Transmission channels of systemic risk: a system wide perspective

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List of Abbreviations

ABS	Asset Backed Securities
BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlement
CDS	Credit Default Swaps
CERII	Centre D'Etudes Prospectives et d'Information Internationales
CSD	Centralised Securities Depository
CSDB	Centralised Securities Database
DCC	Dynamic Conditional Correlation
DTCC	Depository Trust and Clearing Corporation
ECB	European Central Bank
ESCB	European System of Central Banks
ESRB	European Systemic Risk Board
EUR	Euro
FSB	Financial Stability Board
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GDB	Gross Domestic Product
IAIS	International Association of Insurance Supervisors
IMF	International Monetary Fund
IOSCO	International Organisation of Securities Commissions
iTraxx	Credit Default Swap Index for Europe
Libor	London Interbank Offered Rate
LM	Lagrange Multiplier test
LSDV	Least-Squares Dummy Variable

MGARCH	Multivariate Generalised Autoregressive Conditional Heteroscedasticity
OLS	Ordinary Least Squares
OTC	Over-the-Counter
PCA	Principal Component Analysis
SHS	Securities Holding Statistics
SI banks	Systemically important banks
SoFFin	German Financial Market Stabilization Fund
TLAC	Total Loss Absorbing Capacity
UCITS	Collective Investments in Transferable Securities
US	US Dollar
VAR	Vector Autoregression
VDAX	DAX Volatility Index
VSTOXX	Euro Stoxx 50 Volatility Index

Chapter 1

Introduction

> *"One of the greatest challenges for economics and public policy at this time is to restore financial and economic stability, and to improve the future functioning of financial systems. A precondition for meeting this challenge is a deep understanding of the nature of systemic risk."*
> (Jean-Claude Trichet, December 2009)

Analysis of the origins of the crisis (2007-2009) demonstrates that insufficient attention was devoted to systemic risks affecting the whole financial system. This insight has led to a critical assessment and fundamental reform of the existing regulatory framework. The new framework, known as "Basel III", is a first attempt to add to the traditional microprudential view a macroprudential view. The former focuses on the solvency of individual intermediaries. The objective of the latter is to identify and reduce systemic risk.

The International Monetary Fund (IMF), the Financial Stability Board (FSB) and the Bank for International Settlement (BIS) define systemic risk as a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy.[1]

The academic literature similarly refers to systemic risk as "any set of of circumstances that threatens the stability of or public confidence in the financial system" (Billio et al. (2012)), "risk that ... has to do with functioning - or malfunctioning - of the financial system" (Hellwig (2009)), "...excessive balance-sheet shrinkage on the part of multiple financial institutions hit by a common shock" (Hanson et al. (2011)).

This dissertation contributes to the understanding of some of the complex facets of systemic risk which have not been addressed so far. In accordance with the definition of the systemic risk presented above, the analysis takes a system wide perspective focusing on different financial institutions and their contributions to systemic risk. The financial institutions considered in this dissertation include specific types of banks such as the over-the-counter (OTC) dealer banks, custodian banks and other financial institutions such as central securities depositories (CSDs), and insurance companies. At the core of the analysis is contagion within and opaqueness of certain parts of the financial industry.

The academic literature generally distinguishes between three types of contagion channels. The first is based on direct physical exposures related to financial contracts or similar investment strategies of financial institutions (e.g. Allen and Gale (2000). A default of one institution causes write-offs of claims by other

[1]See FSB, IMF and BIS (2009): Guidance to assess the systemic importance of financial institutions, markets and instruments: initial considerations. Report to G-20 Finance Ministers and Central Bank Governors. Note that the definition of systemic risk used by the European Systemic Risk Board (ESRB) is broadly in line with this. See Regulation (EU) on European Union macro-prudential oversight of the financial system establishing ESRB.

institutions. The second channel relates to contagion caused by asset price changes if a distressed institution is forced to conduct “fire sales” . These sales depress prices further, causing the markets to question the solvency of other institutions holding same assets. This channel is called “market-price channel” (e.g. Shleifer and Vishny (2011)). The third is the so-called “information channel” and is related to contagious depositor withdrawals or other funding problems when creditors are imperfectly informed about the type of shocks hitting banks or their physical exposures (e.g. Kodres and Pritsker (2002)).

The second chapter of the dissertation highlights the role of OTC dealer banks in the transmission of contagion (joint with Michael Wedow[2]). The third chapter (joint with Michael Wedow) tests if the interconnectedness of insurers warrants their treatment as systemically important financial institutions (SIFI); institutions whose failure pose a significant risk to the stability of the financial system and the real economy. Both chapters define contagion broadly as a comovement in Credit Default Swaps (CDS) spreads of financial institutions. A comovement of CDS spreads between financial institutions can be caused by contractual relationships, similar investments or information contagion as described above. The fourth chapter studies potential triggers for asset sales. It focuses on the question whether the existence of an alternative source of funding such as the liquidity-providing reverse transactions of the European System of Central Banks (ESCB) which became more easily accessible during the financial crisis prevented asset sales by banks. This study can be seen as an important step towards understanding the reasons for contagion through fire sales. The fifth chapter (joint with Thomas Droll and Michael Wedow[3]) analyses the structure in the custodian-depository industry which so far has received very little attention in the academic literature but may present a potential source of systemic risk.

[2]Michael Wedow, European Central Bank, Sonnemannstraße 20, 60314 Frankfurt.

[3]Thomas Droll, Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt.

The delegation of safe-keeping to foreign sub-custodians can result in opaque structures involving chains of several sub-custodians in different countries. In the case of a sub-custodian defaulting or in cases of fraud, investors stand to lose their investment when local securities laws do not provide adequate protection.

Subsequently, the contents of the chapters are described in more detail.

Before the global financial crisis unfolded, the well know academic literature on contagion has primarily focused on contagious effects between individual institutions within the same financial system (Aharony and Swary (1983), Swary (1986), Pozdena (1991) and De Nicolo and Kwast (2002)) or on crossborder contagion between stock markets (Solnik (1974), King and Wadhwani (1990) and Hamao et al. (1990)). However, regarding the importance of crossborder contagion between financial systems this literature remained largely silent. The second chapter of this dissertation provides an empirical framework to measure the strength and direction of contagion effects emanating from the financial systems of the US, Europe, Asia, Emerging markets to the German financial system using the information content of CDS prices. A more thorough understanding of the significance of contagion between financial systems is important from a financial stability perspective as it could provide guidance for the adoption of regulatory and policy measures to reduce contagion. This is the first contribution of this chapter.

On the second contribution, the chapter further dissects crossborder contagion by examining the role of the different sectors and business activities in the financial system. The structure of OTC markets makes this market and the dealer banks particularly vulnerable to contagion. This is largely due to the high concentration of trading among a few dealers and to the opaqueness of the market. For this

reason, the chapter specifically examines the strength of contagion from dealer banks to the German financial system. In addition, the analysis explores the magnitude of contagion over time. To gain more insights in the contagion mechanism, it considers, inter alia, the impact of the default of Lehman Brothers and the financial stabilization scheme set up in Germany. The analysis is based on weighted CDS spread indices for each financial system to address all these objectives. The reliance on broad indices allows obtaining a comprehensive view of the risk to the German financial system.
The findings suggest that there are strong contagious effects from the US and Europe, but no effects from the Asia-Pacific region and emerging markets on the German financial system. More importantly, the results highlight asymmetries in the contagion effects with regard to different sectors of the German financial system. German dealer banks experience the economically largest impact from other CDS dealers but are immune to changes in the credit spreads from other financial intermediaries. This confirms that the close and highly concentrated network formed by these banks poses a potential threat to the stability of the financial system. This could be related to the highly concentrated network formed by the dealer banks which acts as a risk amplification mechanism in parallel to the traditional risk transmission channels identified in the literature such as interconnectedness via physical exposures and common risk factors.

Many of the OTC dealers banks which are included in the sample of the second chapter are so called SIFIs which have become the focus of the regulatory agenda in the aftermath of the financial crisis. SIFIs or "too-big-to-fail" banks are institutions whose failure poses a significant risk to the stability of the financial system and the real economy. The pervasiveness of the risks emanating from SIFIs was brought into the limelight when many of the globally largest banks were bailed out by their governments (Stolz and Wedow 2010). In some cases, the large scale public bailouts brought even their governments to the brink of default. As a consequence of this experience, in November 2011, the Basel Committee on Banking Supervision finalized rules for global systemically important banks. These rules foresee additional capital requirements to limit negative externalities to the global financial system from banks' cross border activities. In addition, the FSB published a list of 29 banks that will be subject to the new regulation for SIFIs. Insurance companies were not among the institutions on the SIFI list. The next chapter empirically analyses if the interconnectedness of insurers warrants their treatment as SIFIs. For this purpose, the chapter models the interconnectedness between different sectors of the financial system using again the information content of CDS prices. The findings suggest that large insurers transmit risks to other parts of the financial system. The magnitude of these contagion effects is substantially lower than those of large banks that are currently treated as SIFIs. This evidence may justify the exclusion of insurers from the list of SIFIs.

While the two chapters described above define contagion broadly as a comovement in CDS spreads of financial institutions, the next chapter is related to a more specific contagion channel through "fire sales".
Banks that experience high need for liquidity (high demands by their customers or even panic withdrawals) could be forced to sell assets in order to raise money very quickly. Distressed sales can cause a collapse of prices in certain market segments, indirectly forcing other financial institutions with exposures to these markets to adjust the valuations of their assets downwards. In a crisis, with potential buyers sustaining losses of their own, demand by these potential buyers might be limited. Thus, financial institutions might be forced to sell assets at fire

sale prices ((Shleifer and Vishny (1992) and Duffie et al. (2007)) putting downward pressure on prices. However, this fire sales mechanism will not be set in motion if banks are able to find alternative sources of funding. After the fall of Lehman Brothers, the ESCB has broadened the range of the accepted collateral and has become one of the most important alternative sources of funding for many banks (see European Central Bank (2013)).

The contribution of this chapter to the existing literature is twofold. First, it sheds light on the causes for potential fire sales. Even though the risk transmission channel via fire sales has gained much attention both from policy makers and the academic community, the empirical and theoretical evidence is still controversial with regard to the causes of financial institutions selling assets. Second, the analysis distinguishes between sales of ESCB eligible and ESCB non-eligible assets in order to assess the ability of the ESCB's liquidity-providing reverse transactions to reduce the potential for fire sales. While Krishnamurthy (2009) provides general theoretical evidence that liquidity provision by a central bank through its function as lender of last resort alleviates the crisis, the potential of a central bank's liquidity-providing reverse transactions to reduce fire sale has not been, to my best knowledge, empirically analysed at all. This study aims at closing this gap.

More specifically, the chapter tests three hypotheses. First, it analyses whether bank's liquidity and capital position determine its asset sales. Second, it separates net sales into net sales of ESCB eligible and ESCB non-eligible securities to test second hypothesis that banks do not sell securities in reaction to liquidity and capital constraints. Third, it tests hypothesis that stressed banks, such as banks before rescued by the German government and banks with low liquidity and poor capital position have different selling behaviors than non-stressed banks. This hypothesis is based on the assumption that the relation between asset sales and

the liquidity or capital position of a bank is stronger for distressed banks.
The findings show that a bank's liquidity and capital position only determine the overall net sales significantly during the banking crisis, for the period from 2007 Q3 to 2009 Q4. Second, banks do not sell ESCB eligible assets and sell ESCB non-eligible assets in reaction to liquidity shortages. In addition, it seems that, in general, a bank with poor capitalisation would rather sell assets independently of their ESCB eligibility. Third, banks supported by the German government and banks with a liquidity ratio lower than the median sell, on average, more ESCB non-eligible securities. For these banks, the liquidity ratio is a significant determinant for the net sales of the ESCB non-eligible assets. These findings suggest that the measures undertaken by ESCB play an important role and should be taken into account when it comes to analysing the existence and causes of fire sales. Such policy measures could significantly affect a bank's selling behavior.

The global financial crisis uncovered significant agency problems in the custodian industry. Asset custody services consist in holding and administrating financial assets on behalf of customers. Custodian banks who offer these services typically delegate the safe-keeping of foreign securities to other banks acting as sub-custodians located in the countries where the securities have been issued and where they are traded. CSDs play a central role in these chains as they frequently act as sub-custodians and provide a range of additional services for custodians. Key issues in this respect are potential moral hazard on the part of opaque custodian structures and the lack of incentives for depository institutions to act in the interests of investors. This led to an erosion of investor trust during the financial crisis and a massive withdrawal from mutual funds. Against this background, the fifth chapter assesses the asset custody industry with a focus on risks in sub-custodian chains and the role of CSDs in these chains.

The analysis is based on a unique data set from a survey, which was conducted by the Deutsche Bundesbank in July 2011. In this survey, German custodian banks were asked to report detailed quantitative and qualitative data with regard to all securities belonging to German Undertakings for Collective Investments in Transferable Securities (UCITS) funds that were held in safe custody abroad.

The main question which the analysis addresses is whether there is evidence for moral hazard in sub-custodian structures. More specifically, the chapter analyses the length and risk of sub-custodian chains. It hypothesizes that not all custodians adequately managed and monitored the risks in their sub-custodian chains given that they were not liable for any losses. Some custodians delegated the safe-keeping directly to CSDs, which may have taken over the monitoring of the sub-custodian chains. As result, the presence of a CSD as a first sub-custodian could potentially mitigate risks due to inadequate monitoring by the custodian. The contribution of this chapter to the literature on the securities custody industry is twofold. First, the study provides a number of stylised facts on the sub-custodian structure of custodian banks for German UCITS funds. Very little is known to date about this industry. This is the first study which empirically assesses the sub-custodian structure in the custody services industry (to the best knowledge of the authors). The existing literature on the custodian industry is very scant. It has so far focused on competitive issues between central CSDs and custodians (Kauko (2007), Tapking (2007) and Holthausen and Tapking (2004)). Another strand in the literature examines the efficiency of the securities settlement industry and the potential to realize further scale economies (Schmiedel et al. (2006) and van Cayseele and Wuyts (2007)). Second, the study provides an empirical analysis of the sub-custodian structure.

The findings suggest that custodians delegate the safe-keeping of assets via chains of up to five sub-custodians. While most custodians typically delegate the safe-keeping of assets in a country to one sub-custodian, a few custodians rely on numerous sub-custodians in a single country. In addition, the custodian banks in the sample differ in respect of the number of countries to which they are linked via sub-custodians. While a few custodians that are very active in the custody services business have sub-custodians in over 100 countries, some smaller and less specialised custodians maintain only very few links to other countries. Further, the empirical analysis highlights the fact that less informed banks typically have longer sub-custodian chains, which we interpret as evidence for agency problems in the custodian industry. Instead, better informed custodian banks seem to provide safe-keeping of assets in riskier countries. Moreover, better capitalised banks have longer, but less risky sub-custodian chains in terms of country risk. In addition, their chains cross borders less frequently. Foreign custodians, which typically benefit from greater economies of scale and scope, also use shorter chains. However, sub-custodian chains where the first sub-custodian is a CSD are not significantly shorter. In contrast, CSDs as first sub-custodian appear to reduce the country risk in sub-custodian structures highlighting the beneficial role they can play in the delegation of safe-keeping duties. Better capitalised, foreign and large custodian banks are less likely to rely on a CSD as first sub-custodian. These findings suggest that more specialised custodian banks with greater economies of scale and scope can avoid relying on CSDs, given that they can internalise many of the benefits attributed to CSDs.

Chapter 6 of this thesis will summarize all major findings and provide a final discussion of their implications for the macroprudential regulation and policy.

Chapter 2

Crossborder financial contagion to Germany: how important are OTC dealers?

"As long as human behaviour is coupled with free enterprise, it is unrealistic to expect that market crashes, manias, panics, collapses, and fraud will ever be completely eliminated from our capital markets."
(Billio, Getmansky, Lo and Pelizzon (2010))

This chapter is based on a joint research paper with Michael Wedow.[4]

[4] Michael Wedow, European Central Bank, Sonnemannstraße 20, 60314 Frankfurt. This chapter is based on a pre-copy-editing, author produced PDF of an article accepted for publication in International Review of Financial Analysis. For further details on the published paper, please see Podlich and Wedow (2014).

2.1 Introduction

Contagion between financial institutions is a major contributing element for the emergence of systemic risk.[5] As the global financial crisis unfolded, one particularly noteworthy feature was the strong comovement of financial institutions' credit spreads. The magnitude and speed of these comovements caught many observers off guard and highlighted the fact that contagion is an important amplifier of systemic risk. Moreover, comovements were not limited to national financial systems but quickly spread across borders, affecting single institutions and entire financial systems (Moshirian 2011). The global financial crisis thus signaled the need to develop a framework for the surveillance of contagion and systemic risks (International Monetary Fund 2009).

With this analysis, the chapter contributes to the empirical literature on financial contagion in two aspects. First, it studies contagion across borders focusing on the interlinkages between different financial systems instead of individual institutions within the same financial system. Second, it further dissects crossborder contagion by examining the role of different sectors and business activities in the financial system.

With regard to the first contribution, the literature on contagion has so far primarily focused on contagious effects between individual institutions within the same financial system (Aharony and Swary (1983), Swary (1986), Pozdena (1991) and De Nicolo and Kwast (2002)) or on crossborder contagion between stock markets (Solnik (1974), King and Wadhwani (1990) and Hamao et al. (1990)). However, regarding the importance of crossborder contagion between financial systems this literature remains largely silent. The first contribution is thus to provide an em-

[5]From a broader perspective, contagion is one dimension of systemic risk, alongside macroeconomic shocks and the unraveling of imbalances (see European Central Bank (2009).)

pirical framework to measure the strength and direction of contagion effects emanating from the financial systems of the US, Europe, Asia, Emerging markets to the German financial system. A more thorough understanding of the significance of contagion between financial systems is important from a financial stability perspective to understand how systemic risk is transmitted internationally. Such an understanding could then provide guidance for the adoption of regulatory and policy measures to reduce contagion.[6] As a first step in this direction, the chapter assesses the impact of the German financial stabilization scheme set up by the authorities during the financial crisis.

On the second contribution, the chapter studies contagion effects for dealer and non-dealer banks separately. Furthermore, as we rely on data from OTC market for credit default swaps a natural extension of the analysis is to assess contagion between dealer banks. The role of OTC markets in the transmission of shocks through the global financial system has been highlighted by a number of spectacular defaults during the crisis (European Central Bank 2010). The structure of OTC markets makes these markets and the dealer banks particularly vulnerable to contagion. This is largely due to the high concentration of trading among a few dealers and to the opaqueness of the market. Stulz (2010) argues that CDS contracts create a web of exposures between financial institutions whereby a default of one financial institution can lead to the failure of other institutions. This web is particularly pronounced for the dealers in this market. This high concentration is confirmed by data from the Depository Trust and Clearing Corporation (DTCC). Dealers in the CDS market trade more than 88% of all credit products amongst themselves. This figure is even higher for single name contracts where the un-

[6]See Forbes (2012) for a discussion on policy options to contain contagion http://www.kansascityfed.org/publicat/sympos/2012/kf.pdf

derlying entity is a financial institution.[7] As a result, the failure of an important counterparty in CDS contracts can lead to large losses for other institutions, causing contagion that can ultimately destabilize the financial system. Duffie (2010) discusses the mechanism that can lead to the failure of dealer banks, arguing that they differ markedly from conventional commercial banks. He argues that the business model of dealers in the securities and derivative markets make them susceptible to new types of runs which can spread to other dealers and, inter alia, due to fire sales of securities to other financial intermediaries.[8] Our second contribution thus consists in providing evidence for contagion between different financial sectors and particularly dealer banks.

To address these objectives, we use weighted CDS spread indices for each financial system. Each individual index is based on a large number of banks and insurance companies for which data are available. Our reliance on broad indices allows us to obtain a comprehensive view of the risk of the respective financial system. Methodologically, we rely on generalised autoregressive conditional heteroscedasticity (GARCH) models proposed by Engle (1982a) and Engle (1982b) in our analysis. In particular, we apply a univariate GARCH model with multiplicative heteroscedasticity and a multivariate GARCH model to analyze crossborder financial contagion. Therefore, the set up of the model allows us to study contagion effects in the level as well as the variance of our indices. Given our em-

[7]About 90% of all single name contracts where the underlying entity is a financial firm are bought and sold by dealers. The DTCC data may be upward biased given that primarily dealers report data to DTCC.

[8]Please find the overview of the existing literature related to contagion in the appendix to this chapter.

pirical specification, we define contagion as the residual transmission of shocks after controlling for fundamentals.[9]

The findings suggest that there are strong contagious effects from the US and European system to the German financial system. While the magnitude of contagion from the two systems is comparable, contagion from the European financial system affects the German financial system only in the level while the US also leads to an increase in the conditional variance. More importantly, our results highlight significant sectoral asymmetries in the contagion effects. German dealer banks experience the economically largest impact from other CDS dealers but appear immune to changes in the credit spreads of intermediaries that are not active as CDS dealers. This evidence suggests that dealer banks which are typically also larger and more leveraged constitute an important channel for the transmission of shocks across financial systems. This may be partially related to opaque nature of the OTC market and the highly concentrated network formed by the dealer banks. This network acts as a risk amplification mechanism in parallel to the traditional risk transmission channels identified in the literature such as interconnectedness via physical exposures and common factors (fire sales). With respect to policy, the findings of this chapter also cater to the work of the Financial Stability Board on OTC derivatives markets reform and in particular to set up stable OTC market infrastructures.[10]

The next section describes the data and the financial system indices. The third section presents the empirical set up, discusses the results and a number of specifications for the robustness of our results. The final section contains some concluding remarks.

[9] See Forbes (2012) for a discussion of different definitions of contagion and measurement approaches.

[10] See Financial Stability Board (2012).

2.2 Data and financial system indices

CDS spreads offer a number of advantages over alternative market prices used in the literature. First, CDS spreads directly reflect the risk of failure of the underlying entity (Jorion and Zhang 2009). The majority of the literature relies on stock returns to measure contagion effects. While stock returns are a viable source of information, stock prices reflect the discounted future stream of income from holding stock and thus do not reflect credit risk as CDSs (Jorion and Zhang (2007)). In addition, Blanco et al. (2005) have shown that CDS prices have an informational lead over bond prices and are thus a better asset for assessing credit risk. Second, we are particularly interested in studying the risk of contagion to the German financial system. Since a number of significant players in the German financial system are unlisted, CDS spreads allow a more comprehensive assessment.

In order to capture contagious effects in the CDS market, we use daily spreads of single name 5-year senior CDS contracts where the underlying entity was either a bank or an insurer. These contracts are more frequently traded and thus more liquid (British Bankers' Association 2006). For each underlying entity, we choose the CDS contract in the currency with the potentially highest liquidity.[11]

We obtain CDS spread data from the Markit Group for the period January 2004 through January 2011. The sample consists of quotes contributed by more than 30 dealers for all trading days during the period. Once the quotes are delivered by the dealers, Markit screens the quotes, removes outliers and stale observations. Only when more than two contributors remain, does Markit calculate a daily composite

[11] According to DTCC, the majority of CDS contracts are denominated in USD (62%) and EUR (35%).

spread. CDS spread quotes are the most widely used source of CDS data in the literature (Mayordomo et al. 2010).[12]

In selecting financial institutions, we follow Mayordomo et al. (2010), who argue that the information content of CDS spreads is related to firm size. Therefore, we use the weekly list of the 1000 single reference entities with the largest notional amounts of CDS contracts outstanding published by DTCC.[13] We identify more than 360 financial institutions; we were able to obtain CDS spreads for 234 and total assets for 194 of these entities, which we ultimately use to calculate our weighted indices (see Table 1). From a regional perspective, Europe dominates the sample with 96 institutions, followed by banks headquartered in emerging markets and the US with 38 institutions. From a sectorial perspective, banks represent the largest group but a number of insurers are also included. Among the 194 banks, we identify 28 CDS dealers.

Table 1: No. of banks, insurers and dealers by region

Region/Country	No. of Banks	No. of Insurers	No. of Dealers
US	20	18	8
Europe	83	13	12
Asia-Pacific	22	3	5
Emerging	43	0	0
Germany	26	6	3
Total	*194*	*40*	*28*

Note: Europe includes Portugal, Italy, Ireland, Greece, Spain, Switzerland, Sweden, Norway, UK, Denmark, Iceland, France, Austria, Belgium and the Netherlands; ; Asia-Pacific contains Singapore, Japan and Australia; Emerging includes Argentina, Brazil, Chine, India, Indonesia, Kazakhstan, Korea, Malaysia, Russia, Thailand, Turkey, Ukraine. The sample is based on 1837 observations.

[12] A final consideration for the selection of CDS spreads are the restructuring clauses, given that different restructuring clauses are applicable for financial institutions in the US, Europe and Asia. We selected the CDS spread based on the ex-restructuring clause for institutions from North America, modified-modified restructuring for Western Europe and old restructuring for Asia.

[13] See http://www.dtcc.com/products/derivserv/data/index.php.

For each of the five regions, i.e. countries, we calculate a representative index of the financial system as shown in the equation 2.1. This index is based on the weighted CDS spread of the institutions, which form part of the respective financial system. For the weights ω^i, we use the ratio of total assets for each institution from Bankscope over total assets for all the institutions for which we have CDS spreads and total assets available. It should be noted that the weights are not varying over time as we could not obtained continuous and homogenous time series on total assets for all financial institutions. Instead, we use the median weight across different years to reduce jumps in the series when there are observations missing or erroneous changes in total assets in Bankscope. Moreover, we normalize the weights when there are missing observations in the CDS data for individual institutions to avoid breaks in the time series.

$$y_t^{region} = \Sigma_t^i \omega^i CDS_t^i \qquad (2.1)$$

We also considered a number of alternative methods and variables to obtain a suitable index including principal component analysis (PCA), simple means or using market capitalization as the basis for calculating weights. However, each of these alternatives have serious shortcomings or proved inappropriate for the purpose of this analysis. One disadvantage of the PCA methodology, is that the components from the PCA cannot be calculated appropriately when there are missing observations for the CDS spreads. Furthermore, the components are less convenient to interpret. In addition, PCA could potentially yield less representative indices for our analysis. This is due to PCA deriving the weights by considering the volatility of the series regardless of actual importance of the financial institution. A relatively small but volatile financial institution would obtain a very high weight by PCA, which could result in a less representative index. We also considered alternative variables for the calculation of weights such as market capitalization. However, this would considerably reduce the number of financial institutions, particularly for Germany, where a number of major players are not listed on the stock market.

We show the indices for the institutions from Europe, Germany and the US in Figure 1. CDS spreads remained relatively flat prior to the financial crisis and surged upwards around June 2007, with the spreads of US institutions starting to rise already around January 2007. The starting date of the crisis is defined by the first intervention of central banks in the financial markets on the 9th of August 2007, when CDS spreads hiked upwards.[14] Further hikes occurred in March 2008 when Bear Stearns was taken over by J.P. Morgan and, in particular, in September 2008 when Lehman Brothers defaulted. CDS spreads declined markedly after the establishment of the rescue schemes in the US and Europe in October 2008 and again after the US stress-test, which allowed some US banks to repay the capital injections they had received.

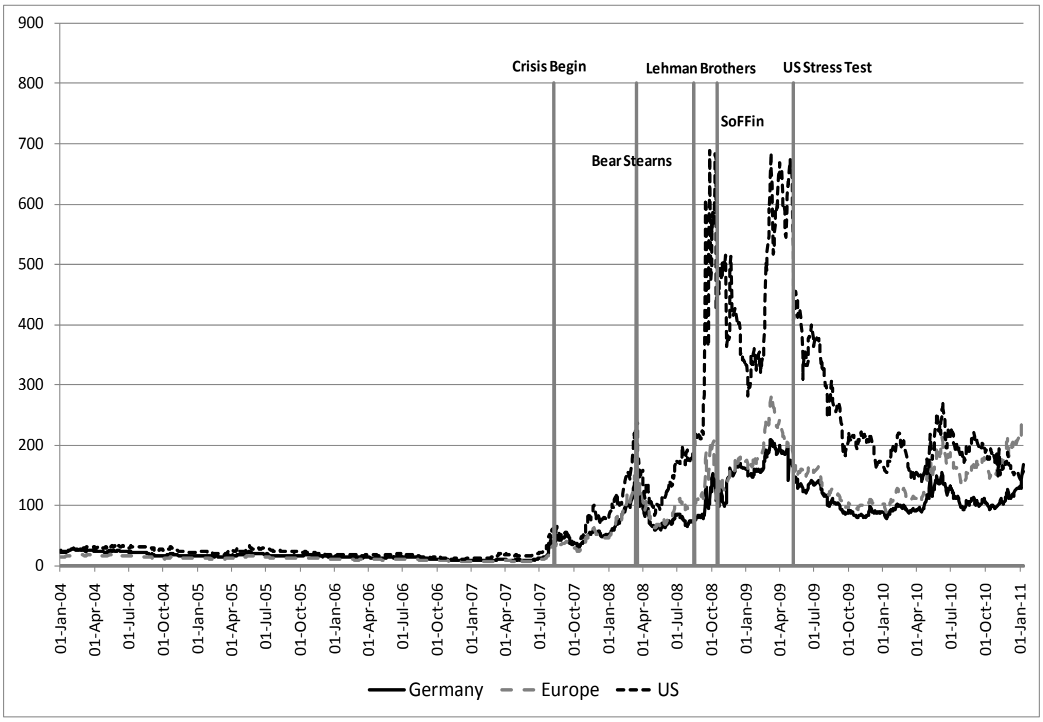
2.3 Empirical analysis

2.3.1 Contagion effects on the German financial system

Forbes and Rigobon (2002) argue that contagion measures such as simple correlation coefficients are inflated by market volatility. After adjusting for this bias, the

[14] For the official statement, see http://www.federalreserve.gov/newsevents/press/monetary/20070810a.htm

Figure 1: CDS spread indices for the financial systems of Europe, Germany and the US in bp., from January 2004 to January 2011



We calculated the indexes using the equation: $y_t^{region} = \Sigma_t^i \omega^i CDS_t^i$. For the weights ω^i, we use the ratio of total assets for each institution over total assets for all the institutions for which we have CDS spreads and total assets available.

spurious contagion measured in the increased correlation between international stock markets typically disappear. In line with this argument, the first step in our empirical analysis is to implement the test suggested by Forbes and Rigobon (2002) to assess if there is evidence for contagion between the German financial system index and the four indices for Europe, the US, the Asia-Pacific region and Emerging market countries after adjusting for increased volatility of these CDS indices. The test shown in Table 2 suggests that the increase in the correlation between the German financial system and other system during the financial crisis is not spurious i.e. due to a rise in volatility. This constitutes a first piece evidence for contagion. All four tests show evidence of a significant rise in the correlation between corresponding financial systems which is statistically significant at the 1 percent level.

Table 2: Forbes-Rigobon test for contagion between Germany and the US, Europe, Asia-Pacific and emerging markets during the global financial crisis

	US	Asia-Pacific	Europe	Emerging Markets
Germany	13.07	40.49	8.51	124.12

Note: The test compares the correlation between two indices before and after a market shock. The starting date for the financial crisis is set on the 9th of August 2007, when central banks intervened in the markets for the first time to facilitate the orderly functioning of the financial markets. If the correlation adjusted value > critical value then the null hypothesis "no change in the co-movement between CDS spreads during a crisis period" can be rejected. Chi2 (1) at 5 % is equal to 3.84 and at 1% equal to 6.64.

In order to estimate contagion effects on the German financial system emanating from the Asia-Pacific region (AP), the Emerging Market countries (EM), Europe (EU) and the US, we analyze the conditional mean and the variance of the index for the German financial system using an GARCH regression with multiplicative heteroscedasticity.[15] One advantage of the GARCH model is that it explicitly allows testing for contagion in the first and second moment of price changes. Furthermore, the conditional variance can be modeled as a time variant variable, which offers a more efficient and realistic estimation approach. More specifically, we employ an GARCH(1,1) model to estimate contagion effects, which has the following form:

[15] Alexander and Kaeck (2008) used a Markov switching model of the determinants of changes in the iTraxx Europe indices. Their tests for regime shifts show strong evidence of switching for all indices apart from the Financial Senior index. Partly for this reason, we rely on a GARCH model but control for for structural breaks and asymmetries in subsection 2.3.3.

$$\Delta y_t^{GE} = \alpha_0 + \alpha_1 \Delta y_{t-1}^{GE} + \alpha_2 \Delta y_{t-1}^{EU} + \alpha_3 \Delta y_{t-1}^{US} + \alpha_4 \Delta y_{t-1}^{AP} + \alpha_5 \Delta y_{t-1}^{EM} + \\ + \beta' \Xi_t + \theta_1 Crisis_t + \theta_2 SoFFin_t + \mu_t \tag{2.2}$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \mu_{t-1}^2 + \lambda_1 \sigma_{t-1}^2 \tag{2.3}$$

Here, y represents one of the four regional indices on day t with GE for Germany and for Europe (EU), the US, the Asia-Pacific region (AP) and the Emerging Market countries (EM). We condition the German index on the CDS indices of other financial systems. The indices of the four regions are lagged by one day to control for reverse causality.[16]. Ξ stands for a vector of control variables. The inclusion of control variables should allow us to capture comovements between the financial system indices instead of effects which result from changes in fundamental factors. In our choice for control variables, we rely on variables that have been identified in the literature but also consider additional variables that have received less attention so far. We use the current yield of German government bonds with a remaining maturity of 15 to 30 years to capture the level of the risk free interest rates. We also considered using alternative variables for the risk free rate such as the swap rate but prefer the rate of government bonds given that swaps rates are indexed to the Libor and thus contain a credit risk premium which experienced large swings during the financial crisis (Houweling and Vorst 2005). Our second control variable is the yield curve given by the difference between government bonds with a maturity of 0.5 and 10 years.[17] A steeper yield curve reflects higher expected future interest rates and facilitates the term transformation of financial intermediaries, thus supporting their profitability. Furthermore, the steepness of the yield

[16]We also included and tested longer lag structures but as these turned out be statistically insignificant, we restricted the specification to one lag

[17]The interest rates for these bonds are derived on the basis of the method suggested by Svensson (1994).

curve provides an indication of future economic activity (see Fama (1984)) thus the yield curve should be negatively associated with credit spreads. We also include the volatility index for the German stock market (VDAX) as a measure of firm value volatility (Alexander and Kaeck (2008) and Beber et al. (2009)) and expect a positive coefficient. In order to control for credit risk developments in the real economy, we additionally include the iTraxx index for non-financial firms. [18] σ_t^2 is the conditional variance of the index for the German financial system at time t.[19] The conditional variance in our baseline specification is modeled as a function of its own past values (GARCH term) and squared errors from the recent period (ARCH term).

As contagion is clearly a dynamic concept particularly during crisis periods or after large shocks, we include two dummies in the mean and variance equations to capture structural shifts. The first dummy (Crisis) is equal to one for the period from the 9th of August 2007 to the end of the sample period. On the 9th of August, central banks intervened in the markets, providing liquidity for the first time.[20] The second dummy is equal to one starting on the 17th of October 2008,

[18]We also test a number of further control variables such as the interbank interest rate Libor. It emerged that the Libor rate was always insignificant in our estimation. We chose to omit these variables given that they are only available for a shorter observation period but results can be obtained upon request.

[19]To avoid the risk of misspecification, we test the residuals after each estimation with the alternative Durbin test. We specified this test to be robust to an unknown form of heteroskedasticity. The test did not reveal any indication of serial correlation of the residuals.

[20]The United States Federal Reserve (Fed) injected a combined 43 billion USD, the European Central Bank (ECB) 156 billion euros (214.6 billion USD), and the Bank of Japan 1 trillion Yen (8.4 billion USD). Smaller amounts came from the central banks of Australia and Canada. We also used the publication date of the US stress-tests on the 7th of May 2009 as the end date for the crisis without materially changing the results.

which is when the German parliament enacted the Financial Market Stabilization Fund (SoFFin) to restore confidence in the financial system.[21] Given that the deadline for applying for financial support elapsed at the end of 2010, the dummy is set to zero from that point onwards. We expect the crisis to have led to a surge in contagion between the financial systems given the information on common exposures of different financial institutions to distressed assets and distressed financial institutions. In contrast, through the provision of different support measures to the German financial system, SoFFin is likely to have reduced contagion to the German financial system (Stolz and Wedow 2010).[22] Table 3 contains summary statistics for the four regional indicators and the four control variables.

Table 3: Summary statistics for financial system CDS indicators and control variables

Variable	No. of Obs.	Mean	Std. Dev.	Min	Max
Germany	1832	59.1	51.6	8.5	209.5
Europe	1832	68.7	69.1	7.0	279.4
USA	1832	125.8	148.1	11.2	688.9
Asia-Pacific Region	1832	59.3	56.1	6.4	242.1
Emerging Markets	1832	117.3	113.9	24.9	715.7
Control Variables					
iTraxx non-financials	1717	76.5	55.4	24.4	282.3
VDAX	1795	22.7	9.7	11.7	83.2
Yield Curve	1794	1.7	1.1	0.0	3.6
Treasury Rate	1794	4.1	0.5	2.6	5.0

Given that the unit root test in Table 7 confirm that all variables except the VDAX contain a unit root, we include them as log-differences in our estimations. Since

[21] The enactment of the German support scheme was briefly preceded by the Troubled Asset Relief Program in the US on the 3rd of October. For this reason, it is difficult to disentangle the effects of the two schemes. However, as we are examining the contagion effects on the German system, we expect the effects from SoFFin to be relatively more important.

[22] The Chow-Test supports our expectations referring to the crisis and the creation of SoFFin. The test results confirm the existence of two structural breaks at the beginning of the crisis and around the creation of SoFFin.

our main interest is the impact of the change of CDS spreads in regions other than Germany on German spreads, we include the financial system indices in the GARCH model with a lag of one time period to reduce possible endogeneity problems. We examined the distribution of the changes in the CDS spreads and the residuals from the GARCH model graphically and using the Shapiro-Wilk test. The graph shows a symmetric distribution with heavier tails, and the test rejects the normality of the variables. We thus specify our GARCH model with the errors following the Student-t distribution with heavier tails.

In Table 4, column 1 contains the results for the GARCH model for the four macroeconomic variables and the two dummy variables which we use as the baseline specification. The four macroeconomic variables have the expected signs and are individually significant. A higher stock market volatility as a proxy of market uncertainty is positively related to the overall credit risk of the German financial system. Similarly, an increase in credit risk in the non-financial sector also causes credit risk in the financial sector to rise. The yield curve and the treasury rate both exhibit a negative coefficient, highlighting the beneficial effect of term transformation and the positive effect of an improving macroeconomic outlook. Both dummy variables turn out to be high significant. The ARCH and GARCH terms are positive and significant, validating our decision to choose a GARCH model.[23] In column 2, we additionally include the four financial system indices. The results highlight that there are significant contagion effects emanating from the European and the US financial system to the German financial system after controlling for exogenous factors.

[23] In a first step, we applied a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) to residuals obtained from OLS regression and found evidence that the errors are autoregressive conditional heteroskedastic. We also used higher order GARCH and ARCH terms in our model but they turned out to be insignificant in most specifications.

Table 4: Contagion to the German financial system

Germany_t	(1)	(2)	(3)	(4)	(5)
			Conditional Mean		
Germany_{t-1}		0.01		0.02	
		(0.190)		(0.693)	
Europe_{t-1}		0.11***		0.11***	0.13***
		(3.881)		(3.884)	(5.702)
US_{t-1}		0.10***		0.10***	0.10***
		(6.208)		(5.818)	(6.083)
$\text{Asia-Pacific}_{t-1}$		-0.00		0.00	
		(-0.115)		(0.031)	
Emerging_{t-1}		0.01		0.00	
		(0.537)		(0.302)	
Crisis	0.01***	0.00***	0.01***	0.00***	0.00***
	(4.369)	(3.186)	(3.666)	(2.667)	(2.589)
SoFFin	-0.00***	-0.00**	-0.00**	-0.00*	-0.00
	(-2.830)	(-2.037)	(-2.413)	(-1.668)	(-1.613)
VDAX_t	0.05***	0.04***	0.04***	0.04***	0.04***
	(5.178)	(5.065)	(4.724)	(4.568)	(4.556)
Yield Curve_t	-0.01***	-0.02***	-0.01***	-0.02***	-0.02***
	(-5.762)	(-6.202)	(-4.705)	(-5.184)	(-5.468)
iTraxx non-fin_t	0.32***	0.29***	0.32***	0.28***	0.28***
	(24.128)	(22.425)	(22.593)	(20.843)	(21.186)
Treasury Rate_t	-0.24***	-0.20***	-0.21***	-0.17***	-0.17***
	(-6.506)	(-5.424)	(-5.503)	(-4.408)	(-4.433)
			Conditional Variance		
σ_{t-1}^{US}			0.43***	0.41***	0.38***
			(2.973)	(2.867)	(3.434)
σ_{t-1}^{EU}			0.10	0.22	0.26**
			(0.629)	(1.403)	(2.116)
σ_{t-1}^{AP}			-0.11	-0.16	
			(-0.795)	(-1.145)	
σ_{t-1}^{EM}			0.14	0.10	
			(0.866)	(0.614)	
Crisis			0.88**	0.63*	0.45
			(2.268)	(1.678)	(1.601)
SoFFin			-0.82***	-0.68**	-0.54**
			(-2.774)	(-2.397)	(-2.549)
No. of Obs.	1,620	1,620	1,620	1,620	1,647

Note: The dependent variable *Germany* includes all financial institutions headquartered in Germany and for which CDS spreads are available. See Table 1 for details. ARCH and GARCH terms are included but not shown. z-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Next, we introduce the financial system indices in the equation for the conditional variance to test for contagion effects between the foreign financial systems and the German financial system in the volatility, e.g. second moment of the CDS spreads distribution. In line with the mean equation, we construct an indicator of the conditional variance for the four indices for the EU, US, AP and EM. Interpreting the conditional variances as "volatility surprises", we derive them from a dynamic conditional correlation multivariate GARCH model (MGARCH), which we estimate jointly for all four regions. The most important advantage of the MGARCH model is that a full causality structure for all four indices can be estimated. For example, in the equation for Europe, we control for changes in the indices for US, Asia-Pacific region and the Emerging Markets. Modeling the "volatility surprises" using a MGARCH allows the immediate interpretation of the coefficients, given that the model controls for all potential relationships and reduces spurious correlations.Given the complexity of the model, it was not possible to use this methodology to assess financial contagion for all regional financial systems jointly including all control and dummy variables of interest. We therefore choose a univariate GARCH model, where we analyze financial contagion in the mean and variance equation using the conditional variances derived from a reduced multivariate GARCH model to complement the univariate GARCH model. The full specification of the satellite model is given by:

$$I_t = \alpha + \beta M_{t-1} + \mu_t \tag{2.4}$$

$$\mu_t = \Omega_t^{1/2} \nu_t \tag{2.5}$$

$$\Omega_t = A_t^{1/2} \Xi_t A_t^{1/2} \tag{2.6}$$

$$\Xi_t = diag(\Theta_t)^{-1/2} \Theta_t diag(\Theta_t)^{-1/2} \tag{2.7}$$

$$\Theta_t = (1 - \lambda_1 - \lambda_2)\Xi_t + \lambda_1 \tilde{\mu}_t \tilde{\mu}_t^{'} + \lambda_2 \Theta_{t-1} \tag{2.8}$$

where I_t is an 4×1 vector with the indices standing for different regions, where financial institutions are located; M_{t-1} is a 4×1 vector of independent variables which contains the lagged dependent variables from I_t, while β is the corresponding regression coefficient and α is 4×1 vector with constant terms. $\Omega_t^{1/2}$ represents the Cholesky factor of time-varying conditional covariance matrix Ω_t and ν_t is a 4×1 vector of independent, and identically distributed innovations, which we assume to follow a multivariate t-distribution. A_t is matrix of conditional variances in which each of $\sigma^2_{1,t}, ..., \sigma^2_{4,t}$ evolves according to a univariate GARCH model of the form $\sigma^2_{i,t} = \gamma_{i,0} + \gamma_1\mu^2_{i,t-1} + \zeta_1\sigma^2_{i,t-1}$ with γ_1 as an ARCH parameter and ζ_1 as a GARCH parameter. Θ_t is introduced to ensure, that Ξ_t is a conditional correlation matrix with $0 \leq \lambda_1 + \lambda_2 < 1$. The tilde over μ in the equation 2.8 implies that the 4×1 vector of residuals is standardized based on $A_t^{-1/2}\mu_t$.

Once we have obtained the conditional variances $\sigma^2_{i,t}$ for all four regions (US, EU, AP, EM) from MGARCH model for each of the four indices, and assuming multiplicative heteroscedasticity,[24] the full specification of the conditional variance equation for the German index in our main model (see equation 2 and particularly 3) is given by

$$\begin{aligned}\sigma_t^2 &= exp(\varrho_0 + \varrho_1\sigma^2_{EU,t-1} + \varrho_2\sigma^2_{US,t-1} + \varrho_3\sigma^2_{AP,t-1} + \varrho_4\epsilon^2_{EM,t-1}) + \\ &+ \varrho_5 Crisis_t + \varrho_6 SoFFin_t + \gamma_1\epsilon^2_{t-1} + \lambda_1\sigma^2_{t-1}\end{aligned} \tag{2.9}$$

Additionally and in line with the mean equation, we include both dummies, Crisis and SoFFin, in the conditional variance equation. Our results in column 3 suggest that volatility surprises from the US lead to a statistically significant volatility effect on the German system. The volatility contagion emanating from Europe becomes statistically significant only in column 5. Given the lack of significance for the Asia-Pacific region or the Emerging Markets, we drop these regions from the conditional mean and variance equation in column 5. This is supported by the

[24]Harvey (1976) shows the advantages of modeling multiplicative heteroscedasticity in comparison to additive heteroscedasticity.

Log-Likelihood test of the models in column 4 and 5, which shows that excluding these four variables does not significantly alter the Log Likelihood and does not reduce the predictive power of the model. With regard to our two shift dummies, the dummy variable "Crisis" is always positive and statistically significant in the mean equation. We interpret this as an indication of a structural shift in line with Figure 1. Table 4 also sheds some light on the effect of the various measures implemented under the German stabilization programme (SoFFin). The dummy for SoFFin in the conditional variance equation is significant and negative suggesting that the measures partially shielded the German financial system. Moreover, we also estimate pairwise Granger causality regressions between the different financial systems to gauge the directional relationships. The results, shown in Panel I of Table 8 in the appendix, suggest similar contagion effects from the US and the European financial system to Germany. The financial systems in the Asia-Pacific region and the emerging markets are not statistically related to Germany supporting our decision to drop these indices from the GARCH specification. The results further confirm a bidirectional relationship running also from Germany to the US and Europe. Interestingly, the coefficient for Germany to the US is negative, which could be interpreted as evidence for possible counterbalancing effects.

2.3.2 Role of OTC dealers in crossborder financial contagion

Due to the sizeable derivative exposures and the lack of transparency regarding these exposures, dealer banks may be particularly prone to contagion. In this subsection, we thus make an attempt to geographically disentangle the contagion effects emanating from dealer banks. In line with our previous approach, we calculate a total asset weighted index for the 25 non-German dealer banks which we call *Dealer*.[25] In addition, we drop dealer banks from the previously used indices for Europe and the US to obtain indices containing only financial institutions that are not active CDS dealers. We calculate the indices along equation 2.1. We model the contagious effects using the GARCH methodology described in the previous section.

Column 1 of Table 5 contains the results when we introduce an index for dealer banks (Dealer) alongside the indices for the US and Europe, which now exclude the dealers. The dependent variable is the index including all financial institutions from Germany. The results reaffirm that dealer banks are a particularly important source of contagion. The dealer index is significantly positive and the magnitude of its coefficient exceeds those of the indices for Europe and the US for non-dealer institutions. We repeat the specification in column 2 but distinguish between dealers from the US and Europe. Overall, the evidence points to the dealers as a major source of contagion. In the conditional variance equation, we include the conditional variance derived from a corresponding MGARCH model. With regard to conditional variance the impact for all dealers, as well as for the European and US dealers separately is statistically insignificant.[26]

Against the evidence that dealer banks are the group of financial institutions which account for most of the contagion to the German financial system, we next exam-

[25] Please refer to Table 1 for a geographical distribution of dealers.

[26] The analysis of Granger Causality using the Dealer index in Panel II of Table 8. The results largely confirm the evidence obtained from the GARCH model. Dealer banks figure prominently as shown by their economically and statistically high coefficients. With the exception of the US, dealer banks appear particularly relevant for Germany but also Europe, Asia-Pacific and the Emerging Markets.

Table 5: Are dealer banks a source of contagion?

	(1) Germany All	(2) Germany All	(3) German Non-Dealer Banks	(4) German Non-Dealer Banks	(5) German Dealer Banks	(6) German Dealer Banks
			Conditional Mean			
Endogenous Var_{t-1}	0.02	0.01	-0.00	-0.00	0.17***	0.18***
	(0.524)	(0.412)	(-0.003)	(-0.033)	(5.679)	(5.806)
Europe excl. $Dealer_{t-1}$	0.03	0.02	0.04	0.03	0.01	0.02
	(0.989)	(0.775)	(1.267)	(1.123)	(0.358)	(0.519)
US excl. $Dealer_{t-1}$	0.03**	0.04**	0.02	0.02	0.04**	0.04**
	(2.313)	(2.317)	(1.426)	(1.319)	(2.387)	(2.155)
$Dealer_{t-1}$	0.14***		0.13***		0.08***	
	(5.594)		(5.401)		(2.690)	
US $Dealer_{t-1}$		0.06***		0.06***		0.06***
		(4.043)		(4.561)		(3.210)
European $Dealer_{t-1}$		0.09***		0.07***		0.00
		(3.730)		(3.143)		(0.128)
Constant	-0.00*	-0.00*	-0.00***	-0.00***	-0.00***	-0.00***
	(-1.706)	(-1.704)	(-2.674)	(-2.690)	(-2.687)	(-2.689)
			Conditional Variance			
σ_t^{US}	0.28	0.44**	0.24	0.33*	0.25	0.35*
	(1.633)	(2.413)	(1.385)	(1.811)	(1.393)	(1.826)
σ_t^{EU}	0.14	0.08	0.25	0.21	0.11	0.02
	(0.820)	(0.371)	(1.466)	(0.939)	(0.669)	(0.111)
$\sigma_t^{AllDealer}$	0.13		0.01		0.24	
	(0.547)		(0.058)		(1.025)	
$\sigma_t^{DealerEU}$		0.15		0.07		0.23
		(0.645)		(0.318)		(1.105)
$\sigma_t^{DealerUS}$		-0.15		-0.13		0.00
		(-0.832)		(-0.746)		(0.027)
Constant	-4.83***	-5.12***	-5.17***	-5.39***	-4.65***	-4.78***
	(-4.166)	(-4.292)	(-4.332)	(-4.400)	(-4.116)	(-4.118)
No. Of Obs.	1,647	1,647	1,647	1,647	1,647	1,647

Note: The variable Germany includes all German financial institutions for which CDS spreads are available. The exogenous variable *All Dealers* excludes the German dealer Banks. Exogeneous variables, dummies for Crisis and SoFFin as well as ARCH and GARCH terms are included but not shown. z-statistics in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

ine if there are asymmetries in contagion between German dealer and non-dealer banks. We create separate indices for all German banks and dealers separately and use each index as a dependent variable in our GARCH model. Column 3 and 4 shows the results for all banks and columns 4 and 5 for the three dealers within the German financial system. The results mark important asymmetries across the two groups with regard to the sources of contagion from different regions and CDS dealers, which are masked when looking at a more aggregate index of the financial system. The results in columns 3 and 4 suggest similar contagion effects from the European and the US financial system to German banks. Non-dealer banks in Europe and the US matter significantly less for German banks both economically and statistically. With regard to the German dealer banks, column 5 appears to confirm that activity in the OTC can give rise to additional contagion effects for this group of institutions. For this subgroup of banks, the only statistically relevant contagion effect stems from other dealer banks. We also differentiated between dealer banks headquartered in Europe and the US for the German dealer banks. The results in column 6 reveal contagion effects primarily from US dealer banks but not from European dealers. The evidence presented here suggests that the most relevant institutions for the spreading of risk across borders are OTC dealer banks.

2.3.3 Robustness: asymmetric effects

As our primary concern in this study is contagion as a major contributory element to systemic risk, an important issue is how extreme movements in markets contribute to the spreading of risk between financial systems. In this section, we examine the relevance of asymmetric contagion effects on both extreme positive and negative movements in regional CDS indices including interaction terms in our analysis. More specifically, our aim is to investigate whether the German financial system responds differently to positive and negative shocks from other financial systems. To achieve this, we create two dummies that are equal to one for the largest positive and largest negative spread movements in the CDS indices for Europe and separately for the US. We denote these dummies as *Extreme Mov.* and interact these dummies with each of the two

CDS indices. We show the results for the specifications including the dummies jointly with the interaction terms for the 10 percent largest positive and negative movements in the two indices in columns 1 to 2 and for the 5 percent largest positive and negative movements in columns 3 to 4 of Table 6.

For the 10 percent largest positive changes in column 1, only the interaction term for the US is positive and significant, suggesting that extreme movements in the index for the US financial system have an asymmetric impact on the German index. However, this effect disappears for the 5 percent largest spread movements shown in column 3.[27] For the 10 and 5 percent largest negative spread movements in columns 2 and 4, the interaction term for EU is negative. This finding supports the notion of negative contagion suggested by Jorion and Zhang (2007). They argue that negative contagion indicates competitive effects when the failure of a competitor improves the position of the remaining market participants. As we are focusing here on the largest decreases in the European index, the finding of a negative effect implies that an improvement in the credit risk of European competitors leads to an increase in CDS spreads of the German financial system.

In column 5 of Table 6 we also show the results for the asymmetric GARCH model suggested by Nelson (1991). In essence, the model allows us to test whether the index for the German financial system reacts differently to unanticipated positive increases than it does to unanticipated decreases. The coefficient of the EARCHA_{t-1} is not significant. In contrast, the symmetric effect EARCH_{t-1} is

[27] We also specified a model containing the extreme positive and negative spread movements jointly. The results are largely identical but we refrain from showing them here due to the size of the table. However, the results can be obtained upon request from the authors.

Table 6: Asymmetric contagion effects to the German financial system

$Germany_t$	(1)	(2)	(3)	(4)	(5)
	90th Percentile	10th Percentile	95th Percentile	5th Percentile	Asymmetric GARCH
Conditional Mean					
$Europe_{t-1}$	0.12***	0.16***	0.12***	0.16***	0.14***
	(4.790)	(5.838)	(5.277)	(6.102)	(6.060)
US_{t-1}	0.09***	0.11***	0.09***	0.11***	0.11***
	(4.739)	(5.555)	(4.877)	(5.700)	(6.448)
Extreme Mov. EU_{t-1}	-0.00	-0.00	-0.01	-0.00	
	(-0.129)	(-1.230)	(-1.111)	(-0.415)	
Extreme Mov. US_{t-1}	-0.01*	0.00	0.00	-0.00	
	(-1.701)	(0.105)	(0.604)	(-0.382)	
Extreme Mov.*$Europe_{t-1}$	0.02	-0.18***	0.16	-0.15*	
	(0.201)	(-2.622)	(1.099)	(-1.826)	
Extreme Mov.*US_{t-1}	0.11**	-0.02	0.02	-0.03	
	(2.027)	(-0.367)	(0.247)	(-0.531)	
Constant	-0.00	-0.00	-0.00	-0.00	0.00
	(-0.186)	(-0.712)	(-0.277)	(-0.401)	(0.032)
Conditional Variance					
σ_{t-1}^{EU}	0.32**	0.31**	0.31**	0.32**	0.16***
	(2.421)	(2.421)	(2.369)	(2.469)	(3.274)
σ_{t-1}^{US}	0.37***	0.37***	0.38***	0.37***	0.13***
	(2.762)	(2.741)	(2.786)	(2.715)	(2.777)
$EARCHA_{t-1}$					-0.01
					(-0.203)
$EARCH_{t-1}$					0.40***
					(6.474)
$EGARCH_{t-1}$					0.59***
					(8.785)
Constant	-3.57***	-3.60***	-3.62***	-3.58***	-0.87***
	(-5.201)	(-5.279)	(-5.230)	(-5.250)	(-3.728)
No of Obs.	1,647	1,647	1,647	1,647	1,647

Note: Exogenous variables for stock volatility, the yield curve, iTraxx non-financials and the government bond rate, Crisis and SoFFin dummies as well as ARCH, GARCH and ARMA terms are included but not shown. z-statistics in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

relevant (0.40) and statistically significant. In fact, the relative magnitudes of the two coefficients imply that the symmetric effect dominates the asymmetric effect. This finding supports our decision to prefer a symmetric GARCH model in our main analysis.

2.4 Conclusion

In this chapter, we examine crossborder financial contagion to the German financial system within a GARCH model. We find that contagion from the US and the European financial system matter most for financial intermediaries in Germany. While the magnitude of contagion in the first moment from the two regions is comparable, contagion from the US financial system also triggers an increase in the conditional variance. Furthermore, our results suggest that introduction of the public support schemes (SoFFin) had a mitigating impact on the CDS spreads of German financial institutions. This may be interpreted as evidence that the support measures provided by SoFFin helped to diminish contagion to German financial system. Also, we find evidence for a structural shift during the global financial crisis as reflected by an increase in the uncertainty measured by the conditional variance. More importantly, our results highlight differences in the contagion effects between the different regions and different sectors of the financial systems. The German financial system experienced a more pronounced impact from international dealer banks. This evidence confirms the notion that the active OTC dealers possibly due to the close and highly concentrated interdealer network poses a potential additional contagion channel. Moreover the German financial system as a whole is equally affected by dealer banks from Europe and US, while German dealer banks, which are arguably the systemically most important financial institutions in the German financial system, experience the economically largest impact from US dealers.

More generally, the evidence found in this study implies a number of relevant policy insights. First, contagion not only within a financial system but also across borders is an important risk factor that should be monitored by macroprudential supervisors. Second, the finding that OTC dealer banks are the most important source of contagion effects for the German financial system highlights the need for more intensive monitoring and regulation of these banks. The monitoring of their interlinkages should not be limited to traditional exposures in the lending market but also include the OTC derivative market. Furthermore, the recent initiatives from the Financial Stability Board on the regulation of the OTC market may alleviate contagion effects. More specifically, the FSB aims to mitigate systemic risk by enhancing transparency in the market through the trading of all standardized derivative contracts on centralised exchanges or electronic platforms which will reduce the opaqueness of this market and thereby reduce information asymmetries. Finally, the empirical approach presented here may serve as a monitoring tool for the continuous supervision of systemic risk. For this purpose, the model can to be continually adapted to emerging risks for the German financial system.

2.5 Appendix to Chapter 2

The substantial body of literature on contagion can be broadly classified into studies on contagious effects between markets and between individual firms. The papers in these two broad strands differ in their empirical approach and the type of data used. The papers taking a market perspective study the international transmission of contagion during financial crises and market-specific shocks using broad market indices for securities' prices. As an early example, Solnik (1974) examines the price generating process for stocks from eight European countries, the US and Japan using an international asset pricing model. He shows that while domestic factors matter most for stock price movements, they are also affected by foreign events. This evidence suggests that international systemic risk is priced into stock prices. A particularly well studied event is the October 1987 stock market crash. Among the papers analyzing this event, King and Wadhwani (1990) develop a model in which contagion occurs when investors infer information from price changes in other markets. They use high frequency data for the stock markets in London, New York and Tokyo showing that price changes in one market spill over to other markets. Moreover, they find that a surge in volatility leads to an increase in contagion between markets. Hamao et al. (1990) also examine contagion between these three stock markets during the period of the October crash by means of a GARCH model. Similarly to King and Wadhwani (1990), they find that price changes in foreign stock markets significantly impact on the domestic market in the conditional mean and variance, though not in all bilateral directions. Malliaris and Urrutia (1992) conduct Granger causality tests for stock market indices in six countries around the October 1987 crash. Their results suggest that before and after the crisis there were no lead-lag relationships between the markets, while during the month of the crash the spillovers increased in both directions for the majority of markets. They interpret these findings to mean that the crash was not caused by any particular stock market but had its origins in all of them simultaneously.

Forbes and Rigobon (2002) suggest an adjustment to the correlation coefficient frequently used to measure the extent of contagion. They take account of the fact that the variance of market returns fluctuates over time, leading to a bias in this measure for contagion. They also apply this adjustment to the US stock market crash in 1987 and find no evidence for contagion. Besides the stock market crash in 1987, a number of other extreme events have received widespread attention in the contagion literature. Among these events, the emerging market crises during the 1990s have received particular attention.[28]

Besides contagious effects between financial sectors, Baur (2011) examines the transmission of distress from the financial sector to real economy during the recent financial crisis. The evidence presented in Baur (2011) document the role of the financial sector in transmitting shocks between countries and to different sectors. More specifically, none of the sectors considered was completely immune to the crisis. However some of sectors suffered less indicating the ability of investors to differentiate between sectors and therefore to maintain the effectiveness of diversification.

In view of the mixed evidence for the existence of contagion, alternative methods have been suggested that take into account the potential non-normality of asset returns and possible non-linear interlinkages between stock returns. Bae et al. (2003) studied the extreme comovements using exceedance correlations for stock prices. Hartmann et al. (2004) employ a non-parametric measure, using extreme value theory to gauge contagion effects between stock and bond markets. Beine

[28]See Claessens and Forbes (2001) for a review of this literature.

et al. (2010) measure stock market coexceedance using quantile regression, showing that financial liberalization leads to a rise in tail comovemement. Fry et al. (2010) propose a new test of contagion focusing on the coskewness of market returns. They apply their new test to study contagion effects between the real estate and equity market within and between countries for the Hong Kong crisis in 1997 and the subprime crisis in 2007. Generally, these papers point to the existence of contagious effects between markets and across national borders. This strand in the literature underlines the importance of the methodology used to gauge contagion and to take into account the non-normality of asset returns.

With regard to contagion studies for financial intermediaries, the literature has studied the effects of adverse events such as a bank's failure on the equity returns of other banks within an event study framework (see Aharony and Swary (1983), Swary (1986) and Pozdena (1991)). Generally, these papers conclude that while there is evidence for contagious effects, they can be largely attributed to fundamentals rather than irrational investor behavior. Slovin et al. (1999) examine the effect of adverse events for US banks. They find that dividend reductions at money center banks have a negative impact on other money center banks and on regional banks. Regional banks, in turn, do not affect money center banks but instead lead to positive abnormal returns for rival banks in the same geographic area, indicating competitive effects.
De Nicolo and Kwast (2002) study the stock return correlation for a sample of large US banks. They measure contagion using pairwise correlation coefficients with a GARCH constant conditional correlation model and find an upward trend in the inter-dependency among banks. Authors argue that the consolidation process in the banking sector is behind this trend and that this increase may lead to more systemic risk.
The majority of this literature has focused on US banks. Schroeder and Schueller

(2003) presents one of the few studies for the European banking system. They estimate bivariate correlations in a GARCH framework for national bank stock indices of the EU countries. In line with De Nicolo and Kwast (2002), they find that the conditional correlation trended upwards, with structural breaks following the implementation of the second banking directive and the introduction of the euro.

Fenn and Cole (1994) and Polonchek and Miller (1999) present two of the few studies that exist on contagion effects for the insurance industry. Polonchek and Miller (1999) argue that contagion effects between insurance firms arise because of monitoring costs. Rationally uninformed investors draw inferences for the entire industry based on adverse information from some firms. Their results reveal that contagion effects within the insurance sector pose an important risk. As pointed out by Stulz (2010) and Duffie (2010), contagion might be particularly prevalent among dealers in the OTC market. One of the few papers which empirically tests for contagion in the OTC market is Clark and Perfect (1996). Using the stock returns of the largest U.S. banks active in the derivative markets they show that large derivatives losses made by four clients of one bank led to negative abnormal returns for other dealers in the derivatives market. While some of these abnormal returns can be explained by fundamentals, the result highlights the importance of contagion effects within this industry.

In sum, the findings in the literature provide support for the claim that contagion between markets and across borders can be important for the transmission of international shocks. However, evidence on the international transmission of shocks between financial institutions is limited so far despite the recent experience during the global financial crisis. The bulk of the literature on contagion between financial intermediaries focused on contagion within the US to detect evidence for contagion. In addition, some of the findings in this research indicate an increase in the role of contagion and thus of systemic risk over the recent years. Finally, the findings by Forbes and Rigobon (2002) highlight that a careful interpretation of the results is needed given that the definition of contagion is ambiguous and any correlation may also reflect interlinkages rather than contagion.

Table 7: Augmented Dickey-Fuller unit-root test

	Test Stat	
	Levels	Diff-Logs
All Dealer	-1.45	-32.599
US	-2.105	-33.98
US Dealer	-2.446	-37.35
US excl. Dealer	-2.258	-37.64
Europe	-0.057	-32.65
European Dealer	-0.825	-32.39
Europe excl. Dealer	0.123	-35.24
Germany	-0.647	-34.64
German Dealer	-1.243	-33.91
Germany excl. Dealer	-0.774	-38.99
Emerging Markets	-1.337	-42.71
Asian Pacific Region	-1.155	-44.61
iTraxx non-financials	-1.838	-46.589
Yield Curve	-1.218	-64.746
Treasury Rate	-1.928	-42.941
VDAX	-3.447	-41.038

Note: The column "Levels" includes the Dickey-Fuller test statistic prior to the transformation, while the column "Diff-Logs" shows the Dickey-Fuller test statistic after the transformation. The critical values for the statistic are: -3.43 for 1%; -2.86 for 5% and -2.57 for 10% significance level. The hypothesis is that the series have a unit root.

Table 8: Granger causality tests

Dependent Variable	(1) Germany	(2) Germany	(3) Germany	(4) Germany	(5) Europe	(6) US	(7) Asia-Pacific	(8) Emerging Mkt.
Panel I: Indicators incl. CDS dealers								
$Germany_{t-1}$	0.05	0.09***	0.17***	0.17***	0.19***	-0.12***	0.31***	0.21***
	(1.478)	(3.789)	(7.995)	(7.542)	(6.076)	(-3.818)	(9.992)	(7.488)
$Europe_{t-1}$	0.15***				0.08***			
	(4.681)				(2.590)			
US_{t-1}		0.13***				0.20***		
		(6.900)				(7.934)		
$Asia\text{-}Pacific_{t-1}$			-0.02				-0.07***	
			(-1.346)				(-2.837)	
Emerging $Mkt._{t-1}$				-0.01				-0.04
				(-0.596)				(-1.466)
No. of Obs.	1,647	1,647	1,647	1,645	1,647	1,463	1,426	1,461
R^2	0.330	0.340	0.322	0.321	0.337	0.313	0.239	0.155
Panel II: Indicators excl. CDS dealers								
$Dealer_{t-1}$	0.18***				0.44***	0.04	0.30***	0.22***
	(8.011)				(15.667)	(1.056)	(8.833)	(9.440)
$Germany_{t-1}$	-0.02							
	(-0.595)							
$Europe_{t-1}$					-0.29***			
					(-8.317)			
US_{t-1}						0.05*		
						(1.870)		
$Asia\text{-}Pacific_{t-1}$							-0.13***	
							(-5.251)	
Emerging $Mkt._{t-1}$								-0.05**
								(-2.074)
No. of Obs.	1,647				1,647	1,463	1,426	1,461
R^2	0.201				0.340	0.166	0.175	0.173

Note: For each column, we only present results for the country or regional financial system indicators while exogenous variables for the CDS index of non-financial firms, the yield curve and a stock market volatility index specific to each country or region are also included but not shown. Panel I shows the financial system indicators based on all financial entities in the respective system. In Panel, II dealer banks are excluded from the financial system indicators used as right hand side variables. As a result, the country or region specific indicators only contain non-dealer financial entities and dealer banks are included in a separate index called *Dealer*. All variables are specified as log differences.

Chapter 3

Are insurers SIFIs? A MGARCH model to measure interconnectedness

"It's a difference in the fundamental business model. It's like trying to put the safety standards of airplanes on cars."
(Julie Spiezio (2014))

This chapter is based on a joint research paper with Michael Wedow.[29]

[29]Michael Wedow, European Central Bank, Sonnemannstraße 20, 60314 Frankfurt. This chapter is based on a pre-copy-editing, author produced PDF of an article accepted for publication in Applied Economic Letters. For further details on the paper, please see Podlich and Wedow (2013).

3.1 Introduction

SIFIs have become the focus of the regulatory agenda. SIFIs or too-big-to-fail banks are institutions whose failure pose a significant risk to the stability of the financial system and the real economy. The pervasiveness of the risks emanating from SIFIs was brought into the limelight when many of the globally largest banks were bailed out by their governments (Stolz and Wedow 2010). In some cases, the large scale public bailouts brought even their governments to the brink of default. As a consequence of this experience, calls for regulation specifically designed for SIFIs were made. In November 2011, the Basel Committee on Banking Supervision finalized rules for global systemically important banks.[30] These rules foresee additional capital requirements to limit negative externalities to the global financial system from banks' cross border activities. In addition, the Financial Stability Board published a list of 29 banks that will be subject to the new regulation for SIFIs.[31]

Most notably is that insurance companies are not among the institutions on the SIFI list.[32] The International Association of Insurance Supervisors (IAIS) published in May 2012 its methodology for the identification of systemically important insurers.[33] The IAIS applied an indicator approach similar to the BCBS methodology and concluded that the systemic risk from insurance companies is limited. In this chapter, we take a more agnostic approach to test if insurance

[30]See BCBS (2011).

[31]See *www.financialstabilityboard.org/publications/r*$_1$11104*bb.pdf*.

[32]It changed on 18 July 2013. Nine global insurance companies have been declared as global systemically important institutions. These firms will be subject to enhanced supervision and increased regulatory requirements in the areas of recovery and resolution planning as well as capital. The implementation deadline for these requirements starts in July 2014, and in case of additional capital requirements, extend to 2019.

[33]See www.iaisweb.org for more information.

companies should be considered as SIFIs. More specifically, we empirically test if the interconnectedness of insurers warrants their treatment as SIFIs. In the IAIS methodology interconnectedness represents one category besides size, global activity, non-insurance activities and substitutability to identify SIFIs.

Our empirical model for modeling interconnectedness relates to the sizeable literature on contagion. More specifically, the paper by De Nicolo and Kwast (2002) is closely related to our study given that they measure contagion between financial intermediaries using a GARCH model. In contrast to our data set of CDS spreads for an international sample of financial institutions, they use stock returns of US banks to assess interconnectedness. Their results underline the increase in the interdependence between financial institutions and the relevance of interconnectedness for systemic risk. They argue that interdependence between banks increased as a result of financial mergers and the creation of systemically important financial institutions. They find a positive trend in the estimated correlation, which supports their hypothesis that the consolidation process contributed to more interconnectedness. Similarly to this chapter, Hammoudeh et al. (2013) explore the relationship between different financial sectors in the US. They use CDS indexes for the banking, insurance and financial service sector and explore if any of the financial sector indexes leads the other sectors. Their findings suggest that the index of the banking sector leads the financial services sector and that banks particulary transmits risks to other sectors. Moreover, they show that the insurance sector exhibits the lowest transmission of shocks across financial sectors.

We contribute to this literature from three perspectives. First, we measure the interconnectedness by simultaneously estimating the interconnectedness between banks and insurance companies in a MGARCH model. The joint estimation of interconnectedness between different financial sectors allows us to directly compare the estimated coefficients. Second, we examine separate indexes for small and large institutions in each sector in order to better capture the interconnectedness of different size groups. Third, we use a sample of international banks and insures which also allows us to capture the interconnectedness of globally active financial firms and particularly across borders. Our findings suggest that the largest insurance companies effectively transmit risks to the broader financial system and particularly to SI banks. However, the magnitude of the transmission is considerably lower than for SI banks which may justify the exclusion of insurers from the list of SIFIs.

3.2 Data and empirical specification

3.2.1 Data and financial system indices

In order to capture contagious effects between different financial sector, we use daily spreads of single name 5-year senior CDS contracts where the underlying entity was either a bank or an insurer. For each underlying entity, we choose the CDS contract in the currency with the potentially highest liquidity.[34] Our sample starts in January 2004 and ends in the January 2011. The observation period thus excludes the period of the sovereign crisis and our results should be largely unaffected by spillovers from sovereigns to the financial sector (Tamakoshi and Hamori 2013).

In order to calculate weighted indices for the banking and the insurance sector, we use 241 financial firms for which total assets are available including 201 banks and 40 insurance companies. The sample of banks includes 28 of the 29 SIFIs on

[34]According to DTCC, the majority of CDS contracts are denominated in USD (62%) and EUR (35%). For more detailed information on the data base used in this chapter see Podlich and Wedow (2014).

the list published by the FSB. The sample is dominated by financial institutions from Europe followed by the US.

For each sector, we calculate a representative weighted index. We use the total assets of each institution over total assets for the sector as weights.[35] In addition, we also use size as a second criterion to assess the interconnectedness between the two sectors and institutions of different size in each sector. Overall, we calculate four indices, two for each sector based on all CDS spreads of financial institutions which are in the 1st and the 4th quartile. Since tests confirmed that all variables contain a unit root, we include them as log-differences in our estimations. Controlling for common factors (more specifically the segments to which banks and insurers could be exposed to), we include the volatility index for the European stock market (VSTOXX) as a measure of firm value volatility as in Alexander and Kaeck (2008) and Collin-Dufresne et al. (2001). In order to control for credit risk developments in the real economy, we additionally include the iTraxx index for non-financial firms.[36] We expect that the CDS spreads of financial firms increase with the iTraxx and the VSTOXX.

Table 9 contains the summary statistics for the four indices and two exogenous control variables. In addition, the number of banks and insurers in each index are shown. There are a number of notable features. First, the average value of the

[35]We use total assets from Bankscope and fix size groups based on the balance sheets in 2007. We also indexes where we fixed the size groups based on total assets for 2009 and indexes with varying total assets for each different year. The results did not change materially and can be obtained upon request. We normalize the weights when there are missing observations for individual institutions to avoid breaks in the time series.

[36]We use variables which are based on data for Europe given that the majority of firms in our sample are from this regions.We also test a number of further control variables such as the interbank interest rate Libor. The Libor turned out to be always insignificant in our estimation.

CDS indices for smaller institutions in both sectors exceeds that of their larger peers in the same sector. Also, the average value for the weighted indices for big and small insurers are larger than for respective bank indices. With regard to the number of institutions in each index, 9/9 insurers and 48/47 banks were identified as big/small banks and insurers. In sum, out of our overall sample of 241 institutions, 113 institutions enter our four indices.

In addition, we also calculate indices specifically for the SI and non-SI banks as an alternative benchmark to estimate the interconnectedness between different sectors and size groups. The two indices are also shown in Table 9. The FSB declared 29 banks as SIFI, but given that we lack data on one SIFI only 28 banks enter the index. It should be noted that all 28 SI banks are also among the big banks included in the respective index and thus the SIFI index serves as an alternative benchmark for comparison with the big insurers.

Table 9: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	No. of Fin. Firms
Big Insurer	1831	132.41	181.70	8.09	1014.26	9
Small Insurer	1831	367.96	367.59	49.68	1907.32	9
Big Banks	1831	64.20	60.07	8.28	250.08	48
Small Banks	1831	198.81	205.23	19.10	1104.60	47
SIF Banks	1831	62.39	58.32	7.81	239.48	28
non-SIF Banks	1831	84.00	80.97	10.74	334.87	173
VSTOXX	1790	23.28	10.42	11.60	87.51	
iTraxx (non-Fin)	1712	76.60	55.44	24.40	282.30	

Note: Our sample starts in January 2004 and ends in January 2011.

3.2.2 Empirical specification

In order to estimate interconnectedness we apply a dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroscedastic (MGARCH) model in which the conditional variances are modeled as univariate generalized autoregressive conditionally heteroscedastic (GARCH) models and the conditional covariances are modeled as nonlinear functions of the conditional variances.[37] This model has several advantages. The most important for our purpose is that it allows the conditional mean to follow a vector-autoregressive (VAR) structure, which means that full causality structure for all four indexes of interest can be estimated within the frame of this model. Furthermore, the conditional variances can be modeled as a time variant variables, which offers a more efficient and realistic estimation approach given that the volatility of CDS enormously changed with the start of the crisis in August 2007. More specifically, we model the conditional means of the CDS indices as a first-order vector autoregressive process and the conditional covariances as a DCC MGARCH process in which the variance of each disturbance term follows a GARCH(1,1) process. The full specification of the model is given by:

$$Y_t = \alpha + \beta X_{t-1} + \theta C_t + \mu_t \tag{3.1}$$

$$\mu_t = \Omega_t^{1/2} \nu_t \tag{3.2}$$

$$\Omega_t = D_t^{1/2} \Xi_t D_t^{1/2} \tag{3.3}$$

$$\Xi_t = diag(\Theta_t)^{-1/2} \Theta_t diag(\Theta_t)^{-1/2} \tag{3.4}$$

$$\Theta_t = (1 - \lambda_1 - \lambda_2)\Xi_t + \lambda_1 \tilde{\mu}_t \tilde{\mu}_t^{'} + \lambda_2 \Theta_{t-1} \tag{3.5}$$

where Y_t is an 4×1 vector with the sectoral indices standing for different types of financial institutions; X_{t-1} is a 4×1 vector of independent variables which contains the lagged dependent variables from Y_t; C_t includes control variables

[37]The dynamic of the conditional quasicorrelation parameters that weight the nonlinear combinations of the conditional variances follow a GARCH-like process as specified in Engle (1982b).

which enter the equation contemporarily, while β, θ are the corresponding regressions coefficients and α is 4×1 vector with constant terms. $\Omega_t^{1/2}$ represents the Cholesky factor of time-varying conditional covariance matrix Ω_t and ν_t is a 4×1 vector of independent, and identically distributed innovations, which we assume to follow a multivariate t-distribution. D_t is matrix of conditional variances in which each of $\sigma_{1,t}^2, ..., \sigma_{4,t}^2$ evolves according to a univariate GARCH model of the form $\sigma_{i,t}^2 = \gamma_{i,0} + \gamma_1 \mu_{i,t-1}^2 + \zeta_1 \sigma_{i,t-1}^2$ with γ_1 as an ARCH parameter and ζ_1 as a GARCH parameter. Θ_t is introduced to ensure, that Ξ_t is a conditional correlation matrix with $0 \leq \lambda_1 + \lambda_2 < 1$. The tilde over μ in the equation 3.5 implies that the 4×1 vector of residuals is standardized based on $D_t^{-1/2}\mu_t$.

3.3 Results

We present the results of our specification using the indices for big and small banks and insurers in Table 10. As expected, the evidence in row 1 suggests that big banks are highly connected with all subgroup indices and particularly the smaller banks. Interestingly, big banks are almost equally interconnected with small banks and with big insurance companies. In addition, neither smaller banks nor smaller insurance companies appear to be statistically interconnected with any of the other subgroups. With regard to our main focus, Big Insurers similarly to Big Banks are also positively and statistically interconnected with all other three subgroups. However, in terms of economic significance, the interconnectedness is of a magnitude lower than for Big Banks. Only the interconnectedness with small insurers is comparable for big banks and insurers.

We re-estimate the MGARCH model for 4 subgroups replacing the indices for small and big banks with indices for SI and non-SI banks. This specification en-

Table 10: Interconnectedness between small and big banks and insurance companies

	(1)	(2)	(3)	(4)
	Insurer$_t$		**Banks**$_t$	
	Small	Big	Small	Big
Big Banks$_{t-1}$	0.05**	0.13***	0.14***	0.22***
	(2.125)	(5.330)	(5.509)	(8.650)
Small Banks$_{t-1}$	-0.00	0.00	-0.07**	-0.00
	(-0.043)	(0.177)	(-2.572)	(-0.538)
Big Insurer$_{t-1}$	0.05**	0.20***	0.06***	0.04**
	(2.476)	(7.839)	(2.921)	(2.197)
Small Insurer$_{t-1}$	0.21***	0.02	-0.00	0.01
	(8.003)	(1.511)	(-0.155)	(0.739)
iTraxx (non-Fin.)$_t$	0.13***	0.21***	0.09***	0.25***
	(7.271)	(11.348)	(5.670)	(13.026)
VSTOXX$_t$	0.03***	0.04***	0.04***	0.06***
	(3.717)	(5.058)	(3.557)	(7.992)
ARCH$_{t-1}$	0.32***	0.26***	0.69***	0.29***
	(12.913)	(9.065)	(8.009)	(9.039)
GARCH$_{t-1}$	0.67***	0.73***	0.30***	0.70***
	(26.542)	(25.215)	(3.553)	(22.010)

Note: z-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. The number of observations is equal to 1650 in all specifications. Constants are included in the mean and variance equation but not shown.

ables us to compare our proxy for interconnectedness of Big insurers more directly with the banks already defined as SIFIs. Table 11 shows that Big Insurers continue as the second most interconnected financial firms after SI banks. In addition, the re-specification also unearths that small insurance companies are also statistically interconnected but to a lower degree than their larger peers in the same sector.

Hammoudeh et al. (2013) suspected that the contagion emanating from the insurance sector to the banking sector is potentially due to a few insurers that sell credit protection to banks. We tested this by replacing AIG in the index for Big insurers. We do not show the results given that they were not materially different from those presented in Table 11. We also used two indexes for CDS dealer and non-dealer banks to measure the interconnectedness between sectors. However, given the large overlap between Big Banks, SI banks and dealer banks the results did also not materially change.[38]

Table 11: Interconnectedness of insurers and SI banks

	(1)	(2)	(3)	(4)
	Banks$_t$		**Insurers**$_t$	
	Non-SIF	SIF	Small	Big
Non-SIF Banks$_{t-1}$	-0.00	0.05*	0.00	0.02
	(-0.021)	(1.926)	(0.179)	(1.057)
SIF Banks$_{t-1}$	0.16***	0.16***	0.03	0.10***
	(8.740)	(5.780)	(1.343)	(4.088)
Small Insurers$_{t-1}$	0.02**	0.03**	0.21***	0.03***
	(2.038)	(2.291)	(8.266)	(2.824)
Big Insurers$_{t-1}$	0.04***	0.07***	0.06***	0.20***
	(2.789)	(3.140)	(2.606)	(7.736)
iTraxx (non-Fin.)$_t$	0.16***	0.26***	0.13***	0.21***
	(11.728)	(12.421)	(7.164)	(11.617)
VSTOXX$_t$	0.04***	0.06***	0.03***	0.04***
	(5.705)	(7.522)	(4.130)	(4.898)
ARCH	0.22***	0.20***	0.34***	0.24***
	(6.988)	(8.202)	(13.729)	(9.818)
GARCH	0.72***	0.79***	0.65***	0.75***
	(22.182)	(32.896)	(25.854)	(30.040)
Constant	-0.00	-0.00	0.00	-0.00***
	(-0.041)	(-0.938)	(1.274)	(-3.798)

Note: z-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1. The number of observations is equal to 1650 in all specifications. Constants are included in the mean and variance equation but not shown.

3.4 Conclusion

In this chapter, we examine the interconnectedness of different subgroups of two financial sectors. More specifically, our results confirm that larger banks and particularly SI banks are statistically and economically more interconnected than any other group of financial firms. More importantly, big insurers are the second most interconnected subgroup. While this may warrant a similar treatment of big insurers as SIFI, the economic magnitude of the interconnectedness is considerably

[38]Results can be obtain from the authors upon request. All SI banks are among the big banks and 16 of the 28 SI banks are dealer banks.

lower than for big banks and may thus provide a rationale for the omitting insurance companies from the list of SIFIs.

Chapter 4

On the role of the Eurosystem's collateral framework in preventing fire sales

"We have [...] used an exceptional set of non-standard policy tools. These tools, combined with the bold action taken by euro area governments over recent months, have played an essential role in preventing a collapse of the financial system and in bolstering confidence..."
(Jean-Claude Trichet, June 2009)

4.1 Introduction

Banks that experience high demand for liquidity owing to unusual demands - panic withdrawals or substantial margin calls - need to raise money very quickly, which could force them to sell assets. In a systemic crisis, distressed sales can cause a collapse of prices as potential buyers of these assets sustain losses on their own and may not be able to buy even the undervalued assets. Given this constraint of the potential buyers, financial institutions may be forced to sell assets at fire sale prices (Shleifer and Vishny (1992) and Duffie et al. (2007)). This fire sales mechanism will not be set in motion if banks are able to find alternative sources of funding. After the fall of Lehman Brothers, the ESCB has broadened the range of the accepted collateral and has become one of the most important alternative sources of funding for many banks (see European Central Bank (2013)).[39]

This chapter analyses banks' selling behavior focusing on the question whether the existence of this alternative source of funding - ESCB's liquidity-providing reverse transactions - which became more easily accessible during the crisis prevented banks from selling assets.[40] This Eurosystem support measure might have been one of the most important reasons that the European financial system did not experience further and heavier disruptions stemming from fire sales and should therefore be taken into account when it comes to the analysis related to bank's fire sales.

More specifically, the chapter tests three hypotheses. First, it analyses whether bank's liquidity and capital position determine its asset sales. Second, it separates

[39] See (Stolz and Wedow 2010) for other support measures implemented by the ECB.

[40] Note that I will use the term securities and assets in connection with the ESCB eligibility interchangeably, although assets also includes loans. In this study and due to data limitation, I include only marketable securities. Further notice, that I will use the term triggers and causes for fire sales interchangeably.

net sales into net sales of ESCB eligible and ESCB non-eligible securities to test second hypothesis that banks do not sell ESCB eligible securities in reaction to liquidity and capital constraints. Third, it tests hypothesis that stressed banks, such as banks before rescued by the German government and banks with low liquidity and poor capital position have different selling behaviors than non-stressed banks. This hypothesis is based on the assumption that the relation between asset sales and the liquidity or capital position of a bank is stronger for distressed banks.

This study is based on two unique data sets: the securities holding statistics and the ESCB statistics on the eligibility of marketable securities. The sample includes 30 banks (including all German systemically important financial institutions) representing 58% of the total assets of all German banks. The data are available on a quarterly basis from the end of 2005 until the end of 2011. The analysis relies on regressions for panel data such as dynamic fixed effects.

With regards to the main results, the analysis does not show that overall sales of securities are generally conditional on the bank's liquidity and capital position. However, the relation between the triggers and the sales becomes statistically significant during the crisis implying that the lower a bank's balance sheet liquidity and the bank's capital ratio the more securities banks sell. Thus, during the crisis, the risk of a fire sale existed. Banks under pressure due to liquidity and capital constraints could have sold assets at prices that are under their fundamental value.[41]

Next, the analysis shows that banks do not sell ESCB eligible assets and sell ESCB non-eligible assets in reaction to liquidity shortages experienced during the crisis. This result provide evidence that the ESCB's liquidity-providing reverse transac-

[41] Please note, the identification of the causes for asset sales is the first step towards understanding the concept of fire sales. Further relevant aspects to be analysed are related to the impact of forced sales on the prices of securities. This chapter focuses on the causes for sales. All the other relevant aspects are beyond the scope of this chapter.

tions reduced the potential for asset sale and therewith the potential for fire sales. Moreover, the fewer ESCB eligible asset a bank owns in comparison to all securities, the more ESCB non-eligible assets a bank will sell. With regard to capital, it seems that, overall, a bank with poor capitalisation would rather sell assets independently of their ESCB eligibility.

In addition, the study presents evidence supporting a non-linear relation between the net sales and the determinants. Banks which have been rescued by the German government and banks with liquidity ratio lower than the median sell, on average, more ESCB non-eligible securities. Again, this is the evidence that asset selling might be a probable reaction path for banks that are under high liquidity pressure.

The contribution of this study to the existing literature is twofold. First, it sheds light on the causes for potential fire sales. Even though the risk transmission channel via fire sales has gained much attention both from policy makers and the academic community, the empirical and theoretical evidence is still controversial with regard to the causes of financial institutions selling assets.

The relevant academic literature on fire sales can be assigned to three different strands: in favor of assets sales as a reaction to funding shortages, mixed evidence and against fire sales.

In the first strand, Allen and Carletti (2006), Adrian and Brunnermeier (2009), Adrian and Shin (2010) argue in favor of the hypothesis that funding liquidity shortages could force banks to sell assets at times when securities markets are illiquid. In addition, Acharya et al. (2011) and Shleifer and Vishny (2011) observe assets diminishing in size in response to banks' funding problems. Additionally, Adrian and Brunnermeier (2009) provide a theoretical model for an amplification mechanism where in an environment of increasing market illiquidity and rising haircuts, a bank experiencing funding and capital problems is forced to sell assets.[42] Moreover, Adrian and Shin (2010) find that leverage constraints similarly to capital constraints lead to a reduction of bank's assets.[43]

In the second literature strand, De Haan and Van den End (2011) provide mixed evidence and find that bank's equity holdings decrease and bank's bond holdings increase as a reaction to shocks of their REPO borrowing and borrowing costs. In addition, Diamond and Rajan (2011) show in a theoretical model that asset sales during periods when markets are illiquid are irrational from the perspective of an individual illiquid institution. Expected future fire sales, which could lead to a bank insolvency, will be priced into the current value of assets. Potential buyers of assets would immediately demand a higher return if they expect that the assets will be sold at fire prices very soon.

Finally, two empirical studies which analyse asset sales for commercial and investment banks (Boyson et al. (2013) and Boyson et al. (2012b) fail to detect empirical evidence for asset fire-selling into falling markets.[44] Financial institutions prefer to sell liquid assets in crises, when they need to raise cash. Moreover, banks' funding needs are significantly related to positive deposit growth and the

[42]Please note, the the authors argue that this mechanism is especially pronounced for investment firms.

[43]The literature for hedge funds and insurance companies is less ambiguous. Ellul et al. (2011) find that US insurance companies which are capital-constrained by regulation are more likely to sell downgraded bonds at prices which deviate from fundamentals. Merrill et al. (2012) find that if an insurance company applies fair value accounting, it improves its regulatory capital position by selling impaired assets even if it has to accept a liquidity discount. Evidence for fire sales for hedge funds is provided by Coval and Stafford (2007). Krishnamurthy (2009) describes an amplification mechanism where hedge funds liquidate assets into illiquid markets as response to asset price shocks.

[44]Boyson et al. (2012a) provide similar evidence for hedge funds.

issuance of equity rather than to asset sales.[45] The evidence provided by Nyborg and Oestberg (2014) show that banks are under selling pressure would rather sell the most liquid assets in their portfolio. However, Manconi et al. (2012) argue that sales of liquid assets will expose banks to higher credit risks and therefore there is a trade-off between high and low quality assets for risk management purposes. On the second contribution of this chapter, the analysis distinguishes between sales of ESCB eligible and ESCB non-eligible assets in order to assess the ability of the ESCB's liquidity-providing reverse transactions to reduce the potential for fire sales. While Krishnamurthy (2009) provides theoretical evidence that liquidity provision by a central bank through its function as lender of last resort can alleviate a crisis, the potential of a central bank's liquidity-providing reverse transactions to reduce fire sales has not been, to my best knowledge, empirically analysed. This study aims at closing this gap.

This chapter is structured as follows. The next section discusses the reasons for a bank to sell assets. The subsequent section provides descriptive statistics and stylized facts, followed by a model specification. The results section is subdivided into three parts closely following the three hypotheses. Section 4.2.5 checks the robustness of the results. Finally, the chapter ends with some concluding remarks.

4.2 Why do banks sell assets?

The important step towards the understanding of the causes for fire sales is the understanding of the causes for asset selling in general. This section is dedicated

[45]Moreover, Chari et al. (2008) and He et al. (2010) find evidence of asset growth during the last crisis rather than curtailed banking activity. On the contrary, German banks started to reduce their securities portfolios in the crisis as is shown in Section 4.3.

to a discussion about the triggers of asset sales which represent one of the two contributions of this study.

The most prominent triggers for asset sales, which have been broadly discussed in the academic literature, are related to the liquidity and the capital position of a bank. Regulatory constraints usually act as amplification mechanisms and determine the level of pressure on a bank to sell assets.

If a bank experiences a high demand for liquidity, owing to unusual demands by the banks' customers or even panic withdrawals of deposits, it has to choose between different alternatives to raise money, depending on the functioning of the funding markets and the urgency of taking action.

Under funding stress, institutions cannot rely on being able to issue new unsecured debt, as this source of funding is most sensitive to market disruptions. The disruption of financial markets will prevent a bank from issuing equity as well. In case collateralised funding is still available, it can be raised only with high quality and liquid assets or high haircuts. Another option which is available during the crisis is to cut dividends and to reduce stock repurchases. However, it is questionable whether this action can make up for the shortfall in bond issuance and secured and unsecured borrowing. Alternatively, the pressure on the bank's balance sheet can be relieved by scaling back loan growth. However, if funding shortages are an urgent matter for a bank, it will seek for alternative options. Selling assets is a valid option for raising money very quickly. However, under liquidity stress, a bank's ability to sell illiquid assets without facing a loss is more limited.[46] Owning high quality and liquid assets, a bank will prefer collateralised borrowing over asset sales (Dang and Holmström (2013)). Selling all high

[46]Please note, that Adrian and Brunnermeier (2009), Allen and Carletti (2006) and Adrian and Shin (2010) argue in favor of the hypothesis that funding liquidity shortages could force banks to sell assets even at times when securities markets are illiquid.

quality and liquid assets will make a bank more vulnerable to credit risk emanating from the remaining bad quality securities in its portfolio (Manconi et al. (2012)).[47] If a bank owns assets which are eligible for the Eurosystem, it will rather prefer borrowing liquidity from the Eurosystem against this collateral. After the default of Lehman Brothers, the ESCB widened its collateral framework in order to support bank lending and liquidity. More specifically, on 22 October 2008, the credit threshold for marketable and non-marketable assets was lowered from "A" to "BBB-" combined with a flat haircut add-on.[48] In addition, the Eurosystem started to accept debt instruments issued by credit institutions, such as certificates of deposit which were traded on non-regulated markets, subordinated marketable debt instruments, and fixed-term deposits held with the Eurosystem. From 14 November 2008, the Eurosystem also began accepting marketable debt instruments issued and denominated in certain foreign currencies, provided that the issuer was established in the European Economic Area and also that the instruments were issued and held/settled in the euro area.[49] With these changes to the collateral framework, central bank liquidity became more easily accessible for banks in need.

The second reason for a financial institution to sell assets is related to its capital position. The liquidity of a bank and its capital position are not fully independent from each other. A bank's capital position plays a key role in its capacity to raise funding from market sources. A well capitalised bank will have better access to funding. Furthermore, a bank with a sufficient capital buffer will be able to

[47]Note that Boyson et al. (2013), Boyson et al. (2012b) and Nyborg and Oestberg (2014) argue in favor of the hypothesis that banks in liquidity needs will sell liquid assets in order to improve their liquidity position

[48]The credit threshold for asset backed securities (ABSs) remained at the "A-" level until 19 December 2011. It was lowered afterwards.

[49]More changes the Eurosystem collateral framework have been implemented in 2010 and 2011. For further details, see European Central Bank (2013) p. 83.

absorb losses on assets or absorb higher cost for refinancing liabilities during a period of stress. Thus, a bank in need of liquidity that has only a poor capital position will not be able to borrow liquidity against collateral, if the haircut of this collateral is high and the bank is not able to finance the haircut with its own capital (see Adrian and Brunnermeier (2009)).

In addition, regulatory capital constraints amplify the need of a bank to sell assets (see Cifuentes and Shin (2005)). Since the capital requirements are binding, a decrease in the credit quality of an asset will decrease the relative ratio of the bank's equity to assets.[50] If a bank is close to the regulatory binding capital requirement, it will sell this asset and replace it with a less risky asset. However, this is only true if fair value accounting is applied to this asset. During the crisis banks were allowed to reclassify (IFRS 7 based on IAS 39) their assets out of the "fair value through profit and loss" and "available-for-sale" category to the "held-to-maturity" category. Assets that belong to the latter category are accounted at amortized costs. Therefore, changes in the market value of assets in this category will not directly impact the balance sheet unless banks were to sell them at a loss. Thus, it is not rational for a bank to sell assets into "frozen" markets, if this bank faces solvency constraints and the option of the reclassification is available.

As the financial turmoil persisted and the economic environment also deteriorated, banks faced losses in their credit portfolios and, due to write-downs owing to credit rating downgrades, the pressure on their capital positions increased. Therefore, several governments decided to support banks with direct capital injections through the acquisition of preferred shares or other hybrid instruments which fulfilled the conditions of Tier 1 capital. Also an increase in

[50] Schnabel and Shin (2004) analyse detailed information on balance sheet data and commodities and find strong evidence on relation between market prices of commodities and bank's balance sheet positions during the crisis of 1763.

deposit insurance and the introduction of the government guarantees for bank bonds were among the rescue measures taken in Europe (see (Stolz and Wedow 2010)). Furthermore, uncertainty about the credit risk of certain assets classes contributed to the reluctance to lend in the interbank market and to extend credit to the private sector. Thus, cleaning up balance sheets became a core part of the rescue efforts in the form of asset removal schemes (transfer of assets to a "bad bank") or asset insurance schemes which kept the assets on the balance sheet. Eleven German banks received support in one form or another, nine banks out of these eleven are included in the sample. The need to sell assets for German banks which benefited from such rescue programmes might have diminished as well after the implementation of the supporting measures.

The main message of this section is that a shortage of liquidity, and the lack of external funding combined with regulatory capital constraints, make it more likely that the reduction of assets through asset sales is the most probable path for the recovery of a bank. However, while a certain theoretically proven relation between potential triggers and asset sales is logical, it might be difficult to find general evidence of bank's selling assets as a response to funding shortages and/or solvency constraints, due to preventive actions taken by the central banks and policy makers during the recent crisis.

4.3 Descriptive statistics

4.3.1 Data sources

The data for the analysis are from various sources. The main source is the Securities Holdings Statistics (SHS) - *Depotstatistik* of the Deutsche Bundesbank, which contains detailed quarterly information on the securities holdings of German banks, excluding derivatives. The data is available from 2005Q3 until 2011Q4, at both the nominal and market value.[51] For the purpose of this analysis, those observations from the sample where a bank holds securities for its customers and those observations where the bank is also the issuer are eliminated. [52]

In addition to securities holdings, the information on the issuance and maturity date of the bonds is obtained from the Centralised Securities Database (CSDB). This information allows to distinguish between actual sales and the normal expiry of bonds. Quarterly data on the eligibility of securities for the Eurosystem and bank specific information regarding liquidity and solvency is obtained from the Deutsche Bundesbank. An indicator of market liquidity is obtained from the

[51]The market value is equal to nominal value times the observed market price at the given quarter.

[52]A major portion of banks' portfolios is given by different types of bonds including floating rate notes, Pfandbriefe (covered bonds), government bonds and other bonds. Their overall share is approximately 84%. The share of asset backed securities amounts to approximately 11.5%. The proportion of shares in the portfolio is less than 1%. I drop the remaining 3.5% of the securities which represent investment certificates. Nominal values for this class of securities are not available and cannot be included in the analysis. For more details on the asset classes and how banks changed their investment strategies over time, see Hildebrand et al. (2012).

ECB.

4.3.2 Asset sales

For the construction of the indicators for banks' asset sales, I use nominal values from the SHS in order to exclude pure price effects. The dependent variable is the overall net sales, the net sales of the ESCB eligible and non-eligible securities. I calculate the net sales as volume sold minus volume bought.

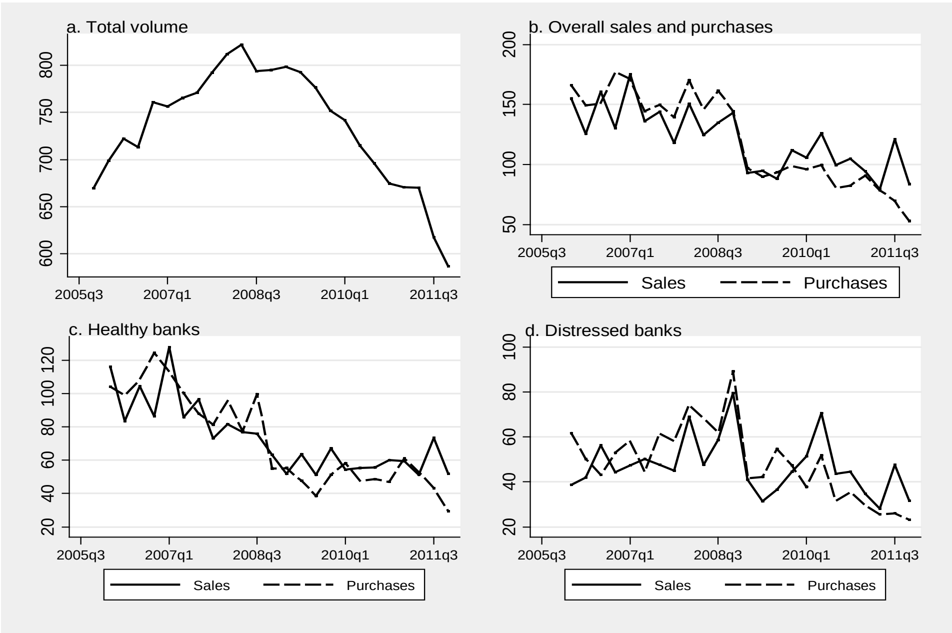
All measures of a bank's selling/purchasing patterns are constructed as a sum of all negative/positive changes of securities held by bank i in each period t in comparison to the previous period $t-1$. Securities whose maturity date is equal to the respective quarter are not included in the aggregate measure in order to better capture actual sales and to avoid distorting the measure by maturing assets.

Finally, I distinguish between "healthy" and "distressed" banks. The latter category is referred to banks which have received support from the German government during the crisis.[53] Panel a of Figure 2 shows that the aggregate securities holdings were at their peak in the second quarter of 2008 and amounted to EUR 822 billions, while at the end of the considered period (2011 Q4), the volume had fallen to approximately EUR 583 billion. This demonstrates that from the end of 2008, the considered banks started to reduce their overall securities positions (see panel (b) in Figure 2).

The first interesting feature to emerge from the data is that the selling and pur-

[53] Due to the policy of the Deutsche Bundesbank, it is not allowed to uncover the identity of the individual banks in the sample. Therefore, I refrain from providing names for banks which have been supported by the German Government and are included in the sample. All in all, 11 German banks received support. This information is publicly available. 9 banks out of these 11 are included in the sample.

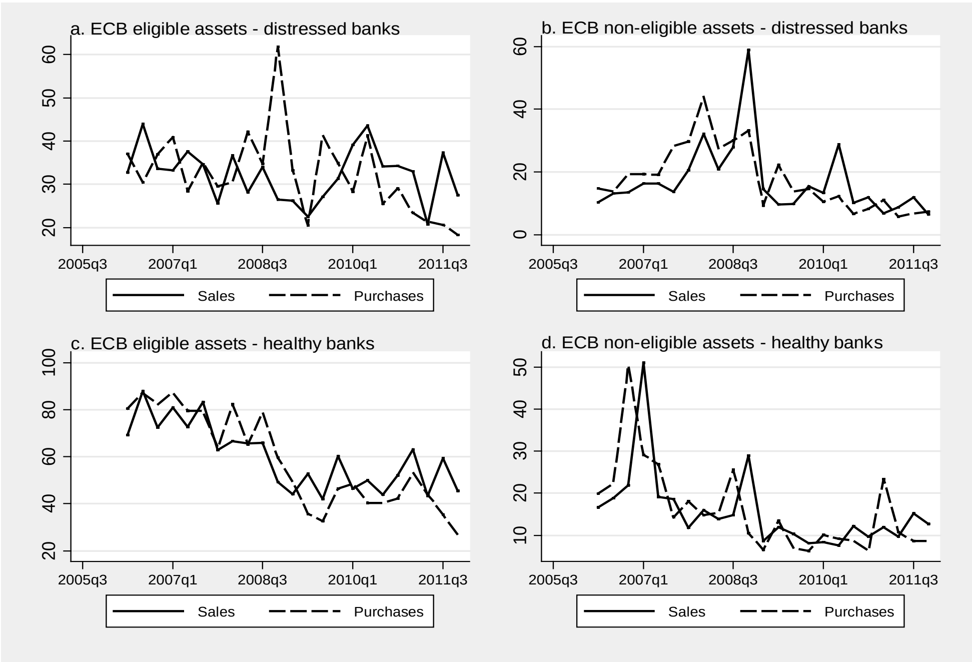
Figure 2: Average portfolio holdings in billion Euro, from Q3 2005 to Q4 2011



Part (a) shows the nominal values of securities holdings. The overall sales and purchases are shown in part (b). Part (c) presents the selling and purchasing for healthy and part (d) those for distressed banks.

chasing behavior of healthy banks differs markedly in terms of amounts bought and sold from that of distressed banks. While healthy banks reduced their trading activity gradually (see panel (c) in Figure 2) over the entire period, distressed banks were very active with regard to both sold and bought volumes around the Lehman Brothers default in Q3 2008 (see panel (d) in Figure 2). Starting in Q1 2010, both groups of banks sold more assets than they bought during the same period. For healthy banks this difference is less pronounced.

Figure 3: Selling and purchasing of ESCB eligible and ESCB non-eligible assets in billion Euro, from Q3 2005 to Q4 2011



This figure illustrates sales and purchases for distressed (a, b) and healthy banks (b, d). The sales are distinguished between ESCB eligible (a, c) and ESCB non-eligible assets (b, d). The nominal volumes are in billions.

Figure 3 illustrates the selling and purchasing patterns of healthy and distressed banks, distinguishing between ESCB eligible and non-eligible assets. The data on collateral eligibility for the ESCB is available for the period from Q1 2006 to Q4 2011.

The second interesting feature is that one quarter after the Lehman Brothers bankruptcy in Q4 2008, distressed banks sold ESCB non-eligible securities in the value of approximately EUR 60 billion and purchased roughly the same volume of ESCB eligible securities. Furthermore, healthy banks bought high volumes of ESCB eligible assets from the beginning of the period under consideration onwards. The ratio (see panel (a) of Figure 4) of ESCB eligible securities to total securities holdings confirms that healthy banks held more ESCB eligible securities in their portfolios over the entire period. The ratio of ESCB eligible securities decreased gradually for distressed banks to a minimum of 67% in Q3 2008, when it started to increase for the first time after the Lehman Brothers bankruptcy.

4.3.3 Market liquidity and ESCB's collateral framework

Bank's selling behavior might be influenced by the market value of its entire securities portfolio. Boyson et al. (2012b) and Boyson et al. (2012a) argue that banks sell rather assets whose market value is above the book value. Selling assets whose market value is above the book value leads to a positive trading return and boosts the bank's capital position. On the contrary, Manconi et al. (2012) argue that sales of liquid assets will expose banks to higher credit risks and therefore there is a trade off between high and low quality assets for risk management purposes. Following their argumentation, I introduce a variable based on the relation between nominal and market asset values (book values are not available) which is calculated as follows:

$$WeightedPrice_{it} = \Sigma_{j=1}^{K} \omega_j \frac{MV_t^j}{NV_t^j}. \tag{4.1}$$

The variable "$WeightedPrice_{it}$" is defined as the relative price for the entire portfolio of bank i at quarter t; ω_j is the weight of security j relative to the whole portfolio held by bank i at the time t. If the ratio of the market value MV to the nominal value NV is less than 1, I assign a negative sign. The ratio stays positive if it equals to 1 or is higher than 1. The higher the overall value of the portfolio is, the more positive is the relative market price of the entire portfolio for the bank i. If the overall value is negative, the assets whose market value was below nominal value overweigh the assets whose market value was higher than nominal value and vice versa.

Figure 4 (panel (c)) points to a substantial drop in relative prices on average, during the period between Q2 2007 and Q3 2008, with a minimum in Q2 2008 and Q3 2008. In Q4 2008, the relative price of banks' portfolios improves considerably for both groups. This could be due to either one of two factors (or a combination of both): banks could have sold securities whose relative price was decreasing, or the market prices of securities started to recover. The latter argument is supported by the development of the market liquidity as shown in Figure 4 (panel (b). The market liquidity increased substantially in Q4 2008. This liquidity indicator includes liquidity sub-measures for bonds, equities, the money market and foreign exchange, and is calculated as a simple average of all liquidity sub-measures normalised over the period 1999-2006.[54]

Regarding the ESCB's liquidity-providing reverse transactions, there was a notable increase in the outstanding amount of ESCB eligible and pledged assets. While the total nominal volume outstanding of all eligible marketable assets went up from approximately €9 trillion to €13 trillion in 2011, the total amount of collateral used increased by 38% from €1.1 trillion in 2007 to €1.8 trillion in 2011.

The most prominent increases of pledged collateral were in ABSs and non-marketable assets (credit claims and fixed-term deposits). The use of ABSs increased from €182 billion to approximately €380 billion in 2011. The use of non-marketable assets increased from €109 billion in 2007 to approximately €400 billion in 2011.[55]

In order to mitigate the risk from accepted collateral,the Eurosystem introduced a

[54]For additional details see Box 9 in ESCB, Financial Stability Review, June 2007 and Bank of England, Financial Stability Report, April 2007.

[55]For more details on the volumes, see European Central Bank (2013) pp.76-81.

range of risk control measures. One of the most important measures was a flat haircut add-on. The valuation haircuts reflects specific characteristics of the assets, including liquidity and credit risk.

The average haircut increased significantly from 3.14% in Q3 2008 to 5.12% in Q4 2008 and to 8.65% in Q1 2009 (Figure 4 (panel d)), reaching its peak in 2009 Q4. Since then the value has remained approximately at the same level. The valuation haircut for a sub-sample (Figure 4 (panel d), dashed line)shows how it has developed, on average, for securities which were eligible prior to the first change in the collateral framework in October 2008. A substantial increase in haircuts could work as a self-selection mechanism. Solvent banks in need for liquidity would benefit from the extension of the collateral framework of the ESCB. In contrast, insolvent banks in need for liquidity will have to sell the assets given that these bank are not able to finance the haircut add-on with their own capital (see Adrian and Brunnermeier (2009)).

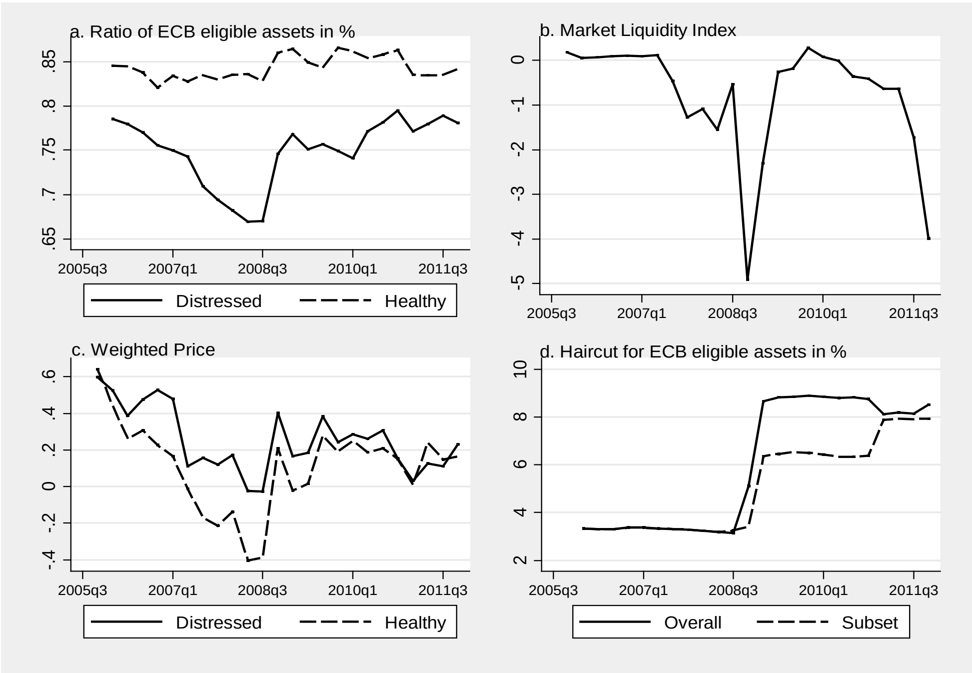
Table 12 summarizes bank-specific variables for liquidity and capital position separately for the two considered groups of banks: healthy and weak banks.[56]

4.3.4 Bank's liquidity and capital

The ratio of liquid assets to short term liabilities shows the number of times the short-term debt obligations with maturity smaller than 1 year are covered by liquid assets. The liquid assets represent the bank's counterbalancing capacity, including cash, high quality and liquid assets such as German sovereign bonds. If the value of the ratio is greater than 1, this means that the short-term obligations

[56] Please note, that the terms weak and distressed are used interchangeably.

Figure 4: Market indicators and statistics for ESCB eligibility, from 2005 to 2011



Part (a) shows the average ratio of the ESCB eligible securities to total securities for distressed and healthy banks. The market liquidity indicator in part (b) includes liquidity sub-measures for bonds, equities, the money market and foreign exchange. Part (c) presents an average ratio for the weighted sum of market value to the nominal value of securities for healthy and distressed banks. The average haircut for all ESCB eligible securities and for securities which were eligible prior to the first change in the collateral framework in October 2008 are presented in part (c).

are fully covered. In general, banks with liquidity ratios higher than 1 are considered to be in a good financial health. While on average, the banks under consideration exhibit a high degree of safety in meeting their current liabilities with liquid assets, a number of banks exhibit vulnerable ratios of less than 1. The statistics show that healthy banks are more liquid than their distressed peers.

On average, both distressed and healthy banks meet the regulatory requirement for core tier 1 capital. Generally, BaFin (the Federal Financial Supervisory Authority in Germany) considers a bank with a core tier 1 ratio higher than 7%

Table 12: Descriptive Statistics

Variables	**Mean**	**Std. Dev.**	**1%**	**99%**	**Obs.**
			Overall		
Liquid Assets	1.57	0.97	0.83	5.11	638
Core Tier1	0.09	0.04	0.04	0.27	585
			Healthy Banks		
Liquid Assets	1.65	1.18	0.88	6.88	413
Core Tier1	0.09	0.04	0.04	0.27	381
			Weak Banks		
Liquid Assets	1.41	0.31	0.80	2.37	225
Core Tier1	0.09	0.05	0.05	0.26	204

Note: This table provides descriptive statistics for a total of 28 German banks for the period from Q4 2005 to Q4 2011. Among these 28 German banks, 9 banks received supported from the German Government. In this table, I refer to these banks as to "Weak banks". The variable "Liquid Assets"" is a ratio of liquid assets to short term liabilities shows the number of times the short-term debt obligations with maturity smaller than 1 year are covered by liquid assets.

as a solvent bank. However, during the financial crisis, the financial supervisory authorities in Europe required a minimum of 9%. This requirement has been changed back to the "normal requirement" in July 2012.[57]

4.3.5 Summary

The descriptive statistics reveal some interesting patterns in the data. First, the data show a pronounced deleveraging of banks over time which results in declining securities portfolios (see panel (a), Figure 2). Starting in Q1 2010, both groups of banks sold more assets than they bought during the same period, although this

[57]Please note the new regulatory requirement on capital will be gradually phased in. The minimum requirement on the core tier 1 will be equal to 4.5% in 2015, to 6.75% in 2016 and to 9.5% (excluding SIFI surcharge) from 2019 on. The definition of core tier 1 eligible equity changed in comparison to the definition of the core tier 1 eligible equity presented in this paper. Thus, both ratios are not comparable.

difference is less pronounced for healthy banks. Second, I find a pronounced difference in the selling and purchasing patterns of healthy and distressed banks. While healthy banks reduced their activity gradually over entire period, distressed banks were very active around the Lehman Brothers collapse. One quarter after this event, distressed banks replaced ESCB non-eligible securities with approximately the same amount of ESCB eligible securities (see panel (a), Figure 4). Third, healthy banks exhibit high and relatively stable ratios of ESCB eligible assets over the entire time period, while for distressed banks the ratio decreased gradually to a minimum in 2008 Q3 and started to increase for the first time after the Lehman Brothers bankruptcy in Q4 2008, when the ESCB extended its collateral framework for the first time. Finally, distressed banks exhibit lower liquidity ratios than their healthy peers. Regarding the Tier 1 ratio, no pronounced difference can be observed.

4.4 Results

This section provides the results of the regression analysis along with the hypotheses.

4.4.1 Triggers

The first hypothesis (H1) assumes that bank's liquidity and capital position determine overall net sales of securities. In order to test the first hypothesis, I estimate a dynamic fixed-effects panel estimation model with a lagged dependent variable as follows:

$$NetSales_{t,i} = \rho NetSales_{t-1,i} + \beta_1 LiquidAssets_{t-1,i} + \beta_2 EligibleAssets^{ESCB}_{t-1,i} + \\ + \beta_3 Tier1_{t-1,i} + \gamma_1 MarketLiq_t + \gamma_2 WeightedPrice_{t,i} + \gamma_3 Size_{t,i} + \alpha_i + \nu_{t,i} \quad (4.2)$$

All regressions rely on heteroscedastic standard errors, clustered at the bank level.[58]

The dependent variable "$NetSales_{t-1,i}$" represents the volume of overall net sales. The higher the dependent variable, the greater the volume that a bank has sold relative to the volume the bank has bought. Positive values correspond to sales exceeding purchases. Against the theoretical background that a liquidity shortage is one of the most important drivers for a bank to sell assets, the model includes the ratio of liquid assets to short-term liabilities ("$LiquidAssets_{t-1,i}$"). If the relation between liquidity and asset sales is in line with Allen and Carletti (2006), Adrian and Brunnermeier (2009), Adrian and Shin (2010), Acharya et al. (2011) and Shleifer and Vishny (2011), who argue that funding liquidity shortages could force banks to sell assets at times when securities markets are illiquid, I will find it to be negative during the banking crisis (from 2007 Q3 to 2009 Q4) which was determined by illiquid markets. Besides this ratio, I add an additional metric for a bank's liquidity: the ratio of its ESCB eligible securities to its total securities ("$EligibleAssets_{t-1,i}$"). A bank owning ESCB eligible assets could raise money very quickly by borrowing at the Eurosystem against these securities. Thus, I hypothesize that the increase in the ratio could decrease the need to sell assets.

Particularly in light of the fact that a well-capitalised bank will have a better access to funding and a bank with a sufficient capital buffer will be able to absorb

[58]Section 4.5 presents results for a dynamic panel estimation in spirit of Kiviet (1995) and Bruno (2005).

higher cost for refinancing liabilities during a period of stress, the model also includes the Tier 1 ratio ("$Tier1_{t-1,i}$"). More specifically, bank's capital position plays a key role in its capacity to raise funding from market sources, to absorb losses on its assets, and to bear the increased refinancing costs of its liabilities during periods of stress (Adrian and Brunnermeier (2009)). Thus, I hypothesize the lower a bank's capitalisation, the more assets the bank will have to sell.

These three variables are included with a time lag of 1 quarter to avoid endogeneity.

In addition, the model controls for market liquidity ("$MarketLiq_t$"), for the relative performance of the bank's portfolio ("$WeightedPrice_{t,i}$") and bank's size ("$Size_{t,i}$"). Finally, βs and γs are the corresponding regressions coefficients, ν is an error term, and the α represent the fixed effects. All variables are expressed in logarithms.[59]

The results of the model specified in Equation 4.2 are presented in Table 13.[60] The dynamic term is always positive and significant supporting the model specification. Besides the dynamic term, none of the possible triggers is significant for net sales (see column (2)).[61]

A sale caused by a bank's poor capitalisation or liquidity position is more likely during episodes when interbank markets have dried up and when there are few alternatives for sources of funding. These are typical characteristics of a crisis. In order to control for the structural shift during the financial crisis, I condition the variable "$NetSale_{t,i}$" on two different dummies for the crisis (columns (3) and

[59]Both parts of the dependent variable, i.e. sales and purchases, are first expressed in logarithms and subsequently subtracted.

[60]Please find the correlation coefficients for the independent variables in the appendix to this chapter, Table 17.

[61]In the first column, the regression is based on all 30 banks in my sample. Since for two banks the liquidity ratio is not available, in all following specifications, 28 banks are included.

(5)). In addition, I interact the dummies with the liquidity ratio, the Tier 1 ratio and the ratio of the ESCB eligible securities to total securities (columns (4) and (6)).

The first dummy ("$Crisis$") is equal to one in the period from 2007 Q3 to 2011 Q4. The second dummy ("$CrisisB$") is equal to one starting in 2007 Q3 and ending in 2009 Q4. This episode was predominantly a banking crisis where even highly rated banks struggled to access wholesale funding markets, including those for secured financing, as pointed out by van Rixtel and Gasperini (2013).

Both dummies are positive and significant (columns (3) and (5)), indicating that during the respective crisis period, banks sold more than they bought in comparison to the non-crisis periods. Both dummies turn, however, insignificant when interaction terms are added, meaning that there is no general shift in the level of net sales. Moreover, in column (4), where I control for the structural break during the entire crisis period, the interaction terms "$Crisis * Tier1_{t-1,i}$" and "$Crisis * LiquidAssets_{t-1,i}$" are both negatively correlated to net sales, but are not statistically significant. This might be due to the fact that measures implemented by the ECB have shown effect and reduced the funding pressures initially experienced by banks during the shorter period of the banking crisis. Besides broadening the range of the accepted collateral, the ECB expanded the volume of the lending facilities, provided longer-term financing and targeted specific securities markets through outright purchases. In addition, the German government implemented rescue schemes, such as capital and liquidity injections, guarantees, and asset protection.

During the banking crisis (column (6)) and in line with my expectation, the relation between the liquidity ratio and net sales is negative and significant (at 5% significance level). The fewer liquid assets a bank has for covering unforeseen withdrawals, the higher net sales. This result is in line with Allen and

Table 13: Triggers for overall sales

$NetSales_{t,i}$	(1)	(2)	(3)	(4)	(5)	(6)
$NetSales_{t-1,i}$	0.28***	0.34***	0.31***	0.31***	0.33***	0.32***
	(7.004)	(7.979)	(7.283)	(7.210)	(7.918)	(7.633)
$Size_{t,i}$	0.61**	-0.00	-0.15	-0.20	0.01	-0.19
	(2.034)	(-0.003)	(-0.494)	(-0.624)	(0.040)	(-0.608)
$MarketLiq_t$	-0.01	-0.04	0.01	0.03	-0.02	0.01
	(-0.139)	(-0.664)	(0.176)	(0.462)	(-0.356)	(0.202)
$WeightedPrice_{t,i}$	0.02	0.19	0.40**	0.46**	0.28	0.34*
	(0.136)	(1.058)	(2.207)	(2.492)	(1.557)	(1.889)
$Tier1_{t-1,i}$		0.23	-0.25	-0.05	0.23	0.52**
		(1.125)	(-1.054)	(-0.129)	(1.102)	(2.247)
$LiquidAssets_{t-1,i}$		-0.11	0.09	0.21	-0.03	0.11
		(-0.472)	(0.365)	(0.819)	(-0.142)	(0.459)
$EligibleAssets^{ESCB}_{t-1,i}$		-0.18	0.16	0.16	-0.04	0.32
		(-0.343)	(0.313)	(0.214)	(-0.081)	(0.487)
$Crisis_{t,i}$			0.52***	0.22		
			(3.892)	(0.220)		
$Crisis*Tier1_{t-1,i}$				-0.19		
				(-0.526)		
$Crisis*LiquidAssets_{t-1,i}$				-0.53		
				(-1.591)		
$Crisis*EligibleAssets^{ESCB}_{t-1,i}$				-0.00		
				(-0.003)		
$CrisisB_{t,i}$					0.21**	-1.36
					(2.118)	(-1.463)
$CrisisB*Tier1_{t-1,i}$						-0.71**
						(-2.444)
$CrisisB*LiquidAssets_{t-1,i}$						-0.67**
						(-2.006)
$CrisisB*EligibleAssets^{ESCB}_{t-1,i}$						-0.35
						(-0.536)
Observations	579	467	467	467	467	467
R-squared	0.093	0.140	0.170	0.175	0.149	0.168
Number of Banks	30	28	28	28	28	28

Note: This table shows the results from the dynamic fixed-effect estimation for the period 2006 Q1 to 2011 Q4 for overall net sales. The dummy "Crisis" is defined for the period beginning in 2007 Q3 and ending in 2011 Q4. The dummy "CrisisB" is defined for the period from 2007 Q3 to 2009 Q4. The constant is included but not shown; t-statistics are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Carletti (2006), Adrian and Brunnermeier (2009), Adrian and Shin (2010), Acharya et al. (2011) and Shleifer and Vishny (2011) who argue that funding liquidity shortages could force banks to sell assets. As for the capital, the relation turns negative and significant (column (6)), implying that poor capitalisation of a bank leads to higher net sales (as in the spirit of Cifuentes and Shin (2005) and

Adrian and Brunnermeier (2009)). The effect is equal to -0.19.
The ratio of the ESCB eligible securities to all securities is not significant. It also remains insignificant when interacted with the crisis dummies.
As for the control variables, market liquidity is not significant. The variable "$WeightedPrice_{t,i}$" becomes significant in columns (3),(4) and (5). It is always positively related to net sales. The better the overall performance of a bank's portfolio in terms of it's market prices relative to nominal prices, the higher net sales and the higher potential return from the sales. A positive return will improve the capital position. This result is in line with Boyson et al. (2012b) and Boyson et al. (2012a).

All in all, the results do not show that, in general, overall net sales of securities are conditional on the bank's liquidity and capital position. The relation between the triggers and the net sales is negative during the crisis, and it turns significant during the banking crisis. The potential for fire sales triggered by the liquidity and capital position of a bank existed but only during the extraordinary period of time during the banking crisis, when liquidity dried up and not many sources for funding existed.

4.4.2 ESCB eligibility of assets

Krishnamurthy (2009) shows that shocks to balance sheets force banks to liquidate assets. The more illiquid the markets, the higher the pressure on the balance sheet to deteriorate further. More importantly, he argues that liquidity provision by the central bank alleviates the crisis. The extension of the ESCB collateral framework, which began in October 2008, provided European banks with additional sources of funding, thus allowing banks to borrow central bank liquidity against a wider set of collateral. This reduced the pressure on banks to sell assets. I thus expect to find differences between the sales of the ESCB eligible assets and the sales of the ESCB non-eligible assets regarding the potential triggers. Banks experiencing funding shortages will not sell ESCB eligible assets. Instead they will pledge ESCB eligible collateral and borrow central bank liquidity. The negative relation between the funding shortages and asset selling found in (H1), will hold for the sales of ESCB non-eligible assets.

The relation between asset sales of the ESCB eligible assets and capital position is more complex. If a bank, due to its weak capital position, is not able to absorb increased haircuts for its collateral (Adrian and Brunnermeier (2009)), it will most probably sell securities regardless of their eligibility for the Eurosystem. Based on this argument, I should not find any differences in the relation between capital and the sales of the ESCB eligible and the sales of the ESCB non-eligible assets. If this is the case, then the central bank's haircuts function as a self-selection mechanism for banks that are either liquidity constrained or also capital constrained.

In this section, I test my second hypothesis (H2) which is "*Banks do not sell ESCB eligible assets but sell ESCB non-eligible assets as a response to funding shortages and solvency limits*". Here, I distinguish between the net sales of ESCB eligible and non-eligible securities, in order to empirically analyse the impact of the potential triggers on the two different types of securities. I estimate a model of the following form:

$$NetSales^{l}_{it} = \rho NetSales^{l}_{t-1,i} + \beta_1 LiquidAssets_{t-1,i} + \beta_2 EligibleAssets^{ESCB}_{t-1,i} + \\ + \beta_3 Tier1_{t-1,i} + \gamma_1 MarketLiq_t + \gamma_2 WeightedPrice_{t,i} + \gamma_3 Size_{i,t} + \alpha_i + \nu_{i,t} \tag{4.3}$$

where l equals the net sales of the ESCB eligible or the ESCB non-eligible assets. Table 14 provides the results for the net sales of the ESCB eligible assets in columns (1) to (5) and of the ESCB non-eligible assets in (6) to (10).

Regarding the ESCB eligible assets, the results indicate that the net sales were higher during the crisis (columns (2) and (3)). As for the triggers, column (3) shows that a decreasing Tier1 ratio is associated with an increase in the net sales of ESCB eligible assets. A 100 basis points decrease in Tier 1 ratio is associated with an increase of net sales at 120 basis points. During the crisis the effect is still negative, however, at a much lower level being equal to -0.08. This result, does not hold in columns (4) and (5), when the dummy for the banking crisis is introduced.

The liquidity ratio is not significant for the net sales of the ESCB eligible assets. Banks with liquidity needs do not sell ESCB eligible assets. With regard to the second metric for liquidity, the proportion of the ESCB eligible securities in the bank's portfolio, it is positively related to net sales of the ESCB eligible securities. The stronger the bank's position in terms of ESCB eligible assets, the more this bank can afford to sell. There is no structural break during the crisis with regard to the impact of this variable on net sales.

Turning to the ESCB non-eligible assets, the relation between capital and net sales is not significant in columns (7) and (8), positive and significant in columns (6), (9) and (10). During the banking crisis the impact is negative and significant equalling -0.09 (column (10)). This ambiguous result for capital shows that the true relation between capital and sales is more complex than it can be modeled in this paper.

The liquidity ratio is negative and significant for the net sales of ESCB non-eligible securities during the crisis (at the 5% significance level for the entire crisis period and at the 10% significance level for the banking crisis). The proportion of the ESCB eligible securities in the bank's portfolio is negatively related to the net sales of the ESCB non-eligible securities. The larger is a bank's portfolio of ESCB eligible securities, which can be used as collateral for central bank fund-

ing, the lower is the pressure on this bank to sell ESCB non-eligible assets. The interaction terms with the crisis dummies are insignificant.
Regarding the control variables, market liquidity is positively correlated with net sales of the ESCB eligible assets and negatively correlated with net sales of the ESCB non-eligible assets.[62] This finding implies that banks sell more ESCB eligible securities in an environment in which market liquidity is high. The opposite is true for net sales of the ESCB non-eligible assets (columns (6) - (10)). The lower is the market liquidity, the more ESCB non-eligible securities a bank sells. It seems that during episodes of low market liquidity, banks do not sell ESCB eligible assets, but use them as collateral. As for the ESCB non-eligible assets, banks sell them into illiquid markets. Also descriptive statstics (see panel (a) Figure 3) showed that some banks replaced ESCB non-eligible assets with ESCB eligible assets during the episode of market illiquidity.The variable "$WeightedPrice$" is, with one exception (in column (6)), positive and significant for the net sales of the ESCB eligible securities in columns (3) and (4). Again, the better the overall performance of a bank's portfolio in terms of it's market prices relative to nominal prices, the higher net sales and the higher potential return from the sales.

[62]Given that the dynamic term is not significant for the net sales of the ESCB non-eligible assets, I excluded it in unreported results. The results did not change.

Table 14: Trigger for net sales of ESCB eligible and ESCB non-eligible securities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$NetSales_{t,i}$	ESCB eligible securities					ESCB non-eligible securities				
$NetSales_{t-1,i}$	0.14***	0.13***	0.13***	0.14***	0.14***	-0.01	-0.01	-0.01	-0.01	-0.02
	(3.358)	(3.120)	(3.070)	(3.388)	(3.370)	(-0.243)	(-0.252)	(-0.236)	(-0.206)	(-0.330)
$Size_{t,i}$	0.71**	0.58*	0.58*	0.73**	0.66*	-0.23	-0.39	-0.48	-0.26	-0.54
	(2.044)	(1.674)	(1.663)	(2.097)	(1.829)	(-0.547)	(-0.913)	(-1.106)	(-0.619)	(-1.243)
$MarketLiq_t$	0.16**	0.20***	0.23***	0.17***	0.19***	-0.29***	-0.26***	-0.23***	-0.27***	-0.22***
	(2.518)	(3.151)	(3.516)	(2.658)	(2.936)	(-3.705)	(-3.216)	(-2.809)	(-3.469)	(-2.737)
$WeightedPrice_{t,i}$	0.18	0.36*	0.44**	0.23	0.26	-0.06	0.10	0.18	0.04	0.22
	(0.898)	(1.781)	(2.144)	(1.147)	(1.252)	(-0.235)	(0.374)	(0.692)	(0.160)	(0.844)
$Tier1_{t-1,i}$	0.03	-0.41	-1.20***	0.03	0.07	0.72**	0.35	0.73	0.74**	1.17***
	(0.128)	(-1.531)	(-2.713)	(0.138)	(0.261)	(2.466)	(1.026)	(0.717)	(2.524)	(3.464)
$LiquidAssets_{t-1,i}$	0.08	0.27	0.18	0.13	0.14	-0.12	0.05	0.19	-0.05	0.12
	(0.286)	(1.010)	(0.618)	(0.466)	(0.484)	(-0.338)	(0.125)	(0.505)	(-0.140)	(0.345)
$EligibleAssets^{ESCB}_{t-1,i}$	1.45**	1.71***	2.02**	1.52**	2.11***	-2.10***	-1.85***	-2.45**	-1.95***	-2.36***
	(2.428)	(2.882)	(2.372)	(2.543)	(2.765)	(-3.099)	(-2.699)	(-2.488)	(-2.860)	(-2.678)
$Crisis_{t,i}$		0.49***	3.19***				0.37**	0.04		
		(3.221)	(2.798)				(2.052)	(0.013)		
$Crisis*Tier1_{t-1,i}$			1.02**					-0.35		
			(2.428)					(-0.333)		
$Crisis*LiquidAssets_{t-1,i}$			-0.42					-0.97**		
			(-1.127)					(-2.122)		
$Crisis*EligibleAssets^{ESCB}_{t-1,i}$			-0.55					0.78		
			(-0.672)					(0.825)		
$CrisisB_{t,i}$				0.13	0.23				0.21	-2.30*
				(1.173)	(0.271)				(1.594)	(-1.806)
$CrisisB*Tier1_{t-1,i}$					0.05					-1.26**
					(0.152)					(-2.504)
$CrisisB*LiqAssets_{t-1,i}$					-0.52					-0.84*
					(-1.399)					(-1.869)
$CrisisB*EligibleAssets^{ESCB}_{t-1,i}$					-0.95					1.14
					(-1.245)					(1.286)
Constant	-12.84*	-11.91*	-13.83**	-13.27**	-11.67*	6.22	7.96	10.28	6.70	12.80
	(-1.949)	(-1.829)	(-2.097)	(-2.013)	(-1.704)	(0.763)	(0.976)	(1.189)	(0.824)	(1.501)
Observations	467	467	467	467	467	467	467	467	467	467
R-squared	0.072	0.096	0.117	0.075	0.086	0.080	0.090	0.102	0.086	0.111
Number of Banks	28	28	28	28	28	28	28	28	28	28

Note: This table shows the results from the dynamic fixed-effect estimation for the period 2006 Q1 to 2011 Q4. Columns (1)-(5) of the table show the results for net sales of ESCB eligible, the columns (6)-(10) show the results for net sales of ESCB non-eligible assets. The dummy "Crisis" is defined for the period beginning in 2007Q3 and ending in 2011 Q4. The dummy "CrisisB" is defined for the period from 2007 Q3 to 2009 Q4. t-statistics are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Such sales improves the capital position. This result is in line with Boyson et al. (2012b) and Boyson et al. (2012a).
All in all, I find that bank's liquidity position significantly determine sales of ESCB non-eligible during crisis period, whereas the relation between liquidity and sales of ESCB eligible assets is not significant. This result indicates the that the extension of the ESCB collateral framework reduced the potential for fire sales and therefore might have alleviated the crisis. With regard to capital, a bank with poor capitalisation would rather sell assets independently of their ESCB eligibility. However, the result for capital is sometimes ambiguous and not always significant.

4.4.3 Stressed banks

The academic literature on fire sales refers to exceptional times when individual banks or the financial system as a whole is in distress. To control for the latter, I included a dummy for the banking crisis (from 2007 Q3 to 2009 Q4) and the whole financial crisis (from 2007 Q3 to 2011 Q4) in the analyses related to (H1) and (H2) in the analysis above. In this section, I explore non-linearities in the relation between the potential determinants and asset sales. My third hypothesis (H3) is "*The relationship between asset sales and the liquidity and the capital position of a bank is stronger for distressed banks.*". More specifically, the aim of this section is to test, using a difference-in-difference approach, whether the relationship between asset sales and the liquidity, and the capital position of a bank is stronger for distressed banks. I define "banks in distress" in different ways. First and more generally, I consider 9 banks out of the 30 in the sample which received support in the form of capital injections and guarantees from the German government to be in distress before the implementation of the rescue measure. Since the origins of problems experienced by banks which were rescued by the German government are heterogenous, I secondly analyse if particularly banks with a low liquidity and capital ratio could sell more assets than the average bank. Hence, I define banks whose Tier 1 is lower than the median as "banks in distress"as their ability to borrow liquidity is rather limited. Furthermore, I define banks whose liquidity ratio is smaller than median are more susceptible to panic withdrawals than their peers with large counterbalancing capacity. Finally, banks with a ratio of ESCB eligible securities to total securities lower than median could be forced to sell assets in order to roll over their debt as their access to the Eurosystem's liquidity is rather constrained.

In order to analyse the non-linearities for the 9 banks which received support from the German government in greater detail, I employ a model with the following form:

$$NetSales^{l}_{t,i} = \rho NetSales_{t-1,i} + \beta_1 LiquidAssets_{t-1,i} + \beta_2 Tier1_{t-1,i} + \\ + \beta_3 EligibleAssets^{ESCB}_{t-1,i} + \gamma_1 MarketLiq_t + \gamma_2 WeightedPrice_{t,i} + \\ + \gamma_3 Size_{t,i} + \eta_1 DummyWeakBank_{t,i} + \eta_2 WeakBank * Int^{k}_{t-1,i} + \alpha_i + \nu_{t,i} \tag{4.4}$$

where l stands for net sales of the ESCB eligible or non-eligible assets. The variable "$DummyWeakBanks_{t,i}$" is equal to 1 prior to the quarter when a bank received support from the German government for the first time. These banks were obviously stressed before they received support. The term "$\eta_2 WeakBank * Int^{k}_{t-1,i}$" represents the interaction between the "$DummyWeakBanks_{t,i}$" and the Tier 1 ratio, the liquidity ratio, and the ratio of the ESCB eligible securities to total securities. The results are presented in Table 16 (columns (1) to (4) for the net sales of the ESCB eligible assets and columns (5) to (8) for the net sales of the ESCB non-eligible assets).

Table 15: Banks rescued by the German government

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		WeakB*Tier1	WeakB*LiqAss	WeakB*EA		WeakB*Tier1	WeakB*LiqAss	WeakB*EA
	ESCB eligible securities				ESCB non-eligible securities			
$\text{NetSales}_{t-1,i}$	0.14***	0.14***	0.14***	0.14***	-0.01	-0.01	-0.03	-0.01
	(3.352)	(3.324)	(3.248)	(3.349)	(-0.299)	(-0.320)	(-0.649)	(-0.309)
$\text{Size}_{t,i}$	0.71**	0.73**	0.83**	0.71**	-0.25	-0.34	-0.65	-0.23
	(2.032)	(2.073)	(2.313)	(2.001)	(-0.596)	(-0.809)	(-1.492)	(-0.534)
MarketLiq_{t}	0.16**	0.16**	0.16**	0.16**	-0.30***	-0.30***	-0.31***	-0.30***
	(2.504)	(2.473)	(2.490)	(2.499)	(-3.845)	(-3.766)	(-3.943)	(-3.832)
$\text{WeightedPrice}_{t,i}$	0.18	0.18	0.22	0.18	-0.08	-0.09	-0.19	-0.07
	(0.894)	(0.932)	(1.092)	(0.890)	(-0.328)	(-0.362)	(-0.778)	(-0.289)
$\text{Tier1}_{t-1,i}$	0.02	-0.08	-0.06	0.02	0.43	0.79*	0.72**	0.48
	(0.090)	(-0.250)	(-0.237)	(0.069)	(1.290)	(1.951)	(2.102)	(1.409)
$\text{LiquidAssets}_{t-1,i}$	0.08	0.07	-0.02	0.08	-0.04	-0.06	0.25	-0.06
	(0.289)	(0.263)	(-0.076)	(0.297)	(-0.110)	(-0.163)	(0.675)	(-0.153)
$\text{EligibleAssets}^{ESCB}_{t-1,i}$	1.44**	1.43**	1.56**	1.40**	-2.22***	-2.21***	-2.45***	-1.99***
	(2.381)	(2.366)	(2.563)	(2.130)	(-3.275)	(-3.264)	(-3.637)	(-2.750)
$\text{DummyWeakBank}_{t,i}$	0.01	0.96	-0.50	0.09	0.45*	-2.13	1.81***	0.05
	(0.050)	(0.664)	(-1.201)	(0.188)	(1.760)	(-1.279)	(3.761)	(0.101)
$\text{WeakBank*Int}_{t-1,i}$		0.39	1.48	0.22		-1.05	-3.99***	-1.16
		(0.665)	(1.466)	(0.188)		(-1.564)	(-3.317)	(-0.914)
Constant	-12.83*	-13.39**	-15.18**	-12.74*	5.75	8.40	13.70	5.44
	(-1.946)	(-2.013)	(-2.240)	(-1.923)	(0.707)	(1.013)	(1.637)	(0.669)
Observations	467	467	467	467	467	467	467	467
R-squared	0.072	0.073	0.077	0.072	0.087	0.093	0.114	0.089
Number of Banks	28	28	28	28	28	28	28	28

Note: This table shows the results from the dynamic fixed-effect estimation for the period 2006 Q1 to 2011 Q4. Column (1)-(4) of the table show the results for net sales of ESCB eligible, the columns (5)-(8) shows the results for net sales of ESCB non-eligible assets. The dummy "DummyWeakBanks" is equal to one prior to the quarter when a bank received support from the German government. The term "$WeakBank * Int^{k}_{t-1,i}$" represents the interaction between the "$DummyWeakBanks_{t,i}$" and the Tier 1 ratio, the liquidity ratio, and the ratio of the ESCB eligible securities to total securities. t-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

For net sales of the ESCB eligible securities, there is no significant difference for the selling behavior between rescued banks and the average bank. In contrast, I find some significant evidence that weak banks sell more ESCB non-eligible assets than an average bank (column (5)). Moreover, the lower the liquidity ratio, the higher the net sales (column (7)). Here, both the dummy variable and the interaction term are statistically significant at 1% level.
In order to analyse the remaining non-linearities in greater detail, I employ a model with the following form:

$$\begin{aligned} NetSales_{it}^{l,k} &= \rho NetSales_{t-1,i} + \beta_1 LiquidAssets_{t-1,i} + \beta_2 Tier1_{t-1,i} + \\ &+ \beta_3 EligibleAssets_{t-1,i}^{ESCB} + \gamma_1 MarketLiq_t + \gamma_2 WeightedPrice_{t,i} + \\ &+ \gamma_3 Size_{t,i} + \eta_1 DummyLow_{t,i}^{k} + \eta_2 Dummy * Int_{t-1,i}^{k} + \alpha_i + \nu_{t,i} \end{aligned} \quad (4.5)$$

where k stands for the liquidity ratio, the Tier 1 capital ratio or the ratio of the ESCB eligible assets. Table 16 contains the result for Equation 4.5. Columns (1) to (6) show the estimation for the net sales of the ESCB eligible securities. The results for the ESCB non-eligible securities are in the columns (7) to (12). In columns (1), (2), (7) and (8), "$DummyLow_{t,i}^{k}$" equals 1 if the Tier 1 capital ratio is lower than the observed median ratio. In columns (3), (4), (9) and (10), "$DummyLow_{t,i}^{k}$" equals 1 if the liquidity ratio is lower than the observed median ratio. In columns (5), (6), (11) and (12), "$DummyLow_{t,i}^{k}$" equals 1 if the ratio of the ESCB eligible assets to total assets is lower than the corresponding observed median ratio. The variable "$Dummy * Int_{t-1,i}^{k}$" is the corresponding interaction term.

There is no significant evidence for banks with low capitalisation selling more of the ESCB eligible securities or of the ESCB non-eligible securities. Similarly, the low liquidity position of a bank does not increase its net sales of the ESCB eligible securities. In contrast, banks with a relative liquidity buffer lower than the median sell, on average, more ESCB non-eligible securities. Further, the lower the ratio is, the more securities they sell. [63]

I find a further non-linearity for the ratio of the ESCB eligible securities to total securities. The results confirm that banks with a ratio lower than the median sell less of ESCB eligible securities than their average peers. [64] In contrast, banks with a low ratio of ESCB eligible securities to total securities sell, on average, more ESCB non-eligible securities. The interaction term is negative and significant, highlighting that the more banks are constrained in terms of their access to the central bank liquidity, the more ESCB non-eligible securities they sell. A 100 basis points decrease in ESCB eligible assets of a bank leads to an increase of 414 basis points in net sales of the ESCB non-eligible assets.

All in all, I find evidence supporting a non-linear relation between the net sales and the determinants. I find that banks supported by the German government and banks with liquidity ratio lower than the median sell, on average, more ESCB non-eligible securities. For these banks, the liquidity ratio is a significant determinant for the net sales of the ESCB non-eligible assets. Furthermore, banks with a low ratio of the ESCB eligible securities to total securities sell, on average, more ESCB non-eligible securities. The more these banks are constrained in terms of their access to the central bank liquidity, the more ESCB non-eligible securities they sell.

[63]The regression's coefficients both for the dummy and the interaction term increase if the regression is performed for the crisis periods only. The results can be received upon request.

[64]The regression coefficient is stronger for the crisis periods. The results can be received upon request.

Table 16: Banks with low capital and low liquidity ratios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$NetSales_{t,i}$	ECB eligible securities						ECB non-eligible securities					
	Tier 1 capital		Liquidity		Eligible Assets		Tier 1 capital		Liquidity		Eligible Assets	
$NetSales_{t-1,i}$	0.14***	0.14***	0.15***	0.14***	0.14***	0.14***	-0.01	-0.01	-0.01	-0.01	-0.00	0.01
	(3.342)	(3.244)	(3.404)	(3.296)	(3.352)	(3.371)	(-0.207)	(-0.216)	(-0.190)	(-0.233)	(-0.104)	(0.186)
$Size_{t,i}$	0.70**	0.74**	0.72**	0.77**	0.73**	0.72**	-0.24	-0.25	-0.22	-0.45	-0.31	-0.20
	(1.997)	(2.094)	(2.066)	(2.199)	(2.101)	(2.043)	(-0.572)	(-0.588)	(-0.526)	(-1.043)	(-0.775)	(-0.506)
$MarketLiq_t$	0.16**	0.16**	0.16**	0.16**	0.15**	0.15**	-0.29***	-0.29***	-0.29***	-0.27***	-0.23***	-0.22***
	(2.510)	(2.531)	(2.455)	(2.443)	(2.324)	(2.294)	(-3.694)	(-3.711)	(-3.627)	(-3.438)	(-3.125)	(-3.000)
$WeightedPrice_{t,i}$	0.17	0.19	0.16	0.18	0.17	0.17	-0.06	-0.07	-0.03	-0.01	-0.06	-0.03
	(0.864)	(0.946)	(0.787)	(0.892)	(0.890)	(0.856)	(-0.256)	(-0.268)	(-0.121)	(-0.033)	(-0.249)	(-0.131)
$Tier1_{t-1,i}$	0.06	-0.23	0.01	0.03	0.05	0.04	0.75**	0.86**	0.73**	0.77***	0.61**	0.62**
	(0.234)	(-0.743)	(0.058)	(0.125)	(0.212)	(0.175)	(2.448)	(2.265)	(2.504)	(2.641)	(2.214)	(2.232)
$LiquidAssets_{t-1,i}$	0.08	0.05	0.12	-0.00	0.08	0.09	-0.11	-0.07	-0.18	0.06	-0.12	-0.18
	(0.312)	(0.188)	(0.442)	(-0.002)	(0.305)	(0.351)	(-0.306)	(-0.197)	(-0.485)	(0.163)	(-0.342)	(-0.537)
$EligibleAssets^{ESCB}_{t-1,i}$	1.45**	1.45**	1.49**	1.46**	2.37***	3.21*	-2.10***	-2.09***	-2.16***	-2.09***	-5.69***	-9.56***
	(2.435)	(2.433)	(2.478)	(2.433)	(3.027)	(1.695)	(-3.099)	(-3.080)	(-3.160)	(-3.081)	(-6.769)	(-4.715)
$DummyLow_{t-1,i}$	0.05	1.91	0.09	-0.21	-1.14*	-1.15*	0.05	-0.70	-0.12	0.80**	4.40***	4.47***
	(0.361)	(1.566)	(0.589)	(-0.744)	(-1.811)	(-1.829)	(0.348)	(-0.446)	(-0.680)	(2.171)	(6.609)	(6.739)
$Dummy{*}Int_{t-1,i}$		0.73		0.97		0.89		-0.29		-3.05***		-4.14**
		(1.536)		(1.289)		(0.484)		(-0.483)		(-2.862)		(-2.097)
Constant	-12.57*	-13.87**	-13.09**	-13.90**	-13.11**	-12.70*	6.48	6.86	6.14	10.16	7.32	4.72
	(-1.894)	(-2.077)	(-1.982)	(-2.097)	(-1.996)	(-1.916)	(0.792)	(0.833)	(0.753)	(1.240)	(0.948)	(0.607)
No of obs	467	467	467	467	467	467	467	467	467	467	467	467
R-squared	0.072	0.078	0.073	0.077	0.080	0.080	0.080	0.081	0.081	0.101	0.176	0.186
No of banks	28	28	28	28	28	28	28	28	28	28	28	28

Note: This table shows the results from the dynamic fixed-effect estimation for the period 2006 Q1 to 2011 Q4. Columns (1)-(6) of the table show the results for net sales of ESCB eligible, the columns (7)-(12) show the results for net sales of ESCB non-eligible assets. In columns (1), (2), (7) and (8), "$DummyLow_{t,i}$" equals 1 if the Tier 1 capital ratio is lower than the observed median ratio. In columns (3), (4), (9) and (10), "$DummyLow_{t,i}$" equals 1 if the liquidity ratio is lower than the observed median ratio. In columns (5), (6), (11) and (12), "$DummyLow_{t,i}$" equals 1 if the ratio of the ESCB eligible assets to total assets is lower than the corresponding observed median ratio. The variable "$Dummy * Int_{t-1,i}$" is the corresponding interaction term. t-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

4.5 Robustness checks

In this section, I first perform robustness checks related to the model chosen to perform the analysis.
The LSDV estimator requires strict exogeneity assumptions "$E(\nu_{it}|x_i, \alpha_i)$". The inclusion of a lagged dependent variable in the standard fixed effect estimation could lead to a bias in the estimated coefficients (so-called Nickell bias). Due to the small N, the more sophisticated estimators for dynamic panel analyses in the spirit of Blundell-Bond and Arellano-Bond are not applicable, since they require a large cross-section. Instead, I estimated a dynamic fixed-effects model in the spirit of Kiviet (1995) and Bruno (2005). The estimator from Bruno (2005) corrects the Nickell bias by using a preliminary consistent estimator. The estimator is especially good for very small N, which is not exactly the case in this analysis. Table 18 depicts the results from specification analogue to Table 13. The results obtained from fixed-effects panel estimation with lagged dependent variable (LSDV) are very similar to those obtained from a dynamic fixed-effects model in the spirit of Kiviet (1995) and Bruno (2005) (LSDVC). The regression coefficient for the dynamic term is higher than the regression coefficient for the dependent lagged variable presented in Table 13. With regard to determinants, dummy variables and interaction terms, no pronounced difference can be observed. Since N in this analysis is not very small, the Nickell bias seems to be negligible.

Further, I test whether extreme sales are particularly sensitive to the potential triggers. In more detail, I use quantile regression techniques to estimate the condi-

tional quantiles of the dependent variable.[65] Methodologically, I rely on a two-step quantile regression analysis for panel data in the spirit of Canay (2011). In the first step of the quantile regression analysis, the fixed effects estimated with equation 4.3 are subtracted from the dependent variable. In the second step the impact of the covariates on the transformed dependent variable is estimated with a quantiles regression methodology for the quantiles of interest.
More technically, $\hat{\alpha_i}$ is equal to $[y_{it} - X'\hat{\theta}]$, where $X'\hat{\theta}$ is a vector including all covariates from the equation (2.3) and $\hat{\theta}$ is a consistent estimator of θ. Moreover, the transformed dependent variable $\hat{y_{it}^{tr}}$ is defined as $y_{it} - \hat{\alpha_i}$. The two-step estimator for the τth sample quantile is then defined as:

$$\hat{\theta_\tau} = argminE_{nT}[\rho_\tau(\hat{y_{it}^{tr}} - X'\hat{\theta})] \tag{4.6}$$

I run quantile regressions for τ from 50% to 95%.

Table 19 presents the results which are subdivided into three parts for overall net sales, net sales of the ESCB eligible and the ESCB non-eligible securities. Overall the results are consistent with the results presented in the previous sections. The results also indicate that potential triggers have a different impact on overall net-sales depending on the considered quantiles. However, this difference is not always pronounced.

[65] Figure 5 shows the densities of net sales for both ESCB eligible and non-eligible assets. While the average value equaling zero (where the value of bought securities equals the value of sold securities) is well represented, the figure shows heavily positive outliers (where sales are higher than purchases) for the net-sales of the ESCB eligible securities (part a).

4.6 Conclusion

This chapter analyses bank's selling behavior focusing on the question whether the existence of the alternative source of funding - ESCB's liquidity-providing reverse transactions - which became more easily accessible during the crisis, prevented banks from selling assets. First, I analysed whether net sales are conditional on the potential triggers, bank's liquidity and capital position, which have been discussed with widely differing views in the theoretical and empirical literature (H1). Second, I separated net sales into net sales of ESCB eligible and non-eligible securities, so as to test hypothesis H2: that banks do not sell ESCB eligible securities in reaction to liquidity and capital constraints. Third, I tested hypothesis H3: that stressed banks, such as the banks rescued by the German government before this event took place, banks with low liquidity and poor capital position, have different selling behaviors than non-stressed banks. I hypothesized that the relation between asset sales and the liquidity or capital position of a bank is stronger for distressed banks.

The results suggest that a bank's liquidity and capital position only determine the overall net sales significantly during the banking crisis, i.e. during the period from 2007 Q3 to 2009 Q4. This result is in line with Allen and Carletti (2006), Adrian and Brunnermeier (2009), Adrian and Shin (2010), Acharya et al. (2011), Shleifer and Vishny (2011) and (Cifuentes and Shin (2005)).

In accordance with H2, I found that banks do not sell ESCB eligible assets but sell ESCB non-eligible assets in reaction to liquidity shortages. In addition, it appears that, in general, a bank with poor capitalisation would rather sell assets independently of their ESCB eligibility. During the banking crisis, banks sell the more ESCB non-eligible assets the lower is their capital position. However, the relation between capital and net-sales is sometimes ambiguous and not significant.

As for the non-linearities of H3, stressed banks before rescued by the German government and banks with a liquidity ratio lower than the median sell, on average, more ESCB non-eligible securities. For these banks, the liquidity ratio is a significant determinant for the net sales of the ESCB non-eligible assets. Furthermore, banks with a low ratio of the ESCB eligible securities to total securities sell, on average, more ESCB non-eligible securities. The more these banks are constrained in terms of their access to the central bank liquidity, the more ESCB non-eligible securities they sell.

The extraordinary measure to expand the ESBC collateral framework made a bank less vulnerable to sudden liquidity constraints during times when the interbank market dried up and alternatives for funding became scarce as it was the case during the banking crisis. The message for the academic literature is that the measures undertaken by the central banks and the government play an important role and should be taken into account when it comes to analysing the existence and causes of fire sales. Such policy measures significantly affect a bank's selling behavior.

The evidence found in this chapter has implications for policy. A bank's liquidity position clearly determine its asset sales. A distressed sale can cause a collapse of prices in certain market segments, indirectly forcing financial institutions with exposures to these markets to adjust their valuations, which ultimately could destabilize the financial system as a whole. Thus, the introduction of liquidity standards is a step in the right direction to address the weaknesses in the regulatory framework and to accommodate systemic risk due to fire sales.[66] In

[66]Please refer to http://www.bis.org/publ/bcbs238.pdf for the Liquidity Coverage Ratio and to http://www.bis.org/publ/d295.pdf for the Net Stable Funding Ratio.

addition, banks with strong capital position prefer borrowing over selling. Thus, straightening their capital positions as it has been foreseen by the new regulatory framework "Basel III" will make banks and therewith the financial sector as a whole less vulnerable to fire sales.[67]

[67] Please refer to http://www.bis.org/publ/bcbs189.pdf.

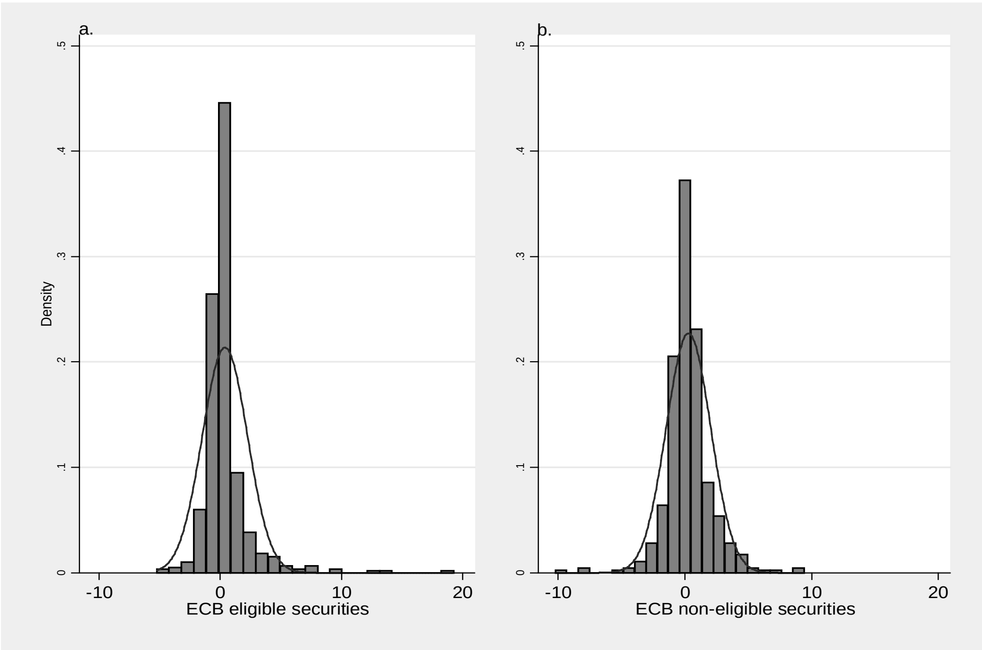
4.7 Appendix to Chapter 4

Table 17: Correlation Matrix

	$Size_{t,i}$	MarketLiq	WeightedPrice	Tier1	LiquidAssets	$EligibleAssets^{ESCB}$
$Size_{t,i}$	1.00***					
$MarketLiq_t$	-0.0150	1.00***				
	(0.6939)					
$WeightedPrice_{t,i}$	0.1379***	-0.0232	1.00***			
	(0.0003)	(0.5433)				
$Tier1_{t-1,i}$	-0.2654***	-0.0761*	-0.0094	1.00***		
	(0.0000)	(0.0777)	(0.8284)			
$LiquidAssets_{t-1,i}$	0.0189	0.1187***	0.1027**	-0.1830***	1.00***	
	(0.6415)	(0.0033)	(0.0111)	(0.0000)		
$EligibleAssets^{ESCB}_{t-1,i}$	-0.3498***	0.0703*	-0.1561***	0.1337***	0.1636***	1.00***
	(0.000)	(0.0782)	(0.0001)	(0.0024)	(0.0001)	

Note: The correlation is based on the data from the sample used for the regressions analysis for the period from 2006 Q1 to 2011 Q4. p-values are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 5: Density of the net-sales (in logs)



The figure shows the densities of the net-sales for both ESCB eligible (part a) and ESCB non-eligible assets (part b). The calculations are based on the data for the period from 2005Q4 to 2011Q4.

Table 18: Triggers for overall sales using Kiviet (1995) and Bruno (2005) estimator

$NetSales_{t,i}$	(1)	(2)	(3)	(4)	(5)	(6)
$NetSales_{-1t,i}$	0.33***	0.39***	0.36***	0.37***	0.39***	0.38***
	(6.769)	(9.591)	(8.854)	(8.818)	(9.587)	(9.508)
$Size_{t,i}$	0.58*	-0.02	-0.17	-0.22	-0.01	-0.20
	(1.896)	(-0.062)	(-0.476)	(-0.608)	(-0.023)	(-0.554)
$MarketLiq_t$	-0.01	-0.04	0.01	0.02	-0.02	0.01
	(-0.157)	(-0.722)	(0.110)	(0.389)	(-0.402)	(0.142)
$WeightedPrice_{t,i}$	0.01	0.17	0.38*	0.44**	0.26	0.32*
	(0.045)	(0.924)	(1.942)	(2.266)	(1.365)	(1.705)
$Tier1_{t-1,i}$		0.23	-0.25	-0.03	0.23	0.51**
		(1.059)	(-1.035)	(-0.074)	(1.045)	(2.002)
$LiquidAssets_{t-1,i}$		-0.09	0.11	0.22	-0.01	0.12
		(-0.321)	(0.369)	(0.784)	(-0.038)	(0.431)
$EligibleAssets^{ESCB}_{t-1,i}$		-0.14	0.20	0.18	0.00	0.34
		(-0.228)	(0.331)	(0.209)	(0.001)	(0.457)
$Crisis_{t,i}$			0.51***	0.16		
			(3.416)	(0.136)		
$Crisis*Tier1_{t-1,i}$				-0.22		
				(-0.508)		
$Crisis*LiquidAssets_{t-1,i}$				-0.53		
				(-1.599)		
$Crisis*EligibleAssets^{ESCB}_{t-1,i}$				0.02		
				(0.026)		
$CrisisB_{t,i}$					0.21*	-1.31
					(1.915)	(-1.460)
$CrisisB*Tier1_{t-1,i}$						-0.69**
						(-2.040)
$CrisisB*LiquidAssets_{t-1,i}$						-0.67*
						(-1.713)
$CrisisB*EligibleAssets^{ESCB}_{t-1,i}$						-0.31
						(-0.410)
Observations	579	467	467	467	467	467
R-squared	0.093	0.140	0.170	0.175	0.149	0.168
Number of Banks	30	28	28	28	28	28

Note: This table shows the results from the dynamic fixed-effect estimation for the period 2006 Q1 to 2011 Q4 for overall net sales. The dummy "Crisis" is defined for the period beginning in 2007 Q3 and ending in 2011 Q4. The dummy "CrisisB" is defined for the period from 2007 Q3 to 2009 Q4. The constant is included but not shown; t-statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 19: Sensitivity of extreme sales

Quantiles	Size_t	MarketLiq_t	$\text{WPrice}_{t,i}$	$\text{Tier1}_{t-1,i}$	$\text{LiqAs}_{t-1,i}$	$\text{ElAs}^{ESCB}_{t-1,i}$	Constant	R-sq.
All securities								
q50	0.02	-0.04	0.18**	-0.36***	-0.04	-0.06	0.67	0.030
	(0.870)	(-0.570)	(2.115)	(-3.598)	(-0.348)	(-0.343)	(1.104)	
q75	-0.14	-0.27**	0.15	-0.46**	-0.10	0.23	4.88**	0.032
	(-1.581)	(-2.197)	(0.831)	(-2.546)	(-0.682)	(0.661)	(2.542)	
q90	-0.44***	-0.30***	0.24	0.35	-0.00	-0.80	10.50***	0.098
	(-4.593)	(-3.279)	(0.875)	(1.308)	(-0.000)	(-1.167)	(5.092)	
q95	-1.11***	-0.57	1.62**	-1.65**	-1.39*	1.62	20.98***	0.280
	(-5.442)	(-1.480)	(2.045)	(-2.215)	(-1.923)	(0.957)	(5.539)	
ESCB eligible securities								
q50	0.70***	0.09	0.06	-0.14	0.06	1.12***	-12.32***	0.234
	(11.696)	(0.995)	(0.548)	(-0.713)	(0.376)	(3.972)	(-10.365)	
q75	0.49***	-0.03	0.16	-0.25	-0.03	1.04***	5.48***	0.126
	(7.138)	(-0.335)	(0.957)	(-1.468)	(-0.198)	(3.299)	(3.786)	
q90	0.22	-0.04	0.47	-0.01	-0.08	1.42**	10.64***	0.039
	(1.533)	(-0.237)	(1.022)	(-0.032)	(-0.161)	(2.122)	(3.227)	
q95	-0.10	0.03	0.76	0.14	-0.45	2.03*	17.66***	0.037
	(-0.434)	(0.150)	(1.110)	(0.282)	(-0.592)	(1.942)	(3.845)	
ESCB non-eligible securities								
q50	-0.21**	-0.27***	0.18	-0.85***	-0.16***	-1.72***	0.32	0.093
	(-2.430)	(-3.611)	(1.152)	(-3.841)	(-2.898)	(-3.239)	(0.175)	
q75	-0.45***	-0.38***	0.23	-0.72***	-0.05	-2.11***	5.13**	0.12
	(-3.708)	(-2.780)	(0.943)	(-4.543)	(-0.187)	(-4.345)	(2.100)	
q90	-0.70***	-0.33***	0.41	0.32	-0.08	-2.09***	9.30***	0.17
	(-5.991)	(-2.812)	(1.160)	(1.115)	(-0.250)	(-3.240)	(4.392)	
q95	-0.91***	-0.11	0.91*	-1.29**	-0.91***	0.51	11.19**	0.192
	(-4.287)	(-0.169)	(1.723)	(-2.125)	(-3.397)	(0.482)	(2.395)	

Note: The table includes the results from the quantile regressions analysis for the period 2006 Q1 to 2011 Q4 for overall net-sales, for net sales of ESCB eligible and for net sales of ESCB non-eligible assets. The analysis is based on 467 observations for 28 banks. t-statistics are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter 5

Out of sight, out of mind? On the sub-custodian structure of depository banks

"Be as polite to the custodian as you are to the chairman of the board"
(H. Jackson Brown, Jr.)

This chapter is based on a joint research paper with Thomas Droll and Michael Wedow.[68]

[68]Thomas Droll, Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt. Michael Wedow, European Central Bank, Sonnemannstraße 20, 60314 Frankfurt. This chapter is based on a pre-copy-editing, author produced PDF of an article accepted for publication in Journal of Banking and Finance. For further details on the paper, please see Droll et al. (2016).

5.1 Introduction

This chapter assesses the asset custody industry with a focus on risks in sub-custodian chains and the role of CSDs in these chains. Asset custody services consist in holding and administrating financial assets on behalf of customers. Custodian banks who offer these services typically delegate the safe-keeping of foreign securities to other banks acting as sub-custodians located in the countries where the securities have been issued and where they are traded.[69] CSDs play a central role in these chains as they frequently act as sub-custodians and provide a range of additional services for custodians.

The asset custody industry has experienced a dramatic growth in recent years due to a rising investor appetite for cross-border investments.[70] However, the delegation of safe-keeping to foreign sub-custodians can result in opaque structures involving chains of several sub-custodians in different countries. In the case of a sub-custodian defaulting or in cases of fraud, investors stand to lose their investment when local securities laws do not provide adequate protection (Micheler (2014)). This risk is further enhanced when various national securities laws applicable to the different levels in a security chain are not compatible Thevenoz (2007). As a consequence, long custody chains that transcend several jurisdictions are inherently more risky than shorter chains.[71] Examples where

[69] According to globalcustody.net assets under custody are heavily concentrated among the top 10 custodian banks. The majority of these custodian banks are on the list of global systemically important banks. At the end of 2013, the top 10 custodian banks managed more than USD110 trillion of assets either directly or as sub-custodians.

[70] See for example `http://www.forbes.com/sites/greatspeculations/2014/08/29/global-custody-banks-continue-to-see-strong-growth-in-asset-base-over-q2/`

[71] For further information, see "Explanatory Notes to the Preliminary Draft UNIDROIT Convention on Harmonised Substantive Rules regarding Securities Held with an Intermediary Examples" in Uniform Law Review 2005-1/2, 36 - 114.

such custody risks have led to losses by investors are so far rather rare but can be material.

The most prominent example is the Madoff case, where investors in investment funds, including European feeder funds, faced losses of assets allegedly held in custody at one of Madoff's entities. Following the Maddoff arrest, 17 Luxembourg based investment had to suspend redemptions leading to a dozen lawsuits against custodians overseeing the funds. UBS and HSBC have been at the centre of these lawsuits and both banks have settled a number of cases.[72] In terms of losses to investors, UCITS funds had an exposure of EUR1.7 billion to Madoff.[73] Moreover, the custodian banks have paid some of the affected investment funds more than USD 138 million in settlements.[74]

Before the financial crisis, the lack of incentives for custodians to act in the interests of investors may have given rise to riskier and more opaque sub-custodian structures. Currie (2010) reports that some custodian banks did not establish a proper sub-custodian risk monitoring system. Instead they relied heavily on input from industry surveys and had limited ability to gain key information on the safe-keeping of assets by their sub-custodians. Especially for the smaller, low-volume markets within their networks, some custodian banks did not conduct regular on-site due diligence.

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[72] According to globalcustodynet, UBS and HSBC were among the 10 largest custodian banks worldwide at the end of 2013.

[73] See official statement by Luxembourgish supervisory authority under `http://www.cssf.lu/fileadmin/files/Publications/Communiques/Communiques_2009/press_release_madoff3.pdf`.

[74] More specifically, HSBC and UBS have paid the Thema Fund, Kalix Fund Ltd. and Lux Alpha USD 62.5, USD 35.5 and USD 40 million respectively. However, the original amounts the investment funds sued for were well above these figures. Lux Alpha and the Thema fund were both UCITS. The amount repaid to Lux Alpha refers to the settlement with Oddo Cie.

In order to address these shortcomings and to enhance investor protection, a set of regulatory reforms have been put in place in Europe. In July 2014, an amendment to the UCITS directive has been adopted, which will be transposed by member states into their national laws by 18 March 2016.[75] The new regulation will tighten the rules on the duties of custodians.[76] More specifically, custodians will be liable to return any financial instruments lost in custody, regardless of whether the loss has been due to the custodian's fault or negligence (so-called "strict liability").[77]

We analyse the structure of sub-custodian chains using a unique data set from a survey, which was conducted by the Deutsche Bundesbank in July 2011. In this survey, German custodian banks were asked to report detailed quantitative and qualitative data with regard to all securities belonging to German UCITS funds that were held in safe custody abroad. The main question which we address with our analysis is whether there is evidence for moral hazard in sub-custodian structures. We approach this question by analysing the length and risk of sub-custodian chains relating these variables to the information custodian banks had on their sub-custodian chains and presence of a CSD in the chain. Our hypothesis is that not all custodians adequately managed and monitored the risks

[75] UCITS refers to Undertakings for Collective Investments in Transferable Securities. See `http://ec.europa.eu/internal_market/investment/ucits-directive/index_en.htm` for more information. At the end of 2013, net assets of UCITS amounted to around EUR 6.9 trillion.

[76] See Directive 2014/91/EU under `http://ec.europa.eu/finance/investment/ucits-directive/index_en.htm`

[77] In October 2014, IOSCO published "Principles regarding the Custody of Collective Investment Schemes' Assets" with the aim of outlining principles to assess the quality of asset custody. In the US, the Securities and Exchange Commission similarly implemented a number of reforms targeted at the supervisory failures that made the Madoff incident possible, including measures to protect investors. See `https://www.sec.gov/spotlight/secpostmadoffreforms.htm` for further information.

in their sub-custodian chains given that they were not liable for any losses. We identify custodians that insufficiently monitored via their ability to provide adequate information during the survey. However, some custodians delegated the safe-keeping directly to CSDs, which may have taken over the monitoring of the sub-custodian chains. As result, the presence of a CSD as a first sub-custodian could potentially mitigate risks due to inadequate monitoring by the custodian.

Our contribution to the literature on the securities custody industry is twofold. First, we provide a number of stylised facts on the sub-custodian structure of custodian banks for German UCITS funds. To our knowledge, very little is known to date about this industry. Second, we provide an empirical analysis of the sub-custodian structure. Our findings suggest that custodians delegate the safe-keeping of assets via chains of up to five sub-custodians. While most custodians typically delegate the safe-keeping of assets to one sub-custodian per country, a few custodians rely on numerous sub-custodians in a single country. Also, the custodian banks in our sample differ with respect to the number of countries they are linked to via sub-custodians. While a few large custodians have sub-custodians in over 100 countries, some smaller and less specialised custodians maintain very few links to other countries.

More importantly, our empirical analysis highlights the fact that better informed banks typically have shorter sub-custodian chains, but provide safe-keeping of assets in riskier countries. Better capitalised banks have longer, but less risky sub-custodian chains in terms of country risk. Moreover, foreign custodians, which typically benefit from greater economies of scale and scope, also use shorter and less risky sub-custodian chains. Sub-custodian chains where the first sub-custodian is a CSD are not significantly shorter. By contrast, CSDs as first sub-custodian appear to reduce the country risk in sub-custodian structures, highlighting the beneficial role they can play in the delegation of safe-keeping duties. When we analyse the choice of a CSD as first sub-custodian, we find that better capitalised, foreign and large custodian banks are less likely to rely on a CSD as first sub-custodian. These findings suggest that more specialised custodian banks with greater economies of scale and scope can avoid relying on CSDs, given that they can internalise many of the benefits attributed to CSDs.

To our knowledge this is the first study which empirically assesses the sub-custodian structure in the custody services industry. The existing literature on the custodian industry is very scant. It has so far focused on competitive issues between CSDs and custodians (Kauko (2007), Tapking (2007) and Holthausen and Tapking (2004)). Another strand in the literature examines the efficiency of the securities settlement industry and the potential to realize further scale economies (Schmiedel et al. (2006) and van Cayseele and Wuyts (2007)).

The next section briefly describes the survey among German custodian banks and provides some observations on the sub-custodian structure. Section 5.3 contains the empirical section and presents the results. The final section concludes.

5.2 Data and stylised facts

5.2.1 The survey

In June and July 2011, the Deutsche Bundesbank conducted a survey among custodian banks active in Germany. The aim of this survey was to gather relevant data to assess the possible impact of a more stringent liability regime on custodian banks for German UCITS funds. UCITS funds play an important role in the European financial markets. Net assets managed by European UCITS funds amounted to nearly EUR 7 trillion at the end of 2013, while German UCITS funds had assets of around EUR 277 billion under management.[78] Under the current UCITS directive there is no uniform EU-wide liability regime for fund custodians, in particular with regard to assets in sub-custody.

The issue of different national rules came to the fore in the context of both the bankruptcy of Lehman Brothers International Europe and the Madoff fraud.

The European Commission advocated harmonizing the respective liability rules and implemented a "strict liability" regime in July 2012, which requires custodians to return instruments lost in custody irrespective of negligence on its own part. This liability regime was more stringent than the existing German law at the time.

The data was reported as of 31 December 2010. The questionnaire was sent to all 52 German custodian banks licensed under Section 21 of the German Investment Act. All 52 banks participated in the survey. During the survey period, two of the custodian banks merged and thus reported consolidated data. As a result, 51 German banks reported back. Of these 51 banks, only 31 banks administered German UCITS funds. Despite repeated inquiries by the Deutsche Bundesbank, one of these banks was unable to report reliable data. This bank was therefore removed from the sample. Of the final 30 reporting custodian banks, 22 were German banks.

The custodian banks were asked to report detailed quantitative and qualitative data as regards all securities belonging to German UCITS funds that were held in safe custody in a foreign country. The specific questions were designed to obtain information on the exact properties of the various custody chains in place for each country. Further, banks were asked to provide the names of all sub-custodians in each custody chain and the market values of the securities in custody in each step

[78] See `http://www.efama.org/statistics/` for data on the European market and `http://www.bundesbank.de/Navigation/EN/Statistics/statistics.html?nsc=truefortheGermanmarket`.

of the custody chain.[79]

During the survey, including a pre-test in May 2011, it became clear that German custodian banks had limited information available on their various sub-custodian chains. Rather than having the data readily available, most of the data had to be gathered from its direct sub-custodians (in particular, global custodians and Clearstream Banking, which acted as a direct sub-custodian for 14 of the 30 German custodian banks). In several instances, the data reported initially was of poor quality and had to be corrected and amended by the respective custodian banks. We used this information to assign a dummy equal to 1 for custodian banks that faced restrictions during the survey. Following these corrections, we now consider the data to be of high quality, in particular as regards the values of, and the sub-custodians involved in, the various custody chains.

5.2.2 Data description

Table 20 provides summary statistics for the variables in the dataset, while Tables 25 and 26 contain a description of the variables and the correlation matrix.

As a starting point, the overall number of sub-custodian chains reported by the 30 custodian banks was 1169, which presents the cross-section of our dataset. At the custodian bank level, the average amount of assets under custody across the 30 custodians banks was EUR 4,502 million and the maximum value equals to EUR 37,774 million. These figures indicate the importance for custodians banks in case they have to assume liability for securities lost.

The overall number of countries with which each custodian banks maintained sub-custodian links varies widely with one bank having links to 101 countries at one end and a bank having only links to 2 countries at the other end. Overall, the

[79] A translation of the questionnaire can be obtained from the authors upon request.

number of countries with which custodian banks active in Germany maintained sub-custodian links for the custody services of UCITS was 103.

With regard to the individual sub-custodian chains, the number of sub-custodians per chain ranges between 1 and 5 with an average of 2.71. The number of sub-custodian chains maintained by a custodian with each country varies widely with the majority maintaining only 1 link per country (624 out of 1065 not shown) and 5 banks maintaining between 13 to 44 chains all to Luxembourg. The very large number of individual links to Luxembourg is due to funds of funds, which invested in funds in Luxembourg. As these Luxembourgish funds at the time relied on fund transfer agents rather than custodian banks the number of links to Luxembourg was relatively large.

We create a dummy indicating banks, which were well informed about the structure of their sub-custodian chains. This dummy is based on the interaction of the Bundesbank staff with the custodian banks during the survey. As mentioned in the previous sub-section a number of custodians experienced significant difficulties to provide the requested information during the survey. While a dummy on the basis of the survey is subjective, a number of measurable facts determined the classification as informed banks including knowledge of sub-custodian chains and the availability of data. Moreover, the evidence in the subsequent empirical analysis supports the view that the simple differentiation in informed and less informed banks significantly contributes in explaining the structure of sub-custodian chains. The dummy shown in Table 20 indicates that 64 percent of all sub-custodian chains were with informed custodian banks.

As we also test the effect of central securities depositories (CSD) on the structure of the sub-custodian chain, we included a dummy equal to 1 if the first sub-custodian was a CSD. We defined CSDs as institutions that operate securities settlement systems and, generally, are situated at the top of a custody chain. In

39 percent of all chains a CSD was the first sub-custodian. In addition, we also show the number of CSDs in sub-custodian chains in Table 20 highlighting the importance of CSDs in sub-custodian chains.

As a further variable to describe the complexity/risk of sub-custodian chains, we use the number of countries within any given chain. We include this variable as we consider a chain to become more complex when the different sub-custodian chains cross several borders. The summary statistics below reveal that the average number of times a chains reaches across borders is around two but reaches up to four which is considerable given that the maximum length of sub-custodian chains is five.

To shed further light on the risk within a chain, we include the numeric rating score of the country of location of the final sub-custodian chain. The idea behind this variable is that the riskier the country of the final sub-custodian, the more a custodian bank should aim to manage the assets at arms length keeping the chain short. The mean value for the rating score of 3.29 approximately corresponds to Moody's Aa2. The long-term foreign currency debt rating for the sovereign serves as a natural proxy for the credit risk of the respective country.[80] The sovereign risk could represent a first order consideration in the setup of a sub-custodian chain i.e. a custodian may choose a specific custodian structure conditional on the risk of the country. Custodians may, for example, choose to delegate the safe-keeping at arms length or aim to have shorter custody chains.

Our dataset also covers several foreign custodians active in Germany. For these custodians we created a dummy equal to 1 to test for any systematic differences. Out of the 30 banks that reported back to the Bundesbank eight banks are foreign banks. Moreover, we add the banks' core capital ratio as a proxy for banks' risk preferences.

[80]We use the long-term foreign debt ratings provided by Moody's at the end of 2010.

We also include two proxies for the geographic and economic distance between the location of the custodian i.e. Germany and the country of the final sub-custodian. The motivation for these two variables is derived from trade gravity models.[81] The basic idea behind trade gravity models is related to Newtonian physics stating that trade volumes - in our case asset custody services - between two countries depend positively on economic mass and negatively on distance and transportation costs. The geographic distance between two countries proxies information costs while economic distance measures the relative size of the economies. We hypothesize that custodians should minimize information costs by maintaining shorter sub-custodian chains with countries that are geographically more distant.

The geographic distance is given in kilometers between Berlin and the capital of the country where the final sub-custodian is located.[82] In contrast, more developed economies are likely to also have more developed financial systems reducing information asymmetries. While a more developed financial system may facilitate shorter sub-custodian chains it may also well be the case that given the ease to obtain information in more developed financial systems, custodian banks may care less about the length than the costs attached to sub-custody services. We are thus agnostic with regard the specific statistical relationship. To measure the economic distance, we use GDP per capita in thousands of US dollar.

Finally, we also explore the strength of Legal Rights Index provided by the World Bank, which aims to measure the degree of bankruptcy and collateral laws.[83] The

[81] This methodology dates back to Tinbergen (1962) and Pöyhönen (1963).

[82] The source of the geographic distance is Centre D'Etudes Prospectives et d'Information Internationales (CEPII). Please see Mayer and Zignago (2011) for further information. The data on GDP per capita comes from the IMF World Economic Outlook.

[83] For further information see `http://data.worldbank.org/indicator/IC.LGL.CRED.XQ/countries`.

underlying hypothesis for the index is that custodians should seek to minimize the length of sub-custodian chains to countries with weaker legal rights.

Table 20: Summary statistics for survey data on sub-custodian structures

Variable	Obs	Mean	Std. Dev.	Min	Max
At Sub-custodian Chain Level					
No. Custodians	1065	2.71	0.87	1	5
No. Chains per Cs	1170	4.25	8.65	1	44
Informed	1169	0.64	0.48	0	1
CSD First	1168	0.39	0.49	0	1
Foreign	1170	0.37	0.48	0	1
Assets in Custody	1090	124	619	0.01	9,539
No. of CSD	1169	1.38	0.91	0.00	4.00
No. Countries in Chain	1169	1.97	0.82	1.00	4.00
Rating Score	1154	3.29	3.53	1.00	19.00
Geo. Distance	1168	3,065	3,915	280	18,387
Eco. Distance	1164	46	29	0.38	104
Legal Rights	1154	6.40	2	1.00	10
At Bank Level					
Capital Ratio	30	0.129	0.059	0.031	0.317
No. of Countries	30	26.70	16.82	2.00	101.00
Assets in Custody	30	4,502	8,021	54	37,774

Notes: The descriptive statistics are based on a survey conducted at the Deutsche Bundesbank. The data was reported as of 31 December 2010. 31 banks administered German UCITS funds. Assets in custody in EUR million.

5.3 Empirical analysis

The summary statistics have highlighted a number of stylised facts about the sub-custodian structure, which require a more detailed analysis.

In this section, we analyse three of these facts given their potential to aggravate the lack of transparency and thus the risk for the custodian bank. First, we examine the length of sub-custodian chains. This is relevant given that longer chains increase the opaqueness of safe-keeping duties and also the risk that assets are lost. Second and closely related to this, we also relate the number of countries in a sub-custodian chain. Similar to the length of a chain, delegating the safe-keeping across several borders potentially increases risks along several dimensions including legal and political risk. Third, in addition to the number countries in the chain, we also empirically model the credit risk based on country ratings, which provides a more risk-based perspective on the structure of sub-custodian chains.

In addition, given the prominent role of CSDs in sub-custodian chains (see Table 20), we also study the decision to delegate the safe-keeping duties to a central securities depository in the first place rather than a custodian bank. Given the significant scale effects (Schmiedel et al. (2006) and van Cayseele and Wuyts (2007)) and the potential competitive price setting of CSDs for cross-border activities suggested by Holthausen and Tapking (2004), we postulate that larger banks are less likely to rely on CSDs in their sub-custodian chains.

5.3.1 Length of sub-custodian chains

The length of a sub-custodian chain should be chosen by a custodian bank based on cost and risk considerations. However, the survey clearly revealed that risk aspects did not necessarily figure prominently in the choice of sub-custodians.

In equation (5.1), we thus condition the length of sub-custodian chains on the custodian's capital ratio as a proxy of a bank's potential risk aversion, the number of links to any particular country as a proxy for diversification as well as economies of scope and scale.[84] In addition, we also include a dummy for custodians that appeared to relatively well informed about their sub-custodian structure, a dummy for foreign custodians active in Germany and a dummy if the first sub-custodian was a CSD. We include a dummy for foreign custodians as they are typically very large and may benefit from scale and scope effects, translating into more efficient

[84] Under principle 7 of International Organization of Securities Commissions (2014), collectives investment schemes are recommended to also assess the financial capacity to safekeep assets. To the extent that this already takes place, the custodian banks in our sample could already have been selected as custodian on the basis of their capital ratio.

sub-custodian structures. Similarly, a CSDs as the first sub-custodian may be better equipped to establish more efficient sub-custodian structures.
Our regression model has the following form:

$$\begin{aligned}\#SubCustodians_{i,c} = \alpha_0 + \alpha_1 CapitalRatio_i + \alpha_2 Foreign_i \\ +\alpha_3 Informed_i + \alpha_4 CSD1_{i,c} + \alpha_5 No.Links_{i,c} + u_{i,c}\end{aligned} \tag{5.1}$$

where the dependent variable $\#SubCustodians_{i,c}$ is the number of sub-custodians in a chain of bank i in country c.
Given that the dependent variable is an ordinal variable varying between 1 and 5, as shown in Table 20, we use an ordered probit model to test which variables determine the observed outcome.[85] We report the results in Table 21.
Column 1 contains the baseline specification shown in equation (5.1). As regards the capital ratio, we find that ceteris paribus banks with higher capital ratios have longer sub-custodian chains. Foreign banks clearly have significantly shorter sub-custodian chains. This is in line with expectations, given that the foreign custodians are typically very large international banks which can exploit economies of scale and scope. The number of chains to any specific country is negative and statistically significant, possibly indicating that there is some diversification element present when banks rely on several different sub-custodian chains to delegate the safe-keeping of assets. Interestingly, the

[85] We also considered a range of alternative estimators including Poisson, negative binomial and OLS on standardised values of the dependent variable. The results are very similar to those shown in Table 21 in terms of sign and statistical significance of the coefficients. Given that our dependent variable is characterised by under- rather than over-dispersion neither the Poisson nor the negative binomial estimator are fully suitable. Moreover, the Akaike information further confirmed a better fit of the data using the ordered probit estimator.

dummy for banks that are better informed about their sub-custodians also reveals statistically significant shorter sub-custodian chains.[86] With respect to the role of CSDs as the first sub-custodian, we hypothesised that this could reduce the length of chains, given that their size and specialisation can provide them with an edge in the delegating of safe-keeping to other sub-custodians. However, our results are not supportive of this view. Instead, we find a positive, though statistically insignificant coefficient for this variable.

In terms of economic significance, the results are also meaningful. The probability to observe a chain with a length of 3 sub-custodians when the explanatory variables take their mean value is 44 percent. With regard to the individual explanatory variables, a one unit change in Informed and Foreign reduces the probability of observing a chain length of 3 by 6 and 7 percent respectively. With regard to the capital ratio, the economic significance is less relevant increasing the probability of a length of 3 by less that 1 percent.[87]

In the subsequent columns 2 to 5, we further explore the length of the chains by considering the role of geographic and economic distance between Germany and the country of the final sub-custodian as well as the World Bank's Legal Rights Index and the Rating.[88] The inclusion of these variables, individually or jointly, does not materially change the results with the exception of the variable "No. of Links" which is insignificant when economic distance is included. When these four control variables are jointly included in the empirical specification only

[86] A simple t-test on the equality of the mean for the length of a sub-custodian chains for informed and uninformed custodians further confirmed that informed banks had statistically significantly shorter chains. The mean value is 2.65 and 2.85 for the informed and uninformed group respectively.

[87] A unit change in the capital ratio corresponding to this marginal effect is 1 percentage point.

[88] We also included lagged values of the Legal Rights Index as well as in logarithms but none turned out to be significant.

economic distance remains statistically significant. The negative coefficient between economic distance and the length of the sub-custodian chains suggests that custodian banks have shorter sub-custodian chains to countries with higher per capita GDP possibly reflecting that fewer sub-custodians are needed to delegate the safe-keeping of securities to countries with more developed financial systems.

Turning to the rating score of the country of location of the final sub-custodian, as shown in column 5, the rating score is statistically significant suggesting that country risk is positively correlated with longer chains. However, when the rating score is included jointly with other control variables the rating turns insignificant possibly due to the correlation with GDP per capita.

To check the robustness of the findings, we exclude observations which may

Table 21: Ordered probit: length of sub-custodian chains

	(1) Baseline	(2) Geo.Distance	(3) Eco. Distance	(4) Legal Rights	(5) Rating	(6) All	(7) excl. LX	(8) excl. Large
Capital Ratio	1.823***	1.808***	1.526***	1.799***	1.533***	1.455***	1.620***	-0.718
	[0.530]	[0.531]	[0.554]	[0.536]	[0.541]	[0.561]	[0.561]	[0.611]
Foreign Banks	-0.554***	-0.577***	-0.608***	-0.563***	-0.596***	-0.637***	-0.649***	-0.905***
	[0.086]	[0.087]	[0.087]	[0.087]	[0.087]	[0.089]	[0.091]	[0.097]
No. of Links	-0.021**	-0.017*	-0.000	-0.020**	-0.018**	0.001	0.031*	-0.006
	[0.009]	[0.009]	[0.012]	[0.009]	[0.009]	[0.012]	[0.019]	[0.011]
Informed	-0.448***	-0.456***	-0.480***	-0.446***	-0.481***	-0.489***	-0.446***	-0.736***
	[0.077]	[0.077]	[0.077]	[0.077]	[0.077]	[0.078]	[0.080]	[0.085]
CSD First	0.040	0.041	0.059	0.037	0.054	0.056	0.041	0.056
	[0.089]	[0.089]	[0.088]	[0.089]	[0.089]	[0.089]	[0.094]	[0.086]
Geo. Distance		0.000**				0.000	0.000*	0.000
		[0.000]				[0.000]	[0.000]	[0.000]
Eco. Distance			-0.006***			-0.005***	-0.002	-0.004**
			[0.002]			[0.002]	[0.002]	[0.002]
Legal Rights				0.011		0.007		
				[0.015]		[0.016]		
Rating Score					0.020**	0.000		
					[0.009]	[0.012]		
No. of Obs.	1,065	1,065	1,061	1,051	1,050	1,038	943	953
Pseudo R^2	0.027	0.029	0.033	0.028	0.030	0.035	0.034	0.056

Notes: The regression analysis is based on data from a survey conducted by the Deutsche Bundesbank. The data was reported as of 31 December 2010. 31 banks administered German UCITS funds. Constants are included, but not reported. Robust standard errors in brackets. ***, **, * indicates significance at 1, 5 and 10 percent levels.

bias the results. In column 6, we exclude observations on sub-custodian chains where the final sub-custodian is located in Luxembourg. We do this because the sub-custodian structure to Luxembourg differs significantly from those of other countries, in particular with regard to the number of chains. To note, four custodian banks maintain more than ten different chains each with sub-custodians to Luxembourg. The mean of the variable "No. of Links" excluding Luxembourg is equal to 1.8 compared with 4.2 when Luxembourg is included (see also Table 20.)

In column 7, we also exclude all sub-custodian chains for the largest custodian bank. This custodian accounted for nearly 10 percent of all sub-custodian chains in our sample and may thus have a material effect on our results. Indeed, when we drop these observations from our sample the capitalisation turns insignificant, while the dummies for informed and foreign banks remain robust

To further assess potential differences across subsets of countries, we estimate equation (5.1) for the G20, EU and euro area countries and the respective non-members in these subsets. We report the results in Table 27 in the appendix. While the results for foreign and informed banks are largely similar across the subsets, there are two noteworthy differences for the capital ratio and the role of CSDs. With regard to the capital ratio, a positive correlation is found for the sample coming outside the G20, EU and euro area countries. This is surprising given that one would expect to see that better capitalised banks, i.e. more risk-averse banks, should be associated with shorter sub-custodian chains to these countries. As to CSDs, they appear to have opposite effects on sub-custodian chains in EU and non-EU countries. Whereas to the former chains are shorter, they are longer for the latter when a CSD is the first sub-custodian.

In addition, we also run a series of regressions to control for reverse causality and using an instrumental variable approach to assess a potential omitted variable bias. As regards the former we used lagged values for the capital ratio in Q2 2010 and Q42009. The results which are not shown in the chapter largely confirm the findings in Table 21.[89] To address concern related to omitted variables, we use two-step least squares IV estimation.[90] More importantly, we use the bank profitability, the lagged capital ratio, CSDFIRST and the legal rights index. Our findings, which are not shown for the brevity, confirm the statistical significance for the capital ratio and the dummies for informed and foreign custodian banks.

5.3.2 Number of countries in sub-custodian chains

The empirical analysis in the previous subsection has provided some underpinnings for the view that the sub-custodian structure may not have been optimally chosen by custodian banks. To further examine the sub-custodian structure, we analyse in this subsection the number of countries in each sub-custodian chain.

From the viewpoint of the custodian bank a larger number of countries may imply higher legal and political risk and thus fewer countries may be preferable.[91] However, Table 20 highlights that, in fact, sub-custodian chains frequently cross more than one border and, in some cases, up to four countries. In order to analyze this issue, we use the empirical framework in equation (5.1) replacing the dependent variable by the number of countries in any given sub-custodian chain. We report the results in Table 22.

We observe a number of robust results across the eight specifications. First, the capital ratio is negatively correlated with the number of countries in sub-custodian chains. This may be an indication that better capitalised banks are more risk-averse and thus minimise the legal and political risk when crossing

[89] Results can be obtained from the authors upon request.

[90] We use the standardised value of the length of the sub-custodian chain.

[91] This is in line with International Organization of Securities Commissions (2014) which highlights country risk as key risk around the custody of client assets.

additional borders. Second, regarding foreign banks, the evidence is less obvious. While the coefficient is positive across all specifications, the statistical significance is weak. The positive sign is an indication that very large and internationally active custodian banks are less averse to country risk possibly due other risk-mitigating factors. Third, the number of links maintained with any specific country is negatively related with the number of counties, possibly showing that the custodian banks also minimise the country risk when diversifying across several final sub-custodians. However, this effect is not robust to the inclusion of our economic distance measure.

Interestingly, better informed banks and a CSD as the first sub-custodian are associated with more countries in the sub-custodian chain. This highlights the finding that the decision to cross more borders may be motivated by more complex decisions than we can model here. The economic distance is also negatively correlated with the number of countries. In line with the result in Table 21 this may indicate that shorter sub-custodian chains and fewer countries are needed to delegate the safe-keeping to a country with higher per capita GDP and, potentially, more developed financial systems.

Moreover, we also include the country rating of the final sub-custodian as well as the average country rating as an explanatory variable. With regard to the former, we do not find any relation with the number countries in the sub-custodian chain, while a higher average rating is negatively related to the number of countries. This may indicate that custodian banks partially offset the riskiness of sub-custodian chains by relying on shorter chains. This interpretation is further underpinned by the results in column 7, where we interact the average country rating with the dummy for informed banks. Apparently, better informed banks choose longer chains across borders when faced with, on average, riskier countries possibly as a way to mitigate these risks.

While the length of the chain is a potential candidate to assess the riskiness of a

Table 22: Ordered probit: number of countries in sub-custodian chains

	(1) Baseline	(2) Geo. Distance	(3) Eco. Distance	(4) Both	(5) Country Rating Sub-Custodian	(6) Av. Rating	(7) Av. Rating* Informed
Capital Ratio	-6.970***	-6.924***	-7.485***	-7.493***	-7.755***	-7.304***	-7.247***
	[0.670]	[0.672]	[0.698]	[0.697]	[0.698]	[0.713]	[0.722]
Foreign Banks	0.152*	0.166*	0.116	0.132	0.104	0.069	0.038
	[0.089]	[0.090]	[0.091]	[0.091]	[0.091]	[0.092]	[0.094]
No. of Links	-0.015***	-0.017***	-0.002	-0.002	-0.004	0.008	0.004
	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Informed	0.400***	0.402***	0.383***	0.385***	0.367***	0.426***	0.145
	[0.083]	[0.083]	[0.084]	[0.084]	[0.084]	[0.085]	[0.128]
CSD First	0.304***	0.301***	0.326***	0.327***	0.327***	0.197**	0.187**
	[0.076]	[0.076]	[0.076]	[0.076]	[0.077]	[0.078]	[0.079]
Geo. Distance		-0.000*		-0.000**	-0.000**	-0.000*	0.00
		[0.000]		[0.000]	[0.000]	[0.000]	[0.000]
Eco. Distance			-0.005***	-0.006***	-0.005***	-0.016***	-0.017***
			[0.001]	[0.001]	[0.002]	[0.002]	[0.002]
Country Rating					0.012		
Sub-Custodian					[0.012]		
Av. Rating						-0.129***	-0.208***
						[0.011]	[0.033]
Av. Rating*Informed							0.092***
							[0.033]
No. of Obs.	1,168	1,167	1,163	1,163	1,149	1,163	1,163
Pseudo R^2	0.09	0.09	0.09	0.09	0.10	0.15	0.15

Notes: The regression anlysis is based on a survey conducted at the Deutsche Bundesbank. The data was reported as of 31 December 2010. 31 banks administered German UCITS funds. Constant variable is included, but not reported. Robust standard errors in brackets. ***, **, * indicates significance at 1, 5 and 10 percent levels.

sub-custodian chain, more direct measures of riskiness are clearly desirable. As a step in this direction, we use three different country rating scores as the dependent variable using the specification in equation (5.1). We use the average rating score across the countries in each sub-custodian chain, the total sum and the rating score of the country in which the final sub-custodian is located. We report the results in Table 23 below.

In contrast to the previous result for the number of countries in the sub-custodian chain, we obtain a positive relation between the custodian banks' capital ratio and the country rating score in column 1 to 3. This suggests that banks' capitalisation is positively correlated when delegating the safe-keeping to sub-custodians in riskier countries. This may also indicate that better capitalised banks can offer a wider range of UCITS products, including investments in riskier countries. With regard to foreign banks, in column 1 we find that they delegate the safe-keeping

Table 23: OLS: dependent variable country rating score

	(1)	(2)	(3)	(4)	(5)	(6)
		Incl. Luxembourg			Excl. Luxembourg	
	Av.Score	Total Score	Final Sub. Score	Av.Score	Total Score	Final Sub. Score
Capital Ratio	5.139***	-0.145	3.193**	5.456***	0.966	4.180***
	[1.952]	[2.618]	[1.481]	[2.099]	[2.775]	[1.546]
Foreign Banks	-0.889***	-0.29	0.189	-0.948***	-0.245	0.28
	[0.311]	[0.388]	[0.205]	[0.314]	[0.384]	[0.198]
No. of Links	0.062***	0.125***	0.073***	-0.308***	-0.324***	-0.181***
	[0.010]	[0.015]	[0.008]	[0.039]	[0.074]	[0.050]
Informed	-0.093	1.193***	0.367**	-0.261	1.097***	0.293*
	[0.261]	[0.328]	[0.181]	[0.270]	[0.330]	[0.176]
CSD First	-1.335***	-1.060***	-0.543***	-1.155***	-0.648**	-0.28
	[0.223]	[0.306]	[0.176]	[0.227]	[0.324]	[0.186]
Geo. Distance	0.000**	0.000**	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Eco. Distance	-0.083***	-0.140***	-0.083***	-0.137***	-0.227***	-0.137***
	[0.005]	[0.007]	[0.004]	[0.008]	[0.011]	[0.005]
Constant	7.254***	11.886***	6.253***	9.756***	15.282***	8.289***
	[0.533]	[0.631]	[0.348]	[0.619]	[0.701]	[0.364]
No. of Obs.	1,163	1,163	1,149	998	998	984
R^2	0.328	0.371	0.403	0.402	0.438	0.5

Notes: The regression anlysis is based on a survey conducted at the Deutsche Bundesbank. The date was reported as of 31 December 2010. 31 banks administered German UCITS funds. Robust standard errors in brackets. ***, **, * indicates significance at 1, 5 and 10 percent level.

of assets to sub-custodian chains which have, on average, less country risk.

As regards the number of links, we present the results including and excluding Luxembourg in columns 1 to 3 and 4 to 6, respectively. The coefficient for all three risk scores changes sign when we exclude sub-custodian chains to Luxembourg. This is likely to be a simple statistical artefact of the large number of chains with and the low rating score for Luxembourg.

Informed banks are associated with riskier overall rating scores and with final sub-custodians in riskier countries. This may reflect a more specialised business strategy, where banks with more sophisticated risk management systems also offer investments in riskier countries. Interestingly, having a CSD as the first sub-custodian is negatively correlated with all three rating scores. This could be due to custodians relying less on CSDs when they provide safe-keeping assets for UCITS that invest in riskier countries. As to the alternative view that CSDs, owing to their larger scale, are better equipped to provide safe-keeping services leading to shorter chains, has already been refuted by our results in Table 21.

All in all, the empirical analysis in this section highlights a number of relevant statistical correlations in our dataset. The most prominent results are that better capitalised banks have longer sub-custodian chains but cross borders less frequently and are also less risky in terms of country risk. This may be due to the potentially wider range of investments offered via their UCITS funds. Foreign banks are associated with shorter and less risky sub-custodian chains. Similarly, better informed custodian banks also have shorter sub-custodian chains, but provide safe-keeping of assets in riskier countries. As regards CSDs, while they are not correlated with the chain length, the evidence suggests that they are negatively related to country risk and positively correlated with longer cross-border chains.

5.3.3 Who chooses CSDs as first sub-custodian?

The evidence in the previous subsections highlighted that CSDs as a first sub-custodian in a chain can materially affect the structure of the sub-custodian chain. In this subsection, we thus examine the choice of a CSD as a first sub-custodian in greater detail.

Given the significant scale effects (Schmiedel et al. (2006) and van Cayseele and Wuyts (2007)) and the potential competitive price setting of CSDs for cross-border activities suggested by Holthausen and Tapking (2004), we postulate that larger banks are less likely to rely on CSDs in their sub-custodian chains. Therefore, we include a proxy for the size of the bank in order to capture potential scale and scope effects which may impact the choice of a CSD. As a our measure of "*Size*" we use the logarithm of total core equity capital but other size proxies for size yield similar results.[92]

[92] As an alternative, we also used the total risk-weighted assets and the total amount of assets under management for UCITS. Results were similar and can be obtained from the authors upon request.

The evidence in Table 24 allows us to draw three main conclusions. Better capitalised, larger and foreign banks are less likely to rely on CSDs as their first sub-custodian. Moreover, the higher the rating of the country of the final sub-custodian is, the less likely custodians were to delegate the safe-keeping of assets to a CSD as their first sub-custodian. When we exclude the largest sub-custodian (column (7)) and all sub-custodians located in Luxembourg (column (8)) the dummy variable "*Informed*" becomes positive and significant, implying that better informed banks rather rely on CSD s their first sub-custodian. As for the variables "*Geo. Distance*" and "*Eco. Distance*", the former is not significant, while the latter is not robust across the eight specifications.

Overall, the empirical analysis suggests some important determinants for the choice of CSDs in the custodian services business.

Table 24: Probit: CSD as first sub-custodian

	(1) Baseline	(2) Geo.Distance	(3) Eco. Distance	(4) Both	(5) Rating	(6) Size	(7) excl. Large	(8) excl. LX
Capital Ratio	-3.127***	-3.140***	-2.803***	-2.808***	-2.743***	-2.974***	-2.334***	-3.069***
	[0.805]	[0.805]	[0.802]	[0.801]	[0.809]	[0.783]	[0.814]	[0.840]
Foreign Banks	-1.264***	-1.249***	-1.213***	-1.209***	-1.196***	-1.283***	-1.183***	-1.289***
	[0.104]	[0.104]	[0.104]	[0.104]	[0.105]	[0.109]	[0.115]	[0.116]
No. of Links	0.010*	0.008	-0.004	-0.004	0	-0.001	-0.003	0.083***
	[0.005]	[0.006]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.026]
Informed	-0.036	-0.037	-0.014	-0.015	-0.004	0.137	0.187**	0.175*
	[0.092]	[0.092]	[0.092]	[0.092]	[0.092]	[0.094]	[0.095]	[0.099]
Geo. Distance		0.00		0.00	0.00	0.00	0.00	0.00
		[0.000]		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Eco. Distance			0.006***	0.006***	0.002	0	0.001	0.006*
			[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]
Rating					-0.055***	-0.053***	-0.049***	-0.033*
					[0.016]	[0.017]	[0.017]	[0.018]
Size						-0.180***	-0.176***	-0.196***
						[0.028]	[0.028]	[0.030]
Constant	0.542***	0.591***	0.232	0.265*	0.597***	1.837***	1.673***	1.497***
	[0.113]	[0.116]	[0.145]	[0.154]	[0.179]	[0.267]	[0.276]	[0.313]
No. of Obs.	1,168	1,167	1,163	1,163	1,149	1,149	1,052	984
Pseudo R^2	0.171	0.172	0.177	0.177	0.18	0.208	0.16	0.22

Notes: The regression analysis is based on a survey conducted at the Deutsche Bundesbank. The data was reported as of 31 December 2010. 31 banks administered German UCITS funds. Robust standard errors in brackets. ***, **, * indicates significance at 1, 5 and 10 percent levels.

5.4 Conclusion

In this chapter, we use a unique data set from a survey, which was conducted at the Deutsche Bundesbank in July 2011 to carve out a number of stylised facts about the custodian services industry. More specifically, we examine the complexity and potential risk embedded in sub-custodian chains as measured by their length in terms of the number of sub-custodians, the number of countries and risk measured by the rating score of the countries in a sub-custodian chain. Given the potential importance of CSDs in sub-custodian structures, we also assess the determinants of choosing a CSD as the first sub-custodian.

As regards our specific results, we find that sub-custodian chains can be relatively long, frequently reach across several countries and that, in many cases, a CSD is the first sub-custodian. Moreover, our empirical analysis highlights that better informed banks typically have shorter sub-custodian chains, which we interpret as evidence of agency problems in the custodian industry. At the same time, better informed custodian banks also seem to provide safe-keeping of assets in riskier countries. Further, better capitalised banks have longer but less risky sub-custodian chains in terms of country risk. In addition, their chains cross borders less frequently. Moreover, foreign custodians, which typically benefit from greater economies of scale and scope, also use shorter chains. However, sub-custodian chains where the first sub-custodian is a CSD are not significantly shorter. In contrast, CSDs as first sub-custodian appear to reduce the country risk in sub-custodian structures, highlighting the beneficial role they can play in the delegation of safe-keeping duties. When we analyse the choice of a CSD as first sub-custodian, we find that better capitalised, foreign and large custodian banks are less likely to rely on a CSD as first sub-custodian. These findings suggest that more specialised custodian banks with greater economies of scale and scope can avoid relying on CSDs given that they can internalise many of the benefits attributed to CSDs. With regard to capitalisation, we interpret the negative relation with the CSD as a strategy to enhance the reputation of their custody services.

All in all, the analysis in this chapter can only be seen as a first step in the direction of providing a better understanding of the custody services business. This industry has so far received very limited attention. Given the intention to implement a strict liability regime, it is likely that the industry will undergo a significant transformation. More specifically, further research is needed to assess how, as a result of regulatory reforms, the sub-custodian structure is changing to reduce the embedded risks in asset custody services. For this purpose, a follow-up survey could be conducted to further assess how the introduction of full liability of assets lost under custody has impacted the custodian services industry. Future research should also assess a broader set of investment vehicles and seek information on the investment vehicles order to provide a better understanding of the underlying motivations for specific structures and a more comprehensive view on the risks of this business activity.

5.5 Appendix to Chapter 5

Table 25: Variable definition

Variable	Definition	Source
No. Custodians	Number of sub-custodian in chain.	BBK Survey
No. Chains per Cs	Number of sub-custodian chains per bank to a single country.	BBK Survey
Informed	Dummy=1 if the bank is informed about its chain.	BBK
CSD First	Dummy=1 if a CSD is the first-sub-custodian in the chain.	BBK Survey
No of CSD	Number of CSDs in each chain.	BBK Survey
No. Countries in Chain	Number of different countries in each chain.	BBK Survey
Capital Ratio	Core Capital Ratio	BBK
Foreign	Dummy=1 if foreign custodian	BBK Survey
No. of Countries	Number of countries with sub-custodian link	BBK Survey
Asset in Custody	Assets under custody in million EUR	BBK Survey
Geo. Distance	Distance in kilometers between Berlin and the capital of the country where the final sub-custodian is located.	Center D'Etudes Prospectives et d'information internationales (CEPII)
Eco. Distance	GDP per capita in USD 1,000 of the country where the final sub-custodian is located.	IMF
Legal Rights	Indicator ranging from 1 to 12. Higher values reflect stronger legal rights, end of 2010	World Bank
Rating Score	Numeric country rating scale, AAA=1 and BBB=9; average across countries in chain	Moody's Long Term Foreign Debt Rating

Table 26: Correlation matrix

	No. Custodians	No. Chains per Cs	Informed	CSD First	No of CSDs	Capital Ratio	No. Countries in Chain	Foreign	Assets in Custody	Rating Score
No. Custodians	1.00									
No. Chains per Cs	-0.01	1.00								
Informed	-0.11	-0.33	1.00							
CSD First	0.14	0.04	0.03	1.00						
No of CSD	0.53	-0.04	0.05	0.64	1.00					
Capital Ratio	0.01	-0.06	-0.08	-0.22	-0.18	1.00				
No. Countries in Chain	0.60	0.03	0.07	0.19	0.56	-0.36	1.00			
Foreign	-0.22	0.02	-0.30	-0.45	-0.34	0.24	-0.20	1.00		
Assets in Custody	-0.08	-0.05	0.08	-0.06	-0.05	0.09	-0.04	0.07	1.00	
Rating Score	-0.02	-0.21	0.10	-0.16	-0.15	0.10	0.01	0.10	-0.09	1.00

Notes: The correlation analysis is based on a survey conducted at the Deutsche Bundesbank. The data was reported as of 31 December 2010. 31 banks administered German UCITS funds.

Table 27: Ordered Probit: length of sub-custodian chains by regional subsets

	(1) non-G20	(2) non-EU	(3) non-Euro Area	(4) G20	(5) EU	(6) Euro Area
Capital Ratio	1.581**	3.644***	2.248***	1.4	0.313	0.328
	[0.722]	[0.985]	[0.771]	[0.916]	[0.783]	[0.924]
Foreign Banks	-0.686***	-0.362**	-0.462***	-0.574***	-0.775***	-0.843***
	[0.113]	[0.163]	[0.128]	[0.147]	[0.111]	[0.129]
No. of Links	0.001	-0.058	0.055	0.057	0.009	0.017
	[0.013]	[0.117]	[0.035]	[0.039]	[0.014]	[0.016]
Informed	-0.427***	-0.307**	-0.356***	-0.588***	-0.573***	-0.611***
	[0.097]	[0.141]	[0.110]	[0.138]	[0.101]	[0.118]
CSD First	0.012	0.730***	0.348**	0.115	-0.169*	-0.189
	[0.112]	[0.193]	[0.143]	[0.151]	[0.102]	[0.117]
Geo. Distance	0.00	0.000*	0.000**	0.00	0.00	0.00
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Eco. Distance	-0.006***	0.005	0.004	0.007	-0.007***	-0.010***
	[0.002]	[0.004]	[0.004]	[0.010]	[0.002]	[0.003]
Legal Rights	-0.001	-0.038	-0.035	-0.018	0.023	0.055*
	[0.021]	[0.033]	[0.028]	[0.035]	[0.020]	[0.028]
Rating Score	-0.002	0.039*	0.026	0.025	-0.015	-0.003
	[0.014]	[0.022]	[0.021]	[0.045]	[0.016]	[0.020]
No. of Obs.	707	353	521	331	685	517
Pseudo R^2	0.036	0.067	0.041	0.047	0.044	0.055

Notes: The regression analysis is based on a survey conducted at the Deutsche Bundesbank. The data was reported as of 31 December 2010. 31 banks administered German UCITS funds. Constant variable is included, but not reported. Robust standard errors in brackets. ***, **, * indicates significance at 1, 5 and 10 percent levels.

Chapter 6

Conclusions

The financial crisis has shown that relatively contained losses on subprime assets in the US market triggered a process that lead to reductions in global wealth and output. According to many scholars, contagious risk transmission channels were the core mechanism responsible for amplification and transmission of systemic risk. The analysis of the origin of the crisis shows that insufficient attention has been devoted to systemic risk which undermined the financial stability.

This dissertation contributes to the understanding of some of the complex facets of the systemic risk transmission mechanisms focusing on contagion channels within and the opaqueness of some parts of the financial industry which were at the core of the financial crisis and still may present systemic risk. The evidence found in this dissertation provides a number of relevant policy insights.

The results of the first study presented in the second chapter show that the German financial system experienced a more pronounced contagion effects from international OTC dealer banks. Thus, contagion not only within a financial system but also across borders is an important risk factor that should be monitored by macro- prudential supervisors. Furthermore, the finding that OTC dealer banks are the most important source of contagion effects for the German financial system highlights the need for more intensive monitoring and regulation of these banks. The monitoring of their interlinkages should not be limited to traditional exposures in the lending market but also include the OTC derivative market. Furthermore, the recent initiatives from the Financial Stability Board on the regulation of the OTC market may alleviate contagion effects. More specifically, the FSB aims to mitigate systemic risk by enhancing transparency in the market through the trading of all standardized derivative contracts on centralised exchanges or electronic platforms which will reduce the opaqueness of this market and thereby reduce information asymmetries. Finally, the empirical approach presented in the second chapter may serve as a monitoring tool for the continuous supervision of systemic risk. For this purpose, the model presented here can be continually adapted to emerging risks for the German financial system.

The results of the third chapter show that larger banks and particularly SI banks are statistically and economically more interconnected than any other group of financial firms. More importantly, big insurers are the second most interconnected subgroup. While this may warrant a similar treatment of big insurers as SIFI, the economic magnitude of the interconnectedness is considerably lower than for big banks and may thus provide a rationale for the omitting insurance companies from the list of SIFIs.

The results of the fourth chapter suggest that measures undertaken by the central banks and the government play an important role and should be taken into account when it comes to analysing the existence and causes of fire sales. Such policy measures significantly affect a bank's selling behavior, making a bank less vulnerable to sudden liquidity constraints during times when the interbank market dries up and alternatives for funding become scarce as it was the case during the banking crisis.

A bank's liquidity position clearly determines its asset sales. A distressed sale can cause a collapse of prices in certain market segments, indirectly forcing financial institutions with exposures to these markets to adjust their valuations, which ultimately could destabilize the financial system as a whole. Thus, the introduction of liquidity standards is a step in the right direction to address the weaknesses in the regulatory framework and to accommodate systemic risk due to fire sales. In addition, banks with strong capital position would prefer borrowing over selling. Thus, straightening their capital positions as it has been foreseen by the new regulatory framework "Basel III" will make banks and therewith the financial sector as a whole less vulnerable to fire sales.

While analysing the opaqueness of the sub-custodian industry, the final chapter finds that sub-custodian chains can be relatively long, frequently reach across several countries and that, in many cases, a CSD is the first sub-custodian. Moreover, better informed banks typically have shorter sub-custodian chains, which can be interpreted as evidence of agency problems in the custodian industry. Moreover, sub-custodian chains where the first sub-custodian is a CSD are not significantly shorter. In contrast, CSDs as first sub-custodian appear to reduce the country risk in sub-custodian structures, highlighting the beneficial role they can play in the delegation of safe-keeping duties. Furthermore, the results show that better capitalised, foreign and large custodian banks are less likely to rely on a CSD as first sub-custodian. These findings suggest that more specialised custodian banks with greater economies of scale and scope can avoid relying on CSDs given that they can internalise many of the benefits attributed to CSDs.

This analysis can only be seen as a first step in the direction of providing a better understanding of the custody services business. This industry has so far received very limited attention. Given the intention to implement a strict liability regime, it is likely that the industry will undergo a significant transformation. More specifically, further research is needed to assess how, as a result of regulatory reforms, the sub-custodian structure is changing to reduce the embedded risks in asset custody services. For this purpose, a follow-up survey could be conducted to further assess how the introduction of full liability of assets lost under custody has impacted the custodian services industry. Future research should also assess a broader set of investment vehicles and seek information on the investment vehicles order to provide a better understanding of the underlying motivations for specific structures and a more comprehensive view on the risks of this business activity.

The financial regulation addressed many weaknesses that contributed to the amplification of the global financial crisis. This has led to a fundamental reform of the regulatory framework. Some examples of the new requirements that address the interconnectedness of banks are the new capital buffer (e.g. GSIB buffer), the large exposure rule, the total loss absorbing capacity (TLAC). In addition, the implementation of the liquidity requirements aims (inter alia) at reducing contagion from excessive wholesale and short term funding. In addition, the Single Supervisory Mechanism (as a part of the European Banking Union), which has been established in November 2014, will allow a more efficient and harmonised supervision of banks across Europe. These measures have already reduced the build up of the systemic risk. Due to a permanent evolution of the financial system and regulatory arbitrage, however, further research is needed in order to completely understand and eliminate the systemic risk.

References

Acharya, V., H. S. Shin, and T. Yorulmazer (2011). Crisis Resolution and Bank Liquidity. *Review of Financial Studies 24*, 1773–1781.

Adrian, T. and M. K. Brunnermeier (2009). CoVar. *Federal Reserve Bank of New York Staff Report 384*.

Adrian, T. and S. Shin (2010). Liquidity and leverage. *Journal of Financial Intermediation 19*, 418–437.

Aharony, J. and I. Swary (1983). Effects of bank failures: Evidence from capital markets. *Journal of Business 56*(3), 305–322.

Alexander, C. and A. Kaeck (2008). Regime dependent determinants of credit default swap spreads. *Journal of Banking and Finance 32*(6), 1008–1021.

Allen, F. and E. Carletti (2006). Credit risk transfer and contagion. *Journal of Monetary Economics 53*, 89–111.

Allen, F. and D. Gale (2000). Finacial contagion. *Journal of Political Economy 108*(1).

Bae, K.-H., G. A. Karolyi, and R. M. Stulz (2003). A new approach to measuring financial contagion. *Review of Financial Studies 16*(3), 717–799.

Baur, D. G. (2011). Financial contagion and the real economy. *Journal of Banking and Finance*.

BCBS (2011, November). Global systemically important banks: assessment methodology and the additional loss absorbency requirement. *Rules Text*.

Beber, B., M. W. Brandt, and K. A. Kavajecz (2009). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *Review of Financial Studies 22*(3), 925–957.

Beine, M., A. Cosma, and R. Vermeulen (2010). The dark side of global integration: Increasing tail dependence. *Journal of Banking and Finance 34*(1), 184–192.

Billio, M., M. Getmansky, A. Lo, and L. Pellizon (2012). Econometric measures of conectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics 104*, 535–559.

Blanco, R., S. Brennan, and I. W. Marsh (2005). An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *Journal of Finance 60*(5), 2255–2281.

Boyson, N. J., J. Helwege, and J. Jindra (2012a). Crisis, Liquidity Shocks and Fire Sales at Hedge Funds. *Working Paper*.

Boyson, N. J., J. Helwege, and J. Jindra (2012b). Crisis, Liquidity Shocks and Fire Sales at Investment Banks. *Working Paper*.

Boyson, N. J., J. Helwege, and J. Jindra (2013). Crisis, Liquidity Shocks and Fire Sales at Commercial Banks. *Working Paper*.

British Bankers' Association (2006). Credit Derivatives Report 2006. *BBA Report*, 1–6.

Bruno, G. S. F. (2005). Estimation and inference in dynamic unbalanced panel-data models with a small number of individuals. *Stata Journal 5(4)*.

Canay, I. A. (2011). A simple approach to quantile regression for panel data. *The Econometrics Journal 14*(3), 368.

Chari, V. V., L. Christiano, and P. Kehoe (2008). Facts and myths about the financial crisis of 2008. *Working Paper*.

Cifuentes, R., F. G. and H. S. Shin (2005). Liquidity risk and contagion. *Journal of the European Economic Association 3*, 556–566.

Claessens, S. and K. J. Forbes (Eds.) (2001). *International Financial Contagion*. Kluwer Academic Publishers, Norwell, MA.

Clark, J. A. and S. B. Perfect (1996). The economic effects of client losses on otc bank derivative dealers: Evidence from the capital market. *Journal of Money, Credit and Banking 28*(3).

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

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*, 479–512.

Currie, B. (2010, Q4). Sub-custodian risk monitoring: analysing shifts in industry practice. *Financial Services Research* (36).

Dang, T. V., G. G. and B. Holmström (2013). Haircuts and repo chains. *mimeo*.

De Haan, L. and W. Van den End (2011). Banks' reposnes to funding liquidity shocks: lending adjustment, liquidity hoarding and fire sales. *DNB Working Paper* (293).

De Nicolo, G. and M. L. Kwast (2002). Systemic Risk and Financial Consolidation: Are they related? *Journal of Banking and Finance 26*, 861–880.

Diamond, D. W. and R. Rajan (2011). Fear of fire sales, illiquidity seeking, and credit freezes. *Quarterly Journal of Economics 126*(2), 557.

Droll, T., N. Podlich, and M. Wedow (2016). Out of sight, out of mind? On the risk of the sub-custodian structures. *Journal of Banking and Finance 68*, 47–56.

Duffie, D. (2010). The failure mechanics of dealer banks. *Journal of Political Perspectives 24*(1), 51–72.

Duffie, D., N. Garleanu, and L. H. Pedersen (2007). Valuation in over-the-counter markets. *Review of Financial Studies 20*, 1865–1900.

Ellul, A., C. Jotikashira, and C. T. Lundblad (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics* (101), 596–620.

Engle, R. (1982a). Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation. *Econometrica 50*, 987–1007.

Engle, R. (1982b). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics 20*, 339–350.

European Central Bank (2009, December). The concept of systemic risk,. Financial Stability Review, European Central Bank.

European Central Bank (2010, April). Report on the lessons learned from the financial crisis with regard to the functioning of European financial market infrastructures. Technical report.

European Central Bank (2013, July). Monthly bulletin. Technical report.

Fama, E. (1984). The information in the term structure. *Journal of Financial Economics 13*(4), 509–528.

Fenn, G. W. and R. A. Cole (1994). Announcements of asset-quality problems and contagion in the life insurance industry. *Journal of Financial Economics 35*(2), 181–198.

Financial Stability Board (2012). OTC Derivatives Market Reforms. Technical report.

Forbes, K. and R. Rigobon (2002). No Contagion, Only Interdependence. Measuring Stock Market Comovements. *The Journal of Finance 57*(5), 2223–2261.

Forbes, K. J. (2012). The Big C: Identifying and Mitigating Contagion. *NBER Working Paper Series No. 18465*.

Fry, R., V. L. Martin, and C. Tang (2010). A new class of tests of contagion with applications. *Journal of Business and Economic Statistics 28*(3), 423–437.

Hamao, Y., R. Masulis, and V. K. Ng (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies 3*(1), 281–307.

Hammoudeh, S., M. Nandha, and Y. Yuan (2013). Dynamics of cds spread indexes of us financial sectors. *Applied Economics 45*(2), 213–223.

Hanson, S., A. Kashyap, and J. Stein (2011). A macroprudential approach to financial regulation. *Journal of Economic Perspectives 25*, 3–28.

Hartmann, P., S. Straetmans, and C. G. de Vries (2004). Asset market linkages in crisis periods. *The Review of Economics and Statistics 86*(1), 313–326.

Harvey, A. C. (1976). Estimating regression models with multiplicative heteroscedasticity. *Econometrica 44*(3), 461–465.

He, Z. I., G. Khang, and A. Krishnamurthy (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics 58*, 118–156.

Hellwig, M. (2009). Systemic risk in the financial sector: an analysis of the subrime-mortgage market financial crisis. *De Economist* (157), 129–207.

Hildebrand, T., J. Rocholl, and A. Schulz (2012). Flight to Where? Evidence from Bank Investments During the Financial Crisis. *Mimeo*.

Holthausen, C. and J. Tapking (2004). Raising rival's costs in the securities settlement industry. *Journal of Financial Intermediation 16*(1), 91–116.

Houweling, P. and T. Vorst (2005). Pricing default swaps: Empirical evidence. *Journal of International Money and Finance 24*, 1220–1225.

International Monetary Fund (2009). Lessons from the global crisis for macroeconomic policy. Technical report.

International Organization of Securities Commissions (2014, October). Principles regarding the custody of collective investment schemes' assets. www.iosco.org/library/pubdocs/pdf/IOSCO454.pdf.

Jorion, P. and G. Zhang (2007). Good and bad credit contagion: Evidence from credit default swaps. *Journal of Financial Economics 84*(3), 860–883.

Jorion, P. and G. Zhang (2009). Credit contagion from counterparty risk. *Journal of Finance 64*(5), 2053–2087.

Kauko, K. (2007). Interlinking securities settlement systems: A strategic commitment? *Journal of Banking and Finance 31*(10), 2962–2977.

King, M. A. and S. Wadhwani (1990). Transmission of volatility between stock markets. *The Review of Financial Studies 3*(1), 5–33.

Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics 68*(1), 53–78.

Kodres, L. and M. Pritsker (2002). A rational expectations model of financial contagion. *Journal of Finance 57*.

Krishnamurthy, A. (2009). Amplification mechanisms in liquidity crises. *American Economic Journal 2*, 1–33.

Malliaris, A. G. and J. L. Urrutia (1992). The International Crash of October 1987: Causality Tests. *Journal of Financial and Quantitative Analysis 27*(3).

Manconi, A., M. Massa, and Y. A. (2012). The role of institutional investors in propagating the crisis of 2007-2008. *Journal of Financial Economics 104*, 491–518.

Mayer, T. and S. Zignago (2011). Notes on cepii's distances measures: The geodist database. *CEPII Working Paper* (25).

Mayordomo, S., Pena, and E. S. Schwartz (2010). Are all credit default swap databases equal? *NBER Working Paper* (16590).

Merrill, C. B., T. D. Nadauld, R. M. Stulz, and S. M. Sherlund (2012). Did capital requirenments and fair value accounting spark fire sales in distressed mortgage-backed securities? *Dice Center Working Paper (03).*

Micheler, E. (2014, July). Custody chains and remoteness: Disconnecting investors from issuers. *SRC Discussion Paper* (14).

Moshirian, F. (2011). The global financial crisis and the evolution of markets, institutions and regulation. *Journal of Banking and Finance 35*(3), 502–511.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica 59*(2), 347–370.

Nyborg, K. G. and P. Oestberg (2014). Money and liquidity in financialmarkets. *Journal of Financial Economics 112*, 30–52.

Podlich, N. and M. Wedow (2013). Are Insurers SIFI? A MGARCH model to measure interconnectedness. *Applied Economics Letters* (20), 677–681.

Podlich, N. and M. Wedow (2014). Crossborder contagion to Germany: How important are OTC dealers? *International Review of Financial Analysis 33(C)*, 1–9.

Polonchek, J. and R. K. Miller (1999). Contagion effects in the insurance industry. *The Journal of Risk and Insurance 66*(3), 459–475.

Pöyhönen, P. (1963). A tentative model for the volume of trade between countries. *Weltwirtschaftliches Archiv 90*(1), 93–100,.

Pozdena, R. (1991, October). Is Banking Really Prone to Panics? *FRBSF Weekly Letter, Federal Reserve Bank of San Francisco*.

Schmiedel, H., M. Malkamaki, and J. Tarkka (2006). Economies of scale and technological development in securities depository and settlement systems. *Journal of Banking and Finance 30*(6), 1783–1806.

Schnabel, I. and H. S. Shin (2004). Liquidity and contagion. *Journal of the European Economic Association 2*(6), 929–968.

Schroeder, M. and M. Schueller (2003). Systemic Risk in European Banking - evidence from Bivariate GARCH Models. *ZEW Discussion Paper 03*(11).

Shleifer, A. and R. W. Vishny (1992). Liquidation values and debt capacity: a market equilibrium approach. *Journal of Finance 47*, 1343–1366.

Shleifer, A. and R. W. Vishny (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives 1*, 29–48.

Slovin, M. B., M. E. Sushka, and J. Polonchek (1999). An analysis of contagion and competitive effects at commercial banks. *Journal of Financial Economics 54*(2), 197–225.

Solnik, B. (1974). The international pricing of risk: An empirical investigation of the world capital market structure. *Journal of Finance 29*(2), 365–378.

Stolz, S. and M. Wedow (2010). Extraordinary measures in extraordinary times: Public measures in support of the financial sector in the EU and the United States. *European Central Bank Occasional Paper 117*.

Stulz, R. M. (2010). Credit default swaps and the credit crisis. *Journal of Political Perspectives 24*(1), 73–92.

Svensson, L. E. O. (1994). Estimating and interpreting forward rates: Sweden 1992 -1994. *IMF Working Paper* (114).

Swary, I. (1986). Stock Market Reaction to Regulatory Action in the Continental Illinois Crisis. *Journal of Business 59*(3), 451–473.

Tamakoshi, G. and S. Hamori (2013). Volatility and mean spillovers between sovereign and banking sector cds markets: a note on the european sovereign debt crisis. *Applied Economics Letters 20*, 262–266.

Tapking, J. (2007). Pricing of settlement link services and mergers of central securities depositories. *ECB Working Paper Series 710*.

Thevenoz, L. (2007). Intermediated Securities, Legal Risk, and the International Harmonisation of Commercial Law. *Stanford Journal of Law, Business, and Finance 13*, 384–452.

Tinbergen (1962). *Shaping the World Economy: Suggestions for an International Economic Policy*. New York: The Twentieth Centry Fund.

van Cayseele, P. and C. Wuyts (2007). Cost efficiency in the european securities settlement and depository industry. *Journal of Banking and Finance 31*(10), 3058–3079.

van Rixtel, A. and G. Gasperini (2013, March). Financial crises and bank funding: recent experience in the euro area. *BIS Working Paper* (406).

Curriculum Vitae

Natalia Podlich, born in 1983 in Kazakhstan, studied economics from 2002 to 2008 at the Rheinische Friedrich-Wilhelms-University of Bonn (Germany). From 2005 until 2006, she studied economics at the Lomonosov University of Moscow (Russia). In 2008, she joined the Banking Supervision Department at the Deutsche Bundesbank. From 2009 to 2014, she worked at the Financial Stability Department at the Deutsche Bundesbank. During the course of these years, she was a member of the financial stability research group. In 2010, she started her doctoral studies as an external doctoral student at the Chair of Prof. Dr. Isabel Schnabel at the Johannes Gutenberg-University of Mainz. In 2014, she joined the Banking Supervision (SSM) of the European Central Bank.