of the presence of a unit root. The structural break in $\ln(\text{CDS})$ occurred in August 2008, while the break point for the yield spread was in October 2008. This coincides with the collapse of Lehman Brothers and the deterioration of the conditions of the banking sector. Similarly, $\ln(\text{House Price Index})$ is significant at a 5% level. Therefore it is possible to reject the null hypotheses and consider $\ln(\text{House Price Index})$ as stationary. The structural break point in the housing market was in March 2008. This corresponds to the period when the CDS spread peaked at 220 basis points, as compared to its pre-crisis value of July 2007, when it averaged 9 basis points. It should be noted that this contradicts the results from ADF, DF GLS, Phillips Perron and KPSS tests which stated that all of the variables in the model were non-stationary. The two variables that still contain a unit root, even after allowing for a structural break, are $\ln(\text{FTSE 100})$ and TED. However, once the Zivot-Andrews unit root for $\ln(\text{FTSE 100})$ and the TED spread is conducted in first differences, both variables became stationary, being significant at 1% level, as shown in table 1.2.

Table 1.2 shows the results of the unit root tests once all the variables are taken in first differences. According to both the ADF and DF GLS tests, expressed in columns 2 and 3 of table 1.2, after considering $\ln(\text{CDS})$, Yield Spread, TED and $\ln(\text{FTSE 100})$ in first differences, the results indicate that the series become stationary (significant at 1% level). Thus, we can reject the null hypothesis of a unit

root and conclude that the data is stationary. The only variable that remains non-stationary is $\ln(\text{House Price Index})$. This is very likely to be a result of the structural shift that occurred during the recent financial crisis. In addition, when the more powerful stationarity tests were undertaken, both Phillips Perron and the KPSS tests showed that the $\ln(\text{House price index})$ along with the $\ln(\text{CDS})$, Yield Spread, TED and $\ln(\text{FTSE 100})$ were all stationary at 1% level.

As previously mentioned, the non-stationarity of the $\ln(\text{House price index})$ (according to the ADF and DF GLS tests) even after taking the variable in first difference, relates to the data sample we are analyzing which includes a period of severe financial crisis (2007-2009). In fact, the non-stationarity of this variable is driven by the structural break(s) that occurred during the financial crisis. Therefore, it is of a paramount importance to consider the outcome of the unit root tests that allow for structural breaks, namely: Zivot-Andrews, Lumsdaine-Papell and Lee-Strazicich tests. Allowing for a single structural break in the level and trend of each series, we follow the procedure of Zivot and Andrews (1992), in order to estimate one endogenous break under the alternative hypothesis of stationarity. Most series turn out to be stationary when applying the ZA test with break at least at 10% level of significance for the sample period. We also consider Lumsdaine and Papell (1997) who extended the Zivot and Andrews (1992) model to accommodate two endogenous breaks under the alternative hypothesis of stationarity. However, these endogenous tests did not consider breaks under the null hypothesis of unit root and hence there may be a tendency for these tests to suggest evidence of stationarity with breaks (Lee and Strazicich, 2003). We therefore consider the Lagrange Multiplier (LM) unit root test developed by Lee-Strazicich, with two endogenous breaks under

the null and the alternative hypothesis of stationarity. The results of Lee-Strazicich test with two endogenously determined structural breaks indicate the rejection of the null of unit root of all variables.

Given that there is evidence that at least two variables in our model are non-stationary depending on the tests considered, this gives rise to the possibility of existence of a cointegrating relationship between our variables. Therefore, in the next section, we conduct the Johansen cointegration test.

4.2.2 Cointegration Tests

In this section we are using the Johansen's cointegration test (Johansen, 1991) in order to identify the existence of any cointegrating relationship. The Johansen method approach is used to investigate which of our variables has better predictive power to explain the behavior of the CDS spread. This method helps to uncover whether a long run relationship exists between the variables, whereas in order to analyze the short run effects, we conduct the structural VAR analysis.

Before conducting this test, we first need to establish the optimal number of lags to be used in our model. For this purpose, we use the VAR Lag Order Selection Criteria. The results are presented in table 1.3.

From table 1.3, the Sequential Modified LR test Statistic, Final prediction error, Akaike and Hannan-Quinn information criteria all indicate that the optimal lag length for our VAR model is 3 lags. We estimate a VAR model with 3 lags as found

to be optimal by the VAR Lag Selection Criteria (as shown in table 1.3). The Johansen test provides evidence that there exists one cointegrating relation using a linear model (with intercept and trend). In table 1.4, the trace test statistics indicates the existence of one cointegrating equation at 5% significance level. Given that the null $r=0$ is rejected at a 5% significance level, implies that there is one meaningful long-run relation between $\ln(\text{CDS})$, $\ln(\text{House Price Index})$, Yield Spread, TED Spread and $\ln(\text{FTSE 100 index})$.

The normalized cointegrating equation can be written as follows:

$$\begin{aligned} \ln CDS_t = & 0.2219 - 26.8960 \ln HP_t - 2.5605 YS_t - 2.6148 TED_t - 13.7485 \ln FTSE_t + 0.2202 T \\ \text{Eq (3)} \end{aligned}$$

[2.8437]
[4.1418]
[1.7687]
[2.5709]
[5.5326]

Where CDS: the Credit Default Swap Spread, HP: House Price Index, YS: Yield Spread TED: spread, FTSE: FTSE-100 Index, T: Time trend. It should be noted that the CDS spread, the house price index, and the FTSE-100 index are all taken in natural logarithms.

In Equation (3), figures in brackets represent the t-values. All the key variables [$\ln(\text{House Price Index})$, Yield Spread, $\ln(\text{FTSE100})$, TED and the Time Trend] included in the normalized cointegrating relation are statistically significant and the signs of the coefficients turned out to be as expected a priori. The long-run relationship equation can be explained as follows. First, an increase (decrease) in the house price index by 1 percent is associated with a decrease (increase) in the CDS spread by about up to 26.90 percent in the sample period. Furthermore, an increase (decrease) in the yield spread by 1 percent is associated with a 2.56 per cent decrease (increase) in the CDS spread. Moreover, an increase (decrease) in the TED spread by

1 percent is associated with a 2.61 per cent decrease (increase) in the CDS spread. Also, we note that an increase (decrease) in the $\ln(\text{FTSE100})$ by 1 percent is associated with a 13.75 per cent decrease (increase) in the CDS spread. Finally, a significant time trend suggests an increase in the CDS spread over the sample period.

From equation (3), it can be clearly observed that there is a negative relationship between the CDS spread and the house price index as expected. CDS contracts work as insurance contracts. The CDS spread is the price that the protection buyer pays to the protection seller in order to benefit from a guarantee that in case of a default, the holder of the CDS will be covered against a default. Thus, as risk increases, the premium on the CDS contract also rises in order to reflect the higher risk. Banks and other financial institutions that were issuing CDS contracts backed on mortgages priced their CDS contracts based on house prices. In fact, when house prices were high, even if a lender defaulted on his/her payment, it was relatively easy for the bank to recover the initial cost of the property given the continuous upward trend in house prices. Thus, the CDS spread was narrow reflecting a low default risk. However by the end of 2006, with the beginning of the housing bubble when house prices started to collapse, the number of defaults suddenly went up. This was reflected in a much larger CDS spreads. In equation (3), the long run equation confirms this negative relationship between the CDS spread and the house price index.

An additional observation from Equation (3) is the negative relationship between the yield spread and the CDS spread. As it was previously mentioned in the literature review, the steepness of the yield curve indicates future economic activity.

Thus, the steeper the yield curve, the higher is the expected future interest rate. In fact, in times of a recession or when firms start defaulting, interest rates tend to be very low, while the CDS spread tends to increase given the higher credit risk. The higher credit risk directly impacts the CDS spread as it is now more expensive for investors to benefit from a protection against default. This is reflected in a rising CDS spread. Therefore, there should be a negative relationship between the yield curve and the CDS spread. This negative relationship between the slope of the term structure, yield spread and the swap spreads was empirically supported by Fehle (2003), In et al. (2003), Fama (1984) and Estrella and Hardouvelis (1991).

Another line of thinking that supports this negative relationship between swap spreads and the slope of the risk free term structure was found by Friedman and Kuttner (1992). The authors explain that the slope of the risk-free term structure was found to be pro-cyclical while the credit spreads could be counter-cyclical. For this reason there should be a negative relationship between swap spreads and the slope of the risk-free term structure. Also Longstaff and Schwartz (1995) find that as interest rates increase, there could be lower probability of default, and thus a narrowing of the credit spread. In addition, we observe that in the long-run, liquidity spread (TED spread) should be negatively related to CDS spread; implying that as liquidity increases, banks have a better ability to sustain a negative credit event. Therefore, the level of CDS spread and credit risk should decrease. Moreover, equation (3) indicates that in the long-run, the FTSE100 is also negatively related to the CDS spread. This means that as the performance of the stock index improves, the level of credit risk should decrease, while the CDS spread should be narrower. The

transmission channel leading to the credit crisis is summarized in figure 1.1 of this chapter.

Having derived the long-run relationship between the UK bank CDS spread and the UK House Price Index, Yield Spread, TED and the FTSE-100 Index, in the next section we will analyse the short-run relationship between our variables using the structural VAR analysis. Regardless of the order of integration, Sims et al. (1990) showed that the OLS estimates of a VAR model in levels are still consistent. Given the mixed results across tests with regard to the stationary properties of the variables, we estimate different recursive VAR models. The optimal lag selection is found to be 3 for the VAR model (see Table 1).

4.3 Structural VAR Analysis

In this section, we discuss the structural VAR model (SVAR) that was employed to analyze the short run effects of changes in house prices.

Having tested the variables for stationarity, it is possible to formulate a structural VAR with the stationary variables so as to analyse the dynamic relations between the variables. It is first important to establish the optimal number of lags to be used in our model. For this purpose, we use the VAR Lag Order Selection Criteria. The results are presented in table 1.3.

From table 1.3 it is clear that the Sequential Modified LR test Statistic, Final prediction error, Akaike information criterion as well as the Hannan-Quinn information criterion all indicate that the optimal lag length for a VAR model is 3 lags. Hence we estimate a VAR model with 3 lags. We now proceed to analyze the significance of these CDS determinants in the short run. For this purpose, a structural

VAR method is implemented by exploring the degree of interdependence between the CDS spread and the house price index, yield spread, TED Spread (liquidity), and the FTSE 100 index.

The short run analysis is achieved by undertaking impulse response based shock analysis via a vector auto-regression (VAR). The main purpose of structural VAR (SVAR) estimation is to obtain orthogonalisation of the error terms for the impulse response analysis. The restricted structural VAR model defines the relationship between the VAR residuals, that is, the unexpected shocks, and the structural shocks, which are exogenous and uncorrelated with each other. This can be defined as follows:

$$Ae_t = Bu_t, \text{ with: } E[u_t u_t'] = I$$

Where: u_t is the vector of structural shocks, while A and B are the matrices that define the linear relationship between the structural shocks and the VAR residuals e_t .

The following recursive structure is imposed to identify the different shocks:

$$\begin{bmatrix} e_{td} \\ e_{yd} \\ e_{ft} \\ e_{hp} \\ e_{cd} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{bmatrix} u_{td} \\ u_{yd} \\ u_{ft} \\ u_{hp} \\ u_{cd} \end{bmatrix}$$

e_{td} is from the TED equation, e_{yd} is the residual from the yield spread equation, e_{ft} from the FTSE equation, e_{hp} from the house price equation, and e_{cd} from the CDS spread equation. This is the assumed ordering of the variables in this model with a recursive sequencing of the contemporaneous restrictions. This recursive structure

means that the first variable in the ordering is not affected by shocks to the other variables, but shocks to the first variable affect the other ones; the second variable affects the third and fourth ones, but it is not affected contemporaneously by them, and so on.

The SVAR was formulated with the following ordering of the endogenous variables: TED spread, Yield Spread, ln (FTSE 100), ln (House Price Index), and ln(CDS spread). The reason behind this specific ordering stems from the theoretical ordering of the variables that should run from the more exogenous to the less exogenous variable. In fact, both the liquidity spread and the yield spread are likely to be determined by the monetary policy and the state of the economy prevailing during the specific period. However, the FTSE 100 index and house price index are less exogenous than the TED spread and the yield spread which are consequently placed later in the ordering. The CDS spread is assumed to be affected by all of the previously included variables and is therefore placed last in the ordering.

This SVAR model with the above recursive identification strategy enables us to perform an analysis of unexpected shocks, interpreting the shocks in economic terms which will not be possible in a simple VAR model. Our SVAR model includes 5 variables. We only impose short-run restrictions as our objective is to identify the five shocks discussed earlier.

Figures 1.3-1.7 shows the responses from the structural VAR model with the change in ordering in Fig.1.8. From figure 1.7 it is clear that the response of CDS spread to a one standard deviation positive shock in House price index is positive

and significant, making the house price channel as a key factor in explaining CDS premiums. Also following a positive shock to credit risk, house price tends to decline. The house price variation also appears to be driven by the yield spread and the liquidity premium (TED spread) as shown in Figure 1.6. Overall, our results indicate that there is negative relationship between CDS spread and house prices, with credit risk driving house prices in the short run.

We examine the effect of a house price shock whether it drives short-run credit risk in the UK. We observe a higher level of credit risk in the medium term following a positive house price shock, as people have easy access to the mortgage market through low interest rates and low cost of borrowing, raising house prices and higher credit risk as in Figure 1.6. However if a shock originates in the loan market as reflected in a shock to the CDS, such a shock gives rise to lower house prices as in Figure 1.7 as the level of borrowing is decreased due to higher credit risk. We also checked for robustness by changing the ordering of variables with CDS being the first in the ordering as opposed to being the last in the variable ordering. However the results remained robust (see Figure 1.8). Moreover the generalized impulse responses tend to be insensitive to variable ordering. Therefore the results we have show that positive house price shocks drive credit risk in the medium run remained robust, and shocks to credit risk contribute to lowering house prices as it happened in the aftermath of the recent credit crisis.

A positive shock to FTSE index on the other hand lowers bank CDS, long-term yield and TED spreads (Fig.1.5), while a shock to the yield spread has a significant positive impact on CDS spread (Fig.1.4). The negative relationship

between the CDS spread and the FTSE 100 index suggests that as FTSE fell during the crisis, much of its market capitalization made up of bank stocks would be indicative of stress in the banking sector thereby raising the bank CDS. While, also in the short-run, a shock to TED spread increases bank CDS (Fig.1.3), a one standard deviation shock in house price index also increases bank CDS, making the house price channel as a key factor in explaining CDS premiums (see Fig.1.6). The result that CDS spread responds positively to a shock in the housing market which remains robust even if we alter the ordering of variables (see Fig. 1.8, last column, first row).

In addition, a positive shock to the CDS spread lowers house prices, because when the overall risk perception in the CDS market increases, financial institutions and banks tend to lend less to borrowers, thereby reducing demand for housing and consequently house prices decline, equity index goes downwards, long-term bond yield increases and TED spread increases. The literature on the relationship between the TED spread and the CDS spread is mixed. This is quite apparent from Fig.1.7 that TED spread initially increases following a shock to the CDS spread and in the medium term, TED spread narrows as short rate declines. The liquidity factors tend to get embedded in the CDS spread, showing a direct relationship between the two at the aggregate level, whereas the story can be different at individual bank level.

We explore this issue further by means of variance decomposition analysis as shown in table 1.5 that shows that the house price shock explains nearly 20% of the long-run forecast-error variance of the credit default swap premium. By contrast, the other shocks each explain under 10% of this forecast-error variance. Table 1.5 also

reveals that the own innovations of CDS spread explain about 60% of the variation in credit risk.

4.4 Conclusion

Credit Default Swap premiums are amongst the most transparent and reliable indicators of credit risk. With the commencement of the financial crisis, serious concerns were raised with regard to the underlying trading incentives and the impact of such instruments on financial stability, especially following the collapse of American International Group. With the drastic house price decrease, many borrowers started heavily defaulting, which has increased the CDS premium. The fourth chapter of this dissertation contributes to the empirical literature on credit default swaps and credit risk by one of the first multivariate analyses of the factors affecting the CDS spread and the overall credit risk. This is the first research to our knowledge that conducts Structural VAR analysis to link the housing market to the credit market in the light of the recent financial crisis.

The fourth chapter of this thesis analyses the factors that determine CDS spreads in the UK banking sector. In particular we analyze the impact of the house price index, the liquidity premium (TED), the yield spread and the FTSE 100 index. As such, the Johansen's Co-integration was used as the long-run method, while the structural VAR was used for the short-run analysis.

We find evidence that house price dynamics are a key-driving factor behind the recent collapse of the corporate CDS market that captures the credit risk of the banking sector. Specifically, there exists a negative relationship between the CDS

spread and the house price index in the UK after controlling for other determinants of credit risk. In addition, a negative relationship exists between the CDS spread and the yield spread that reflects investors' risk aversion following the financial crisis. Also, the TED spread and the CDS spread appear to be positively related in the long-run, while the FTSE100 is also negatively related to the CDS spread. This negative relationship between the stock index and the CDS spread was reflected in the wake of the recent crisis, when FTSE 100 crashed, much of its market capitalization led to a dramatic increase the bank CDS

In the Structural VAR I impose short-run restrictions to identify the five shocks arising from the CDS spread, namely: the house price index, the yield spread, the TED spread, and the FTSE100. Each of these variables are of particular interest given that they represent the housing market, the stock market as well as the money market. The Structural VAR analysis allows us to capture the empirical interrelationships among these variables. The SVAR findings indicate that a positive shock to house prices significantly increases the CDS spread in the medium-term, in the UK banking sector. In addition, apart from its own shock, the house price shock explains a big part of the variance (nearly 20%) in CDS spread. These results remained robust even after changing the ordering of the variables in the Structural VAR.

The findings from chapter 4 of this thesis indicate that the strongest variable that is able to explain the CDS spread is the house price index, which is influenced by yield spread and TED spread. In addition, we find that positive shock to the CDS spread reduces house prices. The rationale for this may be that an increase in the

CDS premium causes financial institutions and banks lend less, reducing the demand for housing and consequently putting downward pressure on house prices. None of the other variables in the model have a direct impact on CDS, but they indirectly influence the CDS premium via their impact on house prices. By undertaking a variance decomposition analysis, we show that the house price shock explains nearly 20% of the long-run forecast-error variance of the CDS premium while shocks in the other variables each explain under 10% of this forecast-error variance.

Table 1.1: Testing for Unit Roots (variables in levels)

	<i>ADF</i>	<i>DFGLS</i>	<i>Phillips Perron Test</i>	<i>Kwiatowski Phillips Schmidt Shin (KPSS)</i>	<i>Zivot-Andrews</i>	<i>Lumsdaine-Papell</i>	<i>Lee-Strazicich</i>
ln(CDS)	-0.5865	-0.3986	-0.7419	0.9086**	-7.5062**	-6.2853	-5.6303**
ln(House Price Index)	-2.2372	-0.9099	-2.5931	0.3303	[August 2008] -5.0826*	[2007:04 2008:04] -5.7720	[2007:02 2007:12] -4.8715**
Yield Spread	-0.8702	-0.8867	-0.6464	0.7456**	[March 2008] -5.6978**	[2007:11 2009:01] -5.0559	[2006:10 2008:10] -5.6644**
TED	-2.1354	-2.0111	-2.1413	0.3437	[October 2008] -3.7427	[2008:04 2009:04] -4.1139	[2008:01 2009:01] -5.9759**
ln(FTSE 100)	-1.9347	-1.2743	-1.7848	0.1908	[February 2008] -3.2745	[2007:03 2008:11] -5.1457	[2007:06 2009:03] -5.2724**
					[September 2009]	[2007:11 2009:03]	[2007:10 2008:09]

Notes for table 1.1: ADF is a test of the unit root null hypothesis where the test regression contains a constant and no deterministic components. *DFGLS* and KPSS tests are known as Dickey-Fuller test with GLS detrending, and the Kwiatkowski, Phillips, Schmidt, and Shin test respectively. The *DFGLS* test involves estimating the standard ADF test equation with the GLS de-trended data as opposed to the original series. The *DFGLS* contains a constant and no deterministic components. The KPSS test differs from other unit root tests in the sense that the time series is assumed to be trend-stationary under the null. The KPSS contains a constant and no deterministic components. Zivot-Andrews (ZA) test allows for structural break in both intercept and trend.

** indicate t-values being significant at 1% level, * indicate t-values being significant at 5% level implying no unit root in the series. The asymptotic 1 per cent critical values for the ADF test is: -3.51. The critical value at 1 percent level for the Elliott-Rothenberg-Stock DF-GLS: -2.60. The asymptotic 1 per cent critical values for the Phillips Perron test is: -3.51. The asymptotic 1 per cent critical values for the KPSS test is: 0.7390. Under KPSS test, the null is stationary. The Critical Values at 1% level for the Zivot and Andrews test are: -5.57 and at 5% level: -5.08, the numbers in brackets are the estimated structural breaks based on the ZA test. Lumsdaine-Papell Unit Root Test critical values are -7.1900 (1% sig level), -6.6200 (5% sig level) and -6.3700 (10% sig level). Critical values of the endogenous two-break LM unit-root test at 10%, 5% and 1% level of significance are -3.504, -3.842 and -4.545 respectively from Table 2 Lee and Strazicich (2003: 1084).

Table 1.2: Testing for Unit Roots (variables in first differences)

	<i>ADF</i>	<i>DFGLS</i>	<i>Phillips Perron Test</i>	<i>Kwiatowski Phillips Schmidt Shin (KPSS)</i>	<i>Zivot-Andrews</i>
$\Delta \ln(\text{CDS})$	-7.2753**	-6.1590**	-7.2984**	0.1263	-
$\Delta \ln(\text{House Price Index})$	-2.7105	-1.1345	-5.0465**	0.2900	-
$\Delta \text{Yield Spread}$	-5.3400**	-4.3868**	-5.3319**	0.2173	-
ΔTED	-9.3110**	-9.3651**	-9.4266**	0.0957	-7.5604** [January 2009]
$\Delta \ln(\text{FTSE 100})$	-8.7291**	-8.1586**	-9.535794**	0.1146	-5.9963** [April 2009]

Notes for table 1.2: ADF is a test of the unit root null hypothesis where the test regression contains a constant and no deterministic components. *DFGLS* and KPSS tests are known as Dickey-Fuller test with GLS detrending, and the Kwiatkowski, Phillips, Schmidt, and Shin test respectively. The *DFGLS* test involves estimating the standard ADF test equation with the GLS de-trended data as opposed to the original series. The *DFGLS* contains a constant and no deterministic components. The KPSS test differs from other unit root tests in the sense that the time series is assumed to be trend-stationary under the null. The KPSS contains a constant and no deterministic components. Zivot-Andrews (ZA) test allows for structural break in both intercept and trend.

** indicate t-values being significant at 1% level, * indicate t-values being significant at 5% level implying no unit root in the series. The asymptotic 1 per cent critical values for the ADF test is: -3.51. The critical value at 1 percent level for the Elliott-Rothenberg-Stock DF-GLS, with a constant is: - 2.59. The asymptotic 1 per cent critical values for the Phillips Perron test is: -3.51. The asymptotic 1 per cent critical values for the KPSS test is: 0.7390. Under KPSS test, the null is stationary. The Critical Values at 1% level for the Zivot and Andrews test are: -5.57 and at 5% level: -5.08, the numbers in brackets are the estimated structural breaks based on the ZA test.

Table 1.3: VAR Lag Order Selection

Lag	LR	FPE	AIC	HQ
0	NA	4.21e-05	4.21e-05	1.324539
1	819.1956	6.26e-10	6.26e-10	-9.596274
2	48.53018	4.64e-10	4.64e-10	-9.703453
3	39.48386*	3.81e-10*	3.81e-10*	-9.713028*
4	19.63113	4.23e-10	4.23e-10	-9.428607
5	19.30998	4.67e-10	4.67e-10	-9.162545
6	14.97610	5.54e-10	5.54e-10	-8.839041
7	15.83245	6.40e-10	6.40e-10	-8.558750
8	16.84717	7.17e-10	7.17e-10	-8.333392
9	19.20207	7.48e-10	7.48e-10	-8.208600
10	19.42243	7.61e-10	7.61e-10	-8.146374

Notes for table 1.3: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, HQ: Hannan-Quinn information criterion. The optimal lag length is found to be 3 months across different lag selection criteria

Table 1.4: Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. Of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.343598	71.73126	63.87610	0.0094
At most 1	0.197909	37.21076	42.91525	0.1655
At most 2	0.141312	19.12702	25.87211	0.2733
At most 3	0.077721	6.634399	12.51798	0.3842

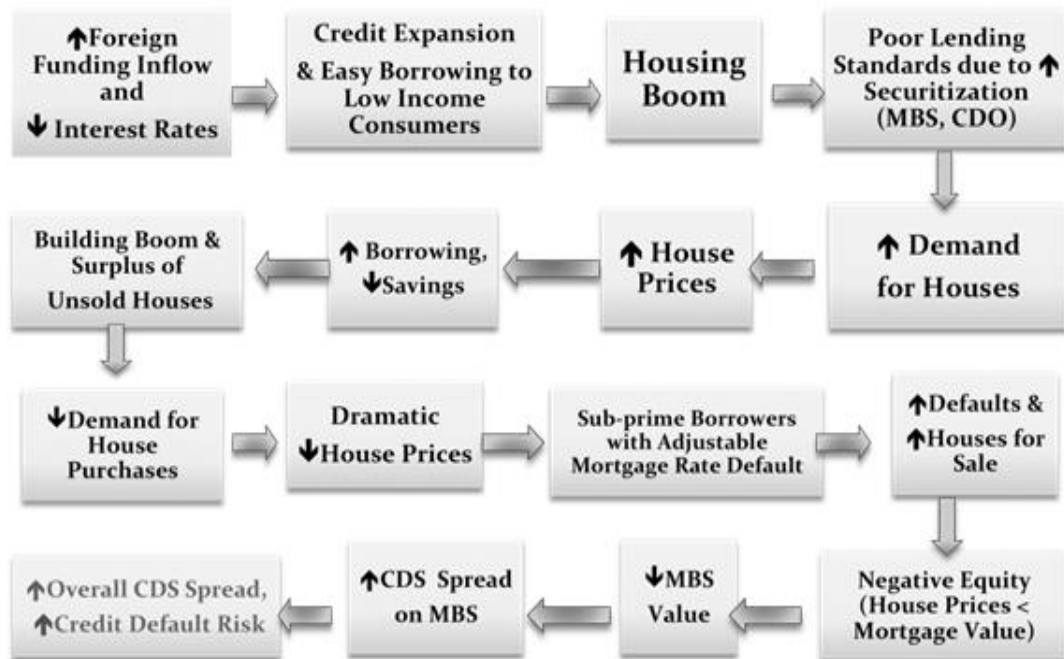
Notes for table 1.4: Trace test indicates 1 cointegrating eqn(s) at the 0.05 level, *denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values. The test confirms existence of one long-run relation.

Table 1.5: Variance decomposition of model variables

Period	S.E.	TED	YELDCURVE	LFTSE	HOUSEPRICE	CDS
Variance Decomposition of TED:						
1	0.17	100.00		0.00	0.00	0.00
6	0.28	75.20		10.39	0.04	0.33
12	0.33	58.47		16.95	0.34	0.44
24	0.37	56.43		15.92	0.41	4.22
36	0.38	51.97		16.64	0.45	4.69
Variance Decomposition of YELDCURVE30:						
1	0.24	10.80		89.20	0.00	0.00
6	0.71	51.27		41.86	3.79	0.04
12	1.05	53.80		20.82	4.19	0.10
24	1.45	33.53		11.59	3.18	1.28
36	1.61	27.76		10.65	3.54	7.39
Variance Decomposition of LFTSE:						
1	0.05	23.14		0.63	76.24	0.00
6	0.08	25.58		7.16	47.03	10.48
12	0.11	16.27		14.55	28.88	14.22
24	0.12	15.05		16.07	22.04	11.98
36	0.12	15.00		16.16	21.55	12.93
Variance Decomposition of LOGHOUSEPRICE:						
1	0.01	1.44		0.40	0.13	98.02
6	0.02	10.72		4.95	0.23	76.41
12	0.03	7.13		13.17	0.50	53.76
24	0.04	5.94		17.01	0.66	35.62
36	0.05	6.45		16.59	0.69	35.02
Variance Decomposition of LOGCDS:						
1	0.23	14.08		1.31	15.26	0.38
6	0.53	9.20		1.55	7.02	0.71
12	0.69	6.31		1.12	5.17	3.49
24	0.84	5.30		3.11	5.36	13.76
36	0.93	7.09		6.46	6.02	19.19

Notes for table 1.5: Cholesky Ordering: TED YELDCURVE LFTSE LOGHOUSEPRICE LOGCDS; The variables in each column denotes shocks or innovations in that variable.

Figure 1.1: The Transmission Channel Leading to the Credit Crisis



Notes for figure 1.1: This figure demonstrates how the housing bubble that originated in the US evolved into subprime mortgage crisis, which later turned into the global financial crisis affecting the world economy. It can be observed that the subprime mortgage crisis suggests a spillover effect, creating volatility in other markets, thus affecting the CDS spread.

Figure 1.2: Graphical illustration of the CDS spread, House Price Index, Yield Spread and the FTSE 100 index series

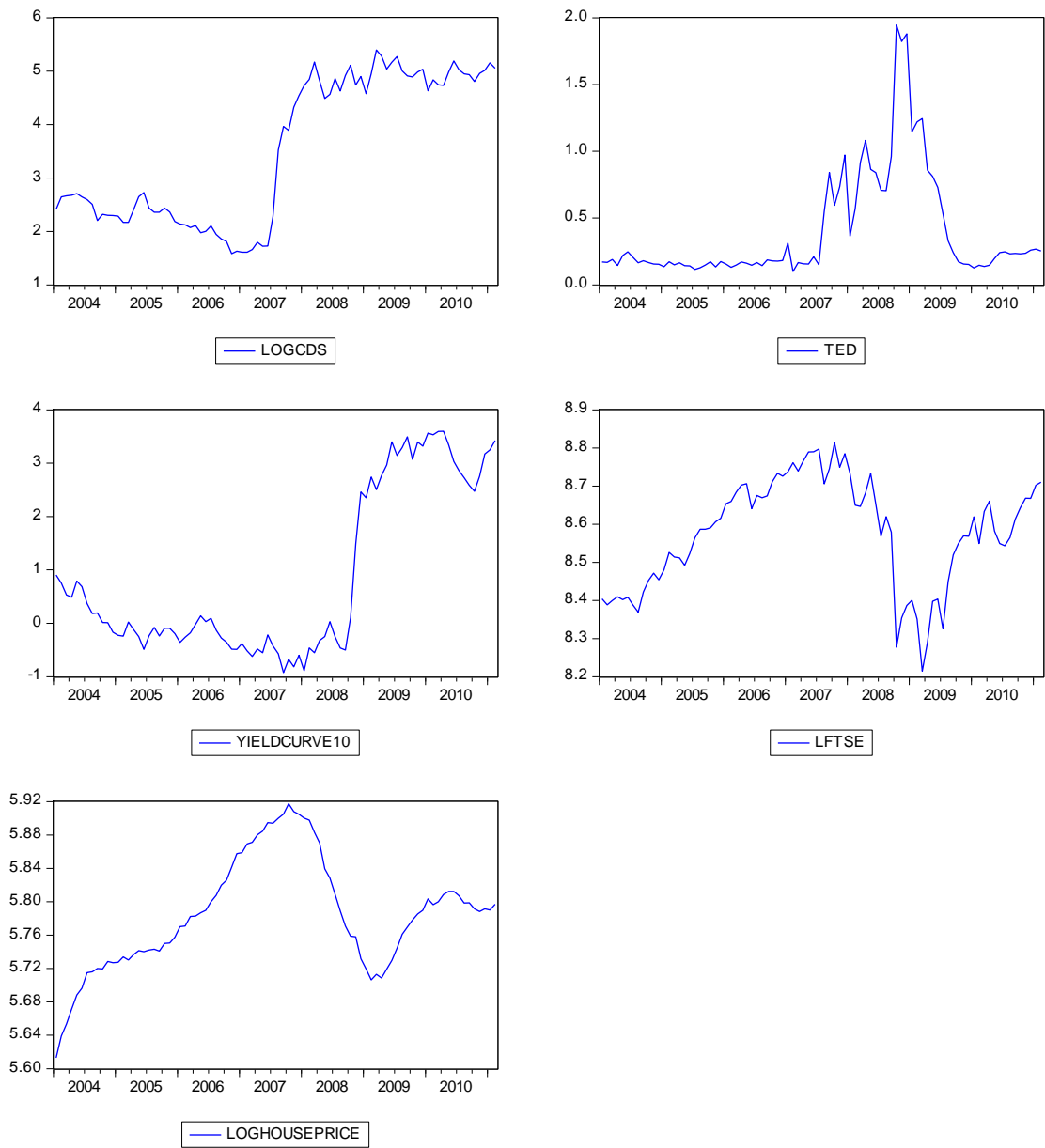
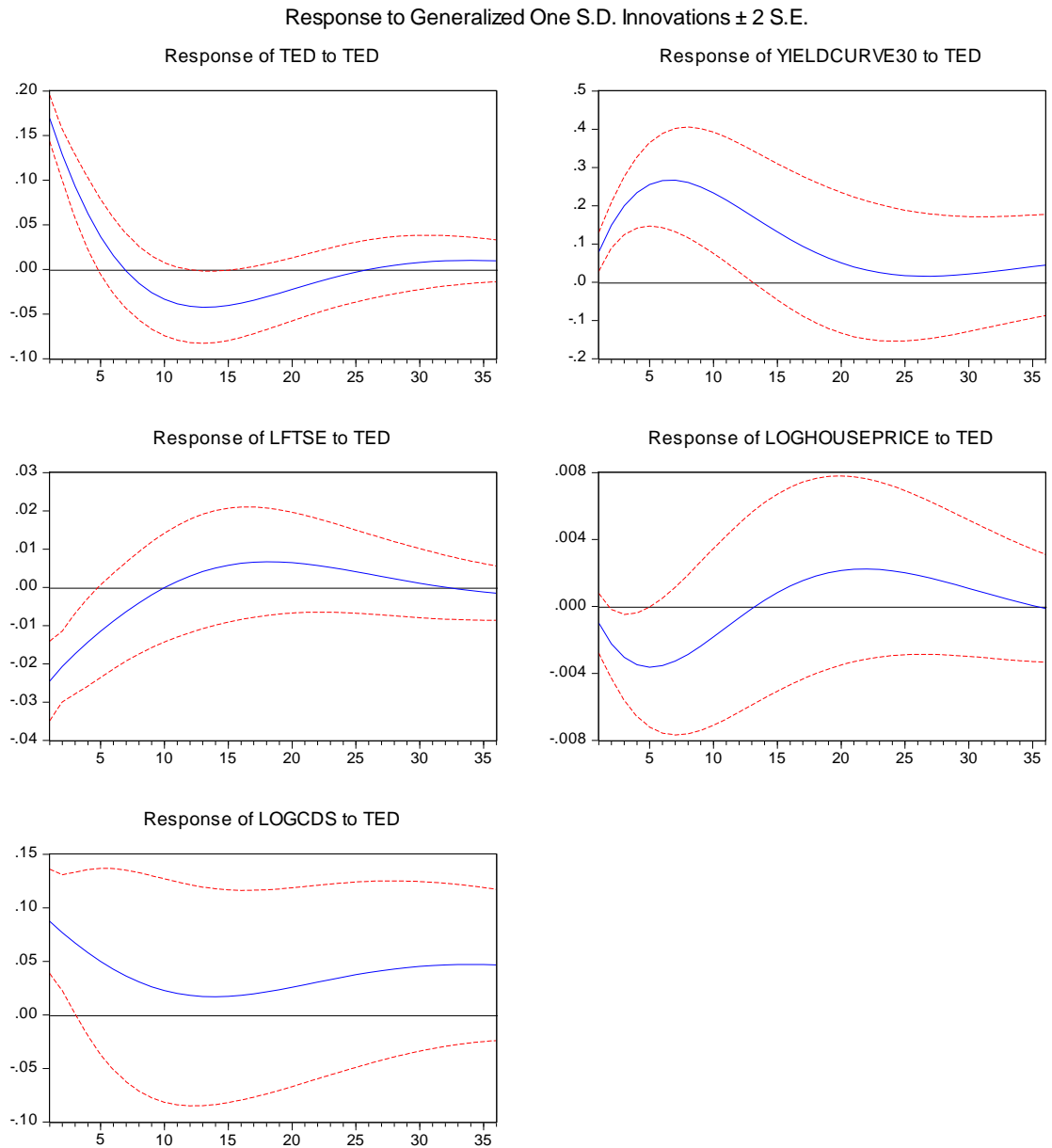


Figure 1.3: Impulse responses to a shock in TED spread



Notes: This figure indicates the outcome of the impulse responses to a shock in TED spread. The SVAR model is formulated as follows: TED spread, Yield Spread, LOG (House Price Index) , LOG (FTSE 100) and LOG (CDS spread) .

Figure 1.4 Impulse responses to a shock in Yield spread

Response to Generalized One S.D. Innovations ± 2 S.E.

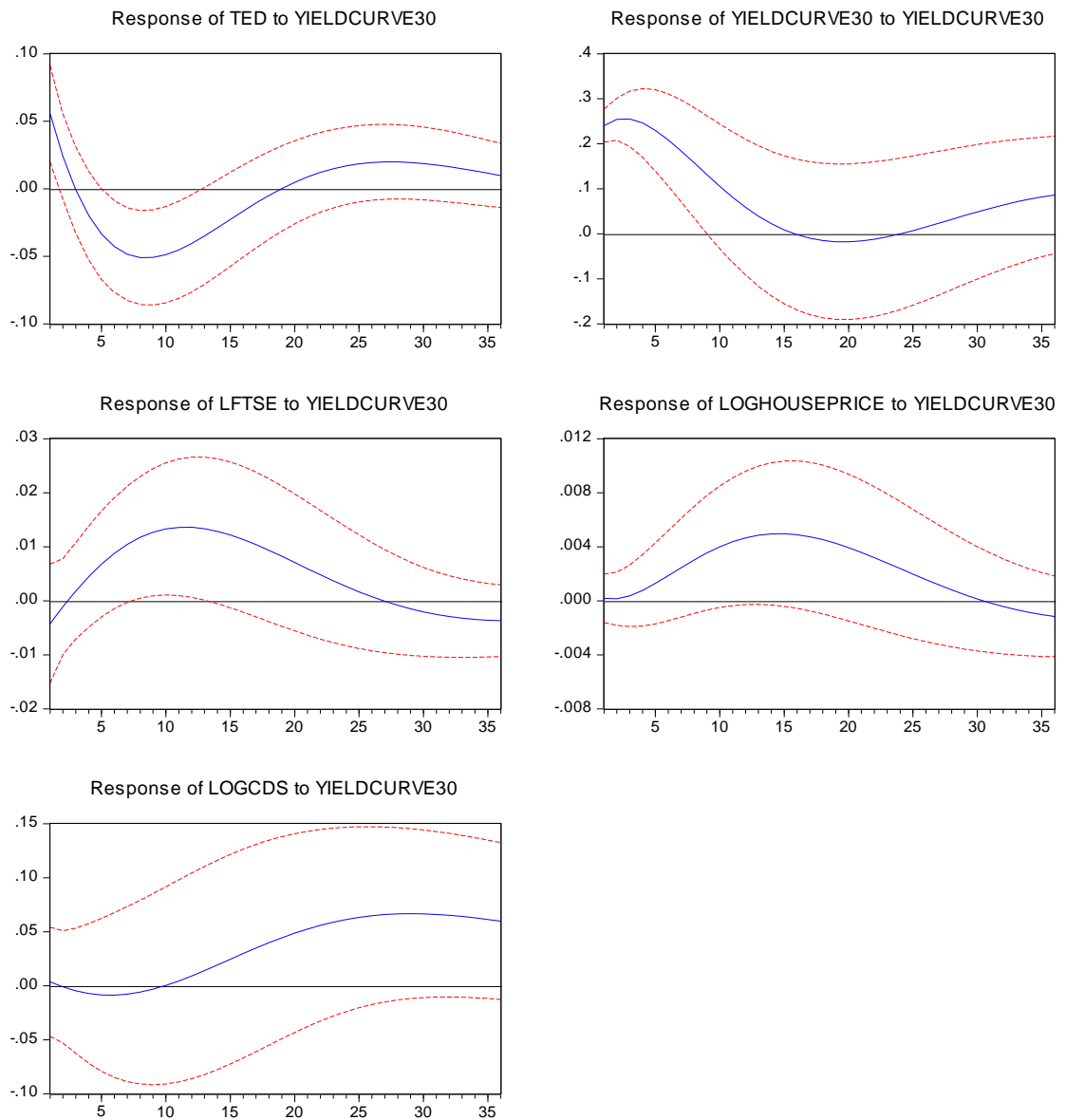


Figure 1.5 Impulse responses to a shock in Share Price

Response to Generalized One S.D. Innovations ± 2 S.E.

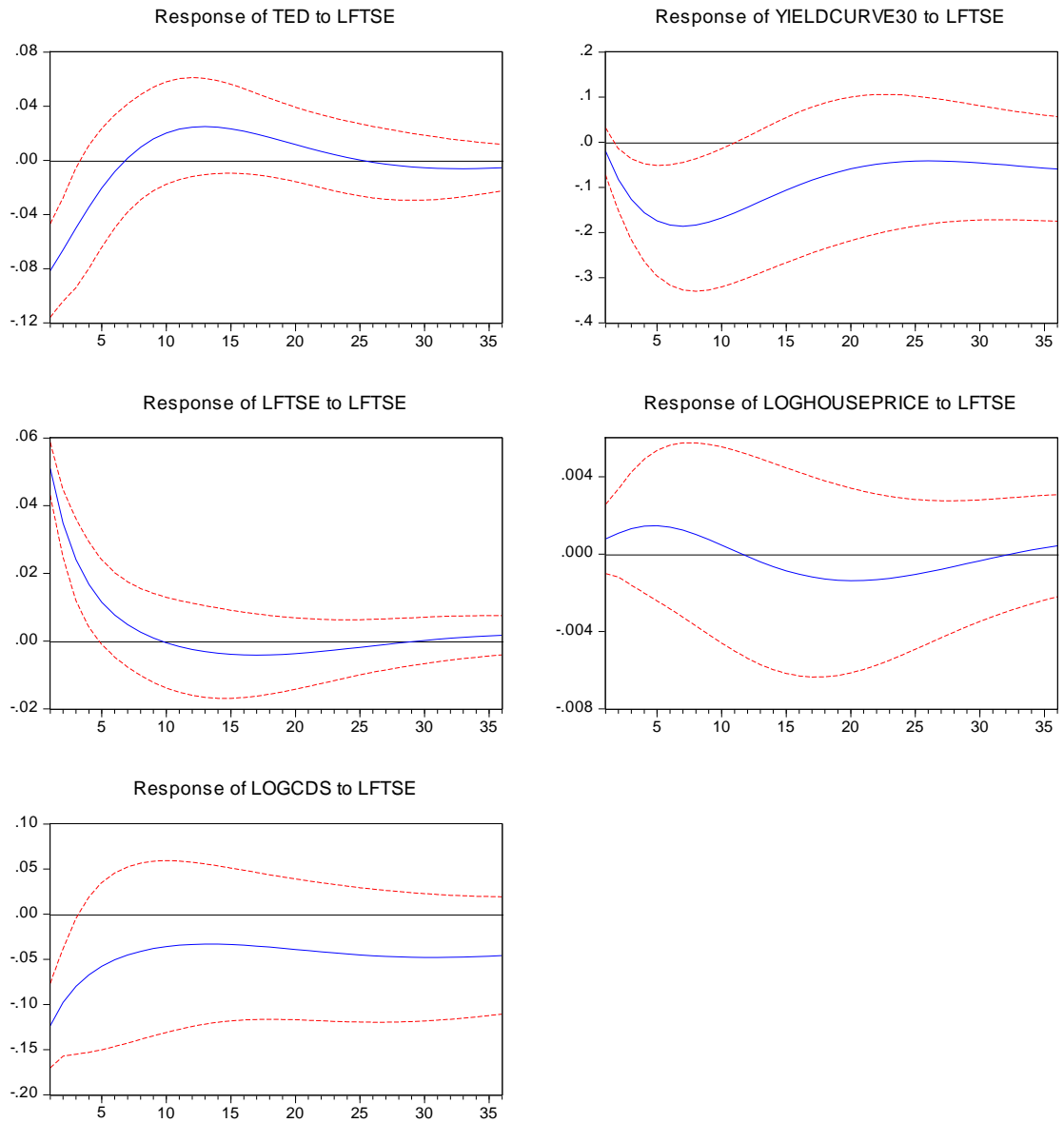


Figure 1.6 Impulse responses to a shock in House Price

Response to Generalized One S.D. Innovations ± 2 S.E.

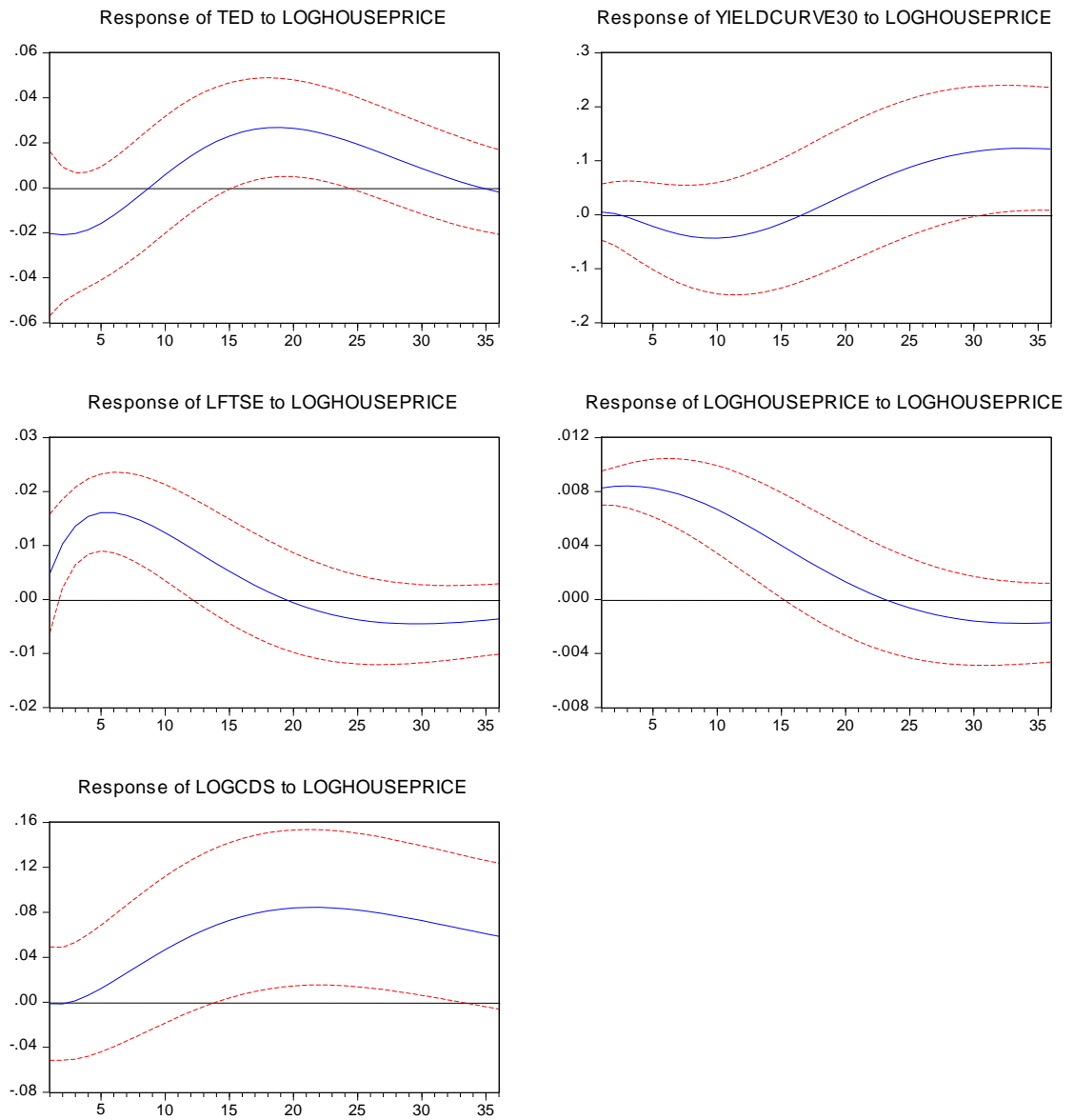
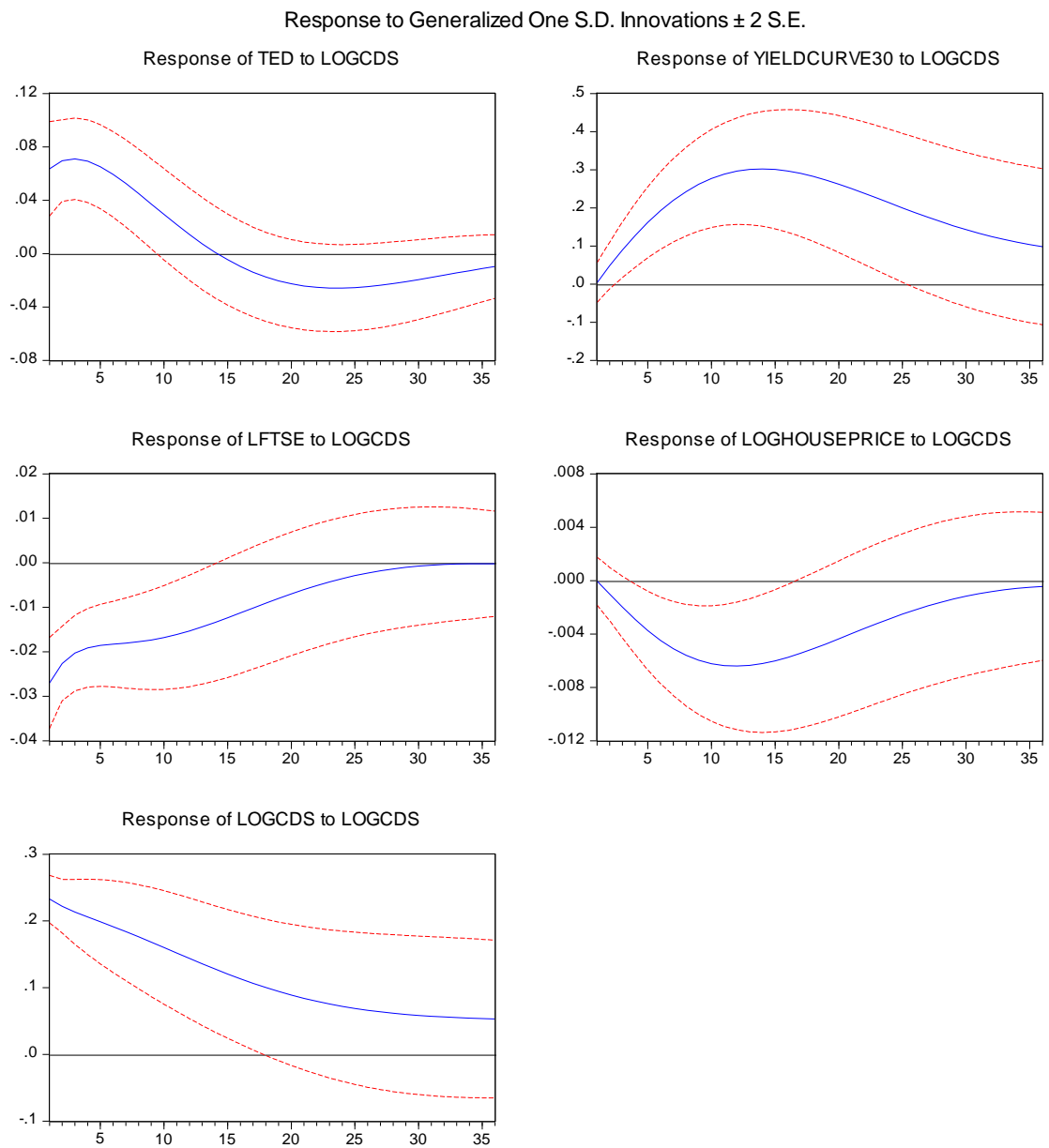
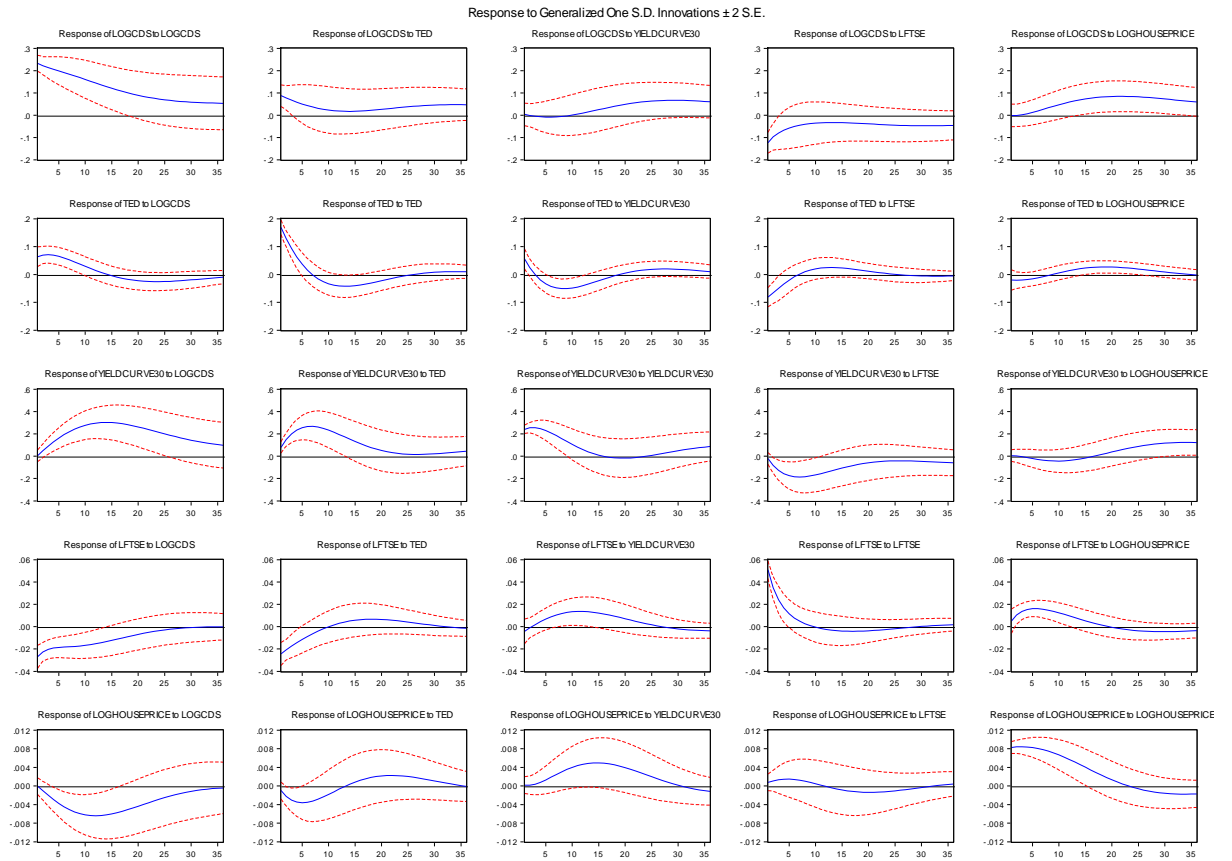


Figure 1.7 Impulse responses to a shock in CDS spread



Notes for figure 1.3

Figure 1.8 Generalised impulse responses with change in ordering for robustness



Notes: The ordering is reversed here as follows: log(cds) ted yieldcurve30 log(ftse) log(houseprice). The graphs that are plotted vertically demonstrate the response of the variables to each shock in the same sequence as the above ordering.

Footnotes:

- (1) The growth of the CDS market over the period was phenomenal in 2001 the outstanding notional amount of \$631.5 billion. In the last quarter of 2007, the total notional outstanding amount of CDS contracts had reached \$62.2 trillion. At the end of 2008, due to the severe financial crisis, this figure more than halved, reaching \$38.6 trillion and continued to decrease further so that at the end of the third quarter of 2009, the notional amount of outstanding CDS contracts averaged \$28 trillion (figures supplied by ISDA 2010).
- (2) CDS data on the UK banking sector was obtained from Credit Market Analysis (CMA) Group. The CDS banking sector data were first launched by the CMA group in 2004. We used the CDS premium mid-rate expressed in basis points. The index covers the banking sector in the UK and is denominated in Pounds. We use log of CDS prices in our analysis. The data include indices with a five-year maturity because they are the most liquid type of CDS.
- (3) In fact, the period between July 2007 and March 2009 was marked by the bankruptcy of large investment banks, including AIG, Lehman Brothers, and Bear Sterns among other major banks that threatened the stability of the overall financial system.
- (4) The test is based upon the recursive estimation of a test regression. The test statistic is interpreted as the minimum t-statistic of the coefficient of the lagged endogenous variable.

Chapter 5

Impact of bank size on CDS spreads:

International evidence before and during the financial crisis

Abstract

The fifth chapter of this thesis identifies the drivers of the CDS spread as a measure of credit risk by considering bank level factors (regulatory capital, leverage, liquidity, asset quality and operations Income ratio) and the housing market, in both developed and emerging countries. In addition, it investigates whether bank size matters in driving credit risk. Our unique dataset allows us to uncover the behavior of the CDS spread and the fluctuations in credit risk both before and during the financial crisis, over the period of 2004-2011. Our sample consists of 30 countries and 115 banks. The findings reveal that the strongest bank-level factors driving the CDS spread were found to be asset quality, liquidity and operations Income ratio. In fact, the more liquid banks, with better quality of assets, were found to face narrower CDS spread and reduced levels of credit risk. Furthermore, banks with higher levels of liquidity were better able to avoid bank-runs and sustain themselves in times of credit shortages. In addition, we find that banks with higher levels of operations Income ratio were found to be more resilient to default risk and therefore faced lower levels of CDS spread. When considering the impact of bank size on the CDS spread, our findings suggest that bigger banks were subject to higher CDS spreads and increased credit risk, while smaller banks experienced relatively lower CDS spreads and were considered to be safer, allowing us to derive an optimal level of bank size. Any financial institution growing beyond that threshold becomes subject to higher credit risk.

5.1 Introduction

The recent financial crisis was considered to be the worst crisis since the great depression of 1929. The high reliance on financial engineering and securitization activities boosted mortgage issuance and allowed a dramatic credit expansion for more than a decade. However, since summer 2007, the credit boom era was officially over. In fact, the housing market collapsed, financial markets froze, and banks and investors started heavily defaulting.

Before the financial crisis, there has been a predominant perception that big banks would always benefit from government protection and intervention, should they face any solvency issues. This gave rise to banks growing beyond their optimal size, exceeding the allowed leverage intakes and excessively increasing their lending activities to low-income (sub-prime) consumers. Most of the large financial institutions believed that by exceeding their optimal size, they would be categorized as *too-big-to-fall* and *too-important-to-fall* and would therefore never have to worry about their solvency. As the financial crisis unveiled, not all systemically important banks benefited from a government bailout. In fact, Lehman Brothers, which collapsed on 15 September 2008, is one of the brightest examples of a systemically important bank that was let go by the Federal Reserve and the Treasury. The bank filed for the Chapter 11 of Bankruptcy, with an outstanding debt of \$613 billion. Its failure engendered a huge crisis globally, which many referred to as the “perfect storm”.

Prior to Lehman Brothers collapse, on 16 March 2008, the financial system witnessed the fall of Bear Sterns that was actively involved in the mortgage and asset

backed securitizations that led to its downfall. In this instance, the Fed offered an emergency assistance that did not prove to be sufficient. Bear Sterns was later taken over by JP Morgan Chase in a fire sale. Similarly, Merrill Lynch, which was also on the verge of collapse, did not benefit from any financial support from the government and had to be acquired by Bank of America. Other financial institutions including AIG, Fannie Mae and Freddie Mac were more fortunate as they received the largest bailout packages in the history; amounting to \$182.3 billion and \$200 billion respectively. The reason for government intervention for these institutions was the impact they had on the public sector and consumers, which was deemed to be far more important than that of large investment banks.

A stream of literature that developed in the last decade investigated the impact of bank size on credit risk, credit ratings, government bailout and bank failures. Gómez-González and Kiefer (2009) looked at bank size and bank failures and found that small financial institutions were more prone to failure when compared to bigger financial institutions that have a better advantage of risk diversification. Demsetz and Strahan (1997) similarly show that big banks can lend more and increase their debt exposure, keeping at the same time a low level of credit risk. Furthermore, Sousa (2000) establishes that banks that are considered to be too-big-to-fail have a competitive advantage when compared to smaller banks, as they find a difference of ratings of three credit notches. In the same vein, Rime (2005) also looked at bank size, credit ratings and the *too-big-to-fail* phenomenon and find that bank size, proxied by total assets and market share, exhibits a positive and strong impact on issuer ratings.

Limited literature considered the recent financial crisis that led to the collapse of many systemically important banks, which despite their big size, were left to go bankrupt. These cases raise important questions of whether big banks are truly safer and face lower credit risk and narrower CDS spreads when compared to smaller banks as it was claimed in most of the past literature. More recent research conducted by Völz and Wedow (2011) show evidence that CDS price is subject to distortion due to bank size effect, especially for banks that are considered to be *too-big-to-fail*. In addition, the authors show that certain banks have surpassed their optimal size to benefit from government support in case there is a negative event and therefore face higher credit risk. Furthermore, there is evidence that big banks were taking over smaller financial institutions to further expand in size (Penas and Unal (2004) and Kane (2000)). Similarly, Demirgüç-Kunt and Huizinga (2013) looked at CDS and equity prices to investigate whether there were banks that were constrained by their big size and conclude that many banks have become *too-big-to-be-saved*.

Past literature also identifies the importance of the housing market, interest rates, yield spread and inflation as significant drivers of credit risk (Alexander & Kaeck (2008); Bevan & Garzarelli (2000); Duffie & Singleton (1999); In, Brown & Fang (2003); Lekkos & Milas (2001) and Naifar (2010)). In addition, more recent literature looked at the bank-level factors driving the CDS spread and finds that leverage, regulatory capital, liquidity, asset quality as well as credit ratings have a strong explanatory power to affect credit risk (Chiaramonte and Casu (2013), Fabozzi et al. (2007); Hull et al. (2004), Collin Dufresne et al. (2001), Campbell and Taksler (2003) and Benkert (2004)).

The fifth chapter of this dissertation addresses two key issues related to the CDS spread as a measure of credit risk. First, it considers the housing market and the bank level factors driving the CDS spread, both before and during the financial crisis, over the period of 2004-2011. The second contribution of this chapter is that it analyses whether bigger banks are subject to higher or lower credit risk when compared to smaller banks and financial institutions. This brings important implications for future policies as developed countries are battling the previous lax regulatory regime. As such, identifying the type of banks that are more prone to default will help authorities to prevent the negative consequences that may arise during economic downturns. This can be achieved by establishing and designing specific set of rules and standards to be followed by riskier banks and financial institutions.

The findings of this chapter indicate that in the pre-crisis period, the housing market and all the bank-level factors were significant drivers of the CDS spread. More specifically, the results indicate the presence of a negative relationship between house prices and the CDS spread, implying that when the housing market is strong, it is easier for banks to recover the initial mortgage value in case there is a negative credit event. Second, higher leverage was found to be positively associated with the CDS spread and credit risk. In addition, there is a negative relationship between asset quality, liquidity and regulatory capital with the CDS spread. During the crisis period, the key driver of the CDS spread was found to be regulatory capital, exhibiting a negative relationship, where banks with stronger capital buffers were better able to cope with defaults in times of financial crisis. When merging the pre-crisis and the crisis sample, the significance of the regulatory capital remained

strong and negatively related to the CDS spread, and leverage was also found to be an important factor affecting the CDS spread, with a positive impact on credit risk, thus implying that banks with higher levels of leverage were facing increased CDS spread due to their inability to repay their short-term liabilities.

When considering the impact of bank size on credit risk, we find evidence of a positive relationship between total assets and the CDS spread. This implies that the bigger the bank, the higher the CDS spread and the level of credit risk. However, when we include a squared term of bank size in order to address the issue of non-linearity in the relationship between bank size and credit risk, we find that the level of credit risk varies significantly depending on the size of the specific bank. As such, our findings imply that smaller financial institutions exhibit lower CDS spread level and credit risk, while larger banks tend to face higher CDS spread and increased credit risk. This suggests the existence of an optimal bank size, which we derive statistically from our estimates. If a particular bank grows beyond that point, it becomes more exposed to credit risk and becomes subject to high CDS spreads.

In section 5.2, we present the methodology. In section 5.3, we present the methodology, while in section in section 5.4, we discuss the empirical findings. Finally, in section 5.4, we conclude.

5.2 Methodology

In this chapter, the results from both fixed effect and random effect estimations are reported. Fixed effects models control for the effects of time-invariant variables with time-invariant effects. Therefore, it permits controlling for any unobserved country-specific time-invariant effects in the data, it does so, by conditioning them out and taking deviations from time averaged sample means. The result of this is the removal of any long-run variation in the dependent variable. In a random effects model, the unobserved variables are assumed to be statistically independent of all the observed variables. Thus, in the next section, we will proceed and explain the benchmark model and the bank size model. The results from both the FE and the RE models are summarised in tables 2.5-2.7.

5.2.1 Benchmark Model

Our objective is to establish the drivers of the CDS spread over the period of 2004-2011, across 30 countries and 115 banks, considering the housing market and the various bank-level factors, namely: asset quality, liquidity, leverage, regulatory capital and operations income ratio. The data covers a particularly interesting period as it looks at both the pre-crisis and the crisis period. As such, we estimate the following model using both Fixed Effect (FE) and the Random Effect (RE) methodologies, which controls for unobserved heterogeneity in country characteristics. The benchmark model is defined as follows:

$$\begin{aligned} \ln \text{BankCDS}_{ijt} = & B_0 + B_1 \ln \text{HP}_{it} + B_2 \text{Asset Quality}_{ijt} + B_3 \text{Liquidity}_{ijt} + \\ & B_4 \text{Regulatory Capital}_{ijt} + B_5 \text{Leverage}_{ijt} + B_6 \text{Operations}_{ijt} + \theta_j + \psi_t + \varepsilon_{ijt} \end{aligned} \quad (1)$$

Where the acronyms stand for:

lnBankCDS: Natural Logarithm of the Bank CDS spread.

lnHP: Natural Logarithm of the House Price Index

Asset Quality: Impaired Loans/Equity

Liquidity: Liquid Assets to Total Deposits and Short-term funding

Regulatory Capital: Tier 2 Capital = Total Capital – Tier 1 Capital

Leverage: Long-term Debt to Common Equity

Operations Income Ratio: EBITA (Earnings Before Interest Tax and Earnings)/ Average Assets

θ_j : Bank fixed effect

ψ_t : Time fixed effect

ε_{ijt} : Disturbance term

i stands for the country

j stands for the banks

t stands for time

We start by estimating the benchmark model, considering the housing market, asset quality, liquidity, regulatory capital, leverage and operations income ratio effect. The results are summarized in tables 2.5 – 2.7, which report the main findings using both the FE and RE estimations, over the period of 2004-2011. In

addition, we report which of the two methods is preferred, based on the p-value from the Hausman test.

5.2.2 Bank Size Model

After considering the bank-level drivers of the CDS spread, we analyse the impact of bank size on the CDS spread, over the period of 2004-2011 periods. The sample looks at 115 banks and 30 countries. The model is defined as follows:

$$\begin{aligned} \ln \text{BankCDS}_{ijt} = & B_0 + B_1 \ln \text{HP}_{it} + B_2 \text{Asset Quality}_{ijt} + B_3 \text{Liquidity}_{ijt} + \\ & B_4 \text{Regulatory Capital}_{ijt} + B_5 \text{Leverage}_{ijt} + B_6 \text{Operations}_{ijt} + B_7 \ln \text{BankSize}_{ijt} + \\ & B_8 \ln \text{BankSizeSq}_{ijt} + \theta_j + \psi_t + \varepsilon_{ijt} \end{aligned} \quad (2)$$

Where the acronyms stand for:

lnHP: Natural Logarithm of the House Price Index.

Asset Quality: Impaired Loans / Equity

Liquidity: Liquid Assets / Deposits and short-term Funding

Regulatory Capital: Tier 2 Capital = Total Capital – Tier 1 Capital

Leverage: Long-term debt to common equity

Operations Income Ratio: EBITA / Average Assets

lnBank Size: Natural Logarithm of Bank Total Assets

Bank SizeSq: Squared term of the Natural Logarithm of Bank Total Assets

θ_j : bank fixed effect

Ψ_t : time fixed effect

ε_{ijt} : disturbance term

i stands for the country

j stands for the banks

t stands for time

The estimates of model 2 are demonstrated in tables 2.8 – 2.9. Having identified the bank-size model, we will now proceed and explain the GMM model.

5.2.3 GMM model

As indicated in previous research conducted by Kiviet (1995) and Judson and Owen (1999) when the number of banks (N) is higher than the number of the years (T) in the data sample, the GMM estimations allow generating a lower Root Mean Square Error (RMSE). Since there are no exogenous instruments in our model with the adequate properties to be considered, that would be correlated with the endogenous variable but uncorrelated with the error term (u), it is appropriate to consider the system GMM model approach that employs instruments with lags of the endogenous variable (*lagged $\ln(\text{BankCDS})$*)

The GMM estimation included instruments for differenced equation. As such, the GMM-type instruments consisted of one lag of $\ln(\text{Bank CDS})$. The

Standard instruments were: $\Delta \ln(\text{BankCDS})$, $\Delta \ln(\text{HousePriceIndex})$, $\Delta \text{AssetQuality}$, $\Delta \text{Liquidity}$, $\Delta \text{RegulatoryCapital}$, $\Delta \text{Leverage}$, $\Delta \text{Operations Income ratio}$, $\Delta \ln(\text{BankSize})$, $\Delta \text{BankSizeSq}$. The instrument for level equation consisted of the GMM-type instrument, namely: $\Delta \ln(\text{BankCDS})_{ijt}$. The GMM model is defined as follows:

$$\begin{aligned} \ln \text{BankCDS}_{ijt} = & B_0 + B_1 \ln \text{BankCDS}_{ijt-1} + B_2 \ln \text{HP}_{it} + B_3 \text{Asset Quality}_{ijt} + \\ & B_4 \text{Liquidity}_{ijt} + B_5 \text{Regulatory Capital}_{ijt} + B_6 \text{Leverage}_{ijt} + \\ & B_7 \text{Operations Income}_{ijt} + B_8 \ln \text{BankSize}_{ijt} + B_9 \ln \text{BankSizeSq}_{ijt} + \theta_j + \psi_t + \varepsilon_{ijt} \quad (3) \end{aligned}$$

Where the acronyms stand for:

$\ln \text{BankCDS}_{ijt-1}$: Lag of the Natural Logarithm of the Bank CDS spread

$\ln \text{HP}$: Natural Logarithm of the House Price Index.

Asset Quality : Impaired Loans / Equity

Liquidity : Liquid Assets / Deposits and short-term Funding

$\text{Regulatory Capital}$: Tier 2 Capital = Total Capital – Tier 1 Capital

Leverage : Long-term debt to common equity

$\text{Operations Income Ratio}$: EBITA / Average Assets

$\ln \text{Bank Size}$: Natural Logarithm of Bank Total Assets

Bank SizeSq : Squared term of the Natural Logarithm of Bank Total Assets

θ_j : bank fixed effect

ψ_t : time fixed effect

ε_{ijt} : disturbance term

i stands for the country

j stands for the banks

t stands for time

Having identified the baseline model, the bank size model and the GMM model, we will now proceed and discuss the findings from these estimations.

5.3 Empirical Results

Before discussing the empirical findings from the baseline, the bank size model and the GMM estimations, it is important to conduct the unit root test in order to check whether our data is stationary. Since the data we are dealing with is an unbalanced panel dataset, the only test that we can conduct in order to check for stationarity is the Fisher Unit Root test. All other stationarity tests (Levin-Lin-Chu, Harris-Tzavalis, Breitung, Lm Pesaran Shin and Hadri LM test) require the data to be strongly balanced. The outcome from the Fisher Unit root test will be discussed in the next section.

5.3.1 Fisher Unit-Root Test

Fisher-type unit-root test is based on augmented Dickey-Fuller test. According to the Fisher unit-root test, the P statistic requires the number of panels to

be finite. As such, the null hypothesis states that all the panels contain a unit root. Therefore, there is an assumption that T tends to infinity. If the number of panels, N , is fixed, then the Fisher test is consistent against the alternative that at least one panel is stationary. If we allow N to tend to infinity, then the number of panels that do not contain a unit root must grow at the same rate as N for the tests to be consistent. Therefore, the null and the alternative hypothesis are the following:

Ho: All panels contain unit roots

H1: At least one panel is stationary

Table 2.3 and table 2.4 summarize the outcomes of the Fisher unit-root test for the $\ln(\text{Bank CDS})$ spread and the $\ln(\text{House Price Index})$ over the period of 2004-2011. It can be clearly observed that we can reject the null hypothesis and conclude that both bank CDS spread and the house price index do not contain a unit root and are therefore stationary.

5.3.2a Baseline model findings

Tables 2.5-2.7 summarize the results from both the fixed effect (FE) and the random effect (RE) estimations for the baseline model. According to the Hausman test, the RE model is the preferred method of estimation. Therefore, we will base our analysis on the results obtained from the RE estimation.

One of the first findings this research uncovers the important relationship linking liquidity to bank CDS spread. Our findings show that liquidity has a strong negative impact on the CDS spread. This implies that more liquidity meant that banks were better able to deal with large bank withdrawals and avoid bank-runs. As such, the only banks that were able to survive the recent financial crisis and maintain a relatively low level of credit risk and narrow CDS spread were the financial institutions that held sufficient liquidity levels.

The main responsibility of financial institutions is to provide liquidity to depositors and creditors by standing ready to offer them cash on demand. In the traditional framework, liquidity risk comes from the risk arising from bank-runs. This is a situation where depositors lose trust in their bank and withdraw their funds, driving investor sentiment down, either as a result of concerns about the bank's financial condition or because they worry that other depositors may also start withdrawing their funds, thus causing bank-runs. Such runs could make banks insolvent by initiating a chain reaction that may force a fire sale of illiquid loans. This in turn can result in bankruptcy of the financial institution.

Before 2007, banks and other financial institutions heavily relied on borrowing from capital markets. In fact, the debt to equity ratios for many large international banks exceeded 20 to 30 multiples. Graph 2.1 illustrates of the fluctuations of the $\ln(\text{CDS})$ spread and leverage, showing that there is a positive relationship between leverage and credit risk (CDS spread). Therefore, in case of a bank-run, there was a high likelihood of bankruptcy, which could potentially

translate into a contagion and cause a systemic collapse of the entire financial system (Antão and Lacerda (2011)).

In the wake of the recent financial crisis, as capital markets and money markets dried, the only banks that were able to survive without the heavy reliance on borrowing from the lemon markets were those that held high liquidity levels. Other banks such as Northern Rock were unable to survive and had to be bailed out by the Bank of England as a result of bank-runs. In fact, as of September 2007, Northern Rock's liquidity gap within 3 months was more than £ 25 billion. As such, in less than one year, Northern Rock was under the obligation to refund £30 billion, with all the associated market risks (Congdon et al. (2009)).

Our results are in line with the research conducted by Annaert et al. (2013) which looked at determinants of Euro-area CDS spreads and found that the most significant driver of credit risk before and during the crisis was the liquidity spread. In addition, Chiaramonte and Casu (2013) also looked at the determinants of CDS spreads, focusing on bank balance-sheet ratios before and during the financial crisis, and showed that liquidity played an important role in explaining credit risk and more specifically the CDS spread. Moreover, other researchers including Chen et al. (2007), Fabozzi et al. (2007) as well as Annaert et al. (2013) found that liquidity is an important determinant of the CDS spread.

Besides the significance of liquidity as a driver of the CDS spread, we also find evidence that asset quality is another important determinant of the CDS spread. From table 2.5, it can be seen that bank CDS spreads reflect the risk captured by the

bank balance sheet i.e. the risk associated with their assets quality. More specifically, the ratio of impaired loans/equity proves to have a significantly positive link with banks' CDS spread. Indeed, the higher the ratio (i.e. as the ratio of impaired loans/equity increases) the more problematic the loans will be and, thus, the positive coefficient of this ratio does reflect higher credit risk as reflected by the deterioration of the assets' quality. As illustrated in graph 2.3, there is a positive relationship between the fluctuations of the ln(CDS) spread and asset quality, which in turn implies that higher impaired loans/equity implies leads to higher credit risk. This finding is consistent with a research conducted by Chiaramonte and Casu (2013), who proxied asset quality with the ratio *Loan Loss Reserve to Gross Loans*, and found that it was a significant driver of the CDS spread before, during and after the recent financial crisis. The authors' findings indicate that the probability of default increases especially for banks that have low quality loan portfolios.

Our third finding relates to the relationship between bank-level leverage and credit risk as reflected by the CDS spread. It can be clearly observed from table 2.5 that as leverage increases; the level of credit risk also goes up, entailing higher credit risk. In fact, before the financial crisis, banks were heavily borrowing from capital markets. As credit conditions were booming, lending to financial institutions was made easy, with consumers blindly investing their savings in banks expecting to earn interest. In addition, financial engineering and securitization also greatly contributed to the increased leverage intakes that banks were subject to. This was reflected in the deteriorations of banks' asset quality. With the beginning of financial crisis, the real leverage ratios came to light revealing that most banks were borrowing well above the authorized norms. Our findings are in accordance with the theory which shows

the presence of a positive and highly significant relationship between leverage and the CDS spread. In fact, in a research conducted by Ericsson et al. (2009), the authors show that leverage, among other factors, explain approximately 23% of CDS spread fluctuations. Table 2.5 below indicates that the higher the leverage level and the wider the CDS spread, reflecting greater credit risk. Thus, banks that borrowed more aggressively experienced much higher CDS spread levels. During the financial crisis, the highly leveraged banks lost access to external funding given that capital markets froze. In addition, consumers lost confidence in the banking sector and were withdrawing their savings.

When considering the impact of macroeconomic drivers on the CDS spread, the housing market appears to be negatively affecting credit risk. As shown in table 2.5, higher house prices are associated with narrower CDS spreads. This follows the economic rationale given that before summer 2007, real estate was continuously appreciating in value, banks were therefore subject to lower credit risk as not only they were able to regain the initial mortgage value if the borrower defaulted, but they could also earn a profit. However, during the crisis period, the picture drastically changed. In fact, when house prices dramatically fell in value, the housing market no longer affected the CDS spread and credit risk.

As a robustness check, in the next section, we have replaced the benchmark explanatory variables with alternative variables that similarly reflect asset quality, liquidity, regulatory capital and leverage.

5.3.2b Alternative Bank Characteristic

In this section, we assess the sensitivity of the benchmark model to the choice of bank characteristics. Therefore, in table 2.7, we: (i) replace the ratio of *Impaired Loans / Equity* with the ratio of *Impaired Loans / Gross Loans*, as a measure of asset quality; (ii) replace the ratio of *Liquid Assets / Deposits & Short-term Funding* with the ratio of *Liquid Assets / Total Deposits & Borrowings* as a measure of liquidity; (iii) replace *Tier 2 Capital Ratio* by the *Total Capital Ratio* as a measure of regulatory capital (iv) replace the ratio of *Long-term Debt to Common Equity* by the ratio of *Equity / Total Assets* as a measure of leverage; (v) replace the ratio of *EBITA (Earnings Before Interest Tax and Earnings) / Average Assets* by *Return On Average Equity (ROAE)*, as an indicator of bank-level operations Income ratio.

The results that are demonstrated in table 2.7 show that the main findings remain unchanged. Therefore, any deterioration in the asset quality ratio leads to an increase in credit risk, while a rise in the degree of liquidity of the assets held by banks reduces their default risk in a significant manner. In addition, the results also show that the level of bank operations Income ratio is negatively related to the CDS spread and credit risk.

As for the regulatory capital and leverage, the findings from table 2.7 do not suggest a significant impact on banks' CDS spread. Yet, the coefficient associated with this of the regulatory capital variable is negative. Besides the numerous positive aspects of high capital regulation, one constraint relates to the potential impact that it has on banks' return on assets: higher capital requirements tend to be costly for a

financial institution and are usually perceived as a burden. The riskier a bank's portfolio, the more capital it will be required to hold. By being forced to keep a certain percentage of capital as a cushion in case there is a negative credit event, a bank's investment may be reduced, which decreases its competitiveness in financial markets. In this respect, our results confirm the importance of bank operations income ratio, measured by (Return on Average Equity (ROAE)), in eroding credit risk, as it has a negative and highly significant effect on bank CDS. The negative relationship between bank operation and bank CDS spread is demonstrated in graph 2.5.

In addition, while leverage was only marginally significant (at a 10% level) in the baseline model, once we replace the long-term debt to common equity ratio by an alternative ratio of equity to total liabilities, it turns insignificant. One of the explanations of the marginal significance of leverage as a driver of the CDS spread relates to the fact that banks used off-balance sheet securitization in order to hide their real leverage intakes to finance their investment activities. In addition, this also translated into bank's ability to escape regulatory requirements by showing less leverage in their balance sheet. This is one of the reasons that explain the sensitivity of the leverage as a driver of the CDS spread.

5.3.3 Bank Size model findings

The tables show that bank size is positively related to the CDS spread over the period of 2004-2011. Bank size would grow as the bank total assets rises. Our findings are demonstrated in tables 2.8 and 2.9. According to the Hausman test, the FE model is the preferred method of estimation. The findings from table 2.8 indicate

that the bigger the bank and the higher the CDS spread. In fact, during the credit boom of early 2000, banks were enjoying high credit injections in a form of foreign funding inflows. This enabled them to expand their lending activities, mostly through the issuance of complex mortgage securities, which in turn boosted their profits. The idea of increasing their size in both the domestic and international markets was appealing to these financial institutions. As such, the phenomenon of the *too-big* and the *too-important-to-fail* gave banks the wrong incentives to grow beyond their optimal size; believing that they would never collapse as the government would always be there to rescue them. However, as the recent financial crisis unfolded, many of these big financial institutions were left to go bankrupt. Therefore, bigger banks were subject to higher credit risk and wider CDS spreads. The only exception was financial institutions that were closely related to the public sector, such as AIG, that did benefit from a government bailout package.

In order to address the issue of any non-linearity in this relationship, in the next section we need to add a squared term of bank size to capture this effect.

5.3.4 Robustness Checks

5.3.4.1 The identification of non-linear effects between Bank CDS spread and Bank Size and the result from the U-test

To assess the empirical validity of the link between bank size and CDS spread, we introduce a quadratic term of bank size ($\ln Bank Size^2$) in equation (2). Results from these specifications are illustrated in tables 2.8-2.9.

Regression output in tables 2.8 and 2.9 implicitly assumes that bank size causes distortions in the CDS spread at different levels. In other words, the CDS spread is linear over all levels of Bank size. A quadratic prediction plot between bank size and the CDS spread showed in graph 2.7 suggest a U-shaped relationship. This means that at low levels of bank size, CDS spread moves negatively with bank size, while there is a critical threshold beyond which further increases in bank size lead to a rise in the CDS spread. However, in order to ensure that the U-shape relationship between the CDS spread and bank size really exist, it is essential to conduct the U-test.

In order to test for the presence of this U-shape relationship between the CDS spread and bank size, we have used the U-test developed by Lind and Mehlum (2010). More precisely, we have followed the approach adapted by Leonida, et al. (2012), the authors investigated the effect of political replacement effect in a panel of 102 countries over the period 1980 to 2005. More precisely, the authors tested for the presence of a U-shape relationship. In addition, they also tested for non-

monotonicity in the relationship between political competition and economic reform, by examining whether the relationship is decreasing at low values and increasing at high values within the data range.

In our analysis, for each model, we report the interval, slope estimated at the minimum and maximum values, the associated t -statistics, as well as the test for the overall significance of a U-shaped relationship. For all of the models, we also report the estimated extreme point together with the associated confidence interval estimated by the Fieller method. Our empirical analysis strongly supports the existence of a U shape relationship between bank CDS spread and bank size. In order to reassert our findings of the presence of a U-shape type of relationship between the CDS spread and bank size, we check our results for robustness using several estimation frameworks, including the FE, RE and alternative Generalized Method of Moments (GMM) approaches. As such, we have undertaken the U-test, developed by Lind and Mehlum (2010), and given our p-value (reported in table 2.10 and 2.11), we can reject the null hypothesis (H_0 : Monotone or Inverse U shape) and conclude that there is a U-shape relationship between the bank CDS spread and bank size. Our findings show that indeed the CDS spread and bank size are negatively related up to a threshold after which this relationship becomes positive. The outcome from the U-test is demonstrated in tables 2.10 and 2.11.

Optimal Bank Size

From table 2.8, the quadratic term of Bank Size is positive and statistically significant at 5% level, while the linear term is negative and also significant at 10% level. In addition, the U-test proves that there is a U-shape relationship linking CDS spread and bank size.

As such, these findings from table 2.8 are supportive of a non-linear relationship and allow us to derive from the estimated equation the critical value of bank size beyond which the CDS spread starts increasing. The u-test for both the FE and RE model confirms the existence of the U-shape relationship. The threshold point can be derived from the above estimated equation as follows:

$$\begin{aligned}\frac{\delta CDS}{\delta Bank Size} &= B_7 + 2B_8 \ln(Bank Size) = 0 \\ \Rightarrow \ln(Bank Size) &= \frac{-B_7}{2B_8} = \frac{7.447025}{2(0.3509253)} \\ &= 10.61\end{aligned}$$

This implies that the optimal bank size in terms of absolute values will be:

$$\exp(10.61) = 40560.7 \text{ Million of Euros}$$

From equation (2), we can figure out that the turning point is equal to 1,645,173,570 Millions of Euros. This point indicates that as bank size increases above this threshold, it causes the CDS spread to widen and the credit risk to subsequently go up and rise. Thus, bank size and the CDS spread are negatively related up till the size of the bank in terms of total assets reaching 1,645,173,570

Millions of Euros. This implies that smaller banks face lower credit risk. After, this threshold, bank size and the CDS spread become positively related, implying that the bigger the bank, the higher the CDS spread and credit risk.

Our results show that the level of credit risk varies across big and small banks. As such, smaller banks typically experience narrower CDS spread and lower level of credit risk. They are therefore safer, although they do not have the same ability to diversify their risk portfolios as bigger financial institutions; these banks are considered to be more cautious with their investment decision-making process.

This finding is in line with the literature on the *too-big-to-save*. In a research conducted by Demirgüç-Kunt and Huizinga (2013), the authors focused on equity prices and CDS spread in the context of public deficit and bailouts. Their findings show that the *too-big-to-save* hypothesis infers that large banks are typically subject to reduced bailout prospects particularly in countries that experience fiscal constraints. Therefore, bigger banks are considered to be riskier, while smaller banks, which conduct small size investment activities, are considered to be safer and more secure.

In the next section, in order to correct for the potential problem of endogeneity, system GMM is used in our analysis.

5.3.5 Generalized Method of Moments (GMM)

Since the number of years in our sample is smaller than the number of banks, in this chapter we have conducted the GMM estimations. As such, the Arellano-Bond (1991) was undertaken in order to test of autocorrelation. As presented in table 2.12, according to the Arellano-Bond test, there is no evidence of second order autocorrelation; therefore our model is correctly specified. The difference equation is instrumented with the lagged levels, one period of the dependent variable and the levels equation with the difference lagged one period.

Moreover, we report Sargan-Hansen test that follows the Chi-squared distribution with (L-K) degrees of freedom. The statistic values test the validity of instruments. Under the null, the instruments included are uncorrelated with the error term, thus they are valid. The outcome of the Sargan test would indicate whether our equation is correctly identified or is over-identified. Under the null hypothesis, the equation is adequately and correctly identified. The alternative hypothesis states that our model is over-identified (i.e. the number of instruments is more than the number of endogenous variables). According to our findings from table 2.12, the *p-values* for the Sargan test for over-identifying restrictions, where the null hypothesis is that the instruments are uncorrelated with the residuals, confirm that the instruments are not correlated with the residuals and they are valid instruments. Furthermore, we are satisfying the condition whereby our number of instruments is 22 and is less than the number of groups, which is equal to 24. The lagged dependent variable is statistically significant reflecting a high degree of persistence in the variables.

Table 2.12 below reports the results from the GMM analysis. The results are consistent with the outcome obtained from both the benchmark model and the bank size model (tables 2.5, 2.7 and 2.8). Our findings indicate that the housing market is significant and negatively related to the CDS spread (table 2.5 and table 2.7). As such, as house prices were increasing before the financial crisis, the level of default and credit risk was low. This ultimately translated into narrower CDS spread. Whereas after the housing bubble and subsequent financial crisis, when the house prices drastically fell, the level of credit risk sharply increased, pushing up the level of defaults and the CDS spread. Therefore, this follows the rationale whereby higher house prices minimize the credit risk, making it always possible for the financial institution granting mortgage contracts to protect itself from a customer defaulting by reselling the property for a higher price in the secondary market

The second finding from the GMM results is the positive relationship between asset quality and the CDS spread, which is demonstrated in table 2.12. In fact, our findings are in line with our previous results from the baseline model and the bank size model (tables 2.5 and 2.8). As such, as the ratio of impaired loans to equity increases, the quality of assets decreases. This implies that the bank becomes more risky when it holds a higher proportion of toxic assets. Before the recent financial crisis, banks heavily invested in highly structured products which were associated with very high risks. This was particularly easy with the increased popularity of securitization activities and financial engineering. As the crisis began, many of banks' assets started defaulting due to their toxic nature. This was despite the excessively high rating most structured products enjoyed before the beginning of the crisis. In fact, credit rating agencies played a predominant role in boosting the

ratings of highly risky instruments to increase their marketability. Our results GMM are in line with the previous findings and confirm our hypothesis which stipulates that a bank with more reliable quality of assets will face reduced credit risk.

Furthermore, the findings from table 2.12 also illustrates the negative relationship between the CDS spread and bank liquidity. As such, banks with higher levels of liquidity were in a better position to avoid bank-runs that resulted from the recent financial crisis. From summer 2007, both money markets and capital markets stopped lending to banks and other financial institutions. Therefore, financial markets froze. In addition, investors' sentiment reached its lowest level as consumers and lenders lost trust in the financial system and decided to withdraw their deposits from banks. The only financial institutions that were able to withstand the crisis were those that kept high liquidity levels and were able to sustain themselves despite the lemon markets. Thus, the banks that had high levels of liquidity were subject to tighter CDS spread and lower credit risk.

Moreover, table 2.12 shows evidence of a negative relationship between the level of bank operations income ratio (*EBITA / Average Assets*) and the CDS spread. As such, banks that are more profitable are better able to cope with negative credit event and are considered to be stronger as compared to banks that have low levels of operations income ratio. This is in line with our initial hypothesis and follows the economic rational.

Last but not the least, our results in table 2.12 demonstrate that, on average, the CDS spread and bank size is positively related. Once the quadratic term is included to capture non-linearity, there is clear evidence in favour of a non-linear relationship that the smaller banks faced narrower CDS spread levels and credit risk as they were deemed to be safer relative to bigger banks. For bigger banks with assets beyond a critical level, we find that the CDS spread is positively related to bank size. In order to reassert out previous findings, after having conducted the GMM analysis, we followed the lead of Leonida et al. (2012) and Lind and Mehlum (2010) and undertook the U-test. Our findings strongly support the evidence that there is a U-shape relationship linking bank CDS spread and bank size, with a t-value of 3.01 (table 2.13). The outcome from U-test conducted following the GMM estimation, which is presented in table 2.13. Therefore, it can be concluded that bank size and the CDS spread are negatively related up until bank size reaches a certain threshold. After that threshold, the relationship between bank size and credit risk turns into becoming positive, meaning that the bigger the bank, the wider the CDS spread and vice versa.

A quadratic prediction plot between bank size and CDS spread shows in Graph 2.8, a U-shaped relationship. As such, when bank size goes up, the CDS spread level moves inversely with bank size. This U-shape type of relationship has been confirmed by the U-test developed by Lind and Mehlum, (2010), and which is reported in table 2.13. There is a critical threshold beyond which further rise in bank size leads to an increase in the CDS spread. .

Following the estimated GMM results, we can derive the bank size optimal point as follows:

$$\frac{\delta CDS}{\delta Bank Size} = B_8 + 2B_9 \ln(Bank Size) = 0$$

$$\Rightarrow \ln(Bank Size) = \frac{-B_8}{2B_9} = \frac{4.880}{2(0.226)}$$

$$= 10.79646$$

The optimal bank size in terms of absolute values will be:

$$\exp(10.79646) = 48847.58 \text{ Millions of Euros}$$

Therefore, as long as bank total assets are below or equal 48847.58 Millions of Euros, bank size and the CDS spread will exhibit a negative relationship. Even with the GMM approach, there is still a critical level of bank size, although the threshold point is at a lower level compared to the optimal size derived in the fixed effects estimation. After this point, bank size and the CDS spread become positively related. Thus, bigger banks face more risk, while smaller banks are safer given that they experience narrower CDS spreads.

5.4 Conclusion

The fifth chapter of this dissertation explores the key bank level drivers of bank CDS spreads, over the period of 2004-2011, across 30 countries and 115 banks. Most importantly, this research significantly contributes to the existing literature as it looks at the impact of bank size on the CDS spread over the period of 2004-2011 and uncovers important findings relating to optimal size of banks and credit risk.

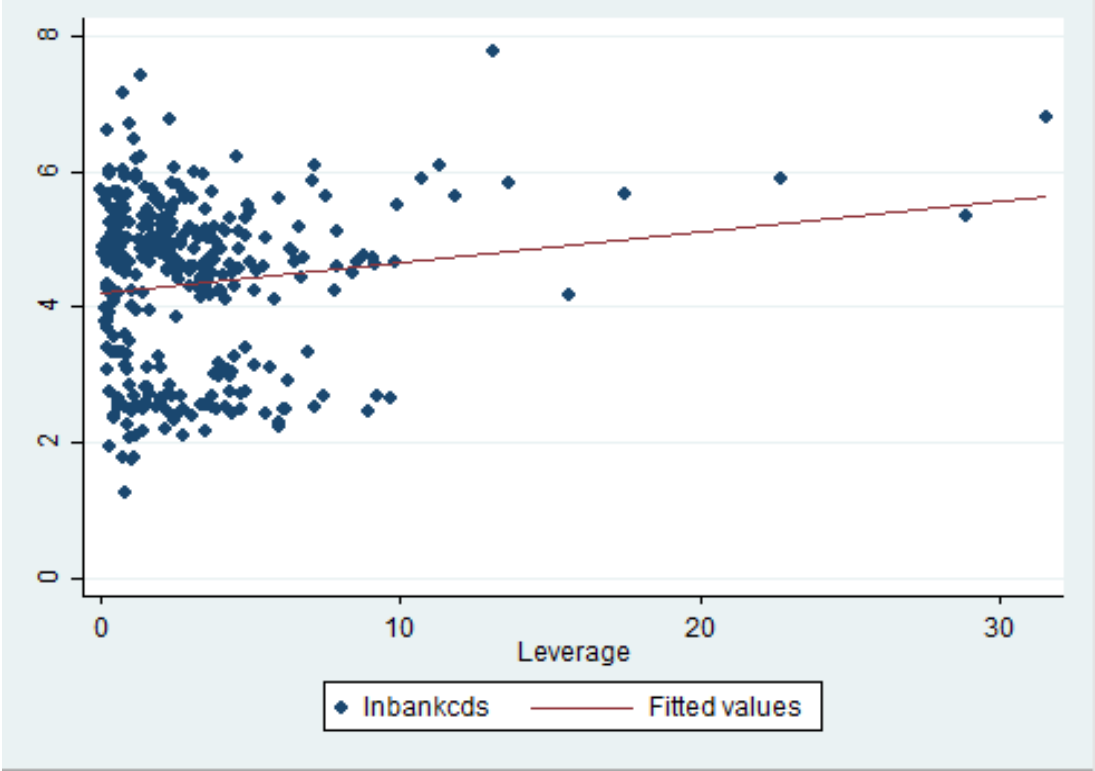
We find that the fluctuations of bank CDS spread strongly depend from: (i) the quality of the bank's balance sheet; (ii) liquidity of banks' assets; and (iii) how profitable banks' operations are. As such, banks' with better asset quality are subject to less credit risk. In addition, higher liquidity enables banks to avoid bank-runs and be more resilient to bankruptcy and insolvency. Finally, banks with higher levels of operations income ratio have more income to withstand a negative credit event such as the recent financial crisis, and therefore face lower CDS spread. We find that both regulatory capital and leverage appear to have a reduced ability to explain the variations in credit risk over the sample period. On a country level, we also uncover the close interconnection between credit risk and the housing market; implying that higher house prices would lead to narrower CDS spread and lower credit risk. Our results are consistent using FE, RE and the GMM estimations.

When considering the impact of bank size on the CDS spread, we demonstrate that total assets and credit risk are negatively related up until a certain point, which we refer to as "bank optimal size". Before this point, banks are considered to be either small or average, and are typically subject to reduced risk.

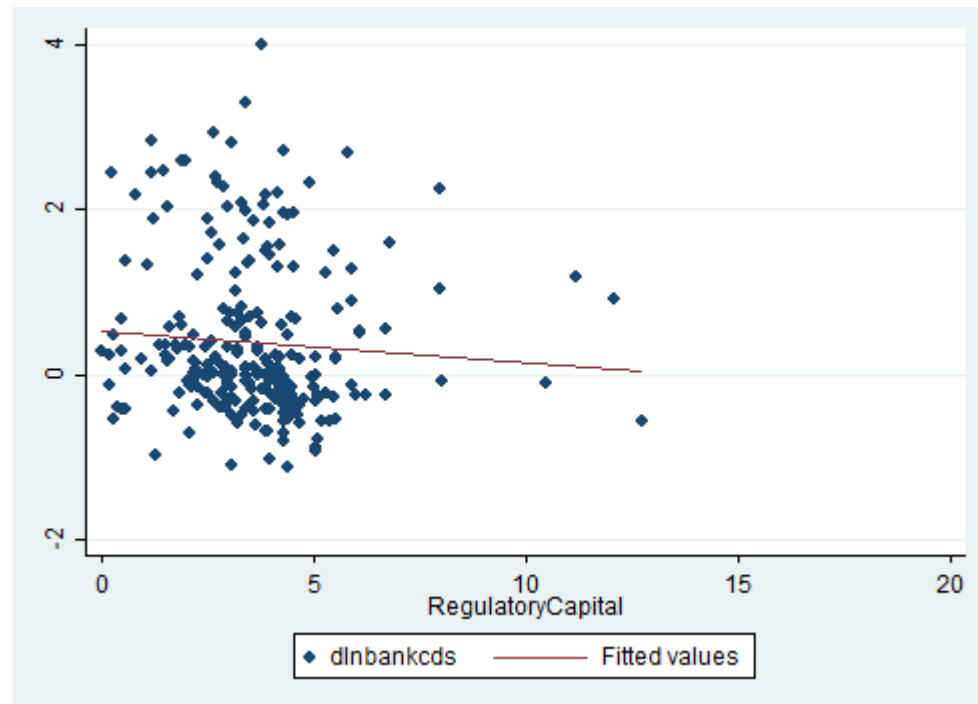
After that point, bank size and the CDS spread become positively related, meaning that the bigger the bank, the higher the CDS spread. Our findings are in line with the previous literature on the *too-big-to-save*. In fact, while most banks during the credit expansion were trying to grow beyond their optimal size thinking that they will benefit from government support in case of a negative credit event, the recent financial crisis revealed that not all big banks are systematically saved. This leads us to the conclusion that smaller and medium sized banks are safer than large banks.

Having analysed the bank-level determinants of CDS spread and after establishing the relationship between bank size and CDS spread, in the next chapter we will investigate whether the difference in financial systems and regulatory structures matter in explaining cross-country bank CDS spreads.

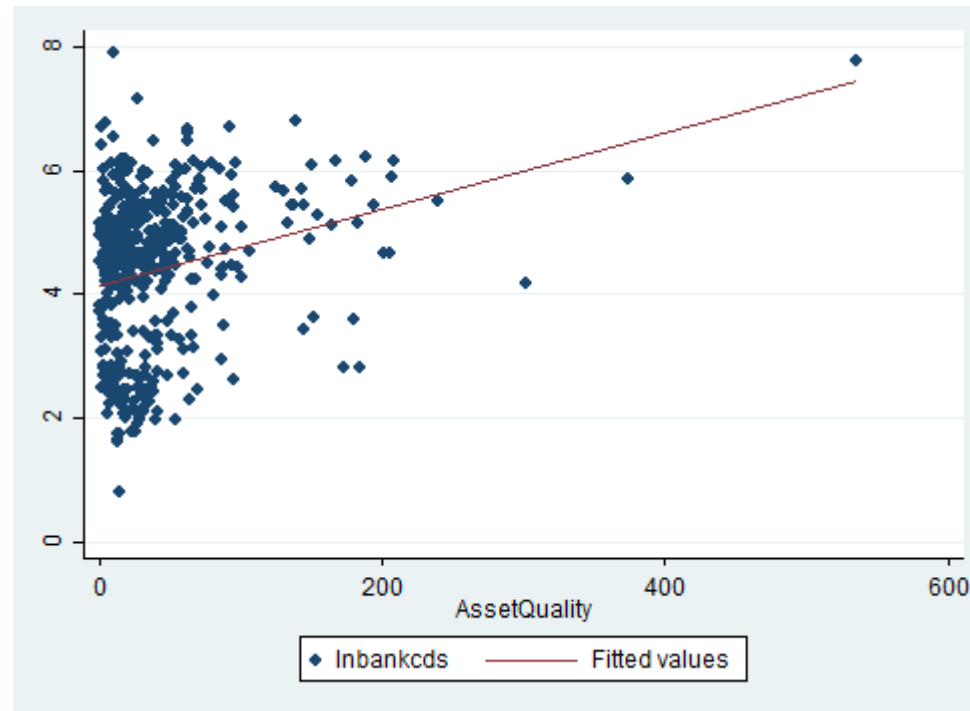
Graph 2.1: Graphical Illustration of the fluctuations of the ln(CDS) spread and Leverage



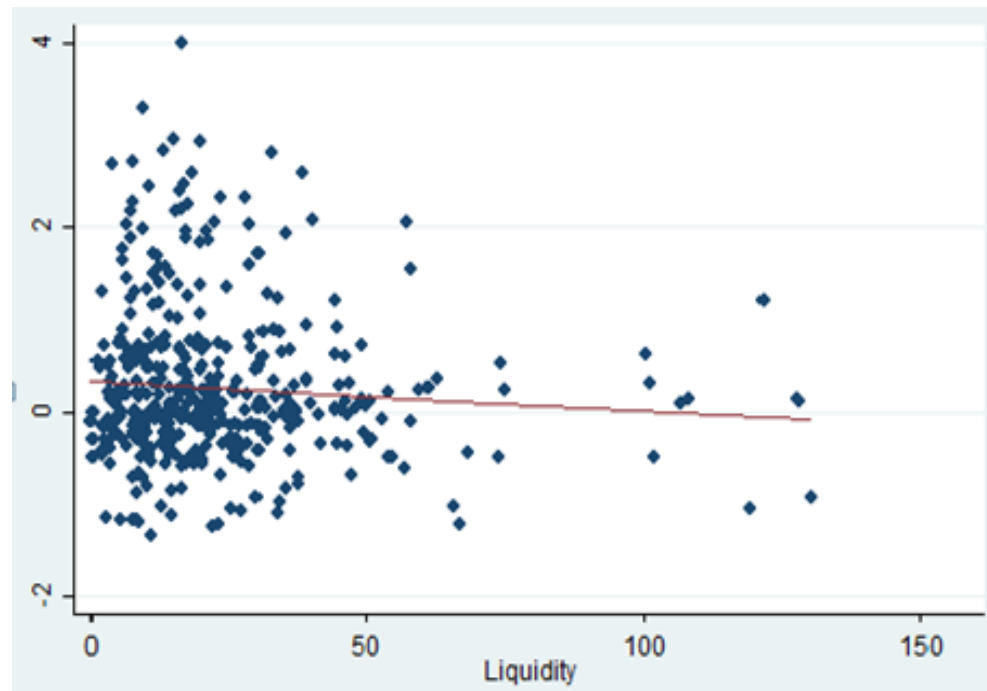
Graph 2.2: Graphical Illustration of the fluctuations of the ln(CDS) spread and Regulatory Capital



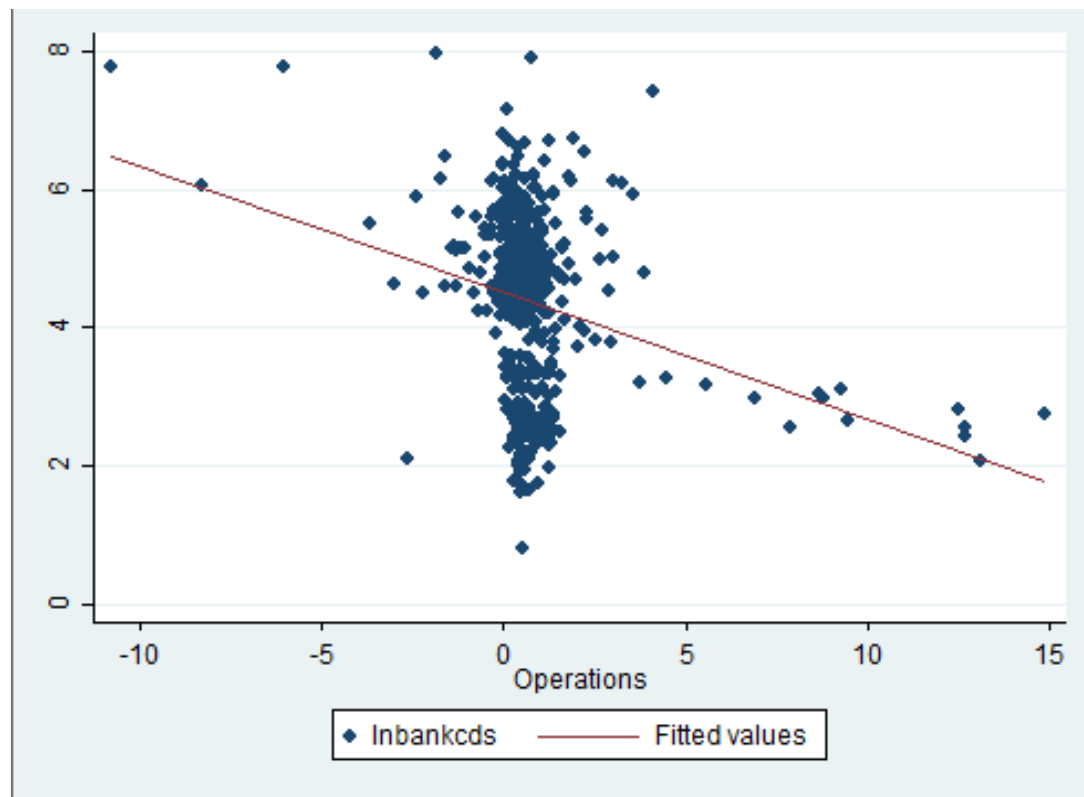
Graph 2.3: Graphical Illustration of the fluctuations of the $\ln(\text{CDS})$ spread and Asset Quality



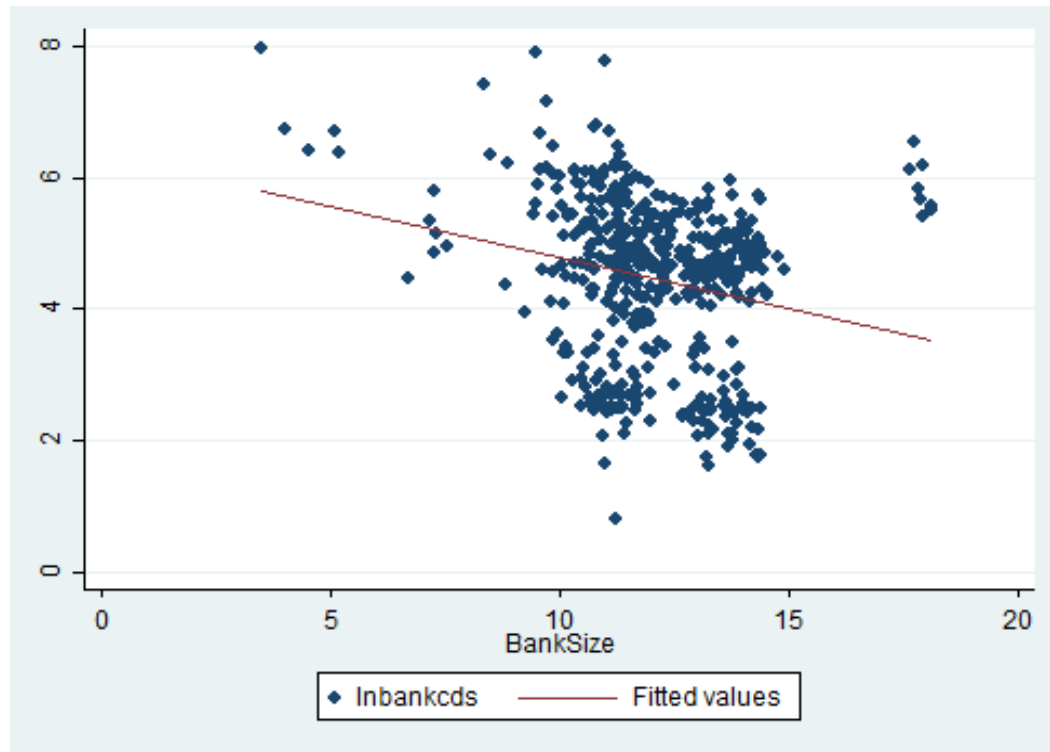
Graph 2.4: Graphical Illustration of the fluctuations of the $\ln(\text{CDS})$ spread and Liquidity



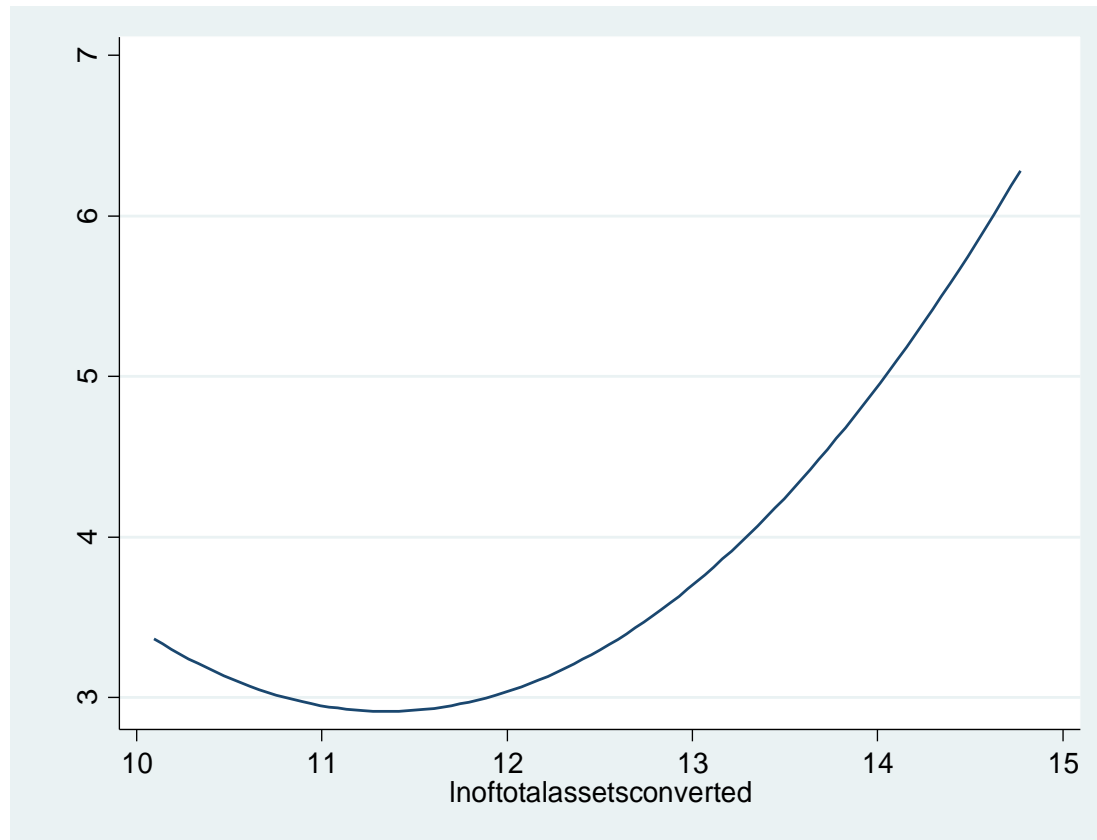
Graph 2.5: Graphical Illustration of the fluctuations of the ln(CDS) spread and Operations Income Ratio



Graph 2.6: Graphical Illustration of the fluctuations of the ln(CDS) spread and Bank Size



Graph 2.7: Bank Optimal Size (FE Robust)



Graph 2.8: Bank Optimal Size (GMM)

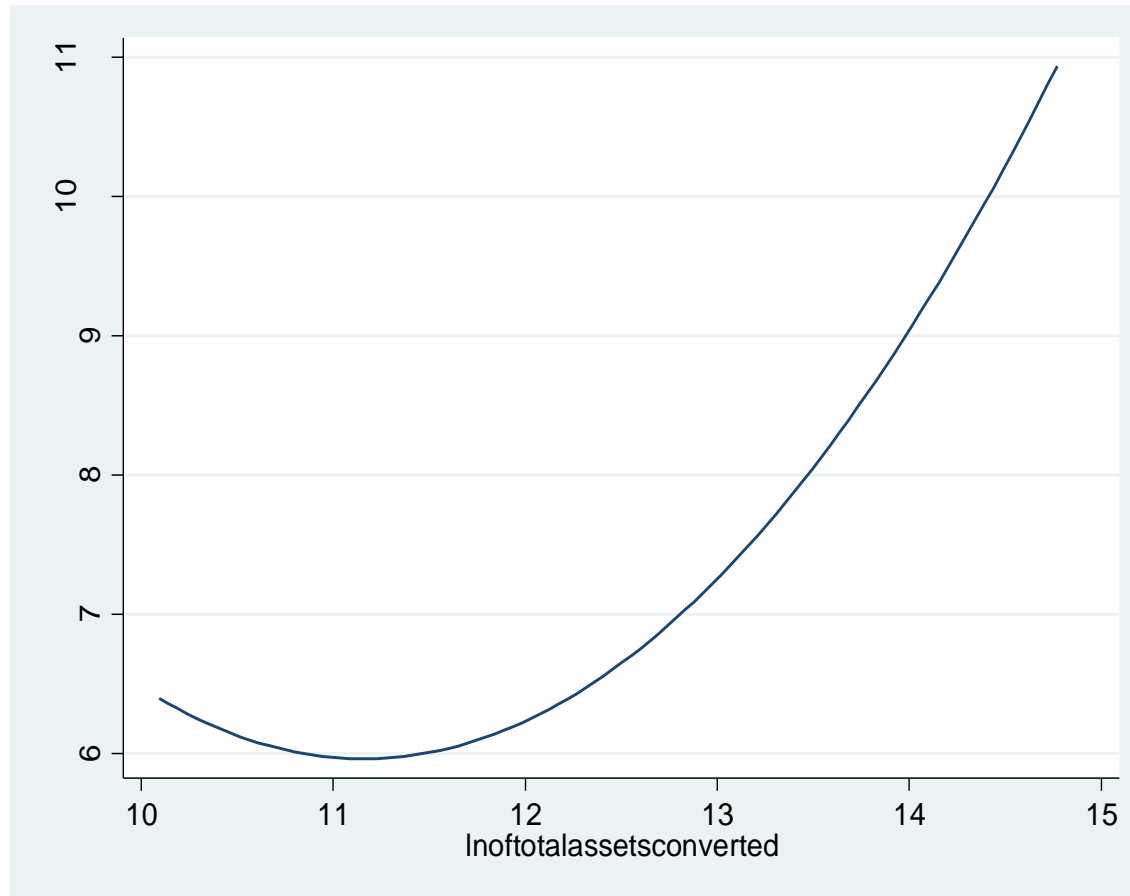


Table 2.1: Source of the Data and Expected Signs on the Coefficients of the Regression

	Type of the Variable	Description and the source of the variables	Predicted Sign
ln(CDS)	Dependant	<ul style="list-style-type: none"> • Natural logarithm of the CDS, 5 year, bank level, mid-spread • Expressed in basis points, denominated in the country's local currency • Published by CMA and retrieved from Thomson Reuters Datastream 	
ln(HP)	Explanatory	<ul style="list-style-type: none"> • Natural logarithm of the House Price Index. • Expressed in basis points • Published by Oxford Economics and retrieved from Thomson Reuters Datastream 	(-)
Regulatory Capital	Explanatory	<ul style="list-style-type: none"> • Tier 2 Capital = Total Capital – Tier 1 Capital. • Expressed as a percentage. Retrieved from Bankscope 	(-)
Leverage	Explanatory	<ul style="list-style-type: none"> • Long term debt to common equity Expressed as a fraction • Published by World Scope Fundamentals and retrieved from Thomson Reuters Datastream 	(+)
Liquidity	Explanatory	<ul style="list-style-type: none"> • Liquid Assets / Dep & ST Funding • Expressed as a percentage • Retrieved from Bankscope 	(-)
Asset Quality	Explanatory	<ul style="list-style-type: none"> • Impaired Loans / Equity • Expressed as a percentage • Retrieved from Bankscope 	(+)
Operations Income Ratio	Explanatory	<ul style="list-style-type: none"> • EBITA / Avg Assets • Expressed as a percentage • Retrieved from Bankscope 	(-)

Table 2.2: Hypothesis of the explanatory variables

Variables	Hypothesis of the variables:
ln(CDS)	<ul style="list-style-type: none"> • Reflects bank level credit default risk – The dependant variable.
ln(HP)	<ul style="list-style-type: none"> • Higher HP, leads to lower credit default risk and CDS spread. • If a borrower defaults, the bank is always able to resell the property and recover the initial mortgage value. Real estate was drastically increasing before the crisis.
Regulatory Capital	<ul style="list-style-type: none"> • The higher the ratio, the higher is the capital buffer. The bank has a better ability to deal with a negative credit event. This leads to a lower is credit risk.
Leverage	<ul style="list-style-type: none"> • The higher the leverage ratio, the higher the debt level of the bank. Thus, default risk increases and so does the total credit risk and the CDS spread.
Liquidity	<ul style="list-style-type: none"> • The higher the liquidity level, the better the bank’s ability to deal with large bank withdrawals and bank runs, which implies a lower credit risk and CDS spread
Operations Income Ratio	<ul style="list-style-type: none"> • Earnings before Interest and Taxes (EBIT) is a measure of profitability that tells investors how much revenue will eventually become profit for a company. It is taken as percentage of average assets. • As long as this figure not volatile, it can be seen as a lower risk form of income. • The higher the ratio and the higher the bank’s revenue. This translates into lower levels of CDS spread.
Asset Quality	<ul style="list-style-type: none"> • Higher Impaired Loans / Equity implies that the bank has a higher proportion of bad debt which deteriorates its asset quality, which subsequently increases its credit risk and the CDS spread.

Table 2.3: Fisher Unit Root Test for ln(BankCDS)

	lnBankCDS, with a drift		lnBankCDS, without a drift	
	Statistics	p-value	Statistics	p-value
Inverse chi-squared (218)P	514.8068	0.0000	308.1825	0.0000
Inverse normal Z	1.8335	0.9666	-6.0148	0.0000
Inverse logit t(504) L*	-4.2132	0.0000	-5.7444	0.0000
Modified inv. chi-squared Pm	14.2145	0.0000	5.0342	0.0000

Notes: Fisher-type unit-root test, Based on augmented Dickey-Fuller tests. P statistic requires number of panels to be finite. Other statistics are suitable for finite or infinite number of panels. Ho: All panels contain unit roots, while H1: At least one panel is stationary. Therefore, ln(Bank CDS) is stationary.

Table 2.4: Fisher Unit Root Test for ln(House Price Index)

	lnHouse Price Index, with a drift		lnHouse Price Index, without a drift	
	Statistics	p-value	Statistics	p-value
Inverse chi-squared (210) P	505.9150	0.0000	441.7546	0.0000
Inverse normal Z	-1.1500	0.1251	-8.8768	0.0000
Inverse logit t(499) L*	-4.3528	0.0000	-9.2317	0.0000
Modified inv. chi-squared Pm	14.4392	0.0000	11.9282	0.0000

Notes: Fisher-type unit-root test, Based on augmented Dickey-Fuller tests. P s statistic requires number of panels to be finite. Other s statistics are suitable for finite or infinite number of panels. Ho: All panels contain unit roots, while H1: At least one panel is stationary. Therefore, ln(House price index) is stationary.

Table 2.5: Baseline Model (RE Robust)

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (House Price Index)	-0.0793	-0.135	-0.140	-0.214	-0.207***	-0.209***
	(0.0918)	(0.0931)	(0.106)	(0.139)	(0.0653)	(0.0664)
Liquidity (Liquid Assets / Dep & ST Funding)		-0.00145	-0.00179	-0.00497**	-0.00529*	-0.00534*
		(0.00109)	(0.00109)	(0.00241)	(0.00290)	(0.00292)
Asset Quality (Impaired Loans / Equity)			0.00390***	0.00507***	0.00767**	0.00785*
			(0.000654)	(0.00128)	(0.00370)	(0.00415)
Regulatory Capital (Tier 2 Capital)				-0.0320	-0.0336	-0.0367
				(0.0288)	(0.0430)	(0.0426)
Leverage (Long-term debt to equity)					0.0288*	0.0297*
					(0.0164)	(0.0175)
Operations Income Ratio (EBITA / Avg Assets)						0.00953 (0.107)
_cons	3.401*** (0.462)	3.776*** (0.459)	3.774*** (0.514)	4.315*** (0.675)	4.162*** (0.359)	4.165*** (0.363)
N	521	457	426	234	130	130
adj. R ²	0.7098	0.7094	0.7272	0.7201	0.7936	0.7939

Notes: Standard errors in parentheses, *** indicate significance at 1% level, ** indicate significance at 5% level, * indicate significance at 10% level. According to the Hausman test, the Prob>chi2 = 0.1144. Therefore, we reject the null hypothesis that the different in the coefficients is not systematic and accept the alternative hypothesis. Thus, preferred method of estimations for the benchmark model is Random Effect.

Table 2.6: Baseline Model (FE Robust)

FE Robust	(1)	(2)	(3)	(4)	(5)	(6)
Ln (House Price Index)	-1.413 (0.915)	-2.271 ^{***} (0.827)	-1.659 ^{**} (0.807)	-1.041 (1.119)	-0.530 (1.253)	0.0294 (1.286)
Liquidity (Liquid Assets / Dep & ST Funding)		-0.000565 (0.00129)	-0.00166 (0.00155)	-0.00473 (0.00288)	-0.00697 (0.00496)	-0.00487 (0.00564)
Asset Quality (Impaired Loans / Equity)			0.00373 ^{***} (0.000877)	0.00607 ^{***} (0.00203)	0.0151 ^{**} (0.00672)	0.0192 ^{***} (0.00540)
Regulatory Capital (Tier 2 Capital)				-0.0582 (0.0356)	-0.0903 (0.0731)	-0.0468 (0.0780)
Leverage (Long-term debt to equity)					0.0382 (0.0256)	0.00747 (0.0227)
Operations Income Ratio (EBITA / Avg Assets)						-0.221 ^{***} (0.0739)
_cons	9.954 ^{**} (4.514)	14.16 ^{***} (3.993)	11.15 ^{***} (3.907)	8.409 (5.478)	5.719 (6.214)	2.952 (6.333)
<i>N</i>	521	457	426	234	130	130
adj. <i>R</i> ²	0.730	0.757	0.763	0.801	0.812	0.825

Notes: Standard errors in parentheses, *** indicate significance at 1% level, ** indicate significance at 5% level, * indicate significance at 10% level.

Table 2.7: Baseline Model, Sensitivity Analysis (RE Robust)

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (House Price Index)	-0.0793 (0.0918)	-0.136 (0.0927)	-0.206* (0.115)	-0.202* (0.115)	-0.214* (0.117)	-0.204* (0.106)
Liquidity (Liquid Assets / Tot Dep & Bor)		-0.00498** (0.00217)	-0.00557** (0.00260)	-0.00497* (0.00275)	-0.00442 (0.00283)	-0.00462* (0.00260)
Asset Quality (Impaired Loans / Gross Loans)			0.0875*** (0.0123)	0.0832*** (0.0134)	0.0847*** (0.0136)	0.0606*** (0.0158)
Regulatory Capital (Total Capital Ratio)				-0.00711 (0.0131)	-0.0123 (0.0139)	-0.00143 (0.0155)
Leverage (Equity / Liabilities)					0.0159 (0.0171)	0.0231 (0.0159)
Operations Income Ratio (Return On Avg Equity (ROAE))						-0.00668*** (0.00234)
_cons	3.401*** (0.462)	3.828*** (0.453)	4.093*** (0.532)	4.076*** (0.561)	4.077*** (0.573)	3.975*** (0.529)
<i>N</i>	521	458	420	396	395	392
adj. <i>R</i> ²	0.7098	0.7107	0.7290	0.7276	0.7283	0.7442

Notes: Standard errors in parentheses, *** indicate significance at 1% level, ** indicate significance at 5% level, * indicate significance at 10% level.

Table 2.8: Bank Size Model (FE Robust)

	(1)	(2)	(3)
Ln (House Price Index)	-0.209*** (0.0664)	0.633 (1.970)	0.928 (1.942)
Liquidity (Liquid Assets / Dep & ST Funding)	-0.00534* (0.00292)	-0.0193*** (0.00629)	-0.0182*** (0.00631)
Asset Quality (Impaired Loans / Equity)	0.00785* (0.00415)	0.0474*** (0.0123)	0.0481*** (0.0120)
Regulatory Capital (Tier 2 Capital)	-0.0367 (0.0426)	-0.0937 (0.122)	-0.100 (0.122)
Leverage (Long-term debt to equity)	0.0297* (0.0175)	-0.0433 (0.0378)	-0.0442 (0.0329)
Operations Income Ratio (EBITA / Avg Assets)	0.00953 (0.107)	-0.366** (0.155)	-0.439** (0.159)
Bank Size (ln(Total Assets))		1.946** (0.881)	-7.447* (4.213)
Bank Size Sq (ln(Total Assets))^2			0.351** (0.159)
_cons	4.165*** (0.363)	-24.32** (9.526)	36.42 (25.23)
<i>N</i>	130	105	105
adj. <i>R</i> ²	0.7939	0.626	0.637

Notes: Standard errors in parentheses, *** indicate significance at 1% level, ** indicate significance at 5% level, * indicate significance at 10% level. According to the Hausman test, the Prob>chi2 = 0.000. Therefore, we fail to reject the null hypothesis that the different in the coefficients is not systematic and accept the alternative hypothesis. Thus, the preferred method of estimations for the bank size model is Fixed Effect.

Table 2.9: Bank Size Model (RE)

	(1)	(2)	(3)
Ln (House Price Index)	-0.209*** (0.0664)	-0.306 (0.190)	-0.254 (0.195)
Liquidity (Liquid Assets / Dep & ST Funding)	-0.00534* (0.00292)	-0.0216*** (0.00494)	-0.0204*** (0.00503)
Asset Quality (Impaired Loans / Equity)	0.00785* (0.00415)	-0.0255*** (0.00530)	-0.0271*** (0.00534)
Regulatory Capital (Tier 2 Capital)	-0.0367 (0.0426)	-0.0259 (0.107)	-0.102 (0.113)
Leverage (Long-term debt to equity)	0.0297* (0.0175)	-0.00663 (0.0338)	-0.00608 (0.0336)
Operations Income Ratio (EBITA / Avg Assets)	0.00953 (0.107)	-0.0479 (0.106)	-0.0608 (0.105)
Bank Size (ln(Total Assets))		0.147 (0.131)	-4.730* (2.673)
Bank Size Sq (ln(Total Assets))^2			0.195* (0.106)
_cons	4.165*** (0.363)	4.279** (1.987)	34.58** (16.74)
N	130	105	105
adj. R2	0.7939	0.3669	0.3751

Notes: Standard errors in parentheses, *** indicate significance at 1% level, ** indicate significance at 5% level, * indicate significance at 10% level. According to the Hausman test, the Prob>chi2 = 0.000. Therefore, we fail to reject the null hypothesis that the different in the coefficients is not systematic and accept the alternative hypothesis. Thus, the preferred method of estimations for the bank size model is Fixed Effect presented above (table 2.8).

Table 2.10: U-test based on FE (Robust) estimations

	Lower bound	Upper bound
Interval	3.517328	18.14844
Slope	-4.978387	5.290466
t-value	-1.593625	2.869668
P> t	.0623356	.0043301
Fieller Extreme Point is at:	10.61056	
95% Fieller interval for extreme point:	[-26.270312; 13.073614]	

Note for the table: H1: U shape, vs. H0: Monotone or Inverse U shape. Overall the U-test indicates the presence of a U-shape: t-value= 1.59, P>|t| = .0623.

Table 2.11: U-test based on RE estimations

	Lower bound	Upper bound
Interval	3.517328	18.14844
Slope	-3.360469	2.338308
t-value	-1.743732	1.96348
P> t	.0420663	.0261174
Fieller Extreme Point is at:	12.14504	
95% Fieller interval for extreme point:	[-Inf;17.337363] U [12.912834;+Inf]	

Note for the table: H1: U shape, vs. H0: Monotone or Inverse U shape. Overall the U-test indicates the presence of a U-shape: t-value= 1.74, P>|t| = .0421.

Table 2.12: GMM Model

VARIABLES	Z
$l. \ln(\text{BankCDS})_{t-1}$	0.325*** [0.062]
ln (House Price Index)	-1.135** [0.491]
Asset Quality	0.015*** [0.004]
Liquidity	-0.042*** [0.007]
Regulatory Capital	0.043 [0.077]
Leverage	-0.011 [0.020]
Operations Income Ratio	-0.336*** [0.072]
ln(Bank Size)	-4.880*** [1.509]
Bank Size Sq	0.226*** [0.060]
Constant	35.353*** [8.909]
Observations	105
Number of id	24
Number of instruments	22
chi2	1174
Arellano-Bond Test for 1st order Autocorr: p value	0.0023
Arellano-Bond Test for 2nd order Autocorr: p value	0.5655
Sargan test for over-identifying restriction: p value	0.188

Note: Robust standard errors reported in parenthesis. ***, **, *, significant at the 1%, 5% and 10% levels, respectively. According to the Arellano-Bond test, the value of the test for second-order autocorrelation presents no evidence of model misspecification. The difference equation is instrumented with the lagged levels, one period of the dependent variable and the levels equation with the difference lagged one period.

The GMM-type instruments consisted of one lag of ln(Bank CDS). The Standard instruments were: $\Delta \ln(\text{BankCDS})_{ijt}$, $\Delta \ln(\text{House Price Index})$, $\Delta \text{Asset Quality}$, $\Delta \text{Liquidity}$, $\Delta \text{Regulatory Capital}$, $\Delta \text{Leverage}$, $\Delta \text{Operations Income Ratio}$, $\Delta \ln \text{Bank Size}$, $\Delta \text{Bank Size Sq}$. The instruments for level equation consisted of the GMM-type instruments, namely: $\Delta \ln(\text{BankCDS})_{ijt}$. The *p values* for the Sargan test for over-identifying restrictions, where the null hypothesis is that the instruments are uncorrelated with the residuals, confirm that the instruments are not correlated with the residuals and they are valid instruments. The lagged dependent variable is statistically significant reflecting a high degree of persistence in the variables. The number of instruments is 22 and is less than the number of groups, which is equal to 24.

Table 2.13: U-test based on GMM estimations

	Lower bound	Upper bound
Interval	3.517328	18.14844
Slope	-3.287294	3.337281
t-value	-3.013213	4.930337
P> t	.0016201	1.54e-06
Fieller Extreme Point is at:	10.77768	
95% Fieller interval for extreme point:	[8.6324106; 11.560559]	

Note for the table: H1: U shape, vs. H0: Monotone or Inverse U shape. We conclude that the overall the U-test indicates the presence of a U-shape: t-value = -3.01, P>|t| = .00162.

Chapter 6

Does the difference in financial systems and regulatory structures matter in explaining cross-country bank CDS spreads?

Abstract

The sixth chapter of this thesis aims at identifying the factors driving bank CDS spread as an indicator of credit risk, across 15 countries with a total of 58 banks, over the period of 2004-2011. It investigates whether the difference in financial systems at country-level (namely the degree financial deepening, financial stability, profitability and financial access) and regulatory structures at bank-level can explain why some countries experience higher levels of credit risk relative to others. The data set is unique as it allows us to shed more light into the factors contributing to credit risk before and during the recent global financial crisis period. In this context, there has been very little focus in the literature considering both bank and country-level drivers of credit risk. The findings from this chapter indicate that the country-level financial deepening as an indicator of credit bubble has contributed to increasing credit risk. In addition, over the period of 2004-2011, financial stability turned out to be insignificant reflecting the fragility of the financial system. When considering bank-level indicators, financial institutions with higher operations income ratio were subject to lower credit risk, while banks with lower asset quality and lower levels of liquidity appeared to be more likely to face high CDS spreads and increased credit risk.

6.1 Introduction

The perception of credit risk in the banking sector has deeply changed since the beginning of the 2007-2009 crisis, when the financial system was hit by a wave of defaults, with the Credit Default Swaps (CDS) spreads reaching record high levels in most major markets. The underlying cause of the crisis of 2007-2009 has been identified to be channels through which banks have transferred credit risk within the financial system either via trading CDS or issuing CDOs (Collateralized debt obligations). CDS spread therefore has been identified as a superior measure of credit risk compared to bond spreads ((Houweling and Vorst (2005), Hull et al., (2004); Blanco et al., (2005); Zhu, (2006)). These CDS spreads can differ across countries depending on the extent to which such activities have been encouraged by the regulators or the financial systems in individual countries, thereby making country-level financial system soundness (stability) and financial market development (financial deepening) as key determinants in reflecting any sign of credit bubble or financial fragility.

Past literature on the CDS spread and its determinants can be split into two groups. The first stream of literature focused mainly on the macroeconomic drivers of the CDS spread, identifying the relevance of interest rates, yield spreads and inflation among other indicators (Alexander & Kaeck (2008); Bevan & Garzarelli (2000); Duffie & Singleton (1999); In, Brown & Fang (2003); Lekkos & Milas (2001); Naifar (2010)). The second stream of literature looked at the bank level determinants of CDS spreads, which included: liquidity, leverage, asset quality, credit ratings and volatility (Casu and Chiaramonte (2013), Fabozzi et al. (2007); Hull et al. (2004), Collin-Dufresne et al. (2001), Campbell and Taksler (2003) and

Benkert (2004)). Little focus has been made in this literature combining both country and bank level determinants of bank CDS spread. While much of the extant literature so far has focused on the bank level indicators in driving credit risk, in this chapter we contribute to this emerging research area by examining whether country-level financial systems can explain differences in bank-level credit risk across countries.

The existing literature linking capital requirement to credit risk states that the minimum regulatory capital banks need to hold will primarily depend on the capital buffer that each financial firm is required to adhere to. From previous experience, there is evidence that banks have the tendency to adjust their levels of capital buffer according to the variations in stock prices and their stockholders' and debt holders' preferences (Flannery (1994); Flannery and Sorescu (1996); Myers and Rajan (1998); Diamond and Rajan (2000)). In addition, there are other factors that affected the minimum level of capital held by banks. Financial institutions used securitization and structured financial products to shift their real debt exposures and evade regulatory requirements. Froot et al. (1993) and Froot and Stein (1998) shed light into how banks jeopardized their lending activities and misused risk management techniques to escape regulatory requirements. Similarly, Dias and Mroczkowski (2012) argue that CDS instruments were used for speculative reasons, while they were originally conceived for hedging purposes.

Limited research however linked the CDS spread to financial stability. In fact, Huang et al. (2009), Cont and Minca (2010), Markose et al. (2012) and Rodríguez-Moreno and Peña (2013) were among the very few authors that investigated the impact of the CDS spread on systemic stability. As of 2008, the

CDS market generated over \$60 trillion (ISDA, 2008). With such a strong market presence, any shock to the CDS market is very likely to cause significant disruptions, if not the collapse, of the already fragile banking system. It is therefore important to address the relationship between the CDS market and financial stability.

In addition, there is a significant gap in the existing literature linking credit risk and the excessive bank lending activities. The credit expansion of early 2000 has significantly contributed to the availability of easy credit. In fact, it increased the banks' ability to provide credit to low-income consumers, who later defaulted on their obligations. Although past literature identified the factors contributing to the beginning of the financial crisis (such as financial imbalances, large foreign funding inflows, lax monetary policy of low interest rates as well as financial innovation) (Bernanke and Gertler (1999), Taylor (2007, 2009) and Jorda et al. (2011)), it failed to address how the excessive credit supply increased CDS spread and the overall credit risk.

Due to the difference in regulatory structures and financial systems across the global financial markets, this chapter aims at understanding why some countries experience higher levels of credit risk relative to others. Our unique dataset allows us to uncover the behavior of bank CDS spread as a measure of credit risk, across 15 countries with 58 banks, over the period of 2004 and 2011. The data on financial systems is unique and new. In the light of the recent financial crisis, it is essential for governments and regulatory authorities to uncover the different drivers of credit risk and come up with an optimal regulatory structure to ensure the soundness of the financial system.

This chapter uses five determinants of the Bank CDS spread at a country-level (namely the degree of financial deepening, financial stability, financial access, financial profitability, and the housing market). In addition, at bank-level, we incorporate five determinants of the Bank CDS spread (namely asset quality, liquidity, regulatory capital, operations income ratio and leverage). Based on our findings, we argue that: (a) at country-level, financial deepening as an indicator of credit bubble has contributed to increasing credit risk. In addition, financial stability emerged as significant reflecting the fragility of the financial system. (b) at bank-level, financial institutions with lower asset quality and decreased levels of liquidity appear to be more likely to face higher CDS spreads and increase in credit risk. Furthermore, banks with high level of operations were better able to sustain the recent financial crisis and were therefore subject to less risk.

The rest of the sixth chapter of this dissertation is organized as follows. Section 6.2 describes the econometric methodology. Section 6.3 reports the empirical results. Section 6.4 concludes.

6.2 Methodology

In this section, we will first discuss the baseline model, which consists of identifying the drivers of the CDS using bank-level determinants (namely: asset quality, liquidity, leverage, operations income ratio and leverage) across 58 banks and 15 countries, over the period of 2004-2011. Furthermore, our analysis will be then extended, by incorporating both country-level characteristics and bank-level CDS spread determinants, in order to identify the factors that make some countries less prone to credit risk compared to others. The results are summarized in Tables 4.2-4.8, which report the main findings using OLS, fixed effect, random effect estimations (depending from the Hausman test) and GMM estimations.

Before defining our models, it is essential to test whether our variables are stationary. Therefore, we will first start by conducting the unit root test.

6.2.1 Unit root Test

Since we are dealing with an unbalanced panel dataset, the only test that we can conduct is the Fisher unit root test.

The Fisher-type test uses p-values from unit root tests for each cross-section i . The formula of the test looks as follows:

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

The test is asymptotically chi-square distributed with $2N$ degrees of freedom ($T_i \rightarrow \infty$ for finite N). The advantage of using Fisher Cointegration test is that it can

handle unbalanced panels. Furthermore, the lag lengths of the individual augmented Dickey-Fuller tests are allowed to vary.

When $\ln p_i$ is close to 0, the null hypothesis is rejected. When $\ln p_i$ closes to $-\infty$ such large p values are identified, implying the rejection of the null hypothesis and the presence of a unit root. However, if p_i approaches the value of 1, the null hypothesis cannot be rejected. In case $\ln p_i$ approaches the value of 0, then a small p value will be identified, and the null hypothesis stating the existence of a unit root will be accepted.

The unit root test represented in Eq. (1) is therefore utilized in order to test the null and the alternative hypothesis of the Fisher-type test based on the p-value. These are summarized as follows:

H_0 : All panels contain unit roots

H_1 : At least one panel is stationary

The results from the Fisher test are presented in table 3.1. The findings indicate that at 1% level, both the natural logarithm of the bank CDS spread and the natural logarithm of the house price index do not contain a unit root and are therefore considered to be stationary. Having conducted the unit-root test, in the section we will identify our baseline model, and the extended model which considers both the bank-level and the country-level factors driving the CDS spread across 15 countries and 58 banks, over the period of 2004-2011, using FE, RE and GMM estimations.

6.2.2 Baseline Model (Bank-level Factors)

We will first start by estimating the baseline model, expressed in equation 2 below, using bank-level characteristics in order to identify the factors that make some banks riskier than others, across different countries. The results are summarized in tables 4.2-4.4, which report the main findings using three econometric methodologies (i.e. pooled OLS and FE and RE estimations, (depending the Hausman test). The baseline model is defined in equation (2) as follows:

$$\begin{aligned} \ln \text{BankCDS}_{ijt} = & \\ & B_0 + B_1 \ln \text{HP}_{it} + B_2 \text{Asset Quality}_{ijt} + B_3 \text{Liquidity}_{ijt} + B_4 \text{Regulatory Capital}_{ijt} + \\ & B_5 \text{Leverage}_{ijt} + B_6 \text{Operations}_{ijt} + \theta_j + \psi_t + \varepsilon_{ijt} \end{aligned} \quad (2)$$

Where the acronyms stand for:

ln(BankCDS): Natural Logarithm of the Bank CDS spread.

ln(HP): Natural Logarithm of the House Price Index

Asset Quality: Impaired Loans/Equity

Liquidity: Liquid Assets to Total Deposits and Short-term funding

Regulatory Capital: Tier 2 Capital = Total Capital – Tier 1 Capital

Leverage: Long-term Debt to Common Equity

Operations Income Ratio: EBITA (Earnings Before Interest Tax and Amortization)/ Average Assets)

θ_j : Bank fixed effect

ψ_t : Time fixed effect

ε_{ijt} : Disturbance term

i stands for the country

j stands for the banks

t stands for time

After estimating the bank-level factors driving of the CDS spread across 58 banks and 15 countries, expressed in equation (2), in the next part of our analysis we will investigate what make some countries subject to less credit risk compared to others countries by incorporating both bank-level factors and country-level factors driving the CDS spread, namely: Financial Deepening, Financial Stability, Profitability and Financial Access. In addition, we will conduct a robustness check by substituting each country-level indicator by its alternative proxy in order to verify whether our results still hold. The model is explained in the next section.

6.2.3 Country Level Indicators

Equation 3 below defines the model that considers both bank and country-level characteristics, which we estimate using the FE and RE estimations (depending from the Hausman test) as follows:

$$\ln \text{BankCDS}_{ijt} = B_0 + B_1 \ln \text{HP}_{it} + B_2 \text{Asset Quality}_{ijt} + B_3 \text{Liquidity}_{ijt} + B_4 \text{Regulatory Capital}_{ijt} +$$

$$\begin{aligned}
& B_5 \text{Leverage}_{ijt} + B_6 \text{Operations Ratio}_{ijt} + B_7 \text{Financial Deepening}_{it} + \\
& B_8 \text{Financial Stability}_{it} + B_9 \text{Profitability}_{it} + B_{10} \text{Access}_{it} + \theta_j + \psi_t + \varepsilon_{ijt} \quad (3)
\end{aligned}$$

Where the acronyms stand for:

lnBankCDS: Natural Logarithm of the bank CDS spread.

lnHP: Natural Logarithm of the House Price Index, across countries.

Asset Quality: Impaired Loans/Equity, at individual bank-level.

Liquidity: Liquid Assets to Total Deposits and Short-term funding, at individual bank-level.

Regulatory Capital: Tier 2 Capital = Total Capital – Tier 1 Capital, at individual bank-level.

Leverage: Long-term Debt to Common Equity, at individual bank-level.

Operations Income Ratio: EBITA (Earnings Before Interest Tax and Amortization)/ Average Assets), at individual bank-level.

Financial Deepening: Deposit money bank assets to GDP (%), at country level for the entire banking sector.

Financial Stability: Bank Z-Score, at country level for the entire banking sector.

Profitability: Overhead costs to total assets (%), at country level the entire banking sector.

Financial Access: Bank branches per 100,000 adults.

θ_j : Bank fixed effect

ψ_j : Time fixed effect

ε_{ijt} : Disturbance term

i stands for the Country

j stands for the banks

t stands for time

Having identified the models that incorporate both bank-level and country-level indicators of credit risk, in the next section, we will explain the GMM model.

6.2.4 Generalized Method of Moments (GMM) Model

It is likely that the above results could be plagued by endogeneity, that is, they may be correlated with the error term. It is for this reason that we adopt the Generalized Method of Moments (GMM) approach to check the robustness of our previously obtained results.

The GMM methodology is the most appropriate estimation technique to analyze the drivers of the CDS spread, considering both bank and country-level factors, because the number of banks (N) in our sample (58 banks) is higher than the number of the years (T) (7 years) (Kiviet (1995) and Judson and Owen (1999)). Our baseline model consists of the CDS spread as the dependent variable. The

explanatory variables consist of the bank-level drivers of the CDS spread, namely: leverage, regulatory capital, liquidity, asset quality and operations Income ratio. In addition, we also consider the country-level drivers of the bank CDS spread, namely: financial deepening, financial stability, profitability, financial access and the house price index. Since there are no exogenous instruments in our model with the adequate properties to be considered, that would be correlated with the endogenous variable but uncorrelated with the error term (u), it is appropriate to consider the system GMM model approach that employs instruments with lags of the endogenous variable (*lagged $\ln(\text{BankCDS})$*)

The GMM estimation includes instruments for differenced equation. As such, the GMM-type instruments consisted of one lag of $\ln(\text{Bank CDS})$. The Standard instruments were: $\Delta \ln(\text{BankCDS})$, $\Delta \ln(\text{HousePriceIndex})$, $\Delta \text{AssetQuality}$, $\Delta \text{Liquidity}$, $\Delta \text{RegulatoryCapital}$, $\Delta \text{Leverage}$, $\Delta \text{Operations Income Ratio}$, $\Delta \text{FinancialDeepening}$, $\Delta \text{Financial Stability}$ and $\Delta \text{Profitability}$. The instruments for level-equation consisted of the GMM-type instruments, namely: $\Delta \ln(\text{BankCDS})$. The GMM model is defined in equation (4) as follows:

$$\begin{aligned}
 \ln \text{BankCDS}_{ijt} = & B_0 + B_1 \ln \text{BankCDS}_{ijt-1} + B_2 \ln \text{HP}_{it} + B_3 \text{Asset Quality}_{ijt} + \\
 & B_4 \text{Liquidity}_{ijt} + B_5 \text{Regulatory Capital}_{ijt} + B_6 \text{Leverage}_{ijt} + \\
 & B_7 \text{Operations Ratio}_{ijt} + B_8 \text{Financial Deepening}_{it} + B_9 \text{Financial Stability}_{it} + \\
 & B_{10} \text{Profitability}_{it} + B_{11} \text{Access}_{it} + \theta_j + \psi_t + \varepsilon_{ijt}
 \end{aligned} \tag{4}$$

Where the acronyms stand for:

lnBankCDS_{ijt-1}: Lag of Natural Logarithm of the bank CDS spread.

lnBankCDS: Natural Logarithm of the bank CDS spread.

lnHP: Natural Logarithm of the House Price Index, across countries.

Asset Quality: Impaired Loans/Equity, at individual bank-level.

Liquidity: Liquid Assets to Total Deposits and Short-term funding, at individual bank-level.

Regulatory Capital: Tier 2 Capital = Total Capital – Tier 1 Capital, at individual bank-level.

Leverage: Long-term Debt to Common Equity, at individual bank-level.

Operations Income Ratio: EBITA (Earnings Before Interest Tax and Amortization)/ Average Assets), at individual bank-level.

Financial Deepening: Deposit money bank assets to GDP (%), at country level for the entire banking sector.

Financial Stability: Bank Z-Score, at country level for the entire banking sector.

Profitability: Overhead costs to total assets (%), at country level the entire banking sector.

Financial Access: Bank branches per 100,000 adults.

θ_j : Bank fixed effect

ψ_j : Time fixed effect

ε_{ijt} : Disturbance term

□ i stands for the Country

□ j stands for the banks

□ t stands for time

Having identified our baseline model, the country-level model and the GMM model, in the next section, we will discuss the empirical findings.

6.3 Empirical Findings

6.3.1 Findings from the baseline model

Our findings from the bank-level analysis are demonstrated in tables 4.2-4.4. According to the Hausman test, ($Prob > \chi^2 = 0.0844$), suggest that the random effect model (RE) is the preferred method of estimation for our baseline model. According to our results, which are presented in table 3.3 (RE model), asset quality, defined as the ratio of *impaired loans to equity*, is strongly and positively related to the CDS spread. In fact, as securitization activities increased during the credit boom of early 2000, banks used financial engineering as a mean to finance more mortgages activities and provide more loans to their consumers. Since financial institutions no longer had to wait for 20 years (average mortgage life) to receive their money back, securitization was a very convenient way to expend their investment activities. This resulted in banks becoming more reckless with the way they accessed the credit worthiness of their borrowers. In fact, most loans and mortgages were granted low-

income consumers. That also implied that the mortgage backed securities primarily consisted of highly risky debt. As a result of the enhanced credit ratings granted by the rating agencies, the structured derivative products did not reflect the real risks that were embedded in them, until the beginning of the housing bubble.

In summer 2007, the most severe financial crisis since the great depression of 1929 began and the toxic nature of the assets that was embedded in the structured products came into light and subsequently negatively affected the investors' that were exposed to it. Our results in table 3.3 are consistent with these events. In fact, after conducting the random effect (RE) regression analysis, asset quality proved to be significant and positively related to the CDS spread. This implies that as banks' asset quality deteriorates, the credit risk increases, which gets reflected in higher CDS spread. Our finding is consistent with a research conducted by Chiaramonte and Casu (2013) who also found that asset quality is a strong driver of the CDS spread. This is in also line with a research conducted by Ötoker-Robe and Podpiera (2010) who reached the same conclusion by analyzing the CDS spread of large and complex financial institutions in the EU area.

In addition, our findings from table 3.3 show that liquidity expressed as the ratio of *Liquid Assets to Total Deposits and Borrowings* also has a strong impact on the CDS spread, being negatively related. As such, high levels of liquidity, decreases credit risk and improve banks' ability to withstand a financial crisis. In addition, higher liquidity also reduces the risk of bank-run and allows financial institutions to meet depositors' demand for cash. This result is in line with the previous literature. More specifically our findings are in line with researches conducted by Chen et al.

(2007), Chiaramonte and Casu (2013), Das et al. (2009), Annaert et al. (2013) and Fabozzi et al. (2007) who confirmed the importance of liquidity as a CDS spread determinant.

Our third finding from the baseline model is that the *house price index* is negatively related to the CDS spread over the period of 2004-2011 (demonstrated in table 3.3). This follows the economic logic given that before the recent financial crisis, as house price were continuously appreciating, credit risk was low. However, when the housing bubble burst the numbers of defaults increased; thus pushing up the CDS spread.

Having identified the most important drivers of the CDS at bank-level, in the next section we will discuss the findings obtained from the analysis that incorporated both bank and country-level, across 58 banks and 15 countries, as drivers the CDS spread.

6.3.2 Findings from Country-level analysis

Our findings are illustrated in tables 3.4-3.6. The preferred method of estimation is the FE method given that according to the Hausman test ($Prob > \chi^2 = 0.000$), we therefore focus on the results illustrated in table 3.5. Our first finding indicates that the *Bank Z-Score* (Financial Stability 1) comes as significant and negatively related to the CDS spread. The Bank Z-score captures the probability of default of a country's banking system. As such, the *Z-score* compares the buffer of a country's banking system (capitalization and returns) with the volatility of those returns. Our finding exhibits a negative relationship, implying that as the volatility of

returns increase, the CDS spread should also go up, reflecting the higher level of credit risk. Since, the *Bank Z score* is found to be highly significant, this reflects the lack of financial stability over the period of 2004-2011.

Furthermore, this chapter uncovers another important finding. By incorporating the ratio of *deposit money bank assets to GDP (%)* (Financial Deepening 1), our results show that higher degree of financial deepening results in a wider CDS spread. In fact, Financial Deepening 1 reflects the general size of the banking sector with respect to the economy of the country. There is evidence that faster growing countries experience greater levels of growth, and higher CDS spreads and credit risk. In the same vein, countries with slower economic growth tend to originate fewer loans from their deposits, thus avoiding the high risk of default. This in turn reduces their overall credit risk exposure. When we use an alternative measure of Financial Deepening, i.e. Financial Deepening 2 (*Financial system deposits to GDP (%)*), which represents an alternative measure of financial intermediation in a country, we reach the same conclusion that a more developed banking sector and a higher level of financial intermediation leads to stronger economic development and the generation of credit. Higher credit supply in turn causes the CDS spread to increase; thus pushing up the overall credit risk. Thus, we find that it is the credit bubble that caused and fuelled the recent financial crisis.

When incorporating the degree of financial profitability, measured by the *Overhead costs to total assets %* (Financial Profitability 1), we found that it was not a significant factor determining the variation in the CDS spread. Moreover, adding the degree of financial Access, measured by the *number of bank branches per*

100,000 adults, did not have an impact on changes in the level of CDS spread. Thus, the degree of a country's financial openness does not affect the level of credit risk.

6.3.3 Robustness Check

In this section, we assess the sensitivity of our model which consists of both bank-level and country-level determinants of the CDS spread. Therefore, in table 3.6, we keep our baseline model and for robustness purposes replace: (i) Financial Deepening 1 (*Deposit money bank assets to GDP (%)*) with Financial Deepening 2 (*Financial system deposits to GDP (%)*); (ii) Financial Stability 1 (*Bank Z Score*) with Financial Stability 2 (*Volatility of stock price index*); (iii) Profitability 1 (*Overhead costs to total assets (%)*) with Profitability 2 (*Return on equity (%)*); and (iv) we keep Financial Access (*Bank branches per 100,000 adults*) as an indicator of easiness to access the banking sector.

Our findings are illustrated in table 3.6 and show that our previously obtained results remain unchanged. In fact, the results indicate that in the baseline model, both Asset quality (*Impaired Loans / Equity*) and Liquidity (*Liquid Assets / Tot Dep & Bor*) are important drivers of the CDS spread. In fact, asset quality proved to be positively related to the CDS spread, indicating that when the asset quality deteriorates, the CDS spread increases. In addition, liquidity appears to be negatively related to the CDS, implying that banks that have more liquidity are better able to deal with credit risk and reduce their default risk in a significant manner. This is reflected in narrower CDS spread. The results from table 3.6 also indicate that leverage (*long term debt over equity*) is a significant driver of the CDS spread. Typically banks that borrow more, find it harder to repay their outstanding debt in times of crisis. Thus, higher levels of leverage increase the CDS spread and credit

risk. This is consistent with the finding obtained by Annaert et al. (2013). Also, while the operations Income ratio (*EBITA / Avg Assets*) is not significant in table 3.6, it is significant in our GMM analysis (table 3.7), which is considered to be the strongest model in our analysis as it addresses the issue of endogeneity. This will be discussed in greater detail in the next section.

In terms of the country-level indicators, our results also remain unchanged. As such, Financial Deepening 2 (*Financial system deposits to GDP (%)*) is highly significant and positively related to the CDS spread, reasserting our previous findings that as the number of deposits increases, the stronger growth of deposits relative to the GDP will ultimately lead to an increase the overall CDS spread. In fact, Financial Deepening 2 reflects the size of the banking sector. Thus, countries with smaller banking sectors are subject to less credit risk and narrower CDS spread. From our results (represented in table 3.7), we can also observe that Financial Stability 2 (*Volatility of stock price index*) is highly significant and positively related to the CDS spread. This implies that as the volatility of the stock price index increases, it is likely to negatively impact on credit risk as it creates more uncertainty in the financial market. As a result, this leads to increased financial instability and higher CDS spread. In addition, as previously found in table 3.5, both Profitability 2 (*Return on equity (%)*) and Financial Access (*Bank branches per 100,000 adults*) remain insignificant. However, it is important to recognize that there might be an issue with endogeneity in our results. Therefore, in the next section, we will conduct GMM analysis.

6.3.4 Generalized Method of Moments (GMM) analysis

Table 3.7 below illustrates the outcome from the Arellano-Bond (1991) test of autocorrelation. As such, according to the Arellano-Bond test, there is no evidence of second order autocorrelation; therefore our model is correctly specified (*AR2 p-value* = 0.9147). The difference equation is instrumented with the lagged levels, one period of the dependent variable and the levels equation with the difference lagged one period.

Moreover, we report Sargan-Hansen test that follows the Chi-squared distribution with (L-K) degrees of freedom. The statistic values test the validity of instruments. As such, the outcome of the Sargan test is conducted in order to test whether our equation is correctly identified. Under the null hypothesis, the equation is adequately and correctly identified. The alternative hypothesis states that our model is over-identified (i.e. the number of instruments is more than the number of endogenous variables). According to our findings, from table 3.7, the *p-values* for the Sargan test for over-identifying restrictions, where the null hypothesis is that the instruments are uncorrelated with the residuals, confirm that the instruments are not correlated with the residuals and they are valid instruments (*Sargan Prob > chi2* = 0.1294). Furthermore, we are satisfying the condition whereby our number of instruments is 23 and is less than the number of groups, which is equivalent to 26 groups. The lagged dependent variable is statistically significant reflecting a high degree of persistence in the variables.

Table 3.7 below reports the results from the GMM analysis. The results are consistent with the findings obtained from both the benchmark model and the model

which considered both the bank-level and the country-level determinants of the CDS spread (FE and RE estimations). As such, we observe a positive relationship between asset quality and the CDS spread. This finding is in line with our previous results from the baseline model and the model which consisted of both bank-level and country-level indicators (tables 3.3 and 3.5 and 3.6). In fact, banks with higher ratio bad loans (*impaired loans/ equity*) have a worse quality of assets and therefore experience more credit risk and higher CDS spread.

Furthermore, the findings table 3.7 also illustrates the negative relationship between bank liquidity (*liquid assets/ total deposits and borrowings*) and the CDS spread. This is consistent with our previous findings (table 3.3). As such, higher levels of liquidity helped financial institutions to sustain a negative credit event and not solely rely on borrowing from the frozen capital markets. In addition, higher liquidity insures that financial institutions are able to provide the necessary cash to its customers upon demand and avoid bank-runs, thus decreasing the credit risk and narrowing the CDS spread. In a similar vein, table 3.7 indicates the presence of a negative relationship between the banks' operations Income ratio (*EBITA / Average Assets*) and the CDS spread. Therefore, banks that achieve higher level of operations are considered to be safer and subject to less credit risk. Also, according to our GMM estimations, the remaining bank-level bank indicators, namely: regulatory capital and leverage proved to be insignificant drivers of the CDS spread in the sample period. Although leverage was significant in the static fixed effect analysis and in the random effect analysis (table 3.3 and 3.6), it turns out to be insignificant in the GMM analysis partly because of the limited variability in the data in a dynamic setting. One of the reasons that explain the non-significance of the regulatory capital

is related to the fact that banks held capital buffers which did not reflect their real risk intakes. In fact, the regulatory cushion and the ability to absorb losses did not reflect the off-balance-sheet securitization activities and the increased level of financial engineering banks were conducting.

On a country-level, our results reassert our previous findings that financial deepening is an important determinant of the CDS spread over the period of 2004-2011. Among the country-level indicators, our results show that there is a positive relationship between financial deepening, which reflects the level of credit in the financial system, and the CDS spread. We find that as banks were excessively lending, the easy credit provision to low-income consumers, lead to an increase in the level of credit risk. According to the GMM estimation, financial stability was insignificant reflecting the fragility of the financial system, while profitability and financial access were less important factors determining credit risk as compared to financial deepening which was significant across both GMM and FE estimations (tables 3.5-3.7).

6.4 Conclusion

In the light of the recent financial crisis, there has been an imminent need to identify the drivers of the CDS spread, as an indicator of credit risk, in order to ensure a systemic stability and avoid another financial crisis. The sixth chapter of this dissertation investigates both bank-level and country-level drivers of the CDS spread across 15 countries and 58 banks, over the period of 2004-2011. It is the first research to our knowledge that considers both bank and country-level drivers of bank CDS spread, before, during and after the financial crisis.

The findings of this chapter show that the strongest bank-level drivers of the CDS spread are asset quality, liquidity and the operations income ratio. In fact, our results show that banks with stronger liquidity levels experienced a reduced exposure to credit risk and had therefore a narrower CDS spread. Similarly, banks with better asset quality were better able to sustain themselves as they had less toxic asset and experienced lower level of defaults. Leverage and regulatory capital however did not turn out to be significant, partly due to the limited variability in the data over the sample period.

Country-level analysis unveils an important finding which directly relates the credit bubble to the CDS spread. In fact, our results show that there is a positive relationship between financial deepening, which reflects the level of credit in the financial system, and the CDS spread. We find that as banks were excessively lending, the easy credit provision to low-income consumers, lead to an increase in the level of credit risk. Therefore, countries that were excessively lending experienced exceptionally high CDS spreads and their banks were more prone to default. In addition, we show evidence that the recent financial crisis caused a systemic instability, which further fragilized financial markets. Furthermore, we find that at country-level, profitability and the degree of financial access to banks does not affect the CDS spread.

Figure 3.1: Country-level CDS spread Determinants

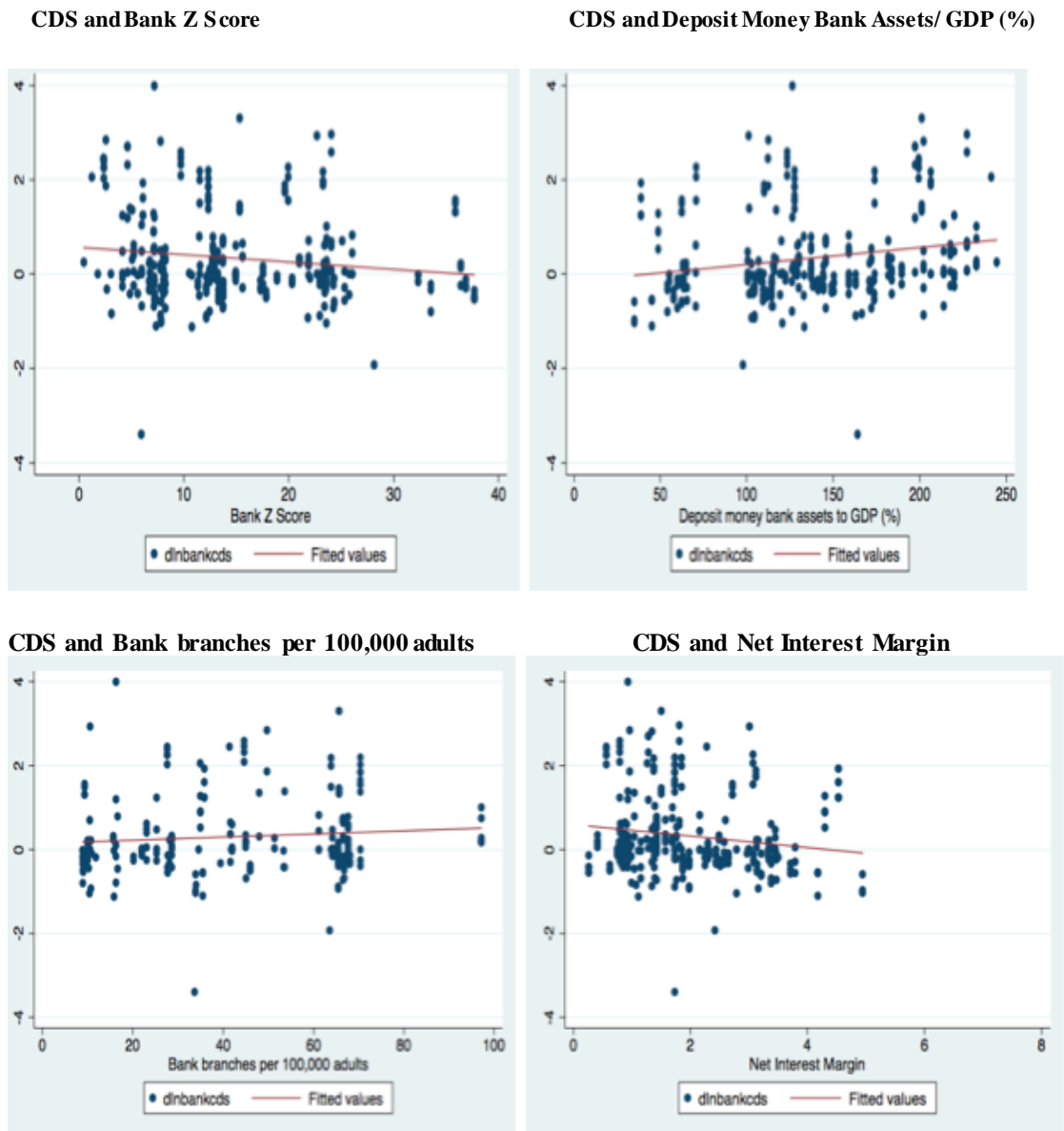


Fig. 4.1a & b. Graphical illustration of the relationship between bank CDS spread and country level indicators (Bank Z score, Deposit Money Bank Assets to GDP (%), and Bank branches per 100,000 adults, Net Interest Margin).

Figure 3.2: Bank CDS spread in Developed and Emerging Countries

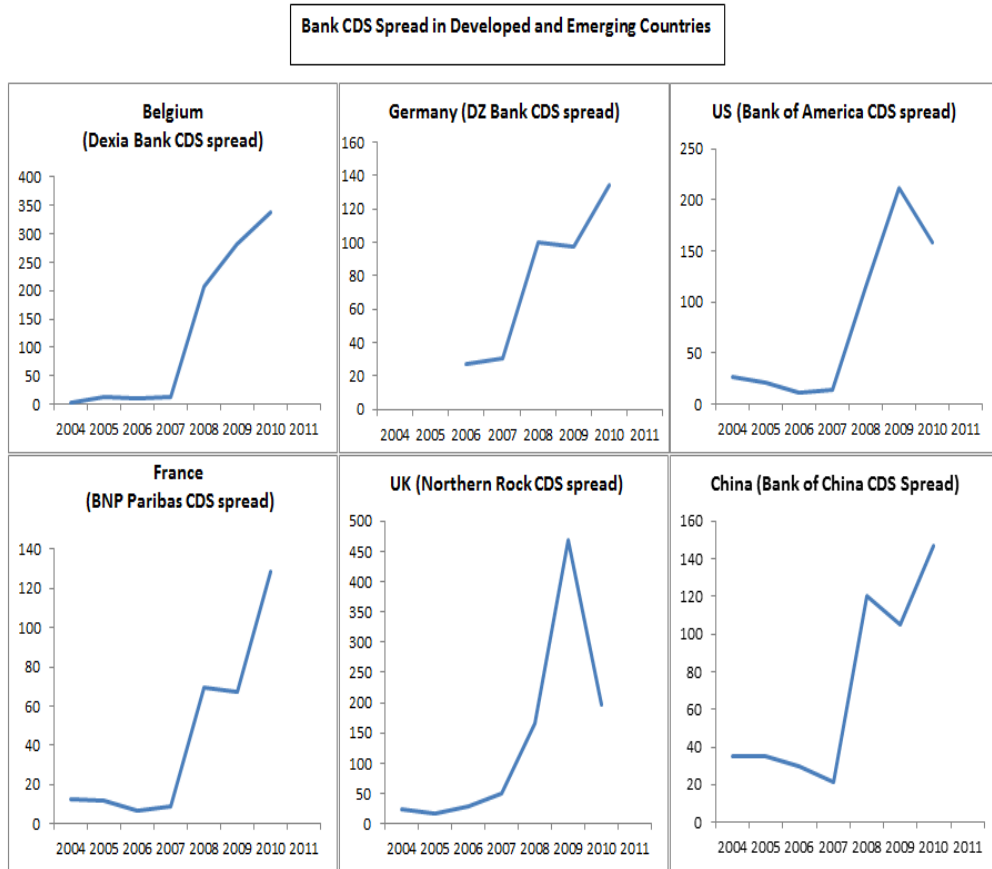


Fig4.2: Graphical illustration of bank CDS spread fluctuation of selected banks, across developed and emerging countries, extracted from the panel sample, over the period of 2004 to 2011: Dexia (Belgium), DZ Bank (Germany), Bank of America Corporation (US), BNP Paribas (France), Northern Rock (UK), Bank of China (China). The Bank CDS spread is expressed in basis points.

Figure 3.3: The transmission of the credit bubble that caused the dramatic increase in the CDS spread and credit risk

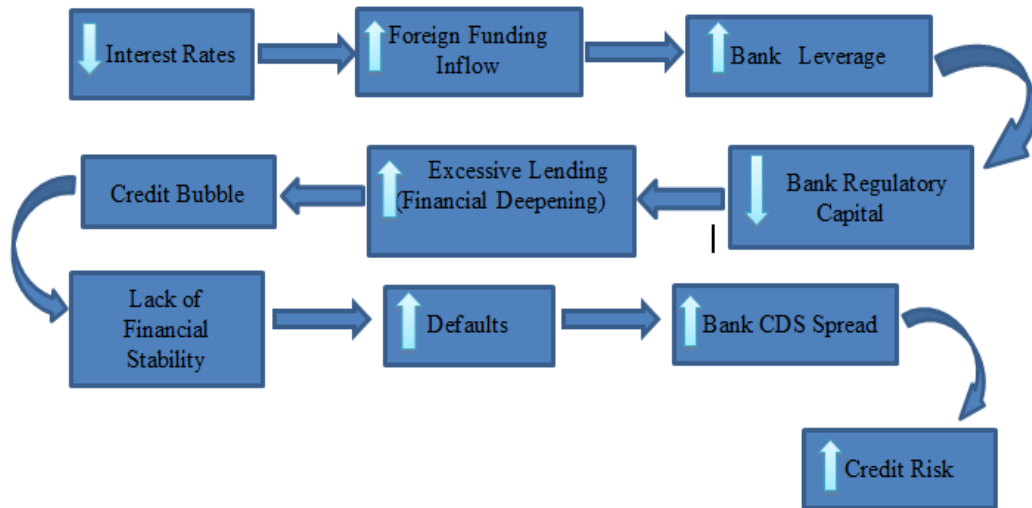


Table 3.1: Fisher Unit Root Test for ln(BankCDS) and ln(HousePriceIndex) and are non-stationary spreads and credit risk.

	ln(BankCDS)		ln(HousePriceIndex)	
	Statistics	p-value	Statistics	p-value
Inverse chi-squared(110) and (98) P	155.8253	0.0027	326.2547	0.0000
Inverse normal Z	-4.4617	0.0000	-11.2148	0.0000
Inverse logit t(279) and (249) L*	-4.2266	0.0000	-11.8235	0.0000
Modified inv. chi-squared Pm	3.0895	0.0010	16.3039	0.0000

Notes: From the p-values, we can safely reject the null-hypothesis and conclude that both ln(BankCDS) and ln(HousePriceIndex) are stationary.

Table 3.2: Bank Level Determinants of the CDS spread – OLS

	(1)	(2)	(3)	(4)	(5)	(6)
In (House Price Index)	-0.00599 (0.0484)	-0.145** (0.0619)	-0.204** (0.0921)	-0.224** (0.103)	-0.210** (0.106)	-0.224** (0.105)
Asset Quality (Impaired Loans / Equity)		0.00431*** (0.00111)	0.00447*** (0.00129)	0.00488*** (0.00145)	0.00769*** (0.00261)	0.00760*** (0.00258)
Liquidity (Liquid Assets / Tot Dep & Bor)			-0.0105*** (0.00391)	-0.0130*** (0.00466)	-0.00956* (0.00510)	-0.00785 (0.00526)
Regulatory Capital (Tier 2 Capital)				-0.0355 (0.0287)	-0.0280 (0.0493)	-0.0309 (0.0491)
Leverage (Long term debt to Common Equity)					0.0275* (0.0161)	0.0317* (0.0167)
Operations Income Ratio (EBITA / Avg Assets)						0.0743 (0.0948)
_cons	2.975*** (0.267)	3.607*** (0.346)	4.155*** (0.496)	4.494*** (0.569)	4.209*** (0.589)	4.089*** (0.583)
<i>N</i>	326	262	255	234	130	130
adj. <i>R</i> ²	0.700	0.711				

Notes: Standard errors are reported in parentheses * $p < 0.10$, ** $p < .05$, *** $p < .01$. All estimation are controlled for time-effect.

Table 3.3: Bank Level Determinants of the CDS spread - RE

	(1)	(2)	(3)	(4)	(5)	(6)
In(House Price Index)	-0.0257	-0.171*	-0.161*	-0.197**	-0.218**	-0.212**
	(0.0710)	(0.0961)	(0.0974)	(0.0930)	(0.105)	(0.107)
Asset Quality		0.00456***	0.00430***	0.00427***	0.00474***	0.00785***
(Impaired Loans / Equity)		(0.00132)	(0.00134)	(0.00131)	(0.00146)	(0.00265)
Operations Income Ratio			-0.0586	-0.0459	-0.0641	0.0137
(EBITA / Avg Assets)			(0.0435)	(0.0425)	(0.0440)	(0.0595)
Liquidity				-0.0104***	-0.0126***	-0.00975*
(Liquid Assets / Tot Dep & Bor)				(0.00392)	(0.00470)	(0.00518)
Regulatory Capital					-0.0355	-0.0317
(Tier 2 Capital)					(0.0287)	(0.0515)
Leverage						0.0289*
(Long term debt to Common Equity)						(0.0176)
_cons	3.093***	3.766***	3.795***	4.178***	4.539***	4.210***
	(0.371)	(0.502)	(0.507)	(0.500)	(0.578)	(0.598)
<i>N</i>	326	262	262	255	234	130
adj. <i>R</i> ²	0.7068	0.7206	0.7155	0.7295	0.7173	0.7893

Notes: Standard errors are reported in parentheses, * $p < 0.10$, ** $p < .05$, *** $p < .01$. According to the Hausman test, the RE model is the preferred method of estimation, Prob>chi2 = 0.0844. All estimation are controlled for time-effect.

Table 3.4: Bank Level Determinants of the CDS spread - FE

	(1)	(2)	(3)	(4)	(5)	(6)
ln(House Price Index)	-0.926 (0.588)	-1.577** (0.710)	-1.265* (0.723)	-1.304* (0.716)	-0.501 (0.815)	-0.0554 (0.973)
Asset Quality (Impaired Loans / Equity)		0.00481*** (0.00164)	0.00508*** (0.00163)	0.00557*** (0.00165)	0.00669*** (0.00178)	0.0187*** (0.00421)
Operations Income Ratio (EBITA / Avg Assets)			-0.113* (0.0580)	-0.113* (0.0579)	-0.143** (0.0599)	-0.208** (0.0820)
Liquidity (Liquid Assets / Tot Dep & Bor)				-0.00762 (0.00573)	-0.0120* (0.00697)	-0.0128 (0.00934)
Regulatory Capital (Tier 2 Capital)					-0.0653** (0.0322)	-0.0451 (0.0684)
Leverage (Long term debt to Common Equity)						0.0109 (0.0246)
_cons	7.603** (2.941)	10.67*** (3.499)	9.256*** (3.550)	9.566*** (3.507)	6.051 (3.983)	3.496 (4.828)
<i>N</i>	326	262	262	255	234	130
adj. <i>R</i> ²	0.750	0.754	0.757	0.761	0.756	0.779

Notes: Standard errors are reported in parentheses, * $p < 0.10$, ** $p < .05$, *** $p < .01$. All estimations are controlled for time-effect. According to the Hausman test, the RE model is the preferred method of estimation.

Table 3.5: Regulatory Structure and Financial System - FE

FE Preferred	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Asset Quality	0.0300***	0.0235***	0.00527***	0.00521***	0.00377**	0.00330*	0.00309*
(Impaired Loans / Equity)	(0.00545)	(0.00564)	(0.00196)	(0.00195)	(0.00189)	(0.00173)	(0.00169)
Operations Income Ratio	-0.360***	-0.256***	-0.136**	-0.135**	-0.0860	-0.0858	-0.0892*
(EBITA / Avg Assets)	(0.0790)	(0.0890)	(0.0597)	(0.0594)	(0.0539)	(0.0521)	(0.0520)
Financial Deepening 1	-0.0121	-0.00613	0.00541	0.00497	0.00994***	0.0115***	0.0112***
(Deposit money bank assets to GDP (%))	(0.00748)	(0.00621)	(0.00375)	(0.00360)	(0.00348)	(0.00316)	(0.00316)
Financial Stability 1	-0.0632**	-0.0155	-0.0320*	-0.0310*	-0.0323*	-0.0309*	-0.0350**
(Bank Z Score)	(0.0270)	(0.0244)	(0.0186)	(0.0183)	(0.0177)	(0.0167)	(0.0167)
Liquidity	-0.000823	-0.0118	-0.0100	-0.00995	-0.00763	-0.00420	
(Liquid Assets / Tot Dep & Bor)	(0.00996)	(0.00957)	(0.00695)	(0.00693)	(0.00659)	(0.00520)	
Regulatory Capital	-0.0934	-0.0706	-0.0643*	-0.0650**	-0.0134		
(Tier 2 Capital)	(0.0688)	(0.0768)	(0.0330)	(0.0328)	(0.0277)		
ln(House Price Index)	-1.529	0.419	-0.620	-0.639			
	(1.366)	(1.022)	(0.817)	(0.813)			
Profitability 1	0.159	0.178	0.0536				
(Overhead costs to total assets (%))	(0.193)	(0.185)	(0.125)				
Leverage	-0.0259	-0.00677					
(Long term debt to Common Equity)	(0.0252)	(0.0274)					
Financial Access	-0.00405						
(Bank branches per 100,000 adults)	(0.0131)						
_cons	12.39*	1.777	6.455	6.679*	3.141***	2.741***	2.744***
	(6.733)	(4.932)	(3.983)	(3.939)	(0.572)	(0.487)	(0.481)
<i>N</i>	83	130	234	234	267	290	297
adj. <i>R</i> ²	0.865	0.779	0.761	0.762	0.730	0.744	0.744

Notes : Standard errors are reported in parentheses, * $p < 0.10$, ** $p < .05$, *** $p < .01$. All estimations are controlled for time-effect. According to the Hausman test, FE is the preferred method of estimation as the Prob>chi2 = 0.0000.

Table 3.6: Robustness Check, Regulatory Structure and Financial System, - FE

	(1)	(2)	(3)	(4)	(5)	(6)
Asset Quality	0.0222***	0.00571	0.00558	0.00594*	0.00618*	0.00607*
(Impaired Loans / Equity)	(0.00591)	(0.00470)	(0.00390)	(0.00353)	(0.00349)	(0.00345)
Liquidity	-0.000886	-0.0232**	-0.0171**	-0.0118*	-0.0125**	-0.0127**
(Liquid Assets / Tot Dep & Bor)	(0.0105)	(0.00949)	(0.00796)	(0.00614)	(0.00600)	(0.00592)
Leverage	-0.0228	0.0678**	0.0674***	0.0602***	0.0647***	0.0663***
(Long term debt to Common Equity)	(0.0294)	(0.0276)	(0.0237)	(0.0224)	(0.0204)	(0.0193)
Financial Deepening 2	-0.0153	0.0177**	0.0159***	0.0137**	0.0135**	0.0137**
(Financial system deposits to GDP (%))	(0.00919)	(0.00845)	(0.00592)	(0.00546)	(0.00543)	(0.00538)
Financial Stability 2	0.0500**	0.0611***	0.0538***	0.0510***	0.0517***	0.0519***
(Volatility of stock price index)	(0.0214)	(0.0147)	(0.0122)	(0.0114)	(0.0113)	(0.0112)
Operations Income Ratio	-0.327***	-0.0446	-0.0356	-0.0126	-0.0131	
(EBITA / Avg Assets)	(0.0784)	(0.0672)	(0.0578)	(0.0531)	(0.0529)	
Profitability 2	-0.00395	0.00435	0.00224	-0.00307		
(Return on equity (%))	(0.00772)	(0.00833)	(0.00678)	(0.00606)		
Regulatory Capital	-0.134**	0.0122	0.0202			
(Tier 2 Capital)	(0.0640)	(0.0396)	(0.0351)			
Financial Access	-0.00661	-0.00978				
(Bank branches per 100,000 adults)	(0.0128)	(0.0140)				
Ln(House Price Index)	0.432					
	(1.527)					
_cons	1.421	1.861**	1.532***	1.701***	1.652***	1.623***
	(7.677)	(0.893)	(0.499)	(0.445)	(0.433)	(0.415)
<i>N</i>	82	109	141	150	150	150
adj. <i>R</i> ²	0.871	0.779	0.817	0.829	0.831	0.832

Notes : Standard errors are reported in parentheses, * $p < 0.10$, ** $p < .05$, *** $p < .01$. All estimations are controlled for time-effect. According to the Hausman test, FE is the preferred method of estimation as the Prob>chi2 = 0.0000.

Table 3.7: GMM

VARIABLES	Z
<i>l.ln(BankCDS)_{t-1}</i>	0.202*** [0.063]
ln(House Price Index)	-0.408 [0.360]
Regulatory Capital (Tier 2 Capital)	-0.051 [0.104]
Leverage (Long term debt to Common Equity)	0.022 [0.019]
Liquidity (Liquid Assets / Tot Dep & Bor)	-0.054*** [0.009]
Asset Quality (Impaired Loans / Equity)	0.008*** [0.003]
Operations Income Ratio (EBITA / Avg Assets)	-0.151*** [0.047]
Financial Deepening (Deposit money bank assets to GDP (%))	0.026*** [0.007]
Financial Stability (Bank Z Score)	-0.012 [0.018]
Profitability (Overhead costs to total assets (%))	0.182 [0.124]
Constant	3.449* [1.819]
Observations	121
Number of id	26
Number of Instruments	23
Number of groups	26
chi2	3573
ar1 (p value)	0.0056
ar2 (p value)	0.9147
Sargan Chi2	17.57061
Sargan Prob > chi2	0.1294

Notes: Robust standard errors reported in parenthesis. ***, **, *, significant at the 1%, 5% and 10% levels, respectively. According to the Arellano-Bond test, the value of the test for second-order autocorrelation presents no evidence of model misspecification. The difference equation is instrumented with the lagged levels, one period of the dependent variable and the levels equation with the difference lagged one period. The GMM-type instruments consisted of one lag of $\ln(\text{Bank CDS})$. The Standard instruments were: $\Delta \ln(\text{BankCDS})$, $\Delta \ln(\text{HousePriceIndex})$, $\Delta \text{AssetQuality}$, $\Delta \text{Liquidity}$, $\Delta \text{RegulatoryCapital}$, $\Delta \text{Leverage}$, $\Delta \text{Operations Income Ratio}$, $\Delta \text{FinancialDeepening}$, $\Delta \text{Financial Stability}$ and $\Delta \text{Profitability}$. The instruments for level equation consisted of the GMM-type instruments, namely: $\Delta \ln(\text{BankCDS})$. The *p values* for the Sargan test for over-identifying restrictions, where the null hypothesis is that the instruments are uncorrelated with the residuals, confirm that the instruments are not correlated with the residuals and they are valid instruments. The lagged dependent variable is statistically significant reflecting a high degree of persistence in the variables. The number of instruments is 23 and is less than the number of groups, which is equal to 26.

Chapter 7

Conclusions

7.1 Summary of findings

The recent financial crisis has underlined the importance of identifying the factors driving credit risk and CDS spreads. Given the high interconnectedness of the financial system, defaults in one sector get easily transmitted to other sectors, ultimately causing contagion in the overall financial system and resulting in crisis across countries. Therefore, it is of a paramount importance to identify the factors that contributed to the recent financial crisis in order to limit future defaults and prevent another crisis from occurring in the future.

This thesis contributes to the existing literature on credit risk in a number of ways. I first start by focusing on the CDS spread in the UK banking sector. Thus, in the fourth chapter, I uncover the crucial linkage existing between the housing market, the stock market, the money market and the credit market. I consider both the long-term (using the Johansen's Cointegration) and the short-term analysis (using the Structural VAR) of the drivers of CDS spread, over the period of 2004-2011. I establish from my empirical findings that the housing market has been the key driver of credit risk in the UK. Thus, before the crisis, as house prices were high, banks confidently boosted their mortgage activities through the process of securitization, not granting enough importance to the quality of borrowers and keeping very little capital aside for the possibility of a negative credit event.

Eventually, the credit boom era came to an end as house prices plummeted and investors started heavily defaulting. This in turn pushed-up the CDS spread and credit risk; thus causing one of the worse financial crisis that economists often compare to the great depression of 1929.

In addition, I also find that the high performance of the stock market prior to the financial crisis enabled financial institutions to expand their borrowings, thus generating lucrative, high return, but also very risky investments. Similarly, I show that liquidity was another pivotal factor that enabled banks to grant subprime loans to sub-prime borrowers. When considering the yield spread, I find that it is negatively related to the CDS spread and credit risk. This is in line with the consumers' risk aversion during the recent financial crisis.

I employ the Structural VAR analysis in order to uncover the short-run impact of the different shocks explaining CDS spread. I imposed short-run restrictions to identify the five shocks namely: the CDS spread, the house price index, the yield spread, the TED spread, and the FTSE100. The SVAR findings indicate that a positive shock to house prices significantly increases the CDS spread in the medium-term, in the UK banking sector. In addition, apart from its own shock, the house price shock explains a big part of the variance (nearly 20%) in CDS spread. These results remained robust even after changing the ordering of the variables in the Structural VAR.

Beside the macro-level factors affecting the CDS spread and credit risk, there were other bank-level factors that also contributed to increased level of defaults. As

such, in the fifth chapter of this thesis, using three different methodologies: fixed effect (FE), random effect (RE) and GMM analysis, I show evidence that across 30 countries and 115 banks, over the period of 2004-2011, banks with low liquidity levels, low level of operations and bad asset quality were subject to wider CDS spreads and historically high credit risk levels. In summer 2007, as financial markets froze and consumers lost confidence in the global financial system, the only banks that were able to sustain themselves were the ones with high liquidity reserves and good asset quality. The rest of financial institutions either went bankrupt or were subject to mergers and takeovers. In addition, I show that the *too-big-to-fail* phenomenon that was so popular before the beginning of the financial crisis was very illusive. In fact, most of the big banks that grew beyond their optimal size before the crisis went bankrupt. The very few financial institutions that survived the crisis were the ones that were closely connected with the public sector and which the government saved through bailouts, using tax payers' money. In my analysis, I conduct the U-test and prove that there exists a U-shape relationship linking bank CDS spread and bank size. I derive the optimal bank size which shows that any bank growing beyond that threshold faced high credit risk and wider CDS spreads. Given that smaller banks were more prudent in conducting their business, they were considered to be stronger, since their investments were smaller in scale and less complex in nature.

In addition, I further expand my research in the sixth chapter of this thesis as I conduct both bank and country-level analysis on the drivers of the CDS spread and credit risk, across banks and countries. The panel regression analyses focus on the period of 2004-2011. As such, I investigate the factors that make banks in certain

countries riskier/safer relative to others. Beside the significance of asset quality, liquidity and operations income, at bank-level, in affecting credit risk, my empirical results suggest that excessive credit lending had a double-sided effect on banks' credit risk profiles. While before the financial crisis the easy availability of credit helped banks to achieve higher profits, get easier access to funding and boost borrowing activities, with the beginning of the financial crisis, excessive credit creation directly contributed to the credit boom as banks that had easy access credit were unable to repay their debts and started heavily defaulting, driving CDS spreads to record high levels.

7.2 Policy implications

A number of policy implications can be derived from the research conducted in this thesis. The fourth chapter sheds light on the close linkage between the housing market, the money market, the stock market and the credit risk. Therefore, a common consensus should be reached between the central bank, financial institutions, building societies and regulators on how to ensure systemic stability and avoid any contagion or spill-over effects. A policy of low interest rates would typically lead to increased borrowing which will have to be matched by increased housing supply in order to keep house prices stable. If any element in the chain is not satisfied, this may give rise to major imbalances that may result into a housing bubble, which in turn can cause another crisis. Therefore, close supervision of the housing market is crucial in order to ensure systemic stability.

My finding from the fifth chapter indicates that bigger banks were more prone to credit risk as compared to smaller banks. Before the financial crisis, small banks were given the wrong incentives to grow beyond their optimal size as there was a belief that the bigger the bank and more certainty that the government will always intervene in case of default. The recent financial crisis served as a great lesson as it showed that smaller scale and more concentrated type of investments lead to a more stable financial system. Therefore, given the high risk that big banks pose on financial and systemic stability, financial regulators should impose on them stricter liquidity and asset quality regulation and ensure that there is more control.

The next recommendation related to the credit provision. My results from the sixth chapter indicate that easy borrowing conditions have led to excessive credit creations which in turn triggered the recent financial crisis and resulted in excessive credit risk and wide CDS spreads. In fact, I find that higher level of financial deepening is directly linked with increased levels of defaults. Thus, excessive credit creation has caused a credit bubble, which transformed into a global financial crisis. Therefore, there is a crucial need for the central bank to tighten the availability of credit through tougher interest rate policy, and to increase regulatory capital requirements at bank-level. My finding is in line with the research conducted by Mallick and Sousa (2013) for the Euro area where the authors show that monetary policy should react to a credit bubble with a higher interest rate that can make loans more expensive although identification of a threshold level of credit (as a per cent of GDP) can be a challenging task for policy makers.

In addition, although the move from traditional to universal banking brought banks and consumers closer, this transition was also associated with higher credit risk and default levels. In fact, banks, building societies and insurance companies started conducting activities in which they have little expertise. Before the recent crisis, banks traded CDS contracts for speculative purposes rather than for hedging. This resulted in an issue of incentives as buyers and sellers of CDS contracts were well aware of the performance of the underlying entity. Thus, knowing that the underlying entity was about to default, consumers purchased CDS contracts hoping the instrument would default in order to get repayment. This leads us to the next recommendation where by a move back to more conservative banking would reduce credit risk and the issue of moral hazard.

7.3 Limitations of this research

One of the limitations of this research stems from the lack of availability of CDS data prior to 2004. However, since the beginning of the financial crisis, regulators and central banks recognized the importance of increasing the transparency of the credit derivative market. The mortgage data related to CDS contracts now exists in Bloomberg and Datastream and is separate for each bank and across many developed and emerging markets. It will be therefore of great interest to relate the CDS contracts on MBS products and collect the associated credit ratings in order to examine the potential impact it had on the overall credit risk, not only before and during, but also after the recent financial crisis.

In addition, I would like improve my research in the fifth and sixth chapter of this thesis by conducting a comparative analysis between developed and emerging

markets. The main challenge relates the lack of availability of data in emerging countries as a result of the lack of disclosures. Therefore, my aim is to collect more data on banks in emerging markets in order to perform a comparative analysis between developed and emerging markets.

In this thesis, I consider the period over 2004-2011. My aim is to include the CDS data after 2011 and investigate whether the factors that affected the CDS spread before and during the crisis, remained significant in the post crisis period, or whether there are now new factors that affect the CDS spread.

Furthermore, my future research plan is to collect the CDS spread data in various sectors and industries. Since I already have data on sovereign CDS spreads, my aim is to link it to bank CDSs and analyze whether there were common factors across the PIGS (Portugal, Ireland, Greece and Spain) countries that contributed to the Sovereign crisis of 2010.

Moreover, for bank-level analysis, my aim is to collect additional data on diversification, more specifically interest-income and non-interest income data, and conduct cross-bank and cross-country analysis in order to investigate whether diversification had any impact on the variations of CDS spreads and credit risk across small and big banks.

On the regulatory side, Basel 3 has been recently introduced as regulators recognized the imminent need to change the way banks complied with regulation. There is great scope to expand the research I conducted in the 5th and 6th chapter of

this thesis by collecting additional data that reflects the improvements of regulatory capital introduced in Basel 3 and compare its effect on CDS spreads using the previous capital implementation from the Basel 1 and Basel 2 Capital Accords.

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