Systemic risk in the banking sector - a network perspective

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To my parents.

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Abstract

This thesis investigates various aspects of systemic risk in financial networks. Chapter 1 explores the existence of a contagion channel to security returns given that banks are connected via overlapping portfolios. Making use of a proprietary dataset on securities held by German banks, I identify the network induced through cross holdings and find higher correlations among the returns on securities held by connected banks. This contagion channel to security returns is stronger for banks which are large, highly leveraged and highly interconnected and especially at work during the recent financial crisis. Chapter 2 establishes a model for bank credit risk interconnectedness based on CDS data, in which defaults can be triggered by systematic global and country shocks as well as idiosyncratic bank-specific shocks. Applying the framework to a sample of large European financial institutions reveals that the credit risk network captures a substantial amount of dependence in addition to what is explained by systematic factors. Chapter 3 analyzes the relation between market-based bank credit risk interconnectedness and the associated balance sheet linkages via funding and securities holdings. Results suggest that market-based measures of interdependence can serve well as risk monitoring tools in the absence of disaggregated high-frequency bank fundamental data.

Resumen

Aquesta tesi investiga diversos aspectes del risc sistèmic en xarxes financeres. El Capítol 1 explora la existència d'un canal de contagi als rendiments dels actius ates que els bancs estan connectats per portafolis superposats. Fent ús d'una base de dades d'actius financers de bancs Alemanys, identifico la xarxa induida a través de participacions creuades i trobo correlacions altes entre els rendiments d'actius en poder de bancs connectats. Aquest canal de contagi a rendiments d'actius és més fort per bancs

que son més grans, altament endeutats i altament interconnectats, i es va intensificar durant la recent crisi financera. El Capítol 2 estableix un model d'interconectivitat de risc de crèdit bancari basat en dades del CDS, en el que l'impagament pot ser causat per shocks sistèmics locals o globals o per shocks específics dels bancs. Aplicant aquest marc de referència a una mostra d'institucions financeres europees grans, es revela que el risc de crèdit de xarxa captura una part substancial de la dependència, a més del que és explicat per factors sistèmics. El Capítol 3 analitza la relació entre l'interconectivitat del risc de crèdit bancari de mercat i les connexions de balanç de situaci associades via finançament i tinences de valors. Els resultats suggereixen que les mesures d'interdependència basades en el mercat serveixen bé com a eines de monitorització del risc en absència de dades bancàries fonamentals.

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Foreword

The recent financial crisis in the United States and Europe has forcefully shown the importance of accurately measuring systemic risk in financial systems. One area of active research focuses on detecting interconnections among banks through various channels and measuring their importance from a systemic risk perspective. In the presence of network structures, shocks that are originally small in size can amplify and become relevant for the financial sector as a whole and the real economy. This creates the need to identify different channels which can induce shock propagation and to monitor these accordingly. This thesis consists of three self-contained chapters which contribute to the field in different respects.

Chapter 1, titled "Fire Sale Spillovers in a Network Perspective", analyzes the network induced through cross-holdings of securities in the German banking sector. In order to shed light on the existence of a resulting contagion channel to security prices, I analyze correlation patterns of portfolio returns as a function of their holding structure. For identification, I make use of a proprietary database containing quarterly securities holdings of German financial institutions at the bank-security-time level between 2006 and 2014. I find that security returns in exclusively held parts of bank portfolios are correlated in a lead-lag relationship given that portfolios contain overlapping elements. A path analysis suggests that a likely underlying channel are sales of commonly held securities following negative returns. This contagion channel to security returns is more pronounced for banks which are large, highly leveraged and central to the asset commonality network. Furthermore, investigating the period surrounding fire sales in summer 2017, I find a potential occurrence of shift-contagion with return correlations increasing comparably more for institutions with higher levels of portfolio overlap. These results are important for systemic risk since they suggest that banks' trading behavior in asset commonality networks can increase correlations in security returns above fundamental levels, a factor which should be taken into account in banks' portfolio choice.

Chapter 2 is co-authored with Christian Brownlees and Eulalia Nualart and titled "Bank Credit Risk Networks: Evidence from the Eurozone". This work proposes a novel methodology to study credit risk interconnectedness in large panels of financial institutions. Building upon the standard reduced form framework for credit risk, we introduce a model for European financial institutions in which defaults can be triggered by systematic global and country shocks as well as idiosyncratic bank specific shocks. The idiosyncratic shocks are assumed to have a sparse conditional dependence structure called the bank credit risk network. We then develop an estimation strategy based on Lasso regression that allows to detect and estimate network linkages from CDS data. Applying this technique to analyze the interdependence of large European financial institutions between 2006 and 2013 shows that the credit risk network captures a substantial amount of dependence in addition to what is explained by systematic factors.

Chapter 3 is titled "Credit Risk Interconnectedness: What Does The Market Really Know?" and co-authored with Puriya Abbassi, Christian Brownlees and Natalia Podlich. This chapter has been published as a separate article in the Journal of Financial Stability, Volume 12, April 2017, Pages 1 - 12. In this work we analyze the relation between the methodology established to estimate the bank credit risk network from CDS data and the associated balance sheet linkages via funding and securities holdings. For identification, we use a proprietary dataset that contains the funding positions of banks at the bank-to-bank level for 2006-13 in conjunction with investments of banks at the security level and the credit register from Germany. We find asymmetries both cross-sectionally and over time: when banks face difficulties to raise funding, the interbank lending affects market-based bank interconnectedness. Moreover, banks with investments in securities related to troubled classes have a higher credit risk interconnectedness. Overall, results suggest that network measures based on market data can serve well as risk monitoring tools in the absence of granular data.

Chapter 1

FIRE-SALE SPILLOVERS IN A NETWORK PERSPECTIVE

1.1 Introduction

The recent financial crisis has shown the relevance of contagion between different financial institutions. In the presence of network interconnections, shocks that are initially small in size can amplify to have a large impact by being transmitted within the financial sector and eventually to the real economy. This poses the question of how contagion between two institutions can occur, and to which extent it might destabilize an entire financial system. The literature identifies two main channels for shock transmission: lending in interbank markets and commonality in securities investments. While the structure and potential for contagion through interbank markets has been researched to a larger extent, we know less about interconnectedness arising from overlapping security portfolios. At the same time, the potential for spillover effects and their impact on the aggregate is largely dependent on the topology of the underlying network. Understanding the network structure of overlapping portfolios can therefore help to evaluate the current state of systemic risk in the financial system and its implications from both a bank and security perspective.

In this work I take a new approach to shedding light on a contagion channel to security returns arising in commonality networks by analyzing return correlations as a function of their holding structure. I make use of a proprietary database which contains security investments for all banks in the German financial system at a security-bank-time level. This allows me to identify a commonality network between banks each quarter at the level of single securities. With the help of this network, I then investigate whether returns on exclusively-held parts of bank portfolios are related differently given that the two banks are connected through other common securities holdings.

I find evidence consistent with the existence of a contagion channel to security prices. That is, I find that returns on exclusively-held parts of bank portfolios are correlated to a larger extent given that those banks hold overlapping securities. This channel is more pronounced if banks are large, highly leveraged and located at the core of the securities holdings network. Furthermore, this channel has been especially active during the recent financial crisis. In order to identify a potential mechanism, I run a path analysis and find that one path runs from negative portfolio returns at the bank level, to higher sales of securities and lower portfolio returns at connected banks. Lastly, I analyze the occurrence of what has been referred to as "shift contagion" by Forbes and Rigobon (2001), defined as a systematic increase in the channel of shock propagation. To test this, I run a difference-in-difference framework of the distance in banks' portfolio returns before and after the initiation of the financial crisis in Germany, for banks with different levels of commonality in securities investments. I find that the distance in portfolio returns of banks with higher portfolio overlap has decreased comparably more after summer 2007, indicating a potential occurrence of shift contagion in this period.

This work relates mainly to two strands in the literature. Firstly, it is related to theoretical models of bank interconnectedness. On networks arising through interbank markets, Allen and Gale (2000), Freixas, Parigi, and Rochet (2000), Iyer and Peydró (2005), Babus (2007), Brusco and Castiglionesi (2007), Gai, Haldane, and Kapadia (2011), Caballero and Simsek (2013), Hale, Kapan, and Minoiu (2013) and Suhua, Yunhong, and Gaiyan (2013) are important examples. Fire sales and resulting asset price contagion have been researched, among others, by Kyle and Xiong (2001), Cifuentes, Ferrucci, and Shin (2005), Pavlova and Rigobon (2008), Wagner (2010) and Caccioli, Shrestha, Moore, and Farmer (2014). On different network structures in the banking sector and their resilience to contagion, Castiglionesi and Navarro (2007), Allen, Babus, and Carletti (2012) and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) are recent examples. Secondly, it relates to empirical work on fire sales in asset commonality networks. Important examples for asset price correlations induced by mutual funds are Coval and Stafford (2007), Jotikasthira, Lundblad, and Ramadorai (2012) and Anton and Polk (2012). Begalle, Martin, McAndrews, and McLaughlin (2016) investigate fire sales in tri-party repo markets and Ellul, Jotikasthira, and Lundblad (2011) focus on corporate bond markets. The potential for asset price contagion induced by the banking sector has been shown by Cont and Wagalath (2014) as well as Greenwood, Landier, and Thesmar (2015) and Duarte and Eisenbach (2015).

The remainder of the paper is organized as follows. Section 1.2 introduces the dataset and variable definitions. Section 1.3 explains the model and estimation methodology. Section 1.4 presents empirical results. And Section 1.5 concludes.

1.2 Data

The main proprietary database used for this project is obtained from Deutsche Bundesbank. For each bank in the German financial system, I have access to micro data on security holdings each quarter, identifiable on a security-bank-time level. The security portfolios comprise fixed income securities, stocks and mutual fund shares and are identified at the level of the ISIN (International Security Identification Number). For each security, it contains additional information regarding the country of origin, the type of issuer (financial, sovereign, corporate) and the security class. The sample contains a total of 1800 banks for 36 quarters from 2006 - 2014. For each security in their portfolio, banks report both the nominal amount of their holding and the current value of the security (i.e. euro total) at the end of each quarter.

I enhance this database in three directions. Firstly, I collect the issuer of each underlying security from Bloomberg in order to identify holdings stemming from the same issuing entity. Secondly, I collect a total return index for each security from Datastream, which gives price quotes adjusted for dividend payouts and accrued interest. And thirdly, I collect monthly balance sheet items such as total assets, equity, deposits and lending to the real economy from the proprietary BISTA database at Deutsche Bundesbank. The full sample of securities holdings consists of roughly four million securities held by 1800 banks over 36 quarters.

I prune this data in a number of ways. Firstly, and most importantly, on the security level I only consider the part of the security portfolio held for banks' own trading purposes, and not on behalf of customer accounts. Within banks' trading accounts, I only consider long positions in debt securities by non-financial issuers. This avoids a network representation arising through cross-holdings of securities issued by neighboring banks. I concentrate the analysis on securities which are traded, identified through the intersection of being listed on Bloomberg and having a return index provided by

Datastream. This step is necessary to have reliable price data on securities used in the analysis, and for effects to be driven by the impact of portfolio decisions on prices. Furthermore, I take out all securities whose total holding in the banking system in a given quarter is less than 1 Mil euros since those are less relevant from a contagion point of view. On a bank level, I take out Landesbanken and mortgage banks, as well as very small banks whose quarterly security portfolio is lower than 100 Mil Euros. On a portfolio level, in each quarterly portfolio I take out securities whose percentage share is less than 0.0002% of a bank's portfolio, a step necessary for computational reasons. The final sample contains data for 1.057 banks and 87.665 securities. This makes up 17.86% of the euro value of the entire holdings, where the largest restrictions are due to the exclusion of securities held in customer accounts and those issued by financial entities.

Securities in the sample are identified at the level of the ISIN, the International Security Identification Number, which is allocated to each security at its issuance, independent of the exchange where it is traded. An example for a security identified by an ISIN would be a 3-months maturity bond issued by Volkswagen on 15.06.2013. With respect to credit risk and price movements of the underlying securities, a natural unit of concentration is the issuer, since developments in several securities issued by one entity are driven by the underlying entity rather than idiosyncratic movements to each security separately. For the remainder of the analysis, I therefore concentrate all securities on the level of the issuer for establishing the asset commonality network of banks. More precisely, I take the sum of the quantities of all securities issues by the same entity in order to define the extent of portfolio overlap between two banks.

1.2.1 Variable Definitions

Banks are indexed by i and j, and securities (on the level of the issuer) are indexed by s. Denote the total security portfolio of bank i at time t as the set S_{it}. The total security portfolio of a bank i is then decomposed into a part held by only bank i and a part held in common with at least one other bank.

$$\mathrm{S}_{it} = \mathring{\mathrm{S}}_{it} \cup \breve{\mathrm{S}}_{it}$$

where S_{it} is a bank's total security portfolio, $\mathring{\mathrm{S}}_{it}$ is the space of securities held only by bank i and no other bank in the system at time t, and $\breve{\mathrm{S}}_{it}$ is the space of securities which is held by bank i and at least one other bank at time t. I will use the notation $\breve{\mathrm{S}}_{ijt}$ for the space of securities which is held in common by bank i and j at time t. Note that $\breve{\mathrm{S}}_{it} \leq \sum_{j \neq i} \breve{\mathrm{S}}_{ijt}$ since $\breve{\mathrm{S}}_{ijt}$ will potentially have overlapping elements again for different j. Furthermore, note that due to the granular nature of the data, I can precisely identify which securities are held by each bank in the sample in each quarter.

Portfolios Returns

I aim at investigating the correlation patterns between banks' portfolio returns over time, given that two banks have some extent of commonality in their portfolios. The identification challenge here lies in the fact that, if two banks hold some securities in common, correlations in their portfolio returns might be driven by assets contained in both portfolios. To circumvent this, I exclude $\breve{\mathrm{S}}_{it}$ from the analysis and compute portfolio returns on $\mathring{\mathrm{S}}_{it}$ for each bank in the sample. The main variable for computing portfolio returns is the total return index computed by Datastream. This return index adjusts security prices for coupon payouts and accrued interest. For each security in the sample, the total return index is calculated as

$$\mathrm{RI}_{st} = \mathrm{RI}_{st-1} \frac{\mathrm{P}_{st} + \mathrm{A}_{st} + \mathrm{NC}_{st} + \mathrm{CP}_{st}}{\mathrm{P}_{st-1} + \mathrm{A}_{st-1} + \mathrm{NC}_{st-1}} \,,$$

where RI is the total return, P is the clean price, A is accrued interest, NC is the next coupon (where adjustment is made when a bond goes ex-dividend) and CP is the value of any coupon received between t and t-1.

To capture market dynamics which drive all security prices simultaneously, I extract the first principal component of returns. The first principal component is defined as the eigenvector which maximally explains the variance of the system and commonly used as a proxy for a market factor. I define the excess variation in security returns as the residuals from an OLS regression on the first principal component.

$$\Delta\epsilon_{st} = \mathrm{RI}_{st} - \beta \Delta PC_{(1)t}$$

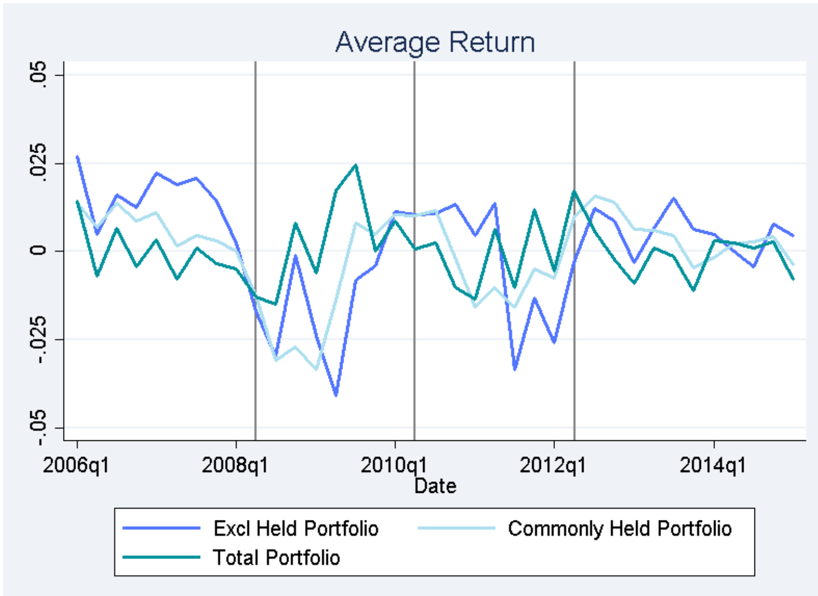
Note that the correlation between the first principal component extracted from security returns and a more standard measure of movements in the market portfolio such as the DAX index amounts to 76.47 %. The portfolio return for each bank $\mathring{\mathrm{R}}_{it}$ is then defined as a weighted portfolio of excess returns for all securities exclusively held by bank i at time t

$$\mathring{\mathrm{R}}_{it} = \sum_{s \in \mathring{\mathrm{S}}_{it}} \omega_{ist} \Delta\epsilon_{st} \,,$$

where ω_{ist} is the portfolio weights of bank i for security s at time t.

One might argue that exclusively held portfolios are not representative subsamples of the total portfolio of a bank, since the nature of securities held by only one bank is different from securities held by a larger number of banks simultaneously. To address this concern, I compute returns separately for exclusively held portfolios and total portfolios of each bank. Figure 1.1 shows the time variation in said returns, calculated as a time-varying mean for the entire sample of banks.

Figure 1.1: Volume-weighted Returns on different Parts of Security portfolios



This figure reports average volume-weighted returns on different parts of banks' security portfolio, calculated over the entire sample of banks at different points in time.

From the graphs we can see that the returns $\mathring{\mathrm{R}}_{it}$ and R_{it} are tightly linked, hinting towards securities contained in $\mathring{\mathrm{S}}_{jt}$ differing solely in their holding structure. However, note that restricting the analysis to exclusively held portfolios on the level of the issuer leads to a further reduction in sample size, since those are not available for all banks. The sample for the remainder of the analysis therefore consists of 937 banks.

Commonality Index

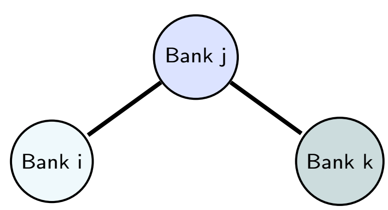
I define a security commonality network based on the overlap in banks' security portfolios $\breve{\mathrm{S}}_{ijt}$. Banks i and j are connected at time t if and only if $\breve{\mathrm{S}}_{ijt} \neq 0$.

In particular, for each bank pair ij in each quarter t I extract the security space held in common $\breve{\mathrm{S}}_{ijt}$. In order to measure the potential impact of contagion at the pair level, I compute for each bank i the share of its portfolio, which is made up by assets held in common with bank j.

$$\Omega_{ijt} = \frac{\breve{\mathrm{S}}_{ijt}}{S_{it}}$$

To take into account only interconnections that are relevant from a contagion point of view, I round numbers lower than 5 % of the security portfolio to 0.[1] For most of the analysis, my interest lies in whether two banks have any overlap in their portfolios or not, hence the variable considered is $\mathbf{1}_{\Omega_{ijt}\neq 0}$. I will later analyze the bank-pair dimension in a difference-in-difference setting, using the continuous value of the commonality index as a treatment variable.

$\mathbf{1}_{\Omega_{ijt}\neq 0}$ gives rise to a network of banks' security portfolios, which can be visualized as follows.



In this network, each bank is a vertex, while two banks having commonality in their security investments will determine the existence of edges. An edge between banks i and j exists at time t if they have some exposure to the same issuer at the same time t, $\mathcal{E} = \{(i, j, t) : \breve{\mathrm{S}}_{ijt} \neq 0\}$, in other words $\mathbf{1}_{\Omega_{ijt}\neq 0} = 1$. In this example, $\mathbf{1}_{\Omega_{ijt}\neq 0} = \mathbf{1}_{\Omega_{jkt}\neq 0} = 1$ whereas $\mathbf{1}_{\Omega_{ikt}\neq 0} = 0$. The degree of bank i at time t, defined as the number of connections to other banks in the system, can then be calculated as $\deg_{it} = \sum_{j\neq i} \mathbf{1}_{\Omega_{ijt}\neq 0}$. In the above example, $\deg_{it} = \deg_{kt} = 1$ whereas $\deg_{jt} = 2$.

[1] All main results are robust to a truncation at 10 % or 15% instead.

1.2.2 Descriptive Statistics

Descriptive statistics for the degree and commonality index are depicted in Table 1.1.

Table 1.1: Descriptive Statistics of Degree and Commonality Index

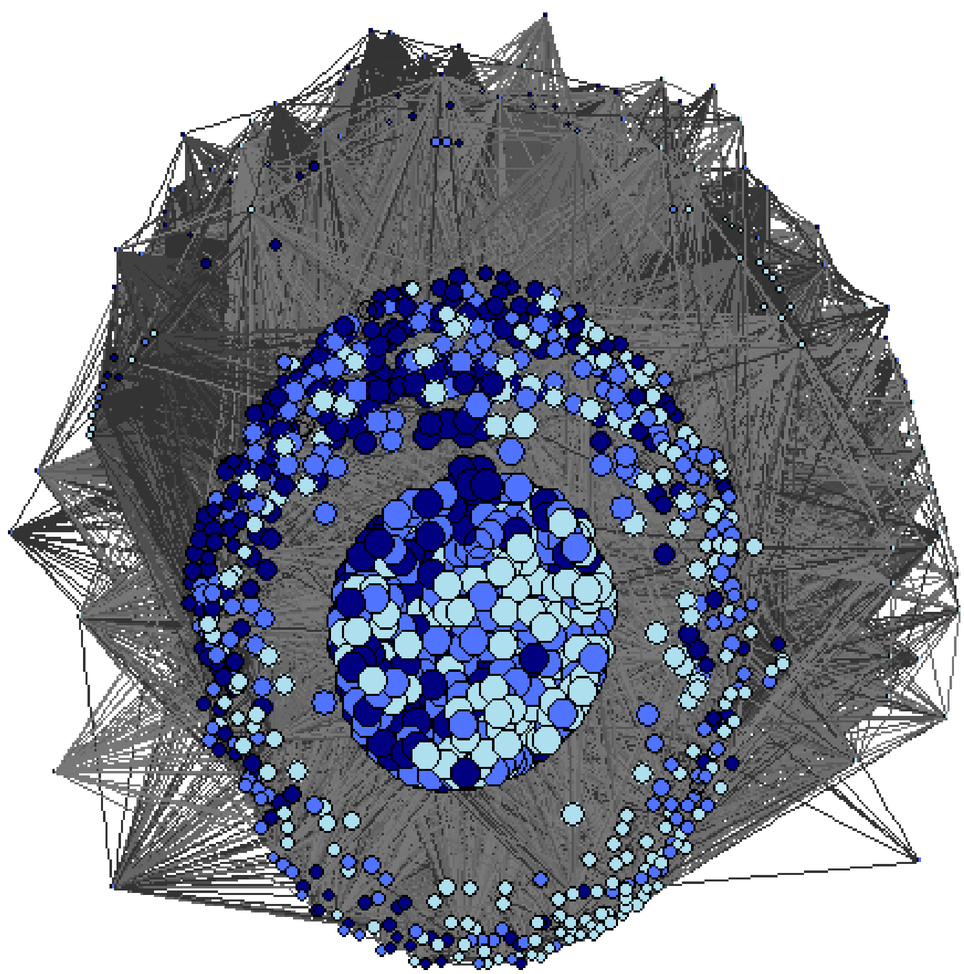
	Mean	Std Dev	P10	P50	P90
Commonality Index	34.55 %	28.11 %	5.71 %	29.13 %	77.29 %
Degree	303.57	376.94	0	69	937

This table shows summary statistics for two variables: bank degree and commonality index Ω_{ijt}. Summary statistics are calculated over the entire sample in the second quarter of 2007.

The average degree of banks in the sample is 303.57. This means that at any point in time, a given bank holds overlapping portfolios at the level of the issuer with on average 304 other banks, or roughly one third of the sample. The degree varies considerably in the cross-section, with banks being interconnected to between 0 and 937 other banks. The strength of the interconnection, defined as the average portfolio share which is made up by a single interconnection, amounts to 34.55%. That is, on average, 34.55 % of bank i's portfolio is also held by bank j at time t, taking into account a concentration at the level of the securities' issuer. Again, the commonality index varies considerably in the cross-section, with common portfolio shares ranging between 5.71 % and 77.29 %.

In what follows, I plot the arising asset commonality network for all banks in the sample. Each bank represents a single node and the color of nodes is chosen according to bank size: light blue represents small banks by total assets, dark blue are large banks. The size of the nodes is determined by the degree such that larger nodes represent banks which are more interconnected in the asset commonality network. The algorithm places more central nodes in the middle, less interconnected ones on in the periphery. For visualization purposes, only linkages above the median are depicted in the graph. Lastly, all banks which have 0 - 3 interconnections with other banks are dropped from the graph for data confidentiality reasons. The time period chosen for the graph is the second quarter of 2007, the last quarter before the start of the financial crisis in Germany.

Figure 1.2: Asset Commonality Network 06/2007 - Coloring by Bank Size



This figure shows the asset commonality network defined through overlap in security portfolios at the level of the issuer in the second quarter of 2007. Nodes are colored according to bank size by total assets: light blue represents small banks, dark blue are large banks. The node size is determined by the degree and more central nodes are placed in the middle, less interconnected ones on in the periphery. Only linkages above the median are shown and all banks with a degree of 0 - 3 are dropped from the graph for data confidentiality reasons.

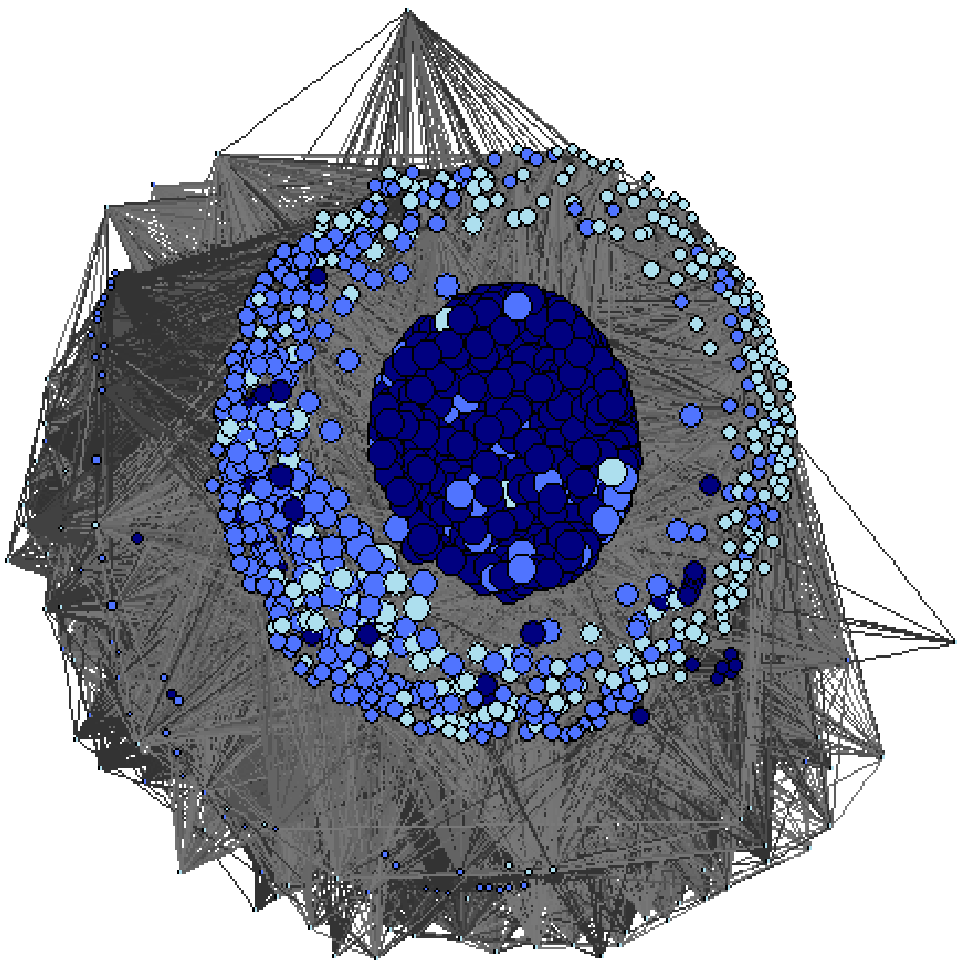
Overall, the arising network structure is rather dense. We can see in the plot that the asset commonality network among banks exhibits a strong core-periphery structure. Furthermore, in terms of bank size, a bi-partite structure is arising, where large banks are more interconnected with large banks, and small banks are more interconnected with small banks.

This type of network structure has also been referred to as assortativity, that is a bias towards node connections with similar characteristics, in this case related to bank size. A second type of assortative mixing that has been frequently researched is related to bank connectivity as expressed by their degree. Figure 1.3 contains the same network representation of the second quarter of 2007, but the color of nodes is chosen according to the degree of banks: dark blue represents highly interconnected banks by degree, and light blue represents banks with few interconnections.

We can see that the security commonality network exhibits a strong pattern of assortative mixing by degree. In a recent paper, Caccioli, Catanach, and Farmer (2012) show that assortativity in node mixing can lead to higher network instability and increase the probability of contagion. That is, in an assortative network by connectivity, nodes that have low degrees are only connected among themselves, and can thus fail easier in cascades following the default of one neighbor.

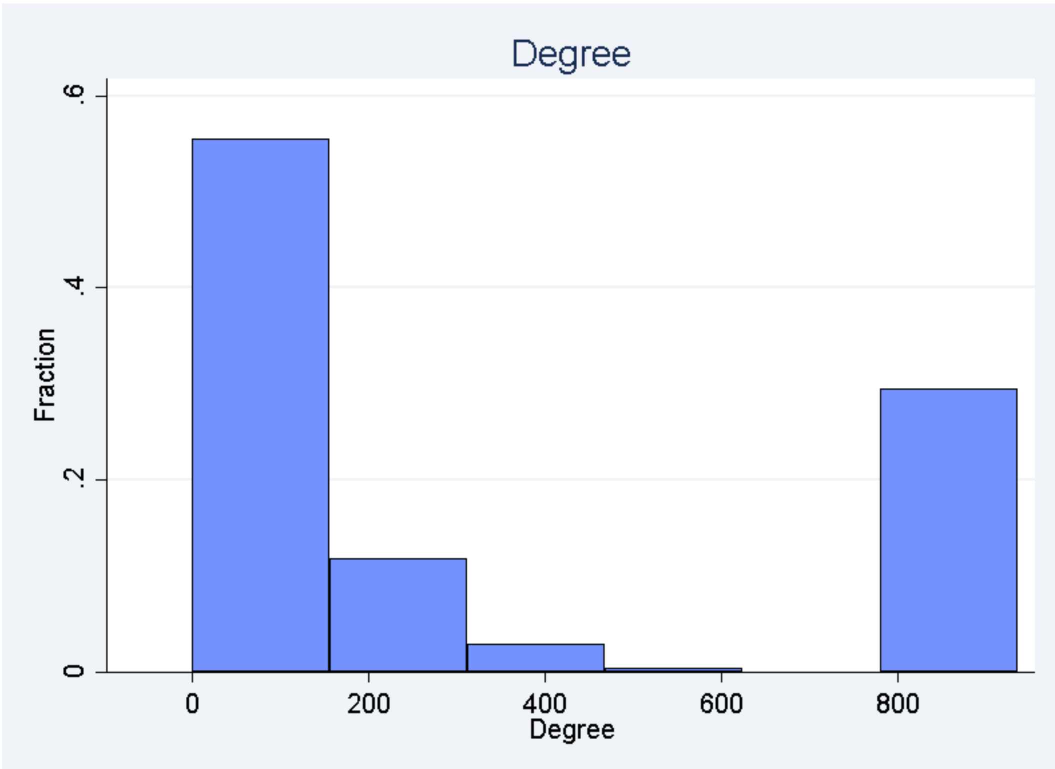
Looking at the degree distribution depicted in Figure 1.4, we can see that it follows a power law. These situations in which only few banks have a large degree and many banks have a small degree are also referred to as scale-free networks. Previous research has shown that while scale free networks can reduce the probability of contagion, they do not reduce its extent once a cascade of failures has started. On the contrary, if the failing node is located at the center of the network, scale-free networks show higher fragility.

Figure 1.3: Asset Commonality Network 06/2007 - Coloring by Degree



This figure shows the asset commonality network defined through overlap in security portfolios at the level of the issuer in the second quarter of 2007. Nodes are colored according to the degree: light blue represents a low degree, dark blue represents a high degree. The node size is also determined by the degree and more central nodes are placed in the middle, less interconnected ones on in the periphery. Only linkages above the median are shown and all banks with a degree of 0 - 3 are dropped from the graph for data confidentiality reasons.

Figure 1.4: Degree Distribution 06/2007



This figure shows the degree distribution across all banks in the sample at the end of the second quarter of 2007. The rather bin width is chosen to comply with confidentiality restrictions. The degree of each bank is defined as the sum of its respective edges in the asset commonality network.

1.3 Methodology

In this work, I use a panel regression framework to shed light on the existence of a fire sales channel to security price correlations in an asset commonality network. I make use of the information contained in bank portfolio returns and regress each bank's return on its exclusively held portfolio $\mathring{\mathrm{R}}_{it}$ on both the average returns on exclusively held portfolios of banks it is connected to and banks it is not connected to at time $t-1$. Note that due to the consideration of exclusively held portfolios, no security issuers are contained in both the LHS and RHS variable.

In particular, denote by c_{it} the number of banks that bank i is connected to at time t, and by u_{it} the number of banks it is not connected to through common portfolio exposures (such that for every i at time t, $N = u_{it} + c_{it} + 1$). For purposes of notation, I will return to the network illustration depicted in Section 3 where $\mathbf{1}_{\Omega_{ijt} \neq 0} = 1$ and $\mathbf{1}_{\Omega_{ikt} \neq 0} = 0$. Then I consider the regression model

$$\mathring{\mathrm{R}}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t) \in \mathcal{E}} \mathring{\mathrm{R}}_{jt-1} + \beta_2 \frac{1}{u_i} \sum_{(i,k,t) \notin \mathcal{E}} \mathring{\mathrm{R}}_{kt-1} + \epsilon_{it} \,, \tag{1.1}$$

where $\mathring{\mathrm{R}}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. To account for time and cross-sectional heterogeneity, I include both bank fixed effects α_i and year fixed effects α_t.

After investigating the general relation between banks' exclusively held portfolios, I am interested in seeing whether the channel operates differently in the cross-section. To see this, I divide all banks in the sample in three subcategories according to bank size, leverage, and their position in the asset commonality network. I then run a variant of the baseline regression model in Equation 1.1 in which I interact banks' portfolio returns with indicator variables for different subsample categories. For the case of bank size defined by total assets, for example, I run the regression model

$$\begin{aligned}\mathring{\mathrm{R}}_{it} =& \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{\mathrm{TA1}} + \beta_2 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{\mathrm{TA2}} \\ &+ \beta_3 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{\mathrm{TA3}} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\mathrm{R}}_{kt-1} + \epsilon_{it} \, ,\end{aligned} \tag{1.2}$$

where $\mathring{\mathrm{R}}_{it}$ is the return on the exclusively held portfolio of bank i at time t. $\mathbf{1}_{\mathrm{TA1}}$ indicates whether bank i belongs to the smallest category of banks according to total assets. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t. I run an analogous analysis to investigate whether the channel has been operating differently during normal and crisis times.

Lastly, I analyze the database at the level of each bank-pair at time t, ijt, to investigate whether shift-contagion has occurred at the onset of the financial crisis in Germany. In this case, shift-contagion (defined as a significant increase in linkages) corresponds to the correlation in asset prices increasing comparably more during the respective period for banks with a higher overlap in their security portfolios. To shed light on this, I use a difference-in-difference approach around the fire sales events taking place in Germany in the late summer months of 2007. I use two pre-treatment periods (Q1 and Q2 2007) and two post-treatment periods (Q3 and Q4 2007). My treatment variable is the continuous value of the commonality index $\Omega_{ij\tau}$. Precisely, I run the dyadic difference-in-difference model

$$|\mathring{\mathrm{R}}_{it} - \mathring{\mathrm{R}}_{jt}| = \alpha_{ij} + \delta_0 \mathbf{1}_{\mathrm{POST}} + \delta_1 \mathbf{1}_{\mathrm{POST}} * \Omega_{ijT} + \epsilon_{ijt} \, ,$$

where $|\mathring{\mathrm{R}}_{it} - \mathring{\mathrm{R}}_{jt}|$ is the distance between exclusively held portfolio returns of banks i and j at time t, $\mathbf{1}_{\mathrm{POST}}$ is an indicator for whether the observation lies in the post-treatment period, α_{ij} is a pair fixed effect and Ω_{ijT} is the value of the commonality index in the second quarter of 2007.

1.4 Empirical Analysis

1.4.1 Baseline Specification

I begin by estimating the baseline regression model of Equation 1.1 introduced in Section 1.3. I consider different variants of the specification with respect to the inclusion of fixed effects.

I hypothesize that excess returns on banks' exclusively held portfolios should be positively related given that two banks have common exposures in other parts of their portfolios. If two banks do not have any commonality in their security investments, then we should not see this effect. Table 1.2 contains the regression results for the baseline regression model.

Table 1.2: VARIANTS OF BASELINE REGRESSION

VARIABLES	(1) Exc Portfolio$_{it}$	(2) Exc Portfolio$_{it}$	(3) Exc Portfolio$_{it}$	(4) Exc Portfolio$_{it}$
Con Portfolios$_{it-1}$	0.0235***	.0234***	.0195***	.0182***
	(.0026)	(.0040)	(.0042)	(.0046)
Uncon Portfolios$_{it-1}$	-.0112***	-.0050	.0040	.0006
	(.0021)	(.0036)	(.0039)	(.0042)
$F(\beta_1 = \beta_2)$	58.79	14.78	8.56	4.14
Number of Observations	32384	32384	32384	32384
Adjusted R Squared	0.0011	0.0236	0.0742	0.0954
Bank Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	No	Yes	No	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table shows coefficient estimates and standard errors for different variants of the baseline regression model

$$\mathring{R}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{R}_{jt-1} + \beta_2 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{R}_{kt-1} + \epsilon_{it} \,,$$

where $\mathring{R}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

I find that banks' excess returns on exclusively held portfolios are positively related given that two banks have an overlap in their securities portfolios. The significance of the coefficient is not affected by the inclusion of different fixed effects, and its magnitude changes only slightly: an increase in the portfolio return of bank i by 1 percentage point is related to an average increase in the portfolio return of bank j by 0.018 percentage points. For two unconnected banks i and k, however, I do not find such effect after controlling for fixed effects related to the time or bank dimension. In all specifications, the difference in coefficients between both groups, connected and unconnected banks, is statistically significant.

In the above specification, we might suspect that two banks which hold overlapping portfolio exposures might be otherwise connected through alternative channels such as loans and deposits, which could then drive results. To address this concern, I run another variant of the baseline specification with additional control variables. Specifically, I include variables to control for the asset side and the liability side of the balance sheet of each bank i at time $t-1$ in the regression framework. In particular, I run

$$\begin{aligned}\mathring{\mathrm{R}}_{it} = &\alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} + \beta_2 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\mathrm{R}}_{kt-1} \\ &+ \beta_3 \mathrm{NFL}_{it} + \beta_4 \mathrm{FL}_{it} + \beta_5 \mathrm{CR}_{it} \\ &+ \beta_6 \mathrm{DEP}_{it} + \beta_7 \mathrm{WF}_{it} + \beta_8 \mathrm{EQ}_{it} + \epsilon_{it}\,,\end{aligned} \tag{1.3}$$

where NFL_{it} is the logarithm of the value of bank i's loans to the non-financial sector at time t, FL_{it} is the logarithm of the value of bank i's loans to the financial sector at time t, CR_{it} is the logarithm of the value of bank i's cash reserves at time t, DEP_{it} is the logarithm of the value of bank i's deposits at time t, WF_{it} is the logarithm of the value of bank i's wholesale funding at time t and EQ_{it} is the logarithm of the value of bank i's equity at time t. Results are shown in Table 1.3.

I find that the additional inclusion of variables capturing both the asset and the

Table 1.3: Variants of Baseline Regression with Alternative Channels of Interconnectedness

VARIABLES	Exc Portfolio$_{it}$	Exc Portfolio$_{it}$	Exc Portfolio$_{it}$
Con Portfolios$_{it-1}$	.0177***	0179***	.0171***
	(.0045)	(.0045)	(.0047)
Uncon Portfolios$_{it-1}$	1.09e-10	.0007	-.0018
	(9.67e-11)	(.0042)	(.0043)
Loans to Fin. Sector$_{it-1}$	-1.96 e-11		2.16e-10
	(1.25 e-10)		(1.74e-10)
Loans to Non-Fin. Sector$_{it-1}$	-2.09e-13		-2.32e-11
	(1.34e-10)		(2.92e-10)
Cash Reserves$_{it-1}$	-1.10e-08		5.58e-09
	(1.75e-08)		(2.48e-08)
Deposits$_{it-1}$		-6.20e-10	2.43e-10
		(1.20e-09)	(1.55e-09)
Wholesale Funding$_{it-1}$	-	2.35e-11	-3.04e-10
		(1.92e-10)	(.2.27e-10)
Equity$_{it-1}$		-1.30e-10	1.39e-09
		(5.86e-10)	(.9.69e-10)
$F(\beta_1 = \beta_2)$	3.88	4.01	4.54
Observations	32344	32345	32343
Adjusted R Squared	0.0951	0.0953	0.0732
Bank Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table shows coefficient estimates and standard errors for different variants of the baseline regression model with additional control variables

$$\mathring{R}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{R}_{jt-1} + \beta_2 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{R}_{kt-1} + \beta_3 \mathrm{NFL}_{it} + \beta_4 \mathrm{FL}_{it} + \beta_5 \mathrm{DEP}_{it} + \epsilon_{it} \,,$$

where NFL_{it} is the logarithm of value of bank is loans to the non-financial sector at time t, FL_{it} is the logarithm of value of bank is loans to the financial sector at time t and DEP_{it} is the logarithm of value of bank is deposits at time t.

liability side of banks' balance sheets in the analysis does not have an effect on the coefficients of interest, neither in terms of significance nor order of magnitude.

While clustering at the bank level is a natural specification for the analysis, I acknowledge that the choice of standard errors has a significant effect on analysis outcomes. I therefore run a last variant of the baseline regression with different standard errors: Huber White standard errors and two-way clustered standard errors along both bank and time. For comparison purposes, I report again the results of this regression with cluster-robust standard errors clustered at the bank level. Results for these specifications are displayed in Table 1.4.

Table 1.4: Variants of Baseline Regression with Different Standard Errors

VARIABLES	(1) Exc Portfolio$_{it}$	(2) Exc Portfolio$_{it}$	(3) Exc Portfolio$_{it}$
Con Portfolios$_{it-1}$	.0181515***	.0181515***	.0181515***
	(.0048354)	(.0045572)	(.0029874)
Uncon Portfolios$_{it-1}$	.0005877	.0005877	.0005877
	(.0043757)	(.0042277)	(.0034385)
$F(\beta_1 = \beta_2)$	3.80	4.14	7.65
Number of Observations	32346	32346	32346
Adjusted R Squared	0.0928	0.0928	0.0928
Bank Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Clustering Dimension	None	Bank	Bank-Time

Respective standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table shows coefficient estimates and standard errors for different variants of the baseline regression model with different standard errors

$$\mathring{R}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{R}_{jt-1} + \beta_2 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{R}_{kt-1} + \epsilon_{it}\,,$$

where $\mathring{R}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. To account for time and cross-sectional heterogeneity, I include both bank fixed effects α_i and year fixed effects α_t.

I find that the choice of the clustering dimension does not alter significance levels of any of the coefficients. I conclude that my empirical findings are robust with respect to the choice of standard errors used to carry out inference.

1.4.2 Extended Specification: Subsample Specific Effects

In order to capture subsample-specific effects, I consider an extension of the baseline specification stated in Equation 1.2. I expect intrinsic bank characteristics to play an important role in the transmission of shocks to security prices, and the network channel to asset price correlations to operate differently for bank categories defined along various dimensions. Regarding the influence of bank size and connectivity on network stability, Caccioli *et al.* (2012) suggest the existence of two different regimes: with low average connectivity, a bank's position in the network plays a more important role than its size. That is, in the presence of low connectivity, too-interconnected-to-fail takes the center stage, leaving the probability of contagion highest for the most interconnected node. In a regime of high average connectivity, the opposite is true: the probability for contagion is most elevated following a failure of the largest bank in the system. Regarding the influence of leverage, several theoretical models find a non-linear effect. Caccioli *et al.* (2014) find a critical threshold below which financial networks are stable, and above which instability increases with growing leverage. Similarly, Nier, Yang, Yorulmazer, and Alentorn (2008) find that for high levels of equity, financial systems are immune to contagion, whereas default risk sharply increases below a certain level of equity.

Following results from the theoretical literature, the first distinction I consider is bank size defined by total assets. I expect that there might be non-linearities in the network channel to asset price correlations depending on the size of the bank in question. To investigate this, I run an extended specification of the baseline model as specified in Equation 1.2 with bank size as defined by total assets. Results are shown in Table 1.5.

I find that banks' returns on exclusively held portfolios are strongly interrelated

Table 1.5: Subsample Specific Effects by Total Assets

VARIABLES	Exc Portfolio$_{it}$
Con Portfolio$_{it-1}\mathbf{1}_{\text{TA1}}$	.0128**
	(.0045)
Con Portfolio$_{it-1}\mathbf{1}_{\text{TA2}}$	.0131**
	(.0047)
Con Portfolio$_{it-1}\mathbf{1}_{\text{TA3}}$	.0299***
	(.0053)
Uncon Portfolio$_{it-1}$	.0003
	(.0040)
$F(\beta_1 = \beta_2 = \beta_3)$	11.26
Number of Observations	32346
Adjusted R Squared	0.0960
Time Fixed Effects	Yes
Bank Fixed Effects	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$\begin{aligned}\mathring{\text{R}}_{it} =& \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\text{R}}_{jt-1}\mathbf{1}_{\text{TA1}} + \beta_2 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\text{R}}_{jt-1}\mathbf{1}_{\text{TA2}} \\ &+ \beta_3 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\text{R}}_{jt-1}\mathbf{1}_{\text{TA3}} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\text{R}}_{kt-1} + \epsilon_{it} ,\end{aligned}$$

where $\mathring{\text{R}}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. $\mathbf{1}_{\text{TA1}}$ indicates whether bank i belongs to the smallest category of banks according to total assets. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

given that their portfolios overlap, at all three categories of bank size. While significance is unaffected by the choice of category, I however find that the magnitude of interrelation differs according to bank size. For banks in the smallest category, an average increase of excess portfolio returns of connected banks by 1 percentage point is associated with an increase of 0.0128 percentage points. This effect is more than twice as large for banks in the largest size category as defined by total assets: an average increase in portfolio returns of connected banks by 1 percentage point is associated with an increase of 0.0299 percentage points.

The second distinction I analyze is the leverage ratio, as defined by total book equity over total book assets. Again, I run an extended specification of the baseline model with three equally sized categories of banks distinguished by book leverage. Results are depicted in Table 1.6.

Similarly to before, I find that significance of the coefficient is unaffected by the choice of category, but that its magnitude is roughly 1.5 times as large for banks that are highly leveraged. Notice, however, that the t test does not reject the coefficients being of equal magnitude.

Third, I run an extended specification where different categories of banks are defined according to their position in the asset commonality network. As a distinguishing variable I choose the degree of each bank, defined as the number of banks that bank i is connected to at time t through overlapping securities holdings, $\deg_{it} = \sum_{j \neq i} \mathbf{1}_{\Omega_{ijt} \neq 0}$. Results are shown in Table 1.7.

Again, I find that significance of the coefficient is unaffected by the choice of category, but that its magnitude is more than twice as large for banks that are highly interconnected. Results are aligned with predictions by theoretical models: security price spillovers among connected portfolios are especially pronounced for banks which are large, highly leveraged and at the center of the asset commonality network. In

Table 1.6: Subsample Specific Effects by Leverage Ratio

VARIABLES	Exc Portfolio$_{it}$
Con Portfolio$_{it-1}\mathbf{1}_{\text{LEV1}}$	.0146**
	(.0048)
Con Portfolio$_{it-1}\mathbf{1}_{\text{LEV2}}$	.0189***
	(.0050)
Con Portfolio$_{it-1}\mathbf{1}_{\text{LEV3}}$	.0217***
	(.0048)
Uncon Portfolio$_{it-1}$	.0005
	(.0040)
$F(\beta_1 = \beta_2 = \beta_3)$	2.14
Number of Observations	32346
Adjusted R Squared	0.0955
Time Fixed Effects	Yes
Bank Fixed Effects	Yes

Cluster robust standard errors in parenthesis

*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$\begin{aligned}\mathring{\mathrm{R}}_{it} =& \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{\text{LEV1}} + \beta_2 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{\text{LEV2}} \\ &+ \beta_3 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{\text{LEV3}} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\mathrm{R}}_{kt-1} + \epsilon_{it} \,,\end{aligned}$$

where $\mathring{\mathrm{R}}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. $\mathbf{1}_{\text{LEV1}}$ indicates whether bank i belongs to the smallest category of banks according to book leverage. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

Table 1.7: Subsample Specific Effects for Degree

VARIABLES	Exc Portfolio$_{it}$
Con Portfolio$_{it-1}\mathbf{1}_{\text{DEG1}}$	.0116*
	(.0051)
Con Portfolio$_{it-1}\mathbf{1}_{\text{DEG2}}$	.0151**
	(.0050)
Con Portfolio$_{it-1}\mathbf{1}_{\text{DEG3}}$	.0265***
	(.0051)
Uncon Portfolio$_{it-1}$	.0005
	(.0042)
$F(\beta_1 = \beta_2 = \beta_3)$	8.34
Number of Observations	32346
Adjusted R Squared	0.0957
Time Fixed Effects	Yes
Bank Fixed Effects	Yes
Security Type Controls	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$\mathring{\mathrm{R}}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{\text{DEG1}} + \beta_2 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{\text{DEG2}}$$
$$+ \beta_3 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{\text{DEG3}} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\mathrm{R}}_{kt-1} + \epsilon_{it} \,,$$

where $\mathring{\mathrm{R}}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. $\mathbf{1}_{\text{DEG1}}$ indicates whether bank i belongs to the smallest category of banks according to their degree. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

terms of coefficient magnitude, I find the largest effect of the fire sales channel to security price correlations for banks which are largest by total assets, hinting towards a too-big-to-fail regime. This result is in line with Caccioli *et al.* (2012) given that the asset commonality network in my case is closer to their second regime, with average connectivity among financial institutions being high.

After investigating differential effects at the level of single banks, I investigate whether we can find a time-varying pattern for crisis versus normal times. To do so, I define a crisis period to run from the third quarter of 2007 until the fourth quarter or 2009. I then run an extended specification of the baseline model where observations are split into two time periods. Precisely, I run

$$\begin{aligned} \mathring{\mathrm{R}}_{it} = & \alpha_i + \alpha_i + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{\text{CRISIS}} \\ & + \beta_2 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} (1 - \mathbf{1}_{\text{CRISIS}}) + \epsilon_{it} \,, \end{aligned} \tag{1.4}$$

where $\mathring{\mathrm{R}}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns and $\mathbf{1}_{\text{CRISIS}}$ indicates whether the observation belongs to the financial crisis period as defined above. I expect the channel to be stronger during the financial crisis period due to the impact of asset liquidity. In the case of high market liquidity, one bank's decision to sell off assets has a relatively small impact, making asset prices insensitive. In illiquid markets, however, one sale can cause large price movements. With market liquidity being procyclical, hence higher in normal times and lower in crisis periods, we should see a higher impact of the network channel to asset price correlations during crisis times. Results are shown in Table 1.8.

From the table we can see that the effect is significantly positive only during the period of the financial crisis: an increase in the portfolio return of bank j by 1 percentage point is related to an average increase in the portfolio return of bank i by 0.0194

Table 1.8: Subsample Specific Effects for Crisis vs. Non-Crisis Periods

VARIABLES	Exc Portfolio$_{it}$
Con Portfolio$_{it-1}\mathbf{1}_{\text{CRISIS}}$	.0194***
	(.0046)
Con Portfolio$_{it-1}(1-\mathbf{1}_{\text{CRISIS}})$	-.0086
	(.0107)
Uncon Portfolio$_{it-1}$	.0002
	(.0042)
$F(\beta_1 = \beta_2 = \beta_3)$	7.36
Number of Observations	32346
Adjusted R Squared	0.0955
Time Fixed Effects	Yes
Bank Fixed Effects	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$\begin{aligned}\mathring{\text{R}}_{it} =& \alpha_i + \alpha_i + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\text{R}}_{jt-1}\mathbf{1}_{\text{CRISIS}} \\ &+ \beta_2 \frac{1}{c} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\text{R}}_{jt-1}(1-\mathbf{1}_{\text{CRISIS}}) + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\text{R}}_{kt-1} + \epsilon_{it}\,,\end{aligned}$$

where $\mathring{\text{R}}_{it}$ is the weighted return on bank i's exclusively held portfolio at time t after filtering out a common factor to all security returns. $\mathbf{1}_{\text{CRISIS}}$ indicates whether the observation belongs to the financial crisis period running from the third quarter of 2007 until the fourth quarter of 2009. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

percentage points.

1.4.3 Path Analysis

Above results raise the question of the channel underlying asset price contagion among banks holding overlapping portfolios. One potential channel has been brought forward in Greenwood *et al.* (2015) and is related to sell-offs of securities contained in various bank portfolios. In their model, banks sell assets after being hit by an adverse shock in order to return to target leverage, which creates a negative impact on the price of these assets given that they are not perfectly liquid. This, in turn, can affect the balance sheets of banks holding the same asset. In order to investigate whether said channel could potentially underlie the observed pattern, I run a path analysis of banks' portfolio returns and selling behavior. In particular, I compute for each bank the quantity of assets sold from one quarter to the next as the sum of negative changes in their portfolio holdings,

$$B_{it} = \sum_{s \in \mathrm{S}_{it-1}} \Delta q_{sit} \mathbf{1}_{\Delta q_{sit} < 0} \, ,$$

where q_{sit} denotes the quantity of security s held by bank i at time t. Note that portfolio sales are computed on the entire bank portfolio S_{it}, and not on exclusively held portfolios $\mathring{S}_{it}$.

I then run two types of analyses. In the first analysis, I use the above defined variable in order to investigate whether the contagion channel to asset price correlations is stronger at work for banks with higher portfolio sales. That is, I run the extended specification defining categories according to the magnitude of B_{it}. In particular, I run

$$\mathring{\mathrm{R}}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{B_{it}=0} + \beta_2 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{B_{it}<\tilde{B}_t}$$
$$+ \beta_3 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} \mathbf{1}_{B_{it}\geq\tilde{B}_t} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\mathrm{R}}_{kt-1} + \epsilon_{it} \,,$$

where $\mathring{\mathrm{R}}_{it}$ is the return on the exclusively held portfolio of bank i at time t. $\mathbf{1}_{B_{it}=0}$ indicates that bank i did not sell any securities from time $t-1$ to time t, and $\mathbf{1}_{B_{it}<\tilde{B}_t}$ and $\mathbf{1}_{B_{it}\geq\tilde{B}_t}$ indicate non-zero portfolio sales above or below the median with respect to portfolio sales for all banks in the sample in the respective quarter. Results are shown in Table 1.9.

We can see that banks with no portfolio sales do not show a correlation in portfolio returns with their connected banks in the respective quarter. On the contrary, I find a positive and significant effect given that banks sell parts of their security portfolios. This effect is stronger given that portfolio sales are higher. These results are in line with the hypothesis that observed return correlations could originate from banks' trading behavior related to securities potentially held in common with connected banks.

This motivates me to carry out a path analysis of portfolio sales B_{it} and portfolio returns $\mathring{\mathrm{R}}_{it}$. If the channel outlined above is potentially underlying the results, we should see the path run from low portfolio returns at time $t-2$, to higher sales of securities at time $t-1$, to lower returns of connected banks at time t.

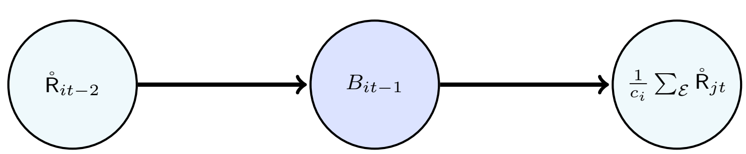


Table 1.9: Subsample Specific Effects for Portfolio Sell-Offs

VARIABLES	Exc Portfolio$_{it}$
Con Portfolio$_{it-1}\mathbf{1}_{B_{it}=0}$	-.0030
	(.0046)
Con Portfolio$_{it-1}\mathbf{1}_{B_{it}<\tilde{B}_t}$	.0188***
	(.0045)
Con Portfolio$_{it-1}\mathbf{1}_{B_{it}\geq\tilde{B}_t}$	.0212***
	(.0049)
Uncon Portfolio$_{it-1}$	-.0017
	(.0038)
$F(\beta_1 = \beta_2 = \beta_3)$	7.79
Number of Observations	32346
Adjusted R Squared	0.0944
Time Fixed Effects	Yes
Bank Fixed Effects	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$\mathring{\mathrm{R}}_{it} = \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{B_{it}=0} + \beta_2 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{B_{it}<\tilde{B}_t}$$
$$+ \beta_3 \frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1}\mathbf{1}_{B_{it}\geq\tilde{B}_t} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t)\notin\mathcal{E}} \mathring{\mathrm{R}}_{kt-1} + \epsilon_{it} \,,$$

where $\mathring{\mathrm{R}}_{it}$ is the return on the exclusively held portfolio of bank i at time t. $\mathbf{1}_{B_{it}=0}$ indicates that bank i did not sell any securities from time $t-1$ to time t, and $\mathbf{1}_{B_{it}<\tilde{B}_t}$ and $\mathbf{1}_{B_{it}\geq\tilde{B}_t}$, indicate non-zero portfolio sales above or below the median with respect to portfolio sales for all banks in the sample in the respective quarter. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

Specifically, I run

$$
\begin{aligned}
B_{it-1} &= \alpha_i + \alpha_t + \beta_1 \mathring{\mathrm{R}}_{it-2} + \epsilon_{it} \\
\frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt1} &= \alpha_i + \alpha_t + \beta_2 \mathring{\mathrm{R}}_{it-2} + \beta_3 B_{it-1} + \epsilon_{it}\ ,
\end{aligned} \tag{1.5}
$$

where $\mathring{\mathrm{R}}_{it}$ is the return on the exclusively held portfolio of bank i at time t and B_{it} indicates the magnitude of its portfolio sell-offs. Following previous findings, I restrict the sample to banks for which $B_{it} \geq \tilde{B}_t$. Results are depicted in Table 1.10.

Table 1.10: Path Analysis

VARIABLES	Portfolio Sell-Offs$_{it}$	Con Portfolios$_{it}$
Exc Portfolio$_{it-2}$	-96001.54*	.0155766*
	(38974.52)	(.0074349)
Portfolio Sell-Offs$_{it}$		-6.20e-12*
		(3.03e-12)
Number of Observations	16721	15822
Adjusted R Squared	0.1579	0.2845
Time Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$
\begin{aligned}
B_{it-1} &= \alpha_i + \alpha_t + \beta_1 \mathring{\mathrm{R}}_{it-2} + \epsilon_{it}\ (1) \\
\frac{1}{c_i} \sum_{(i,j,t)\in\mathcal{E}} \mathring{\mathrm{R}}_{jt-1} &= \alpha_i + \alpha_t + \beta_1 \mathring{\mathrm{R}}_{it-2} + \beta_2 B_{it-1} + \epsilon_{it}\ ,\ (2)
\end{aligned}
$$

where $\mathring{\mathrm{R}}_{it}$ is the return on the exclusively held portfolio of bank i at time t and B_{it} indicates the magnitude of its portfolio sell-offs. To account for time and cross-sectional heterogeneity, I include both bank-fixed effects α_i and year fixed effects α_t.

I find a negative and significant effect running from banks' portfolio returns at time $t-2$ to their portfolio sales at time $t-1$. This means that banks with lower portfolio returns sell higher quantities of their security portfolios. In a second step, I find a positive and significant effect running from banks' portfolio sales to the portfolio returns of connected banks. That is, I observe that if a bank sells a higher quantity of securities at time $t-1$, portfolio returns at banks to which it is connected through common security holdings at time t are lower. The results are in line with the model established by Greenwood *et al.* (2015), such that their outlined mechanism could be a potential channel driving the effects I observe.

1.4.4 Difference-in-Difference Analysis

Lastly, I run a difference-in-difference analysis to investigate the occurrence of what has been referred to as shift-contagion during the financial crisis period. Shift-contagion is characterized not only by a transfer of effects between different entities but also by a significant increase in linkages during the respective period. In my specific case, shift-contagion refers to a comparably higher increase in asset price correlations for bank pairs with a higher overlap in their security portfolios.

The time period chosen for the difference-in-difference analysis is the outbreak of the financial crisis with the burst of the United States housing bubble and the decline in subprime lending in July and August 2007, leading to fire sales across the German financial system. I chose this time period over the bankruptcy of US investment bank Lehman Brothers in September 2008, since the latter occured at a period of high financial turmoil in general, making it more difficult to isolate specific effects. Precisely, I use two pre-treatment periods, which are the first and second quarter of 2007, and two post-treatment periods, which are the third and fourth quarter of 2007.

The outcome variable in the analysis is the absolute value of the difference in banks' returns on their exclusively held portfolio at the level of the bank-pair, $|\mathring{\mathrm{R}}_{it} - \mathring{\mathrm{R}}_{jt}|$. Note that the outcome variable is designed such that lower levels indicate a smaller distance in two banks' portfolio returns, corresponding to a higher level of asset price correlations. The treatment variable is the continuous value of the commonality index $\Omega_{ij\tau}$ in the second quarter of 2007, where higher values indicate a higher level of overlap between banks' security portfolios.

Results for the analysis are displayed in Table 1.11.

Table 1.11: Difference-in-Difference Regression

VARIABLES	(1) Return Distance ijt	(2) Return Distance ijt	(3) Return Distance ijt
Strength of Portfolio Overlap	-.0010 ***	-.0011*	-.0011*
	(.00002)	(.0005)	(.0005)
Pair Fixed Effect	No	Yes	Yes
Time Fixed Effect	No	No	Yes
Observations	3511952	3511952	3511952
Adjusted R Squared	0.0032	0.1353	0.2830

Cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05

This table reports coefficient estimates and standard errors for the regression model

$$|\mathring{R}_{it} - \mathring{R}_{jt}| = \alpha_{ij} + \delta_0 \mathbf{1}_{\text{POST}} + \delta_1 \mathbf{1}_{\text{POST}} * \Omega_{ijT} + \epsilon_{ijt}\,,$$

where $|\mathring{R}_{it} - \mathring{R}_{jt}|$ is the distance between exclusively held portfolio returns of banks i and j at time t, $\mathbf{1}_{\text{POST}}$ is an indicator for whether the observation lies in the post-treatment period, α_{ij} is a pair fixed effect and $\Omega_{ij\tau}$ is the value of the commonality index in the second quarter of 2007.

I find that the distance in returns on exclusively held portfolios has decreased significantly more for banks with higher levels of portfolio overlap. An increase in the commonality index by 0.1, that is an increase in the portfolio overlap of ten percent of the total portfolio of bank i at time t, is accompanied by a decrease in the return distance by 0.0001. Expressed in standard deviations, an increase in the portfolio overlap between two banks by one standard deviation is accompanied by a decrease in return distance by 0.025 standard deviations. This magnitude of the coefficient is robust to the inclusion of a pair fixed effect and a time fixed effect, and the significance decreases only slightly.

1.5 Conclusion

Network interconnections among financial institutions enhance the amount of instability which can be induced to a financial system by shocks which are initially small in size. One example of links which can turn to be contagious in periods of financial turmoil are overlaps in banks' security portfolios through common holdings. The resulting potential for contagion among said security portfolios is largely dependent on the network topology, such that investigating its structure is a necessary exercise from a systemic risk perspective.

In this work I make use of a proprietary database containing security investments of all banks in the German financial system. This allows me to establish an asset commonality network between banks each quarter at the level of the issuer of single securities. I then investigate the topology of the resulting asset commonality network and whether returns of separate bank portfolios show different correlation patterns based on underlying connections.

Making use of banks' exclusively held parts of their portfolios, which I define as securities held by only one bank in the sample at a given point in time, I find evidence pointing to a contagion channel to security prices in said portfolios. This channel is more pronounced for banks that are large, highly leveraged and located at the core of the commonality network. Through a path analysis I detect that a potential underlying channel can be banks' trading behavior following negative returns affecting institutions with overlapping holdings. Lastly, I find evidence for the occurrence of shift-contagion in the summer of 2007 using a difference-in-difference framework of the distance in banks' portfolio returns.

The results established in this paper are relevant from a systemic risk perspective. They indicate a potential contagion channel to asset price correlations which increases those above fundamental levels depending on the underlying holding structure. This, in turn, calls for close monitoring of the asset commonality network of banks, and its potential to spread adverse shocks to the portfolios of single institutions through an entire financial system.

Chapter 2

BANK CREDIT RISK NETWORKS: EVIDENCE FROM THE EUROZONE

2.1 Introduction

One of the lessons learnt in Europe in recent years is the systemic relevance of the financial sector and the potential risks of excessive interconnectedness. In Germany, several banks suffered a sharp increase in their CDS prices in January 2009 following financial turmoil at Commerzbank surrounding their takeover of Dresdner Bank. In Italy, a scandal about secret derivative trading to conceal losses conducted by Monte dei Paschi di Siena lead to a surge in CDS prices of the entire Italian banking sector in January 2013. In both cases, cross-border linkages with banks in the Eurozone propagated the distress throughout Europe. As a result, several European countries introduced costly rescue packages for banks perceived as “too big to fail” or “too interconnected to fail” in order to mitigate the crises in their banking sectors. In response to these events, current bank regulation focuses on systemically relevant institutions. However, the detection of the network of credit risk interconnections between financial institutions and the identification of highly interconnected firms is still to this date an empirically challenging task.

The finance literature identifies two broad channels that induce dependence in the default risk of financial institutions: common exposure to a systematic shock and dependence between the idiosyncratic shocks of individual banks. As explained in Ang and Longstaff (2013), the systematic channel is associated with both macroeconomic or financial shocks. The effect of macroeconomic or financial shocks on the financial system has been the scope of extensive research, such as Calomiris and Mason (2003), Kritzman, Yuanzhen, Page, and Rigobon (2011) and Stein (2012). At the same time, dependence can arise among the idiosyncratic shocks to banks, both through direct and indirect connections. Direct counterparty exposures between banks stem from the interbank market or obligations such as syndication and have been studied in Allen and Gale (2000), Mistrulli (2011), Suhua *et al.* (2013) or Hale *et al.* (2013). Additionally, banks can be linked indirectly when holding similar portfolios, as shown in Gai *et al.* (2011), and Caballero and Simsek (2013).

Ang and Longstaff (2013) develop a credit risk model that focuses on systematic shocks. The authors build upon the standard reduced form models for pricing credit derivatives used in the finance literature (e.g. Duffie and Singleton, 1999) and propose a multifactor affine model in which defaults of individual financial institutions can be triggered by either systematic or idiosyncratic shocks. Dependence across the idiosyncratic shocks of different institutions is however ruled out by assumption, and default dependence only arises because of the systematic channel.

Despite the fundamental relevance of the systematic channel, in a study of forty three financial crises Alfaro and Drehmann (2009) find that only half of them occurred before the macroeconomy experienced adverse economic shocks. This motivates us to extend the Ang and Longstaff (2013) modelling approach by allowing for network type dependence among the idiosyncratic shocks of individual banks. More specifically, we assume that the idiosyncratic shocks have a sparse conditional dependence network structure, which we call the bank credit risk network. The network is defined as an undirected graph where vertices represent financial institutions and the presence of an edge between vertices i and j denotes that the financial institutions i and j are not independent conditional on all other entities in the panel. We work under the assumption that the network is sparse, which in this work means that each financial institution is not connected with all other financial institution in the panel (i.e. the network is not complete). In our framework, the conditional dependence network structure is entirely characterized by the inverse covariance matrix (also known as concentration matrix) of the idiosyncratic shocks. Exploiting well known results from the graphical literature (Dempster, 1972), we have that in our model i and j are conditionally independent iff the (i, j) entry of the inverse covariance matrix is zero. This implies that assuming that the idiosyncratic shocks have a sparse conditional dependence network structure can be more simply characterized by assuming that the inverse covariance matrix is sparse.

We develop an estimation strategy to recover the bank credit risk network from CDS data. The systematic default intensity for each entity is identified as the one of the respective sovereign. We begin by noting that standard pricing formulas for single-name Credit Default Swap (CDS) contracts derived in Ang and Longstaff (2013) still apply despite the network assumption. This allows to use standard procedures to bootstrap risk neutral default intensities from CDS data. In a second step, we estimate the covariance matrix of the idiosyncratic shocks as the covariance matrix of the idiosyncratic risk neutral intensity first difference. Last, we apply a LASSO type regularization algorithm to regularize the covariance (cf Yuan and Lin, 2007; Friedman, Hastie, and

Tibshirani, 2011; Banerjee and Ghaoui, 2008). The procedure allows to simultaneously estimate the elements of the concentration matrix of the idiosyncratic shocks and select the non-zero entries. Our modelling approach has a number of highlights. Through bootstrapping intensities rather than working with CDS spreads directly we can make use of the entire term structure of CDS contracts, and interpret obtained partial correlations as interconnections between the default probabilities of two entities rather than their CDS prices. It is also important to emphasize that the bootstrapped intensity adjusts for the yield curve, which indeed changed dramatically throughout the sample period of our analysis. Overall, our estimation approach can be used to estimate the bank credit risk network in large panels of financial institutions and can serve well as a tool for measuring and monitoring interconnectedness.

We apply this methodology to study a sample of top financial institutions from ten selected Eurozone countries in between 2006 and 2013. The sample includes two dramatic periods for banks in the Eurozone: the financial crisis of 2007–2009 and the European sovereign debt crisis of 2010–2012. A number of empirical findings emerge from our analysis.

First of all, we find that the network channel captures a substantial amount of cross sectional dependence. The important implication of this is that the probability of joint defaults can be severely underestimated when one does not take into account the network channel. Estimation results reveal that the channel is more relevant for core countries. We interpret this as a consequence of the sovereign debt crisis. As the crisis widens and credit risk increases, GIIPS banks become more tightly interrelated with their respective sovereigns.

As far as the structure of the network is concerned, we find evidence of both intra- and inter-country linkages between banks in Europe. The network reveals that the most central banks are typically large financial institutions located in core Eurozone countries. In particular, the analysis shows that BNP Paribas and Deutsche Bank are two of the most central institutions. Last, the network contains a small percentage of links but it has a power law structure implying small world effects in credit risk interdependence.

A rolling-window analysis shows that during crisis periods, heavily affected financial institutions become hubs in the center of the bank credit risk network, with both a high number and increased strength of connections. This is relevant from a contagion perspective, since otherwise healthy institutions in core countries can be affected by idiosyncratic shocks to troubled banks in the periphery. In crisis periods, these hub institutions can quickly spread adverse shocks and lead to major downturns, such that their identification and monitoring is crucial for the health of the financial system.

Finally, an out–of–sample validation exercise is used to evaluate our methodology. We use our model to forecast the out–of-sample covariance matrix of idiosyncratic intensities and contrast results with a number of alternative benchmarks. Results show that our network based estimator provides the most accurate forecasts of credit risk interdependence between banks.

This research is related to a number of contributions in the literature. First, this work is related to the literature on credit risk through cds in finance and financial econometrics which includes the work of Duffie and Singleton (1999), Lando (1998) and Longstaff, Mithal, and Neis (2005). Second, our paper is related to the literature on network estimation techniques. The list of contributions in this area is rapidly growing and it includes, among others, the work of Billio, Getmanksi, Lo, and Pellizzon (2012), Diebold and Yilmaz (2011), Hautsch, Schaumburg, and Schienle (2014), and Barigozzi and Brownlees (2013).

The rest of the paper is structured as follows. Section 2.2 introduces the model and the estimation procedure. Section 2.3 contains the empirical analysis of the paper.

Concluding remarks follow in Section 2.4.

2.2 Methodology

We introduce a reduced form credit risk model in which default dependence among financial entities arises through three channels: a global factor, a country factor and a bank network channel. The model is a variant of standard affine multifactor models used in the credit risk literature. The notation we adopt to describe the model is drawn from Aït-Sahalia, Laeven, and Pellizzon (2014).

2.2.1 Credit Risk Model

Global Credit Risk Factor

Credit events are modelled as jumps of a Poisson process with stochastic intensity.

The global shock is modelled as the jump of a Poisson process $M_G(t)$ with intensity parameter λ_G that follows a standard square root process,

$$d\lambda_G(t) = a_G(m_G - \lambda_G(t))dt + b_G\sqrt{\lambda_G(t)}dW_G(t)\,,$$

where $W_G(t)$ denotes a Brownian motion.

Sovereign

We consider a panel of s different sovereigns, observed over n days. The default of sovereign ℓ can be triggered by two different types of credit events: The first type is a systematic global shock, affecting all sovereigns in the panel simultaneously. Conditional on each global shock, the probability that sovereign ℓ defaults is denoted as $\gamma_{\ell,G} \in (0,1)$.

The second type is a country-specific shock that triggers default of the respective sovereign with certainty. It is modelled as the jump of a Poisson process $M_\ell(t)$ with intensity parameter λ_ℓ that follows a standard square root process,

$$d\lambda_\ell(t) = a_\ell(m_\ell - \lambda_\ell(t))dt + b_\ell\sqrt{\lambda_\ell(t)}dW_\ell(t)\,,$$

where $W_\ell(t)$ denotes a Brownian motion independent of the one driving the global intensity process $W_G(t)$.

Banks

We consider a panel of m financial entities each belonging to one of the s sovereigns, and equally observed over a period of n days.

The default of institution i can now be triggered by three different types of credit events: a systematic global shock, a systematic sovereign shock and an entity-specific idiosyncratic shock.

The probability that entity i defaults following a systematic global shock is denoted as $\gamma_{i,G} \in (0, 1)$, while the probability of default following a systematic sovereign shock is denoted as $\gamma_{i,\ell} \in (0, 1)$.

The idiosyncratic shock of firm i is modelled as the first jump of a Poisson process $N_i(t)$ with intensity parameter ξ_i that follows a standard square root process,

$$d\xi_i(t) = \alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t)\,,$$

where $B_i(t)$ denotes an entity specific Brownian motion independent of the one driving the systematic global intensity process $W_G(t)$ and the systematic sovereign intensity process $W_\ell(t)$. Following an idiosyncratic shock, firm i defaults with certainty.

Also, we denote by $\mathcal{F}_t$ the natural σ-algebra generated by the Brownian motions

$B_i(t)$, $W_G(t)$ and $W_\ell(t)$.

The literature typically assumes that the Brownian motions $B_i(t)$ driving the idiosyncratic shocks are independent, as, *inter alia*, in the model of Ang and Longstaff (2013). In this model we work under the more general assumption that the Brownian motions have a sparse conditional dependence network structure. The conditional dependence network of the Brownian motions $B_i(t)$ is defined as an undirected graph $\mathcal{N} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = 1, ..., m$ is the set of vertices and $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$ is the set of edges. If the Brownian motions $B_i(t)$ and $B_j(t)$ are conditionally independent given all others then vertices i and j are not connected by an edge in the network (and vice versa), that is

$$B_i(t) \perp B_j(t) \mid \{B_k(t) : k \neq i, j\} \Leftrightarrow (i, j) \notin \mathcal{E} \ ,$$

where $X \perp Y$ means that the random variables X and Y are independent. As it is well known since at least Dempster (1972), the conditional dependence graphical structure of the Brownian motions is entirely characterized by their inverse covariance matrix, which is also known as concentration matrix. Let $\Sigma = [\sigma_{ij}]$ denote the instantaneous covariance matrix of the Brownian motion vector $B(t) = (B_1(t), ..., B_m(t))'$, that is, $B(t) \sim \mathcal{N}(0, \Sigma t)$, and let $K = [k_{ij}]$ denote its inverse. It can be shown that if i and j are conditionally independent then k_{ij} is equal to zero (and vice versa). This implies that the network structure of the Brownian motions is entirely encoded in the sparsity structure of the concentration matrix K, that is,

$$\mathcal{E} = \{(i, j) : k_{ij} \neq 0\} \, .$$

Thus, assuming that the Brownian motions have a sparse conditional dependence network structure representation corresponds to assuming that the concentration matrix K is sparse.

It is straightforward to check that idiosyncratic intensity vector $\xi(t) = (\xi_1(t), ..., \xi_m(t))'$ have the same network conditional dependence structure of the Brownian motion vector $B(t)$. The instantaneous covariance matrix $\Sigma_\xi(t)$ of the intensity vector $\xi(t)$ is

$$(\Sigma_\xi(t))_{ij} = \sqrt{\xi_i(t)\xi_j(t)}\,\sigma_{ij}.$$

The integrated covariance matrix Σ_ξ^* of the intensity vector $\xi(t)$ over the time interval $[0, n-1]$, which measures the total covariation over the entire sample, is given by

$$\left(\Sigma_\xi^*\right)_{ij} = \sigma_{ij} \int_0^{n-1} \sqrt{\xi_i(t)\xi_j(t)}\, dt,$$

and the corresponding integrated concentration matrix is $K_\xi^* = (\Sigma_\xi^*)^{-1}$. It can be shown that if K is sparse then K_ξ^* is also sparse. Indeed, since the trajectories of the intensities ξ_i are a.s. continuous, we can apply the mean value theorem for integrals, and we get the existence of a point $s \in (0, n-1)$ such that

$$\int_0^{n-1} \sqrt{\xi_i(t)\xi_j(t)}\, dt = (n-1)\sqrt{\xi_i(s)\xi_j(s)} \quad \text{a.s.}$$

Therefore, we have that

$$\Sigma_\xi^* = (n-1) D_s \Sigma D_s,$$

where D_s is the diagonal matrix with the vector $(\sqrt{\xi_1(s)}, ..., \sqrt{\xi_n(s)})$ on the diagonal. In particular, the integrated concentration matrix can be written as

$$K_\xi^* = \frac{1}{n-1} D_s^{-1} K D_s^{-1},$$

which proves that if K is sparse so will be K_ξ^* (almost surely). Observe that in our argument we have also used the fact that $\xi_i(s) > 0$ almost surely.

We define the bank credit risk network as the sparse conditional dependence dependence network implied by the integrated concentration matrix K^*_ξ of the idiosyncratic intensity vector $\xi(t)$. We use the partial correlations implied by the integrated concentration matrix K^*_ξ as a measure of the strength of the relationship between the idiosyncratic intensities. The partial correlation between entity i and j is defined as

$$\rho^{ij} = \frac{-k^*_{ij}}{\sqrt{k^*_{ii} k^*_{jj}}},$$

and measures the correlation between the idiosyncratic intensities of bank i and j obtained after netting out the influence of the other intensities in the panel.

2.2.2 CDS Pricing

One of the key quantities of interest for credit derivative pricing is the $\mathcal{F}_t$-conditional probability of survival to a future time T for a financial entity. In our framework, the probability that entity i has not defaulted by time T equals the probability that no idiosyncratic shock occurs until time T times the probability that the entity does not default following any of potentially many global shocks (with probability $1 - \gamma_{i,G}$ each) and systematic shocks (with probability $1 - \gamma_{i,\ell}$ each). In terms of conditional probabilities, this writes as

$$
\begin{aligned}
&p_i(t,T) \\
&= \mathsf{P}\left(N_i(T)-N_i(t)=0 \,|\, \mathcal{F}_t\right) \mathsf{E}\left((1-\gamma_{i,G})^{M_G(T)-M_G(t)} \,|\, \mathcal{F}_t\right) \mathsf{E}\left((1-\gamma_{i,\ell})^{M_\ell(T)-M_\ell(t)} \,|\, \mathcal{F}_t\right) \\
&= \mathsf{E}\Bigg(\exp\left(-\int_t^T \xi_i(s)\,ds\right) \times \sum_{g=0}^{\infty} \frac{1}{g!} \exp\left(-\int_t^T \lambda_G(s)\,ds\right) \left((1-\gamma_{i,G}) \int_t^T \lambda_G(s)\,ds\right)^g \\
&\qquad\quad \times \sum_{j=0}^{\infty} \frac{1}{j!} \exp\left(-\int_t^T \lambda_\ell(s)\,ds\right) \left((1-\gamma_{i,\ell}) \int_t^T \lambda_\ell(s)\,ds\right)^j \,|\, \mathcal{F}_t\Bigg) \\
&= \mathsf{E}\left(\exp\left(-\int_t^T \left(\gamma_{i,G}\lambda_G(s)+\gamma_{i,\ell}\lambda_\ell(s)+\xi_i(s)\right) ds\right) \,|\, \mathcal{F}_t\right),
\end{aligned}
$$

where we are assuming that all computations are done under a risk-neutral probability measure. It follows from the last equation that the standard reduced form framework can be applied for valuing credit derivatives by setting the instantaneous probability of default for entity i proportional to $\gamma_{i,G}\lambda_G(s)+\gamma_{i,\ell}\lambda_\ell(s)+\xi_i(s)$. Also notice that in this modelling framework the instantaneous firm default intensity has a factor type representation.

A Credit Default Swap (CDS) is a financial swap agreement through which the CDS seller compensates the CDS buyer in case of a credit event (e.g. default). We denote by $s_{i\,t}^k$ the CDS spread of entity $i=1,...,m$ on day t with maturity k equal to $1,...,5$ corresponding to the maturities of 2, 3, 5, 7 and 10 years. We assume the spread to be paid continuously. Next to the CDS spread, we assume that there exists a risk-free asset, and we denote the associated (continuously compounded) risk-free rate by r_t and the price at time t of the zero-coupon bond with maturity T by $D(t,T)$, so that $D(t,T)=\mathsf{E}\left[\exp\left(-\int_t^T r(s)ds\right) \,|\, \mathcal{F}_t\right]$. We assume that the risk-less rate is independent of all intensity processes.

The CDS contract consists on two legs, the spread leg and the protection leg. The value of the CDS spread leg at time t of entity i is given by

$$s_{it}^k \int_t^T D(t,s)\mathsf{E}\left[\exp\left(-\int_t^s (\gamma_{i,G}\lambda_G(u) + \gamma_{i,\ell}\lambda_\ell(u) + \xi_i(u))du\right) \mid \mathcal{F}_t\right] ds.$$

with T equal to $t+2$, $t+3$, $t+5$, $t+7$ and $t+10$ for k equal respectively to $1, ..., 5$. The value at time t if the CDS protection leg of entity i is given by

$$\begin{aligned}\text{CDS(protection leg)}_t = \omega \int_t^T D(t,s)\mathsf{E}\Big[&(\gamma_{i,G}\lambda_G(s) + \gamma_{i,\ell}\lambda_\ell(s) + \xi_i(s)) \\ &\times \exp\left(-\int_t^s (\gamma_{i,G}\lambda_G(u) + \gamma_{i,\ell}\lambda_\ell(u) + \xi_i(u))du\right) \mid \mathcal{F}_t\Big]ds,\end{aligned} \tag{2.1}$$

where $1-w$ is the recovery rate. To meet the no arbitrage condition, the protection leg and the premium leg of a CDS contract must be equal, and we can get out the value of premium payments,

$$s_{it}^k = \frac{\text{CDS(protection leg)}_t}{\int_t^T D(t,s)\mathsf{E}^Q\left[\exp\left(-\int_t^s(\gamma_{i,G}\lambda_G(u) + \gamma_{i,\ell}\lambda_\ell(u) + \xi_i(u))du\right) \mid \mathcal{F}_t\right] ds}.$$

As shown in the Appendix, we can rewrite the CDS spread for each entity i as

$$s_{it}^k = \frac{\text{CDS(protection leg)}_t}{\int_t^T D(t,s) F_{s,t}^{i,G}(\lambda_G) F_{s,t}^{i,\ell}(\lambda_\ell) G_{s,t}(\xi_i) ds}, \tag{2.2}$$

where

$$\begin{aligned}\text{CDS(protection leg)}_t = \omega \int_t^T D(t,s)\Big(&\big(\gamma_{i,G} I_{s,t}^{i,G}(\lambda_G) F_{s,t}^{i,\ell}(\lambda_\ell) \\ &+ \gamma_{i,\ell} I_{s,t}^{i,\ell}(\lambda_\ell) F_{s,t}^{i,G}(\lambda_G)\big) G_{s,t}(\xi_i) + F_{s,t}^{i,G}(\lambda_G) F_{s,t}^{i,\ell}(\lambda_\ell) H_{s,t}(\xi_i)\Big) ds,\end{aligned}$$

where $\lambda_G = \lambda_G(t)$, $\lambda_\ell = \lambda_\ell(t)$ and $\xi_i = \xi_i(t)$, and the functions F, G, I, H are standard and defined in the appendix. It is important to stress that despite the idiosyncratic shocks network dependence assumption the pricing of single–name CDS carries through unaltered.

2.2.3 Estimation

We carry out inference on the bank credit risk network by combining standard estimation techniques based on CDS prices (Duffie and Singleton, 1999; Ang and Longstaff, 2013; Aït-Sahalia *et al.*, 2014) together with LASSO type estimation (Tibshirani, 1996; Friedman *et al.*, 2011).

First, we estimate the bank credit risk model parameters $\alpha_i, \mu_i, \sigma_i$ for each bank in the panel by minimizing the squared pricing errors between the model implied CDS prices $\hat{s}^k_{i\,t}$ and the observed CDS price $s^k_{i\,t}$, that is

$$\hat{\theta}_i = \arg\min_{\theta_i} \sum_{t=1}^{n} \sum_{k=1}^{5} (s^k_{i\,t} - \hat{s}^k_{i\,t})^2 \ ,$$

where $\theta_i = (\alpha_i, \mu_i, \sigma_i, \gamma_i)'$.

Note that the evaluation of this objective function requires performing a series of intermediate optimizations. For a given value of θ_i we "bootstrap" the corresponding idiosyncratic intensity ξ_i for each day. That is, for each day we find the ξ_i which minimizes the squared CDS pricing error across all maturities keeping the value of the parameters fixed to θ_i. This is not available in closed form but can be easily computed by nonlinear least squares. Then, the value of the objective function is computed as the sum the squared CDS pricing errors corresponding to θ_i and the sequence of bootstrapped idiosyncratic intensities ξ. The CDS mispricing error objective function is then minimized using a gradient based algorithm. As Ang and Longstaff (2013) point out, note that ξ captures the level of the CDS term structure while the α, μ, σ capture its shape. In order to estimate the bank credit risk model we need to identify the systematic intensity λ. This is identified with the intensity of the corresponding sovereign of each bank and it is bootstrapped from the factor credit risk model using sovereign CDS prices following the same estimation strategy used for the bank credit risk model.

Next, we estimate the integrated covariance matrix Σ^*_ξ using the bootstrapped idiosyncratic default intensity $\hat{\xi}(t)$ using the bank credit risk model estimates obtained in the previous step. This is estimated using the idiosyncratic intensity realized covariance matrix, that is

$$\widehat{\Sigma}^*_\xi = \sum_{t=2}^{n} (\hat{\xi}(t) - \hat{\xi}(t-1))(\hat{\xi}(t) - \hat{\xi}(t-1))' \ .$$

Realized covariance estimators have a long tradition in finance (cf Merton, 1980) in the estimation of equity volatility, and have recently been rediscovered in the financial econometrics literature (cf Andersen, Bollerslev, Diebold, and Labys, 2003) which has thoroughly analysed the properties of these type of estimators.

Finally, we use the Graphical LASSO procedure (GLASSO) to estimate the integrated concentration matrix K^*_ξ and the bank credit risk network. The estimator is defined as

$$\widehat{K}^*_\xi = \arg \min_{K \in \mathcal{S}^n} \left\{ \mathrm{tr}(\widehat{\Sigma}_\xi K) - \log\det(K) \ + \kappa \sum_{i \neq j} |k_{ij}| \right\} \ , \tag{2.3}$$

where $\kappa \geq 0$ and $\mathcal{S}^n$ is the set of $n \times n$ symmetric positive definite matrices. We denote by $(\widehat{k}_{ij})$ the entries of the realized network estimator $\widehat{K}^*_\xi$. The bank credit risk network estimator is a shrinkage type estimator. If we set $\kappa = 0$ in (2.3), the estimator is equal to the inverse realized covariance estimator $(\widehat{\Sigma}^*_\xi)^{-1}$. If κ is positive, (2.3) becomes a penalized objective function with penalty equal to the sum of the absolute values of the non-diagonal entries in the estimator. The important feature of the absolute value penalty is that for $\kappa > 0$ some of the entries of the realized network estimator are going to be set to exact zeros. The highlight of this type of estimator is that it simultaneously estimates and selects the nonzero entries of K^*_ξ. Numerically, Friedman *et al.* (2011) show that minimizing the objective function in (2.3) is equivalent to carrying out a series of LASSO regression. An appealing feature of this LASSO estimator is that it is guaranteed to provide a sparse positive definite matrix estimate of the concentration matrix. Moreover, the algorithm is suitable for the analysis of sparse large dimensional systems containing, say, hundreds of series. Note that the estimator depends on the choice of the tuning parameter κ which determines the sparsity of the K^*_ξ which is chosen in a data drive way using the BIC model selection criterion, which is widely used in the literature (Yuan and Lin, 2007; Peng, Wang, Zhou, and Zhu, 2009).

2.3 Empirical Analysis

We use the methodology introduced in Section 2.2 to study the bank credit risk network of our sample of Eurozone financial institutions. We carry out both static and dynamic network analysis. The static analysis consists of estimating the network over the full sample while in the dynamic analysis we use a rolling window estimation scheme to obtain a time series of networks. Lastly, we carry out a forecasting exercise to assess if our network methodology is able to produce accurate predictions of the future degree of interdependence among the institutions in the panel.

2.3.1 Data

We consider a sample of large Eurozone financial institutions from January 1st, 2006 until December 31st, 2013. Note that, for simplicity, in what follows we refer to all of our financial institutions as banks. We focus on financial firms headquartered in Austria (AT), Belgium (BE), Germany (DE), Spain (ES), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL) and Portugal (PT). For each of these countries we select all financial institutions for which CDS data is available for the entire sample period. The complete list of banks included in the sample is reported in Table 2.1.

For each bank in the sample we obtain daily mid-market spreads for one-year, two-year, three-year, five-year, seven-year and ten-year CDS contracts. Additionally, we include spreads for sovereign CDS contracts of the same maturity for all ten countries. The data used in this study are obtained from Markit, who collects CDS quotes from more than thirty market participants on a daily basis, and provides a composite spread only if on a given date observations from at least two different participants are available.[1] In order to calculate the values for zero-coupon bonds in the CDS pricing formulas, we refer to the Nelson-Siegel-Svensson curves estimated by Deutsche Bundesbank with daily frequency.

In the presentation of the empirical results we often consider four sub–periods capturing different phases of the recent history of the Eurozone financial system. The first period runs from January 1st, 2006 until August 1st, 2008 and is what we refer to as the pre financial crisis period preceding the bankruptcy filing of Lehman Brothers on September 15th, 2008. We let the pre financial crisis period end some weeks before the actual filing for Chapter 11 protection to avoid including a period of anticipation in the first subsample. The second period runs from August 1st, 2008 until April 1st, 2010 and is what we refer to as the financial crisis period. April 2010 is chosen as a breaking point, since it coincides with the official filing for financial help by Greece on April 23rd. We take this as a starting point for our third subsample, which we refer to as the sovereign debt crisis. This third period finishes on September 1st 2012, reflecting the initiation of the legal framework for Outright Monetary Transactions by the ECB to

[1] We make use of CDS contracts for which the notional is denominated in Euro whenever available, and enhance our sample with notional denominated in US dollars otherwise. Since the CDS spreads themselves are denominated in basis points, we do not face the challenge of currency conversion. Whenever both series are available, we can see that their correlation, both in levels and in first differences, is close to one.

Table 2.1: European Financial Instituts

Abbreviation	**Name of the institution**	Abbreviation	**Name of the institution**	Abbreviation	**Name of the institution**
	Austria		**Spain (cont'd)**		**Italy**
WAG	Austria	PAS	Banco Pastor, S.A. (PAS)	ASG	Assicurazioni Generali
ERS	Erste Bank Group	SAB	Banco de Sabadell, S.A.	LAV	Banca Nazionale de Lavoro
RAI	Raiffeisen Bank International	SAB	Banco de Sabadell, S.A.	LEA	Banca Italease S.p.A.
	Belgium	MED	Caja de Ajorros del Mediterraneo	MED	Mediobanca S.p.A.
FOR	Fortis N.V. / Ageas Holding N.V.	CAV	Caixa de Ahorros de Valencia, Castelln y Alicante / Bancaja	INT	Intesa Sanpaolo S.p.A
KBC	KBC BANK	INT	Bankinter, S.A.	MIL	Banca Popolare di Milano
DEX	Dexia Crédit Local	SOP	Sophia GE	MPS	Banca Monte dei Paschi di Siena S.p.A
	Germany		**France**	UDP	Unione di Banche Italiane SCPA
ALL	Allianz AG	AXA	AXA France	POP	Banco Popolare S.C.
DBA	Deutsche Bank AG	BQE	Banque Fédérative du Crédit Mutuel	UNI	UniCredit S.p.A.
COM	Commerzbank AG	PEU	Banque PSA Finance		**Netherlands**
DBZ	DZ Bank	BNP	BNP Paribas	SAN	Espirito Santo Financial Group, SA
MRV	Münchner Rückversicherung	AGR	Crédit Agricole	AEG	Aegon NNV
NLB	Norddeutsche Landesbank	CIC	Crédit Industriel et Comercial	NIB	NIBC Bank NV
HSH	HSH Nordbank	LYO	Crédit Lyonnais	RAB	Rabobank
LBW	Landesbank Baden-Württemberg	WEN	Wendel	SNS	SNS Bank NV
BLB	Bayerische Landesbank	SOC	Société Générale	SNS	SNS Bank NV
LBB	Landesbank Berlin		**Greece**	VAN	F. van Lanschot Bankiers NV
LHT	Landesbank Hessen - Thühringen	NBG	National Bank of Greece	ING	Ing Bank NV
HRE	Hypo Real Estate Holding AG	EFG	EFG Eurobank Ergasias S.A.	ABN	Abn Amro Bank NV
WLB	West LB / Portigon AG	GEC	Gecine	ROD	Rodamco Europe NV
	Spain		**Ireland**	ACH	Achmea Holding NV
SAN	Banco Santander S.A.	ANG	Anglo Irish Bank		**Portugal**
BBV	Banco Bilbao Vizcaya Argentaria S.A.	DEP	Depfa PLC	BCO	Banco Comercial Portugues, SA
CAB	Caja de Ahorros y Pensiones de Barcelona	GOV	Governor and Company of the Bank of Ireland	CAI	Caixa Geral de Depositos, SA
MPM	Caja de Ahorros y Monde de Piedad de Madrid	NAT	Irish Nationwide Bank	BPI	Banco Portugues de Investimiento
POP	Banco Popular Espanol, S.A.	ILP	Irish Life and Permanent		

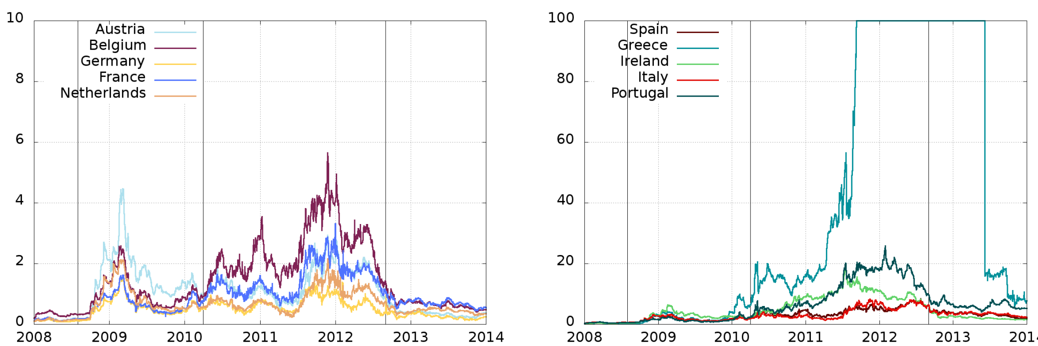
This table reports a list of all financial institutions included in the sample with their country of origin and an abbreviation used in the remainder of the paper.

face the European debt crisis. Our fourth subsample accordingly runs from September 2012 until the end of our sample period on December 31st, 2013.

2.3.2 Default Intensities

We begin by estimating the credit risk model introduced in Section 2.2 and bootstrapping the risk–neutral default intensities of each sovereign and bank in the panel. Figure 2.1 plots the bootstrapped sovereign/systematic risk–neutral default intensities, divided into core (Austria, Belgium, France, Germany, Netherlands) and periphery (Spain, Greece, Ireland, Italy, Portugal) countries.

Figure 2.1: SYSTEMATIC DEFAULT INTENSITY



(a) Core (b) Periphery

This figure shows the time series of sovereign default intensities for core countries bootstrapped from CDS prices of 1-year, 3-year, 5-year, 7-year and 10-year maturity and corresponding risk-neutral rates. The intensity is measured in basis points.

The scale of the plot is such that an intensity level of one corresponds approximately to a 1% probability of default over the next year. The time series profiles of the sovereign default intensities are similar but there are clear differences in the levels of the series for core and periphery countries. A principal component analysis on the first differences of the sovereign intensities shows that the amount of variability explained by the first principal component is 40%. The mean default intensity for core and periphery countries amounts to, respectively, 71 and 424 basis points. Note that through the height of the sovereign debt crisis, CDS spreads for Greek sovereign debt increased up to more than 23'000 basis points (or 230 percentage points) for 5-year CDS contracts, implying an instantaneous default probability higher than 100% for the period from September 21, 2011 to June 6, 2013.[2] Figure 2.2 plots the bank idiosyncratic default intensity 90% quantile range for each country.

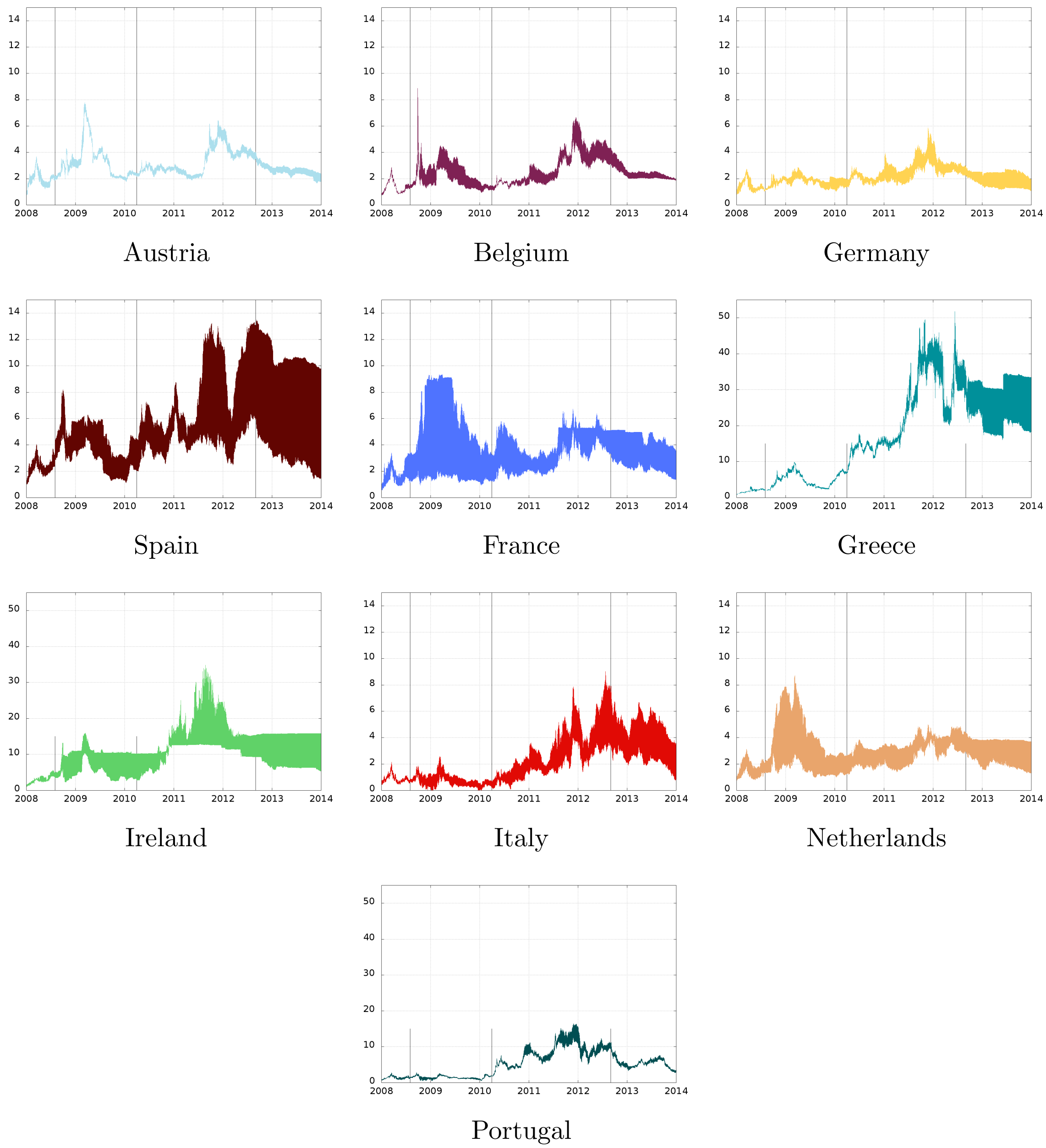
The figure shows that there is a moderate degree of heterogeneity in the dynamics of idiosyncratic intensities. In particular, we note that the period of maximum distress for individual banks in core countries is in the financial crisis (with the exception of Germany) while for periphery countries it is during the sovereign debt crisis. Again, a principal component analysis on the first differences of the bank intensities shows that the amount of variability explained by the first principal component is less than 20%.

2.3.3 Static Analysis

We estimate the bank credit risk network over the full sample and report the network plot in Figure 2.3. The shrinkage parameter κ used to estimate the network is set to obtain a degree of sparsity equal to 15%.[3] The optimal level of κ chosen by the BIC would have delivered a degree of sparsity of roughly 30%, which albeit being sparse is too interconnected for visualization purposes. Furthermore, 50% of the partial correlations selected by the BIC have a small economic magnitude (they are in between -0.06 and 0.03). To this extent, and in this section only, we set the shrinkage parameter κ to have a degree of sparsity of 15% in order to visualize the network associated with the largest partial correlations (in absolute value) only. The network layout algorithm[4] chosen to create the plot is such that the most interconnected banks in the network correspond

[2] In our analysis we truncate the default intensities at 100%.
[3] That is, the number of links in the network is 15% of the total possible number of linkages.
[4] We use the Fruchterman & Reingold (1991) force-direct graph drawing algorithm.

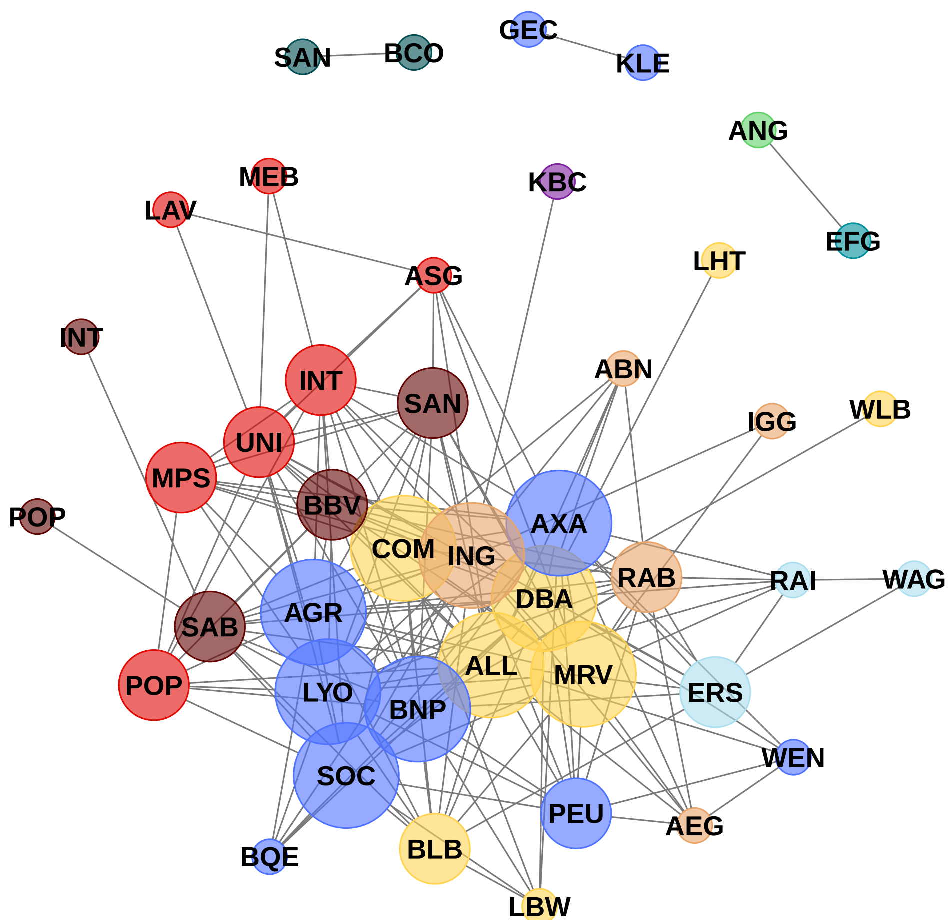
Figure 2.2: Idiosyncratic Default Intensity



This figure shows quantiles for instantaneous default intensities for all banks in a certain country bootstrapped from CDS spreads of 1-year, 3-year, 5-year, 7-year and 10-year maturity and corresponding risk-neutral rates. All intensities are measured in basis points.

to the most central vertices in the plot. The vertex size is proportional to its degree (that is, the number of connections to others) and the vertex color is set according to the bank's country of origin.

Figure 2.3: (Full Sample) Bank Credit Risk Network



This figure shows the bank credit risk network obtained over the full sample period.

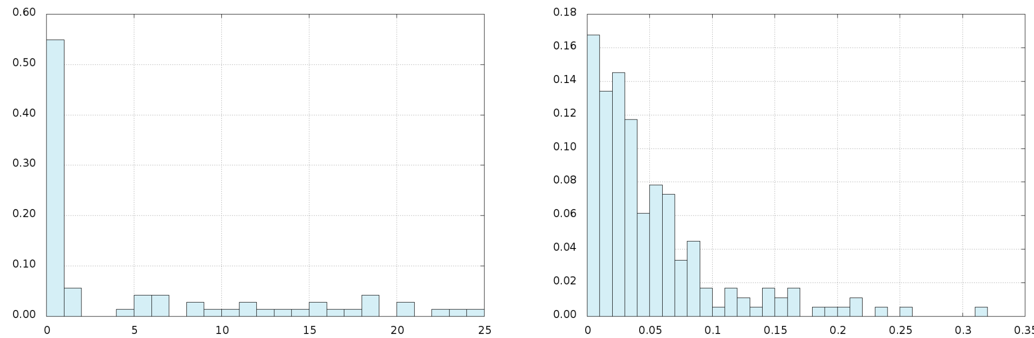
The analysis of the network provides interesting insights on the interdependence structure of Eurozone financial institutions.

First, we use the partial correlation and degree distributions, which are reported in

Figure 2.4, to summarize the global properties of the network. The partial correlation distribution shows that all of the dependence in the network is positive. This facilitates the interpretation of the graph in Figure 2.3 in that the presence of an edge always signals that the idiosyncratic default intensity of a bank is positively related to the one of its neighbours. Turning to the degree distribution, we note that there is strong heterogeneity in the number of connections of the banks in the network, and that the highest interconnected banks have a large proportion of linkages relative to the total. These empirical regularities are interesting in that they are typical features of power law networks, that is networks in which the degree distribution follows a power law. Power law networks are popular in network analysis in that this class of graphs fits well a large number of real world phenomena. One of the main characteristics of this class of models is that they exhibit "small world effects", that is the distance (i.e. the smallest number of connecting edges) between any two nodes is proportional to the log of the total number of vertices. Small world effects imply that even if the network is large and sparse, all banks in the system are strongly interrelated. More specifically, in our context small world effects imply a non–negligible probability of joint distress of a substantial number of institutions following the idiosyncratic shock to an individual entity.

A number of interesting country clustering patterns also emerge from the network. To investigate these in more detail, in Table 2.2 we report the total number of linkages among Eurozone countries in the network. The table shows that there is a high proportion of within–country linkages: after controlling for the sovereign/systematic factor, banks belonging to the same country still exhibit a high degree of interdependence. This phenomenon is referred to as national fragmentation and has been documented by, among others, Betz, Hautsch, Peltonen, and Schienle (2016a). These are particularly high in the French and Italian banking systems where the proportion of within–country

Figure 2.4: Degree and Partial Correlation Distribution



(a) Degree Distribution (b) Partial Correlation Distribution

This figure shows histograms for the distribution of degree and partial correlation.

linkages is, respectively, 33.7% and 42.4%.

As far as between–country linkages are concerned, we observe that banks headquartered in France, Germany, Italy and Netherlands (in this order) have the highest number of connections. It is interesting to note that the number of cross-border linkages is correlated with banks' international exposures. The comparison of the table with the BIS statistics shows that the country ranking based on the number between–country linkages essentially coincides with those based on the total foreign claims computed over the entire sample period. Last, we study which banks are most central in the network

Table 2.2: Number of links

	Austria	Belgium	Germany	Spain	France	Greece	Ireland	Italy	Netherlands	Portugal	Links
Austria	12.5	0.0	25.0	12.5	37.5	0.0	0.0	0.0	12.5	0.0	16
Belgium	0.0	0.0	16.7	0.0	61.1	0.0	0.0	0.0	22.2	0.0	18
Germany	3.9	2.9	17.6	8.8	30.4	0.0	0.0	13.7	16.7	5.9	102
Spain	3.4	0.0	15.3	16.9	25.4	0.0	0.0	20.3	10.2	8.5	59
France	3.5	6.4	18.0	8.7	33.7	0.0	0.6	9.9	14.5	4.7	172
Greece	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
Ireland	0.0	0.0	0.0	0.0	25.0	0.0	50.0	0.0	25.0	0.0	4
Italy	0.0	0.0	14.1	12.1	17.2	0.0	0.0	42.4	6.1	8.1	99
Netherlands	2.4	4.7	20.0	7.1	29.4	0.0	1.2	7.1	23.5	4.7	85
Portugal	0.0	0.0	18.2	15.2	24.2	0.0	0.0	24.2	12.1	6.1	33

This table shows the total number of links between any pair of countries for the full sample analysis after applying shrinkage.

using the page–rank algorithm and report rankings of the top ten banks in Table 2.3.

Inspection of the rankings reveals that size is an important determinant of interconnectedness: the most central banks in the network correspond to the largest banks in the sample. Moreover, the most interconnected banks are typically headquartered in core countries, especially in France and Germany. Central banks in the network can be interpreted as yellow canaries of distress in the system, that is highly interdependent institutions whose distress coincides with distress in a large fraction of the entire system.

Table 2.3: Centrality Analysis

1	France	BNP Paribas
2	Germany	Deutsche Bank
3	Netherlands	Ing Bank NV
4	Germany	Allianz AG
5	France	Crédit Agricole
6	France	Crédit Lyonnais
7	Germany	Commerzbank
8	France	AXA France
9	France	Société Générale
10	Spain	Banco Bilbao Vizcaya Argentaria S.A.

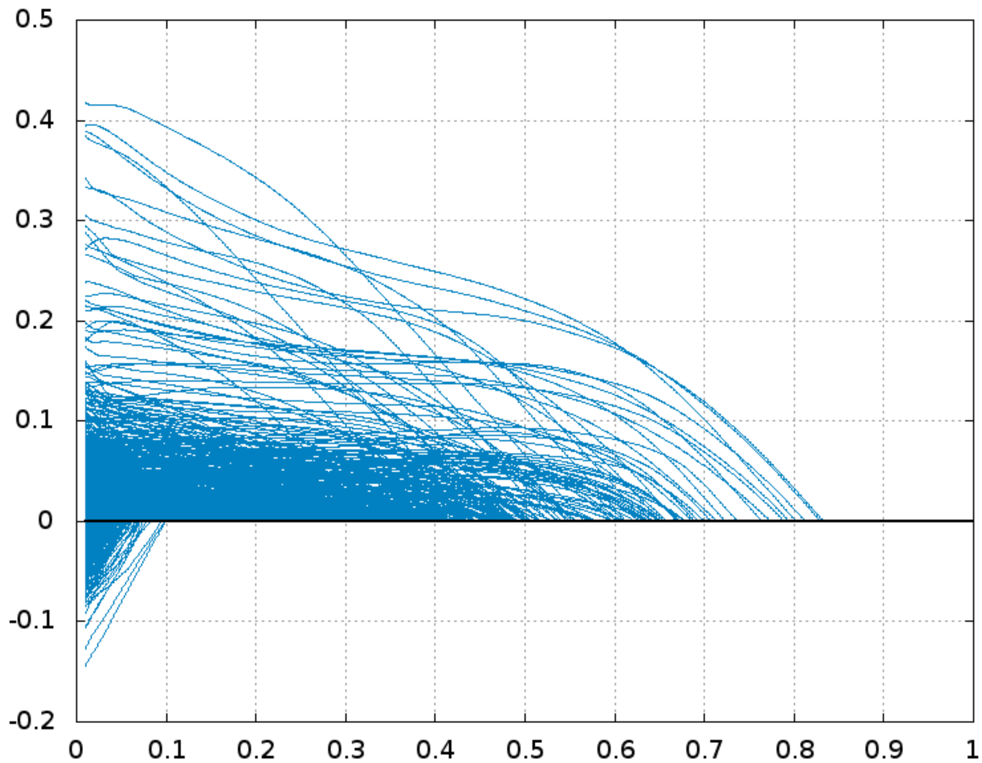
This table shows a ranking of the 10 most central banks by eigenvector centrality.

In order to get insights on the network estimation sensitivity, in Figure 2.5 we report the so called trace plot. The trace plot shows the graph of the estimated partial correlations as a function of the amount of shrinkage used in the estimation. The trace plot shows that most of the partial correlations are positive irrespective of the degree of shrinkage. We can find negative dependence only when very little shrinkage is applied to the estimator and the magnitude of such negative correlation is small.

2.3.4 Time–Varying Analysis

In this section we carry out a time–varying analysis to study the evolution of the bank credit risk network throughout the sample. The network time series is obtained by

Figure 2.5: Trace plot



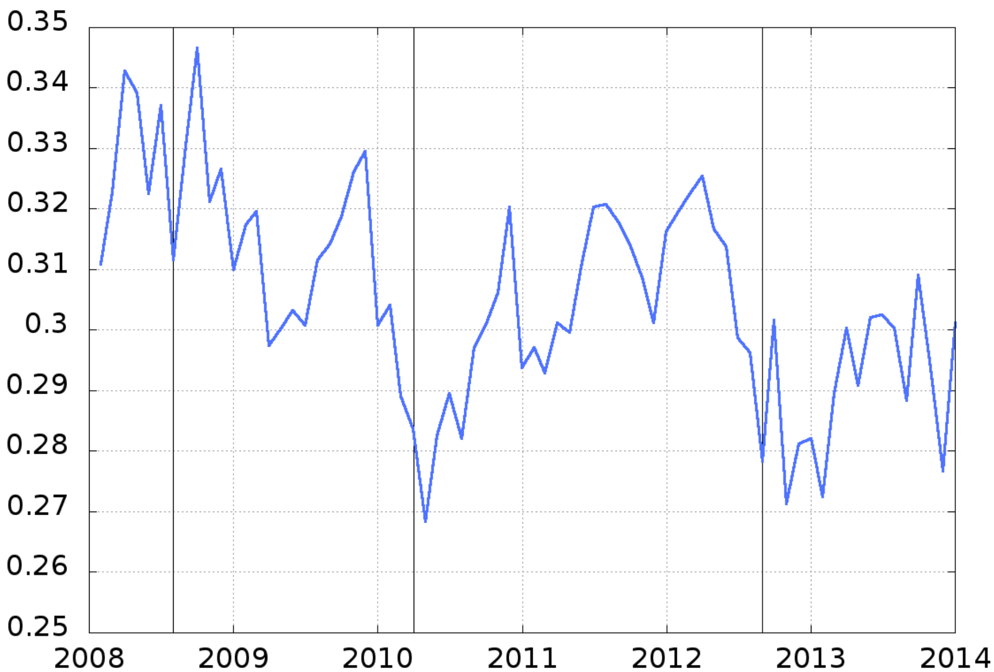
This figure shows the number and magnitude of links in the bank credit risk network as a function of the shrinkage parameter, next to the values of the AIC criterion for determining the optimal amount of shrinkage.

estimating the model at the end of each month from X to Y using the last two years of observations available. The BIC is used to select the optimal amount of shrinkage.

Figure 2.6 shows the time series plot of the degree of network sparsity. Sparsity is on average approximately 30% but it exhibits substantial time series variation throughout the sample. In particular it peaks in correspondence of the demise of Lehman and with the worsening of the sovereign debt crisis in Europe, and it falls at the end of the financial crisis (before Greece files for bankruptcy) and with the beginning of the Outright Monetary Transaction program of the ECB.

In order to quantify the amount of dependence captured by the factor and network

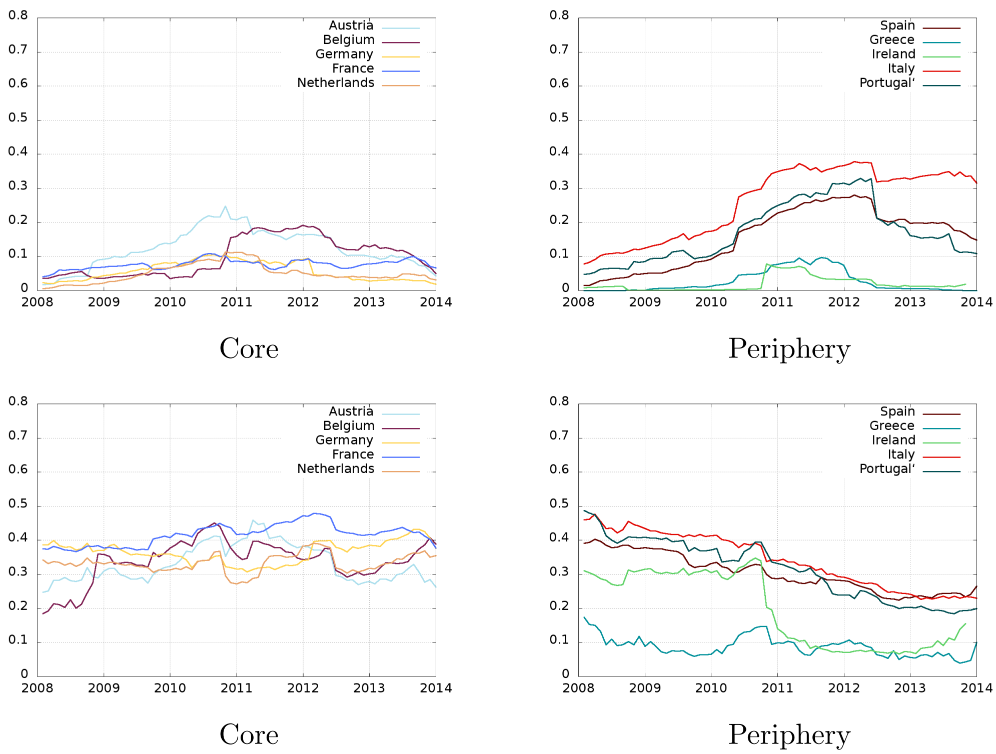
Figure 2.6: Network Density



This figure shows the network density as a function of time.

components of the model, we define R^2 type goodness of fit indices that we call factor and network R^2. The factor R^2 of a bank is defined as the R^2 of the regression of its log–CDS spread difference on the log–CDS spread difference of its respective sovereign. The network R^2 of a bank is defined as the additional R^2 obtained by adding as explanatory variables of the previous regression all the log–CDS spread differences of all the neighbouring banks detected in the bank credit risk network. The factor and network R^2 are computed on the basis on rolling estimates in order to have a time series of values. Figure 2.7 shows the plot of the factor and network R^2 averages by country. The left and right panels show respectively the plots for the core and periphery countries. For core countries we note that the network channel is more relevant than the factor one and that the time series profile of the R^2s is roughly stable over time. On the hand for periphery countries exhibit a rather different behaviour. At the beginning of the sample, the network channel dominates the factor. However, as the sovereign debt crisis unwinds, banks progressively become more dependent with their respective sovereign and the relevance of the interconnectedness with other banks declines. This trend stops in the second half of 2012 in correspondence with the beginning of the Outright Monetary Transactions program of the ECB. Overall, the plots convey that both the factor and the network channel explain a significant amount of comovement and exhibit different time series evolution throughout the sample.

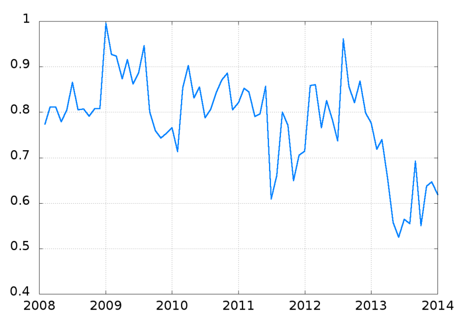
Figure 2.7: Factor and Network R Squares



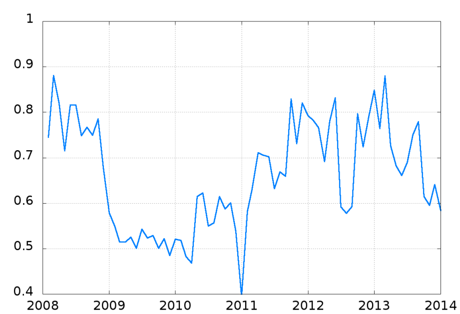
This figure shows the time-variation in factor and network R squares for core and periphery countries.

Figure 2.8 shows the plot of the eigenvector centrality index as a function of time for two banks in our sample: Commerzbank and Monte dei Paschi di Siena. Commerzbank was facing major difficulties in the times surrounding the acquisition of Dresdner Bank starting from December 2008. In May 2009, Commerzbank received a liquidity injection by the government effectively constituting a partial nationalization of the bank. These events are reflected in the the time-varying patter of Commerzbank eigenvector centrality where we see a sharp increase in December 2008 and a subsequent fall in mid 2009. Monte dei Paschi di Siena in January 2013 news surrounding the scandal surrounding derivative deals to conceal previous losses materialized leading to a large drop in stock prices. Accordingly, the eigenvector centrality plot shows that the centrality of Monte dei Paschi peaked around the same time.

Figure 2.8: CENTRALITY



Commerzbank



Monte Dei Paschi

This figure shows the time-variation in eigenvector centrality for Commerzbank (Germany) and Monte dei Paschi di Siena (Italy) as a function of time.

2.3.5 Predictive Analysis

We carry out a predictive analysis to assess if the bank credit risk network methodology provides advantages for forecasting. From an estimation perspective, the network estimation methodology we propose can be interpreted as a regularization procedure of a moderately large dimensional covariance matrix. As forcefully put forward, among others, by Ledoit and Wolf (2004), precise estimation of a covariance matrix is challenging when the number of series considered is large, and in these cases covariance regularization can provide substantial gains.

The objective of the predictive exercise is to assess if the bank credit risk network provides precise prediction of the future degree of idiosyncratic dependence among the banks in the panel. We design our predictive evaluation exercise as follows. On the last day of each month from X to December 2012, we compute the bank credit risk network concentration matrix estimator $\widehat{K}_\xi$ (using the BIC to choose the shrinkage parameter κ) as well as the realized covariance of the idiosyncratic shocks over the following 12 months, which we denote as $\widehat{\Sigma}_\xi^{\mathsf{out}}$. The network estimator is compared against two alternatives: the inverse of the in–sample realized covariance estimator based on the ξ differences; and the inverse realized covariance estimator with all its off–diagonal entries truncated to zero. The loss function we use to measure the quality of different concentration matrix estimators is the negative (predictive) log likelihood

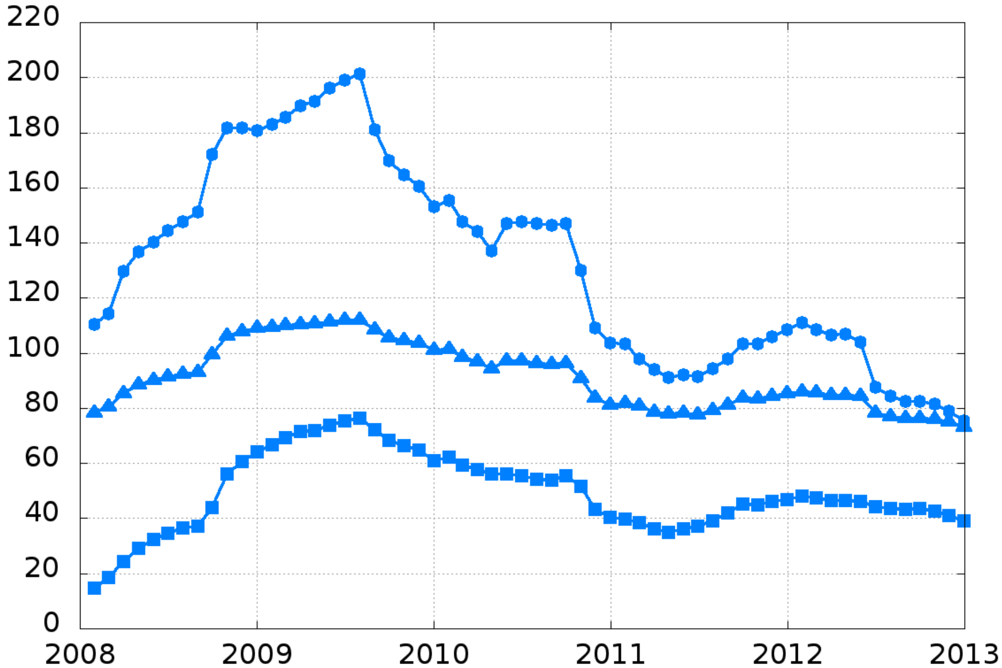
$$\mathcal{L}(K) = \mathrm{tr}(\widehat{\Sigma}_\xi^{\mathsf{out}} K) - \log\det(K)\,.$$

Recall that because of the invariance property of the log–likelihood, evaluating the covariance matrix or the covariance is the same.

We report the results of the predictive analysis in Figure 2.9 where we show the negative predictive log–likelihood associated with three estimator on each month from X to December 2012. The ranking between the different estimators is clear. The bank credit risk network estimator provides more accurate predictions uniformly over the entire out–of–sample period.

As it has been widely documented in the large dimensional covariance estimation literature in finance (Ledoit and Wolf, 2004), adding some degree of regularization to the covariance matrix, and, in particular in this case, truncating entries which are close to zero reduces substantially the variability of the estimator. Thus overall, the bank credit risk network methodology is not only useful to represent the dependence structure

Figure 2.9: OUT–OF–SAMPLE EVALUATION



This figure shows our of sample forecasts using three different covariance matrices: the proposed network methodology (squares), diagonal (triangles) and unconstrained (circles).

of idiosyncratic shocks but it also provides more precise estimates of the covariance of the idiosyncratic shocks when the conditional dependence structure of these shocks is sufficiently sparse.

2.4 Conclusion

The recent financial crisis in Europe has forcefully shown the potential impact of high levels of interconnectedness in the financial system and brought forward a renewed interest in monitoring the current state of interconnections in the financial sector as well as identifying its most central institutions. However, in the absence of regulatory data, this remains a challenging task empirically.

In this work we introduce a new approach to estimating interconnectedness through extending the standard reduced form credit risk model commonly used in finance. In our proposed model, interdependence in credit risk stems from two components: common exposure to a systematic factor and pairwise dependence among idiosyncratic shocks. We then use this methodology to study credit risk interdependence in a sample of financial institutions located in ten selected Eurozone countries over an eight-year period from 2006 to 2013.

We find that the network channel captures a substantial amount of interdependence on top of what is explained by systematic factors. A cross-sectional analysis shows that the network channel is more relevant in core countries, whereas systematic factors dominate for periphery countries. This effect is potentially due to the outbreak of the sovereign debt crisis which leads to a stronger connection between banks in periphery countries and their respective sovereigns. We find evidence of linkages both intra- and inter-country even after controlling for each respective sovereign. Furthermore, the structure of the credit risk network is power law, implying that the number of steps between any two institutions is small and adverse shocks can spread through the network quickly.

A time-varying analysis reveals that affected financial institutions become hubs in the credit risk network during crisis times. These hub institutions can spread negative shocks within the network through an increased number as well as strength of linkages, making their monitoring an important task for financial stability.

Our results have important implications from a systemic risk perspective. First, we find that frequently used models which do not account for pairwise dependence can severely underestimate the joint default probability of two institutions. By failing to account for bilateral interconnections among banks, sources of pairwise interdependence go unnoticed. Second, our time-varying analysis shows that the network position and potential for spreading contagion of single institutions can vary over time, creating the need for constant monitoring of systemic importance which is not just defined by more stable characteristics such as bank size.

2.5 Appendix: Proofs

The characterization of the integrated partial correlation network is convenient for estimation. The detection of the network structure among the entities is equivalent to recovering the zeros of the concentration matrix from the data. Moreover, it is well known that if we write $B_i(t)$ as

$$B_i(t) = \sum_{j \neq i} \beta_{ij} B_j(t) + u_i(t),$$

then $u_i(t)$ is independent of $B_j(t)$ for all $i \neq j$ if and only if

$$\beta_{ij} = \rho^{ij} \sqrt{\frac{k_{jj}}{k_{ii}}}.$$

Moreover, for such defined β_{ij},

$$u(t) \sim \mathcal{N}(0, Ut),$$

where U is the variance-covariance matrix with ij-th entry $\frac{k_{ij}}{k_{ii}k_{jj}}$.

In order to simplify the exposition, we assume that $t = 0$ and $T = t$ in (2.1). Then, we are going to show that the functions in (2.2) are given by

$$\begin{aligned} F^{i,j}(\lambda_j, t) &= F_1^j(t) \exp(F_2^j(t)\lambda_j), \quad \text{for} \quad j = G, \ell \\ G(\xi_i, t) &= G_1(t) \exp(G_2(t)\xi_i) \\ H(\xi_i, t) &= (H_1(t) + H_2(t)\xi_i) \exp(G_2(t)\xi_i) \\ I^{i,j}(\lambda_j, t) &= (I_1^j(t) + I_2^j(t)\lambda_j) \exp(F_2^j(t)\lambda_j), \quad \text{for} \quad j = G, \ell \end{aligned}$$

with

$$
\begin{aligned}
F_1^j(t) &= \exp\left(\frac{-a_j m_j (a_j - \psi_{i,j})t}{b_j^2}\right)\left(\frac{\nu_{i,j}-1}{\nu_{i,j}-e^{t\psi_{i,j}}}\right)^{\frac{2a_j m_j}{b_j^2}} \\
F_2^j(t) &= \frac{a_j - \psi_{i,j}}{b_j^2} - \frac{2\psi_{i,j}e^{t\psi_{i,j}}}{b_j^2(\nu_{i,j}-e^{t\psi_{i,j}})} \\
G_1(t) &= \exp\left(\frac{-\alpha_i\mu_i(\alpha_i-\Phi_i)t}{\Gamma_i^2}\right)\left(\frac{\theta_i-1}{\theta_i-e^{t\Phi_i}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}} \\
G_2(t) &= \frac{\alpha-\Phi_i}{\Gamma_i^2} - \frac{2\Phi_i e^{t\Phi_i}}{\Gamma_i^2(\theta_i - e^{t\Phi_i})} \\
H_1(t) &= \frac{\alpha_i\mu_i}{\Phi_i}(e^{\Phi_i t}-1)\exp\left(\frac{-\alpha_i\mu_i(\alpha_i-\Phi_i)t}{\Gamma_i^2}\right)\left(\frac{\theta_i-1}{\theta_i-e^{\Phi_i t}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}+1} \\
H_2(t) &= \exp\left(\frac{-\alpha_i\mu_i(\alpha_i-\Phi_i)t}{\Gamma_i^2}+\Phi_i t\right)\left(\frac{\theta_i-1}{\theta_i-e^{\Phi_i t}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}+2} \\
I_1^j(t) &= \frac{a_j m_j}{\psi_{i,j}}(e^{\psi_{i,j}t}-1)\exp\left(\frac{-a_j m_j(a_j-\psi_{i,j})t}{b_j^2}\right)\left(\frac{\nu_{i,j}-1}{\nu-e^{\psi_{i,j}t}}\right)^{\frac{2a_j m_j}{b_j^2}+1} \\
I_2^j(t) &= \exp\left(\frac{-a_j m_j(a_j-\psi_{i,j})t}{b_j^2}+\psi_{i,j}t\right)\left(\frac{\nu_{i,j}-1}{\nu_{i,j}-e^{\psi_{i,j}t}}\right)^{\frac{2a_j m_j}{b_j^2}+2}
\end{aligned}
$$

and

$$
\begin{aligned}
\psi_{i,j} &= \sqrt{a_j^2 + 2\gamma_{i,j}b_j^2} \\
\nu_{i,j} &= \frac{a_j+\psi_{i,j}}{a_j-\psi_{i,j}} \\
\Phi_i &= \sqrt{\alpha_i^2 + 2\Gamma_i^2} \\
\theta_i &= \frac{\alpha_i+\Phi_i}{\alpha_i-\Phi_i} \\
\Gamma_i^2 &= \sum_{j,k\neq i}\beta_{ij}\beta_{ik}\sigma_{jk} + \frac{1}{k_{ii}}.
\end{aligned}
$$

In order to prove this formulas, we rearrange the terms in (2.1), so that the it can be expressed as

$$
\begin{aligned}
&\text{CDS(protection leg)}_t = \omega \int_0^T D(t) \\
&\Bigg(\gamma_{i,G}\mathsf{E}\left[\lambda_G(t)\exp\left(-\int_0^t \gamma_{i,G}\lambda_G(s)ds\right)\right]\mathsf{E}\left[\exp\left(-\int_0^t \gamma_{i,\ell}\lambda_\ell(s)ds\right)\right]\mathsf{E}\left[\exp\left(-\int_0^t \xi_i(s)ds\right)\right] \\
&+\gamma_{i,\ell}\mathsf{E}\left[\lambda_\ell(t)\exp\left(-\int_0^t \gamma_{i,\ell}\lambda_\ell(s)ds\right)\right]\mathsf{E}\left[\exp\left(-\int_0^t \gamma_{i,G}\lambda_G(s)ds\right)\right]\mathsf{E}\left[\exp\left(-\int_0^t \xi_i(s)ds\right)\right] \\
&+\mathsf{E}\left[\exp\left(-\int_0^t \gamma_{i,G}\lambda_G(s)ds\right)\right]\mathsf{E}\left[\exp\left(-\int_0^t \gamma_{i,\ell}\lambda_\ell(s)ds\right)\right]\mathsf{E}\left[\xi_i(t)\exp\left(-\int_0^t \xi_i(s)ds\right)\right]\Bigg)dt.
\end{aligned}
$$

Solving F

Set

$$F(\lambda,t) = F^i(\lambda_j,t) = \mathsf{E}\left[\exp\left(-\int_0^t \gamma_{i,j}\lambda_j(s)ds\right)\right],$$

where $\lambda := \lambda(0)$. Applying Itô's formula to the discounted prices, which we also denote by $F(\lambda(t),t)$, we have that

$$dF = F_t dt + (a(m-\lambda(t))dt + \sqrt{\lambda(t)}dW(t))F_\lambda + \frac{1}{2}b^2\lambda(t)F_{\lambda\lambda}dt - \gamma_i\lambda(t)F dt$$

where

$$F_t = \frac{d}{dt}F(\lambda(t),t),\, F_\lambda = \frac{d}{d\lambda}F(\lambda(t),t),\, F_{\lambda\lambda} = \frac{d^2}{d\lambda^2}F(\lambda(t),t).$$

Since the discounted prices are martingales with respect to the risk-neutral measure, we get that

$$\frac{b^2}{2}\lambda(t)F_{\lambda\lambda} + a(m-\lambda(t))F_\lambda + F_t - \gamma_i\lambda(t)F = 0$$

subject to $F(\lambda,0)=1$.

In accordance with the CIR, we decompose

$$F(\lambda,t) = F_1(t)\exp(F_2(t)\lambda).$$

Then $F_1(t), F_2(t)$ need to fulfill the Riccati equations

$$\frac{b^2}{2}F_2(t)^2 - aF_2(t) - \gamma_i + F_2'(t) = 0$$

$$amF_2(t) + \frac{F_1'(t)}{F_1(t)} = 0$$

subject to $F_1(0) = 1$ and $F_2(0) = 0$. The solution is given by

$$\begin{aligned} F_1(t) &= \exp\left(\frac{-am(a-\psi_i)t}{b^2}\right)\left(\frac{\nu_i - 1}{\nu_i - e^{t\psi_i}}\right)^{\frac{2am}{b^2}} \\ F_2(t) &= \frac{a-\psi_i}{b^2} - \frac{2\psi_i e^{t\psi_i}}{b^2(\nu_i - e^{t\psi_i})} \end{aligned}$$

where

$$\begin{aligned} \psi_i &= \sqrt{a^2 + 2\gamma_i b^2} \\ \nu_i &= \frac{a+\psi_i}{a-\psi_i}. \end{aligned}$$

Solving I

Set

$$I(\lambda, t) = I^i(\lambda_j, t) = \mathsf{E}\left[\lambda_j(t)\exp\left(-\int_0^t \gamma_{i,j}\lambda_j(s)ds\right)\right].$$

Applying Itô's formula to the discounted prices also denoted by $I(\lambda(t), t)$, we get that

$$dI = I_t dt + (a(m - \lambda(t))dt + b\sqrt{\lambda(t)}dW(t))I_\lambda + \frac{1}{2}b^2\lambda(t)I_{\lambda\lambda}dt - \gamma_i\lambda I dt.$$

Under the risk-neutral measure, the discounted prices are martingales, so we get

$$\frac{b^2}{2}\lambda(t)I_{\lambda\lambda} + a(m - \lambda(t))I_\lambda + I_t - \gamma_i\lambda(t)I = 0$$

subject to the boundary condition $I(\lambda, 0) = \lambda$.

Again, we decompose

$$I(\lambda, t) = (I_1(t) + I_2(t)\lambda)\exp(F_2(t)\lambda).$$

Then, we obtain the Riccati equations

$$(am + b^2)F_2(t) - a + \frac{I_2'(t)}{I_2(t)} = 0$$

$$amI_2(t) + amI_1(t)F_2(t) + I_1'(t) = 0.$$

Substituting $F_2(t)$ and solving the equations using the initial conditions $I_1(0) = 0$ and $I_2(0) = 1$, we get that the solution is given by

$$I_1(t) = \frac{am}{\psi_i}(e^{\psi_i t} - 1)\exp\left(\frac{-am(a-\psi_i)t}{b^2}\right)\left(\frac{\nu_i - 1}{\nu - e^{\psi_i t}}\right)^{\frac{2am}{b^2}+1}$$

$$I_2(t) = \exp\left(\frac{-am(a-\psi_i)t}{b^2} + \psi_i t\right)\left(\frac{\nu_i - 1}{\nu_i - e^{\psi_i t}}\right)^{\frac{2am}{b^2}+2}.$$

Solving G

Recall that for each $i = 1, ..., n$

$$G(\xi_i, t) = \mathsf{E}\left[\exp\left(-\int_0^t \xi_i(s)ds\right)\right],$$

where $\xi_i := \xi_i(0)$. Applying Itô's formula, we get that

$$dG = G_t dt + G_{\xi_i} d\xi_i + \frac{1}{2} G_{\xi_i \xi_i} < d\xi_i, d\xi_i > .$$

Therefore, the discounted prices satisfy

$$dG = G_t dt + (\alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t))G_{\xi_i} + \frac{\Gamma_i^2}{2}\xi_i(t)G_{\xi_i\xi_i}dt - \xi_i(t)Gdt$$

where

$$\Gamma_i^2 = \sum_{j,k\neq i} \beta^{ij}\beta^{ik}\sigma_{jk} + \frac{1}{k_{ii}}.$$

Under the risk-neutral measure, discounted prices $G(\xi_i(t), t)$ are martingales, so it holds that

$$\frac{\Gamma_i^2}{2}\xi_i(t)G_{\xi_i\xi_i} + \alpha_i(\mu_i - \xi_i(t))G_{\xi_i} + G_t - \xi_i(t)G = 0$$

subject to the boundary condition $G(\xi_i, 0) = 1$.

Again, we decompose

$$G(\xi_i, t) = G_1(t)\exp(G_2(t)\xi_i).$$

Then, for the partial differential equation to be satisfied, $G_1(t)$, $G_2(t)$ need to fulfill the Riccati equations

$$\frac{\Gamma_i^2}{2}G_2^2(t) - \alpha_i G_2(t) + G_2'(t) - 1 = 0$$
$$\alpha_i\mu_i G_2(t) + \frac{G_1'(t)}{G_1(t)} = 0$$

subject to the initial conditions $G_1(0) = 1$ and $G_2(0) = 0$. Observe that these are the same equations than for $F_1(t)$ and $F_2(t)$ with $\Gamma_i = b$, $\alpha_i = a$, $\mu_i = m$ and $\gamma_i = 1$. Hence, the solution is

$$G_1(t) = \exp\left(\frac{-\alpha_i\mu_i(\alpha_i - \Phi_i)t}{\Gamma_i^2}\right)\left(\frac{\theta_i - 1}{\theta_i - e^{t\Phi_i}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}}$$
$$G_2(t) = \frac{\alpha - \Phi_i}{\Gamma_i^2} - \frac{2\Phi_i e^{t\Phi_i}}{\Gamma_i^2(\theta_i - e^{t\Phi_i})}$$

where

$$\Phi_i = \sqrt{\alpha_i^2 + 2\Gamma_i^2}$$
$$\theta_i = \frac{\alpha_i + \Phi_i}{\alpha_i - \Phi_i}.$$

Solving H

Recall that for each $i = 1, ..., n$

$$H(\xi_i, t) = \mathsf{E}\left[\xi_i(t)\exp\left(-\int_0^t \xi_i(s)ds\right)\right].$$

Applying Itô's formula to the discounted prices also denoted by $H(\xi_i(t), t)$, we get that

$$dH = H_t dt + H_{\xi_i} d\xi_i + \frac{1}{2} H_{\xi_i\xi_i} < d\xi_i, d\xi_i > .$$

Hence,

$$dH = H_t dt + (\alpha(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t))H_{\xi_i} + \frac{\Gamma_i^2}{2} H_{\xi_i\xi_i} dt - \xi_i H dt.$$

Under the risk-neutral measure, the discounted prices $H(\xi_i(t), t)$ are martingales, so we need that

$$\frac{\Gamma_i^2}{2}\xi_i(t)H_{\xi_i\xi_i} + \alpha_i(\mu_i + \xi_i(t))H_{\xi_i} + H_t - \xi_i(t)H = 0$$

subject to the boundary condition $H(\xi_i, 0) = \xi_i$.

Once again, we decompose

$$H(\xi_i, t) = (H_1(t) + H_2(t)\xi_i)\exp(G_2(t)\xi_i).$$

Then, for the partial differential equation to be satisfied, $H_1(t)$, $H_2(t)$ need to fulfill the Riccati equations

$$\frac{H_2'(t)}{H_2(t)} - \alpha_i + (\Gamma_i^2 + \alpha_i\mu_i)G_2(t) = 0$$
$$H_1'(t) + \alpha_i\mu_i H_1(t)G_2(t) + \alpha_i\mu_i H_2(t) = 0$$

subject to the initial conditions $H_1(0) = 0$ and $H_2(0) = 1$. Observe that these are the same equations than the ones we have for $G_1(t)$ and $G_2(t)$ with again $\Gamma_i = b$, $\alpha_i = a$, $\mu_i = m$ and $\gamma_i = 1$. Therefore, the solution is given by

$$H_1(t) = \frac{\alpha_i\mu_i}{\Phi_i}(e^{\Phi_i t} - 1)\exp\left(\frac{-\alpha_i\mu_i(\alpha_i - \Phi_i)t}{\Gamma_i^2}\right)\left(\frac{\theta_i - 1}{\theta_i - e^{\Phi_i t}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}+1}$$
$$H_2(t) = \exp\left(\frac{-\alpha_i\mu_i(\alpha_i - \Phi_i)t}{\Gamma_i^2} + \Phi_i t\right)\left(\frac{\theta_i - 1}{\theta_i - e^{\Phi_i t}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}+2}.$$

Chapter 3

CREDIT RISK INTERCONNECTEDNESS: WHAT DOES THE MARKET REALLY KNOW?

3.1 Introduction

The recent financial and sovereign debt crises in Europe have forcefully shown the importance of bank interconnectedness for the stability of the financial system. In order to measure bank interconnectedness empirically, a number of authors have recently put forward network estimation techniques based on market information. [1] There is, however, a challenge in the identification of the propagation channels of financial shocks, as well as the quantification of their relevance. Market-based measures do not allow

[1] Contributions in this area include the work of Diebold and Yilmaz (2015), Billio, Gray, Lo, Merton, and Pelizzon (2015), Zhang, Schwaab, and Lucas (2014), Betz, Hautsch, Peltonen, and Schienle (2016b) and Brownlees, Hans, and Nualart (2016).

for disentangling between the transmission of idiosyncratic shocks through the financial system (contagion) and endogenous shocks initiated by excessive risk-taking, rational revisions, or pure panics (Freixas, Laeven, and Peydro, 2015). Any identification of the propagation channels requires granular datasets at disaggregated levels that are not always available, even to supervisors and regulators. Thus, overall it is still unclear if these market information-based measures capture actual bank balance sheet linkages and risks, and, if yes, to which extent. The objective of this study is to shed light onto this question by studying the relationship between market-based measures of credit risk interconnectedness and actual common exposures of banks through their funding and securities holdings (liability-asset structure).

On the theoretical front, there is a growing literature that analyzes how balance sheet channels such as interbank lending, loan syndication or asset commonality induce interconnectedness among banks and propagate distress (*inter alia*, research by Freixas *et al.* (2000), Iyer and Peydró (2005), Gai *et al.* (2011), Greenwood *et al.* (2015), Caballero and Simsek (2013), Duarte and Eisenbach (2015), Hale, Kapan, and Minoiu (2016) and Suhua *et al.* (2013)). On the empirical side, there is a large literature which focuses on measuring credit risk interconnectedness from market data (Kritzman *et al.* (2011), Zhang *et al.* (2014), Barigozzi and Brownlees (2013), Podlich and Wedow (2014) and Betz *et al.* (2016b)). However, it seems unclear why high frequency market data should reflect bank fundamentals (actual balance sheet information), that - at best - are only available annually. To the best of our knowledge, ours is the first study to document that market-based measures of bank interconnectedness reflect actual balance sheet information.

Despite the importance of this link both for policy and macro-finance, its quantification has so far been elusive. This is due to the lack of exploitation of comprehensive balance sheet data, such as detailed wholesale funding relations and individual portfolio compositions. In this work we overcome this hurdle and analyze this question by taking advantage of a unique proprietary dataset of the German banking sector for 2006-13, which contains data on banks' funding and asset allocations. Our study investigates the link between market-based measurement of bank credit risk interconnectedness stemming from CDS data and underlying balance sheet channels. In particular, our methodology allows us to assess empirically the relevance of the balance sheet channels as drivers of credit risk interdependence. The contribution of this study is two-fold. First, it sheds light on the relative quantitative importance of both direct and indirect channels of interconnectedness for the market's perception of bank credit risk interdependence. Second, by assessing to what extent market-based measures of interconnectedness reflect balance sheet exposures, we evaluate the use of such measures of interdependence as risk monitoring tools in the absence of granular data.

The literature has established a number of direct and indirect channels which can induce interdependence in bank credit risk. In the recent crises, the propagation of distress can be traced back to the way banks managed their liquidity on both sides of the balance sheet. Banks relied heavily on the short-term interbank money market and thus became highly exposed to funding risk, which particularly unraveled in the aftermath of Lehman's failure. But also, the misjudgment of the quality of asset-backed securities and the bias towards fixed-income products issued by periphery euro-area member states made banks particularly vulnerable to the deteriorating market liquidity of the underlying asset. Both the funding and market liquidity risk triggered a liquidity spiral (Brunnermeier (2009) and Brunnermeier and Pedersen (2009)) with self-enforcing dynamics for a given bank and the banking sector as a whole. This motivates us to construct indices that focus on capturing these channels. The funding side of banks' balance sheets is identified through bilateral exposures in the wholesale funding market, which has become an increasing source of funding risk with banks' increased reliance on short-term funds. Asset allocations are decomposed into banks' securities investments and loans granted to the real economy. Note that interbank exposures are an example of a direct channel, whereas the latter two are indirect balance sheet channels of interconnectedness.

We measure market-based interconnectedness between banks using idiosyncratic partial correlations, which are a natural choice for our analysis. The idiosyncratic partial correlation between two banks is defined as their correlation after netting out the influence of (i) common systematic factors and (ii) all remaining entities in the panel. While simple correlation between two banks might be spurious and could be driven by common dependence with a third party, partial correlation does not suffer from this drawback as it nets out the influence of all remaining entities. In order to focus on credit risk dependence, we construct our partial correlation index based on banks' idiosyncratic default intensities implied by CDS prices, building upon Ang and Longstaff (2013) and Brownlees *et al.* (2016). For simplicity, we call our market–based measure of bank interconnectedness based on idiosyncratic partial correlations simply as realized interconnectedness.

Two main results emerge from the analysis. First, we find that realized interconnectedness strongly reflects both direct (wholesale funding market) and indirect channels (securities management and credit supply) and is influenced by banks' liquidity management on both sides of the balance sheet. On the funding side, we find that bank pairs in the case of which both counterparties have higher Tier 1 capital-weighted interbank exposure show higher realized interconnectedness. On the asset allocation side, we document that both banks' exposure to the real economy and their securities investments, have an impact on realized network connections. Bank pairs with more similar lending practices to the real economy show up as more interconnected. Moreover, we find higher realized interconnections among bank pairs with higher exposures to risky securities.

Second, we show that the relation between realized interconnectedness and the balance sheet positions exhibits asymmetries both cross-sectionally and over time. We find that interbank lending is a relevant driver of realized interconnectedness during crisis times. On the asset allocation side, we show that banks' securities investments have asymmetric effects in the cross-section: bank pairs with higher exposures to the troubled security classes show up as more interconnected. On the contrary, commonality in securities investments related to crisis-unaffected security classes does not induce higher dependency.

This work relates mainly to two different strands in the literature. First, it is related to literature on balance sheet channels of bank interconnectedness. Important examples on direct channels such as interbank lending include Iyer and Peydró (2005), Dasgupta (2004), Freixas *et al.* (2000), Fourel, Héam, Salakhova, and Tavolaro (2013), Memmel and Sachs (2013) and Ippolito, Peydró, Polo, and Sette (2016). On the relevance of indirect sources of interconnectedness, Allen and Carletti (2009) as well as Duarte and Eisenbach (2015) are recent examples. Furthermore, Nier, Yang, Yorulmazer, and Alentorn (2010) relate bank interconnectedness to bank-specific balance sheet information. Secondly, it is related to empirical papers estimating systemic risk and bank interconnectedness from market data. Contributions in this area include the work of Adrian and Brunnermeier (2016), Acharya, Pedersen, Philippon, and Richardson (2016), Diebold and Yilmaz (2016), Zhang *et al.* (2014), Billio *et al.* (2015), Betz *et al.* (2016b), Diebold and Yilmaz (2015), Brownlees *et al.* (2016), Cetina, Paddrik, and Rajan (2016) and Constantina, Peltonen, and Sarlin (2016).

The remainder of the paper is organized as follows. Section 3.2 introduces the dataset and variable definitions. Section 3.3 explains the model and estimation methodology. Section 3.4 presents empirical results and Section 3.5 concludes. A detailed description of the network estimation technique we use can be found in Appendix 3.6.

3.2 Data

The sample consists of 78 bilateral bank connections stemming from a database of 13 large German banks between January 2006 and December 2013. The sample of banks included in the analysis is the one of large German banks for which reliable CDS data is available over the entire sample period. Overall, our sample covers nearly 60 % of assets of the German banking sector.

We combine different data sources to construct the dataset used in this paper: Markit pricing data on CDS contracts as well as the Deutsche Bundesbank credit register, borrowers statistics, security holdings statistics and banking statistics.
From Markit pricing data we obtain daily mid-market spreads for one-year, two-year, three-year, five-year, seven-year and ten-year senior CDS contracts. The sample consists of quotes contributed by more than 30 dealers for all trading days. Markit CDS spread quotes are one of the most widely used sources of CDS data in the literature (Mayordomo, Peña, and Schwartz, 2014).
The Deutsche Bundesbank credit register contains data on large exposures of banks to individual borrowers. The institutions are required to report if their exposures to an individual borrower or the sum of exposures to borrowers belonging to one borrower unit exceeds the threshold of 1.5 million euro. In our analysis, we use interbank loans. The credit register applies a broad definition of loan including traditional loans, bonds, off-balance sheet positions and exposures from derivative positions (excluding trading book positions). The quarterly reporting is pair-wise, such that for each observation we are able to uniquely identify both the borrower and the lender.[2]

[2]Since a typical interbank loan is relatively large, we think that the threshold of 1.5 million euro does not cause a bias.

The Deutsche Bundesbank borrowers statistics are used to extract banks' domestic lending practices to the German real economy. This is a database to which banks report outstanding loan amounts to all German borrowers itemized across 23 industries on a quarterly basis.

We gather data on bank portfolios from the Deutsche Bundesbank securities holdings statistics, which contain detailed quarterly information on all securities holdings of German banks in terms of volume (i.e. euro total) excluding derivatives. This data is very fine-grained so that we can identify securities at the ISIN level. For the purpose of our analysis, we eliminate those observations from the sample where a bank holds securities for its customers and those observations where the holder is equivalent to the issuer. A major portion of banks' portfolios consists of different types of bonds including floating rate notes, Pfandbriefe (covered bonds), government bonds and other bonds.

Lastly, we collect data on banks' Core Tier 1 ratio, equity, leverage ratio (calculated as total assets over Core Tier 1 capital) and risk-weighted assets from the Deutsche Bundesbank banking statistics.

In carrying out the analysis, we convert all variables to weekly frequency. One of the challenges we are facing is the mixed frequency in the original data: the banking network is computed at daily frequency, while all explanatory variables are only available quarterly. Therefore, we decide to run regressions on a basis of weekly data. For converting the bank credit risk network to weekly frequency, we take the average of the values for all trading days within a week obtained through the rolling analysis, and date them to the respective Friday. In order to increase the frequency of the explanatory variables to weekly, we perform one-dimensional linear interpolation separately for each bank pair.

We carry out the analysis both in a baseline specification over the full sample period and an extended specification with subsample-specific coefficients. For the extended specification we consider four subperiods in line with important macroeconomic and financial events. We define a pre-crisis period to run from the beginning of our sample until July 31st, 2008. This period length is chosen such that it ends roughly six weeks before the failure of investment bank Lehman Brothers, in order to take out any anticipation effects from the sample. The banking crisis period is defined to run from August 1st, 2008 until March 31st, 2010, so that it ends with the Greek claim to a sovereign bailout scheme by the IMF on April 10th, 2010. The sovereign debt crisis period runs accordingly from April 1st, 2010 until August 31st, 2012. Its end is assumed to be the announcement of Outright Monetary Transactions by the ECB on September 6th, 2012. The last period, which we carefully dub "post-crisis" then runs from September 1st, 2012 until the end of our sample.

3.2.1 Variable Definitions

Realized Bank Interconnectedness

In this work we define interconnectedness among banks on the basis of standard reduced form credit risk models used in the finance literature. More precisely, we draw upon the Ang and Longstaff (2013) credit risk model. In this model the default intensity of a financial entity is decomposed into a common systematic factor and an entity-specific idiosyncratic component. We associate interconnectedness between banks with the partial correlation among those idiosyncratic intensity components. In this context, partial correlation measures linear dependence between two banks conditional on all other institutions in the panel, and thus captures pair-wise relations and is not affected by spurious effects.

We make use of CDS data to back out partial correlations implied by market prices. We provide a detailed description of the estimation approach in Appendix 3.6 and summarize here the main steps here. First, we identify the systematic default intensity as that of the German sovereign. Making use of the full term structure of CDS prices and corresponding risk-neutral rates, we apply a standard bootstrapping algorithm to obtain instantaneous default intensity for all banks in the sample as well as the German sovereign, which we denote respectively as $\lambda_{i\,t}$ and $\lambda_{f\,t}$. We obtain idiosyncratic default intensities for each bank as the residuals of the regression of the bank default intensity $\lambda_{i\,t}$ on the systematic default intensity $\lambda_{f\,t}$ (in first differences). Finally, we estimate partial correlation among the idiosyncratic intensities as the residuals of the first step. We call this realized interconnectedness and denote it $\rho_{i\,j}$.

Partial correlations are estimated daily on a rolling basis. The window length used throughout the paper amounts to 500 trading days, roughly equaling 2 years of data. The partial correlation obtained from the rolling procedures are denoted by $\rho_{i\,j\,t}$.

Table 3.1 summarizes CDS spreads for all banks in the sample, from which we back out individual instantaneous default intensities. Figure 3.1 shows the term structure of sovereign CDS spreads for Germany, which we use to identify the systematic default intensity. Figure 3.2 shows the risk-neutral default intensity for the German sovereign resulting from the bootstrapping procedure.

Table 3.1: Summary statistics of bank CDS spreads

	Mean	Std. Dev.	Min.	Median	Max.
Bank A	66.77	42.42	5.93	69.27	192.08
Bank B	100.81	72.15	5.62	103.5	346.07
Bank C	104.84	84.5	7.97	84.54	364.12
Bank D	89.36	59.55	8.92	92.51	317.8
Bank E	89.91	49.04	10.25	103.31	189.63
Bank F	69.97	41.72	7.92	69.9	155.8
Bank G	154.29	104.35	7	167.16	445.19
Bank H	102.79	64.47	7.29	119.19	259.97
Bank I	120.65	87.98	5.69	112.95	361.54
Bank J	101.39	71.38	5.91	113.06	355.33
Bank K	103.21	69.45	5.95	116.33	302.56
Bank L	48.55	26.04	5.63	50.93	125.64
Bank M	99.38	68.91	5.77	109.97	334.66

Figure 3.1: Term structure of 1-year, 5-year and 10-year CDS spreads for German sovereign

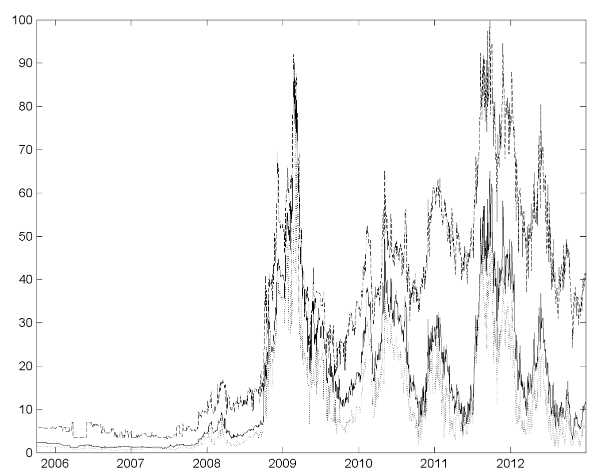
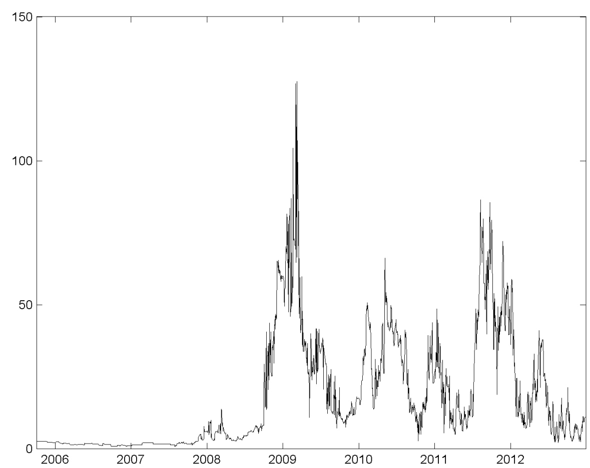


Figure 3.2: CDS-implied default intensity of German sovereign



Interbank Exposure

We construct an interbank exposure index using interbank lending data from the Deutsche Bundesbank credit register. As suggested in, for example, e.g. Upper (2011) we calculate interbank lending over capital as

$$\mathsf{IB}_{ijt} = \frac{1}{2}\left(\frac{IBL_{i\to jt}}{CT1cap_{it}} + \frac{IBL_{j\to it}}{CT1cap_{jt}}\right)$$

where $IBL_{i\to jt}$ denotes the amount of interbank lending from bank i to bank j at time t and $CT1cap_{it}$ is the Core Tier 1 capital of bank i at time t. We take the average of both interbank positions weighted by capital since, in case of a default on interbank positions, both sides are affected, for the lender the position constitutes a credit risk which can potentially wipe out part of his capital in case of default. For the borrower, however, this constitutes a funding risk: in case of default the corresponding position has to be substituted by another interbank relation.

Similarity in Lending Practice

The second channel assessed in this paper is similarity in lending practices of two banks. For obtaining a measure of pair-wise distance, we rely on the methodology proposed in Cai, Saunders, and Steffen (2016). Their measure is constructed in such a way that a lower distance between two banks implies greater similarity in terms of their lending portfolios. Categories in the lending register are defined along two dimensions: borrower type and loan type. We compute portfolio weights for each bank according to the defined categories.[3] Denote by w_{ilt} the relative portfolio weight of bank i in loan

[3] Examples of borrower types distinguished in the database are enterprises and self-employed private individuals or salaried individuals and other private individuals. Loans granted to the enterprises and self-employed individuals category are then further distinguished into industries such as agriculture, forestry, fishery and aquaculture or wholesale, retail trade and repair of motor vehicles and motorcycles. Loan types include, e.g., acceptance credit and credit for housing construction.

category l at time t. Let L be the total number of loan categories defined, and notice that for bank i we have that $\sum_{l=1}^{L} w_{ilt} = 1$ at each time t. Then the distance between two banks i and j at time t is defined as

$$\mathsf{LD}_{ijt} = \sqrt{\sum_{l=1}^{L} (w_{ilt} - w_{jlt})^2}$$

For interpretation purposes, we standardize the distance variable to be between 0 and 1, where 0 refers to the lowest distance between two banks in our sample.

Commonality in Securities Investments

Next we construct an index measuring commonality in securities investments on the basis of the Deutsche Bundesbank securities holdings register. We decompose commonality into "safe" and "troubled" security classes. We consider securities issued in Germany as safe and, because of the time period of this analysis, securities issued in Greece, Ireland, Italy, Portugal and Spain as troubled. We define safe exposures for the (i, j)–th pair at time t as

$$\mathsf{SE}_{ijt} = \log(D_{it}) \log(D_{jt}).$$

where D_{it} denotes the total monetary value of bank i's exposures to securities issued in Germany at time t, and analogously troubled exposures as

$$\mathsf{TE}_{ijt} = \log(GIIPS_{it}) \log(GIIPS_{jt}).$$

where $GIIPS_{ijt}$ is the sum of bank i's exposures to Greece, Ireland, Italy, Portugal and Spain at time t. In the case that at least one of the counterparties does not have any exposures to said securities, this value is replaced by zero. This specification allows us to relate the impact of commonality in securities investments to specific security classes over different time periods for each bank pair.

3.3 Methodology

We use a regression framework to analyze the relation between realized interconnectedness and the balance sheet channels. In particular, we regress partial correlations on indices capturing the various balance sheet channels, together with a set of controls and fixed effects. The peculiarity of our regression exercise is that the data has a paired structure. This type of regression often appears in social network or trade flows analysis and is commonly referred to as "dyadic regression" (cf Krackhardt, 1988). Inference on the dyadic regression model parameters is carried out here by standard OLS while computation of the robust standard errors requires appropriate clustering that takes into account the special correlation structure of the model.

More precisely, we consider the dyadic regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt} + \beta_2 \mathsf{LD}_{ijt} + \beta_3 \mathsf{TE}_{ijt} + \beta_4 \mathsf{SE}_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}\,, \quad (3.1)$$

where IB_{ijt} denotes the interbank exposure, LD_{ijt} is the measure of distance in lending practice, and TE_{ijt} and SE_{ijt} correspond to pair-wise security class exposures, respectively. To account for time and cross-sectional heterogeneity, we include both bank-fixed effects α_i, α_j and time-fixed effects α_t. The vector $z_{ij,t-1}$ contains control variables. Controls are constructed as the pairwise product of a set of bank characteristics: (log) banks' equity, (log) risk-weighted assets, Core Tier 1 capital ratio and the leverage ratio total book equity over total book assets plus off-balance sheet exposures. In the analysis, control variables are lagged by one period. Table 3.2 contains summary statistics of the variables used to construct the controls.

Table 3.2: SUMMARY STATISTICS OF BANK BALANCE SHEET DATA

	Mean	Std. Dev.	10% Quantile	Median	90% Quantile
Core Tier 1 Capital Ratio	9.54	2.57	6.28	9.19	12.94
Core Tier 1 Capital	12005.19	2313.97	8614.27	13448.45	14914.86
Equity	16256.97	2100.42	13519.12	17045.22	19006.38
Risk-weighted Assets	127140.59	23959.46	97678.19	135479.37	158233.81
Leverage Ratio	36.51	5.75	29.46	37.05	44.42

Because of the dyadic structure of the panel in our model, the error term is correlated across observations that have an element in common. More specifically, the error term is assumed to be zero mean, uncorrelated with the explanatory variables, and have nonzero correlation only with the errors which either have i and j in common, that is,

$$\mathrm{E}(\epsilon_{ij\,t}\epsilon_{kl\,t}|x_{ij\,t}, x_{kl\,t}) = 0 \quad \text{unless} \quad i = k \text{ or } i = l \text{ or } j = k \text{ or } j = l,$$

where $x_{ij\,t}$ denotes a vector containing the regressors of Equation (3.1). In order to take into account the correlation pattern of the dyadic regression, standard errors are clustered along both dimensions of the pair.

In order to capture sub-sample-specific effects, we also consider a variation of the baseline model in (3.1) in which we interact the channels with indicator variables for the different subsample periods. This specification allows the various balance sheet channels to have different impacts in each phase of the crisis. For instance, for the interbank lending channel we consider the specification

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt}\mathbf{1}_{pre} + \beta_2 \mathsf{IB}_{ijt}\mathbf{1}_{ban} + \beta_3 \mathsf{IB}_{ijt}\mathbf{1}_{sov} + \beta_4 \mathsf{IB}_{ijt}\mathbf{1}_{post} + \gamma' z_{ij,t-1} + \epsilon_{ijt}\,, \tag{3.2}$$

where $\mathbf{1}_{pre}$, $\mathbf{1}_{ban}$, $\mathbf{1}_{sov}$ and $\mathbf{1}_{post}$ are dummy variables equal to 1 if the observation lies within the defined subsample period, and 0 otherwise. We define analogously the interacted specifications for LD_{ijt}, SE_{ijt} and TE_{ijt}.

3.4 Empirical Results

3.4.1 Baseline Specification

We begin by estimating the baseline dyadic regression model of Equation (3.1) introduced in the previous section. We consider different variants of the specification. Table 3.3 contains the regression results.

The first channel we investigate are bilateral exposures in the interbank market. We hypothesize that interbank lending between two banks can lead to higher realized interconnectedness in credit risk if and only if the exposure is large relative to the lender's Core Tier 1 capital. Quantile statistics for interbank lending over Core Tier 1 capital are shown in Table 3.4. In our sample, the average interbank loan between two banks amounts to 0.19 % of the lender's Core Tier 1 capital.

Table 3.3 shows the result for the baseline regression model. We find that higher amounts of interbank exposure between two banks are related to higher realized interconnectedness, given that we include both time and bank-fixed effects. In the first specification which does not control for time, we do not find any significant effect. The magnitude of the coefficient changes only slightly for different variants: with both time- and bank-fixed effects and including a set of control variables, we find that an increase of interbank lending weighted by Core Tier 1 capital by one percentage point is related to a 4.518 percentage point increase in partial correlations.

In order to detect non-linear effects of different magnitudes of interbank lending, we divide the variable into four regions: the 1st region contains values of bilateral interbank lending lower than 0.1 % of the lender's Core Tier 1 Capital, which captures approx. the lower 40 % of the distribution. The second region contains all values that lie between 0.1 and 0.3 % of the lender's Core Tier 1 capital, which captures another 40 % of the distribution. The two highest regions divide the remaining 20 %, such that

Table 3.3: Variants of Baseline Regression

VARIABLES	(1) ρ	(2) ρ	(3) ρ	(4) ρ	**(5)** ρ	(6) ρ	(7) ρ	(8) ρ	(9) ρ	**(10)** ρ	(11) ρ	(12) ρ	(13) ρ	(14) ρ	**(15)** ρ
IB Lending	3.388				**3.756***	4.161+				**4.759****	4.006+				**4.518****
	(2.066)				(1.669)	(2.120)				(1.575)	(2.202)				(1.643)
Lend. Distance		-0.0615*			**-0.0626***		-0.0631*			**-0.0644***		-0.0677*			**-0.0694***
		(0.0288)			(0.0290)		(0.0308)			(0.0320)		(0.0283)			(0.0290)
Troubled Exp.			0.00471***		**0.00444****			0.00588***		**0.00600*****			0.00705***		**0.00708*****
			(0.00122)		(0.00144)			(0.00156)		(0.00166)			(0.00125)		(0.00106)
Safe Exp.				-0.00106	**-0.000315**				-0.00146	**-0.00136**				-0.00108	**-0.00112**
				(0.00411)	(0.00396)				(0.00406)	(0.00383)				(0.00377)	(0.00325)
Number of Banks	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Observations	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779
Adj. R-squared	0.141	0.145	0.141	0.137	0.153	0.148	0.151	0.149	0.143	0.164	0.154	0.158	0.156	0.149	0.171
Control Variables	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Two-way cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table shows coeffient estimates and standard errors for different variants of the baseline regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt} + \beta_2 \mathsf{LD}_{ijt} + \beta_3 \mathsf{TE}_{ijt} + \beta_4 \mathsf{SE}_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors are based on two-dimensional clustering along both banks contained in the dyad.

Table 3.4: QUANTILE STATISTICS FOR EXPLANATORY VARIABLES

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Interbank Lending	0.0499 %	0.0710 %	0.0889 %	0.1077 %	0.1432 %	0.1612 %	0.2039 %	0.2596 %	0.3949 %
Lending Distance	0.051	0.095	0.144	0.194	0.247	0.312	0.379	0.445	0.552
Security Holdings Germany	0	0	0	0	3.157	3.769	4.201	4.471	4.998
Security Holdings GIIPS	0	0	0	0	2.268	2.847	3.324	3.663	4.279

This table shows quantiles statistics for confidential explanatory variables: Interbank Lending, Lending Distance, Troubled Exposures and Safe Exposures. The value of 0 for the lower quantiles of pair-wise exposures refers to cases in which at least one of the counterparties does not have any exposures to the respective securities.

region 3 contains all values between 0.3 and 0.4 % of the lender's Core Tier 1 capital, and the fourth region contains all values above.[4] Results for the effects of the four different regions of interbank exposures are displayed in Table 3.5. The specification again includes both time- and bank-fixed effects and the set of control variables.

Table 3.5 shows that the positive relation between interbank exposures and realized interconnectedness is highly significant in all four regions. In terms of magnitude of the coefficients, the effect is strongest in the lowest region: a percentage point increase in interbank lending weighted by Core Tier 1 capital leads to relatively higher interconnectedness when interbank exposures between the counterparties are initially low.

The second channel we investigate is similarity in lending practice. We hypothesize that two banks with more similar lending practices have a higher common exposure to specific risk factors and should therefore be perceived as more interconnected by the market. Quantile statistics for the distance variable are depicted in Table 3.4.

Recall that the distance measure is constructed such that a higher value per dyad indicates less similar lending practices to the real economy, hence we expect the coefficient to have a negative sign. Table 3.3 confirms this hypothesis: two banks with less similar lending practices show lower realized interconnectedness, and the coefficient

[4]Our results are robust to changes in the way we define the regions.

Table 3.5: Differential effects for regions of Interbank Lending

VARIABLES	ρ
IB Lending 1st Region	39.83*
	(16.92)
IB Lending 2nd Region	18.16*
	(7.942)
IB Lending 3rd Region	20.76***
	(5.701)
IB Lending 4th Region	5.033*
	(2.073)
Number of Banks	13
Observations	20779
Adj. R-squared	0.173
Control Variables	Yes
Bank Fixed Effects	Yes
Time Fixed Effects	Yes

Two-way cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table reports coefficient estimates and standard errors for the regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt}\mathbf{1}_{\mathsf{IB1}} + \beta_2 \mathsf{IB}_{ijt}\mathbf{1}_{\mathsf{IB2}} + \beta_3 \mathsf{IB}_{ijt}\mathbf{1}_{\mathsf{IB3}} + \beta_4 \mathsf{IB}_{ijt}\mathbf{1}_{\mathsf{IB4}} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. The binary variable $\mathbf{1}_{\mathsf{IB1}}$ is equal to one if the observation lies in the first region of Interbank Lending as defined in Section 3.4. $\mathbf{1}_{\mathsf{IB2}}$, $\mathbf{1}_{\mathsf{IB3}}$ and $\mathbf{1}_{\mathsf{IB4}}$ are defined analogously.

is significant at the 5 % level. An increase of 1 percentage point in lending distance is associated with a decrease in partial correlations of 0.06 percentage points. The magnitude remains largely unchanged and significance increases when enhancing the specification with both bank fixed effects and control variables.

For detecting non-linear effects in the cross-section, we again divide the variable into four different regions. Since there is no intuitive interpretation of specific values, we make use of quartiles for determining cutoff points. Results are depicted in Table 3.6.

Table 3.6: Differential effects for quartiles of Distance in Lending Practice

VARIABLES	ρ
Lend. Distance 1st Quartile	-0.452***
	(0.136)
Lend. Distance 2nd Quartile	-0.219**
	(0.0753)
Lend. Distance 3rd Quartile	-0.165***
	(0.0379)
Lend. Distance 4th Quartile	-0.0991**
	(0.0324)
Number of Banks	13
Observations	20779
Adj. R-squared	0.160
Control Variables	Yes
Bank Fixed Effects	Yes
Time Fixed Effects	Yes

Two-way cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table reports coefficient estimates and standard errors for the regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{LD}_{ijt}\mathbf{1}_{\mathsf{LD1}} + \beta_2 \mathsf{LD}_{ijt}\mathbf{1}_{\mathsf{LD2}} + \beta_3 \mathsf{LD}_{ijt}\mathbf{1}_{\mathsf{LD3}} + \beta_4 \mathsf{LD}_{ijt}\mathbf{1}_{\mathsf{LD4}} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. The binary variable $\mathbf{1}_{\mathsf{LD1}}$ is equal to one if the observation lies in the first quartile of the Lending Distance variable. $\mathbf{1}_{\mathsf{LD2}}$, $\mathbf{1}_{\mathsf{LD3}}$ and $\mathbf{1}_{\mathsf{LD4}}$ are defined analogously.

The negative relation between distance in lending practice and realized interconnectedness is highly significant at any value of the distance variable. The magnitude of the coefficient varies strongly in the cross-section and is highest when the distance between two banks is very small: within the lowest quartile, a percentage point decrease in the lending distance between two banks is associated with a 0.4 percentage point increase in partial correlations.

The third channel we investigate are common exposures to similar securities. Recall that, as explained in Section 3.2.1, we decompose pair-wise common securities holdings into two different categories: "troubled exposures" proxied by securities issued in one of the GIIPS countries, and "safe exposures" proxied by securities issued in Germany. We hypothesize that two banks with higher common exposures should have higher credit risk interconnectedness. Disentangling the "troubled" and the "safe" securities allows us to additionally investigate whether those have different effects on realized interconnectedness. Quantile statistics for exposures to Germany and the GIIPS countries are shown in Table 3.4.

Again, results for the relation between commonality in securities investments and results interconnectedness are depicted in Table 3.3. Results confirm our hypothesis: two banks with higher exposures to securities issued in one of the GIIPS countries are perceived as more interconnected by the market, and this effect is significant at the 1 % level. Note that the commonality variable is calculated as a pair-wise log: a percentage increase in exposures to the GIIPS countries for one of the banks is associated with a 0.444 percentage point increase in partial correlations in the first variant, keeping exposures of the counterparty stable. This coefficient increases slightly in magnitude when adding control variables and time fixed effects and significance increases. We do not find any significant effect for exposures to securities issues in Germany. We conclude that the market perceives stronger links between banks with higher common holdings given that these are related to troubled exposures.

Last, we divide exposures to securities issued in one of the GIIPS countries into four different regions again defined by quartiles, and let coefficients vary among those. Results are shown in Table 3.7.

Table 3.7: Differential effects for quartiles for Troubled Exposures

VARIABLES	ρ
Troubled Exp. 1st Quartile	0
	(0)
Troubled Exp. 2nd Quartile	0.00757
	(0.00894)
Troubled Exp. 3rd Quartile	0.00171
	(0.00305)
Troubled Exp. 4th Quartile	0.00958***
	(0.00186)
Number of Banks	13
Observations	20779
Adj. R-squared	0.158
Control Variables	Yes
Bank Fixed Effects	Yes
Time Fixed Effects	Yes

Two-way cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table reports coefficient estimates and standard errors for the regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{TE}_{ijt} \mathbf{1}_{\mathsf{TE1}} + \beta_2 \mathsf{TE}_{ijt} \mathbf{1}_{\mathsf{TE2}} + \beta_3 \mathsf{TE}_{ijt} \mathbf{1}_{\mathsf{TE3}} + \beta_4 \mathsf{TE}_{ijt} \mathbf{1}_{\mathsf{TE4}} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Troubled Exposures are defined as the product of two banks' log exposures to assets issued in GIIPS countries. The binary variable $\mathbf{1}_{\mathsf{TE1}}$ is equal to one if the observation lies in the first quartile of the Troubled Exposures variable. $\mathbf{1}_{\mathsf{TE2}}$, $\mathbf{1}_{\mathsf{TE3}}$ and $\mathbf{1}_{\mathsf{TE4}}$ are defined analogously.

The relation between pair-wise holdings of troubled exposures and realized interconnectedness is significant only in the highest quartile: two banks are perceived as more interconnected if and only if their common exposures to troubled security classes are large. Note that the value of zero in the first quartile stems from pairs where at least one bank does not have any exposures to securities issued in one of the GIIPS countries. An increase in securities holdings of GIIPS countries of one of the counterparties by 1 percent is associated with a 0.96 percentage point increase in partial correlation.

While two-way clustering along both dimensions in the pair is a natural approach to the peculiar correlation structure of our model, we acknowledge that the small number of clusters (K=13) might lead to an over-rejection of the null hypothesis in some cases. Thus, we run the third variant of the baseline regression with both bank- and time fixed effects as well as a set of control variables with two different kinds of standard errors: Huber-White standard errors and cluster-robust standard errors with clusters at the pair level. For comparison purposes, we report again the results of this regression with standard errors clustered along both dimensions of the dyad. Results for these specifications are displayed in Table 3.8.

We can see that Hubert-White standard errors are considerably smaller for all variables, whereas standard errors increase slightly when clustering at the pair level. Using simple Hubert-White standard errors should lead to overly small standard errors and narrow confidence intervals and hence overestimate the significance of the coefficients. On the other hand, clustering at the pair level underestimates the correlation structure of the model, since we do not allow for standard errors to be correlated across pairs containing common elements. The standard errors, and thus significance levels, of the coefficients we obtain with our default approach are in the middle of these two cases. The significance of interbank lending varies substantially with the choice of standard errors. The variable has a highly significant effect using Hubert-White standard errors, while significance vanishes when clustering standard errors at the pair level. For similarity in lending practices and exposures to troubled securities we find significant effects irrespective of the clustering of standard errors.

In a second robustness check of our results we run another variant of the baseline specification with both time and pair fixed effects for ruling out omitted variable bias at the pair level. Results are displayed in Table 3.9.

Note that this variant controls for all observable and unobservable characteristics

Table 3.8: Variant of Baseline Regression with Different Standard Errors

VARIABLES	(1) ρ	(2) ρ	(3) ρ	(4) ρ	**(5)** ρ	(6) ρ	(7) ρ	(8) ρ	(9) ρ	**(10)** ρ	(11) ρ	(12) ρ	(13) ρ	(14) ρ	**(15)** ρ
IB Lending	4.006***				**4.518*** **	4.006				**4.518+**	4.006+				**4.518** **
	(0.269)				(0.264)	(2.447)				(2.344)	(2.202)				(1.643)
Lend. Distance		-0.0677***			**-0.0694*** **		-0.0677*			**-0.0694***		-0.0677*			**-0.0694***
		(0.00344)			(0.00344)		(0.0301)			(0.0298)		(0.0283)			(0.0290)
Troubled Exp.			0.00705***		**0.00708*** **			0.00705**		**0.00708** **			0.00705***		**0.00708*** **
			(0.000367)		(0.000362)			(0.00230)		(0.00228)			(0.00125)		(0.00106)
Safe Exp.				-0.00108*	**-0.00112***				-0.00108	**-0.00112**				-0.00108	**-0.00112**
				(0.000498)	(0.000483)				(0.00481)	(0.00446)				(0.00377)	(0.00325)
Number of Banks	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Observations	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779
Adj. R-squared	0.154	0.158	0.156	0.149	0.171	0.154	0.158	0.156	0.149	0.171	0.154	0.158	0.156	0.149	0.171
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Respective standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table shows coeffient estimates and standard errors for a variant of the baseline regression model

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt} + \beta_2 \mathsf{LD}_{ijt} + \beta_3 \mathsf{TE}_{ijt} + \beta_4 \mathsf{SE}_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors differ across three specifications: Columns 1-5 show heteroskedasticity robust standard errors, columns 6-10 show standard errors clustered at the pair level and columns 11-15 standard errors clustered along both dimensions in the dyad.

Table 3.9: Baseline Regression with Pair Fixed Effects

VARIABLES	(1) ρ	(2) ρ	(3) ρ	(4) ρ	(5) ρ	(6) ρ	(7) ρ	(8) ρ	(9) ρ	(10) ρ
IB Lending	-2.914				**-1.237**	-0.755				**-0.568**
	(6.589)				(1.032)	(7.236)				(6.492)
Lend. Distance		-0.0723+			**-0.0693+**		-0.0715+			**-0.0667+**
		(0.0393)			(0.0362)		(0.0425)			(0.0396)
Troubled Exp.			0.00412**		**0.00369****			0.00511*		**0.00474***
			(0.00134)		(0.00131)			(0.00189)		(0.00200)
Safe Exp.				-0.00613*	**-0.00704*****				-0.00598	**-0.00767***
				(0.00252)	(0.000817)				(0.00500)	(0.00346)
Number of Banks	13	13	13	13	13	13	13	13	13	13
Observations	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779
Adj. R-squared	0.507	0.510	0.510	0.508	0.514	0.508	0.511	0.511	0.509	0.533
Control Variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pair Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Two-way cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

This table shows coeffient estimates and standard errors for a variant of the baseline regression model with pair-fixed effects

$$\rho_{ijt} = \alpha_{ij} + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt} + \beta_2 \mathsf{LD}_{ijt} + \beta_3 \mathsf{TE}_{ijt} + \beta_4 \mathsf{SE}_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors are based on two-dimensional clustering along both banks contained in the dyad.

of within-bank relationships. The coefficient thus picks up only the time-varying part of variation at the pair-level within the same pair and measures whether, controlling for the average pairwise level of realized interconnectedness, we find differential effects associated to our set of explanatory variables. Similarity in lending practice between two banks remains significant at the 5% level with a slight increase in magnitude of the coefficient: controlling for all within-pair characteristics, an increase in the distance between two banks by one percentage point is associated with a decrease in partial correlations by 0.077 percentage points. Pair-wise exposures to securities issued in the GIIPS countries are related to an increase in realized interconnectedness, and this effect is significant at the 1% level. Note that, also here, the coefficient changes only slightly in magnitude. In contrast, we do not find any significant result for interbank lending once we take out all within-pair variation. This result is due to the stable nature of interbank lending, where the relation comes at the individual pair level without much variation over time.

Focusing on the time-varying part of variation within the same pair, we find a significant positive effect for pairwise exposures to securities issued in Germany: two banks with higher pairwise exposures are perceived as less interconnected by the market. This assigns a stabilizing role of common exposures to non-troubled securities: two banks which have safer security portfolios individually are also perceived as less interconnected in terms of credit risk. This is in line with the results of Brownlees *et al.* (2016) who find that perceived interconnectedness increases with the extent of "troubledness" of individual banks, and is thus lower for safer individuals.

To shed light on the robustness of results to using different standard errors, we again run the specification with Hubert-White standard errors and standard errors clustered at the pair level in addition. Results for three variants are displayed in Table 3.10.

Similarly to previous results, significance levels we obtain with two-way clustering

Table 3.10: Baseline Regression with Pair Fixed Effects and different Standard Errors

VARIABLES	(1) ρ	(2) ρ	(3) ρ	(4) ρ	(5) ρ	(6) ρ	(7) ρ	(8) ρ	(9) ρ	(10) ρ	(11) ρ	(12) ρ	(13) ρ	(14) ρ	(15) ρ
IB Lending	-0.755				**-0.568**	-0.755				**-0.568**	-0.755				**-0.568**
	(0.675)				(0.663)	(4.508)				(3.965)	(7.236)				(6.492)
Lend. Distance		-0.0715***			**-0.0667*** **		-0.0715*			**-0.0667+**		-0.0715+			**-0.0667+**
		(0.00455)			(0.00456)		(0.0325)			(0.0338)		(0.0425)			(0.0396)
Troubled Exp.			0.00511***		**0.00474*** **			0.00511**		**0.00474***			0.00511*		**0.00474***
			(0.000310)		(0.000308)			(0.00195)		(0.00195)			(0.00205)		(0.00200)
Safe Exp.				-0.00598***	**-0.00767*** **				-0.00598	**-0.00767+**				-0.00598	**-0.00767***
				(0.000636)	(0.000603)				(0.00432)	(0.00414)				(0.00500)	(0.00346)
Number of Banks	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Observations	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779	20779
Adj. R-squared	0.508	0.511	0.511	0.509	0.533	0.508	0.511	0.511	0.509	0.533	0.508	0.511	0.511	0.509	0.533
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pair Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Respective standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table shows coeffient estimates and standard errors for a variant of the baseline regression model with pair-fixed effects and different standard errors

$$\rho_{ijt} = \alpha_{ij} + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt} + \beta_2 \mathsf{LD}_{ijt} + \beta_3 \mathsf{TE}_{ijt} + \beta_4 \mathsf{SE}_{ijt} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

Rho denotes the idiosyncratic partial correlation between two banks implied by CDS prices. Interbank Lending is the average interbank exposure between two banks weighted by the lender's Core Tier 1 capital. Lending Distance is the standardized Euclidean distance between two banks' lending composition to the real economy. Troubled Exposures and Safe Exposures refer to the product of two banks' log exposures to assets issued in GIIPS countries and Germany, respectively. Standard errors differ across three specifications: Columns 1-5 show heteroskedasticity robust standard errors, columns 6-10 show standard errors clustered at the pair level and columns 11-15 standard errors clustered along both dimensions in the dyad.

along both dimensions of the pair lie in between the ones resulting from Hubert-White standard errors and clustering on the pair level.

3.4.2 Extended Specification: Subsample Specific Effects

In order to capture subsample-specific effects, we consider an extension of the baseline specification stated in Equation (3.2). We expect channels to have different impacts depending on the subperiod. Results for the analysis are shown in Table 3.11.

Interbank lending is strongly related to market-perceived interconnectedness starting with the banking crisis period: a percentage point increase of interbank exposure weighted by capital is associated with a 5.956 percentage point increase in partial correlation between two entities, and this effect is significant at the 1% level. The coefficient on interbank lending remains largely stable in the two following periods, as already indicated by the results in Table 3.9. Results are intuitive: starting with the banking crisis period, options for banks to obtain outside funding were largely limited, with higher information asymmetry, lower confidence in the financial system and deteriorating financing conditions. As shown in, for example, Bolton, Freixas, Gambacorta, and Mistrulli (2016) and Braeuning and Fecht (2016), interbank positions, which are typically long-term relationships, become an important source of funding for banks in troublesome times thanks to informational advantages. Furthermore, when banks are financially constrained, bilateral interbank positions become harder to substitute in case of a default on the obligation. This positive effect of interbank lending on realized interconnectedness continues to hold good for the remainder of the sample period.

The time pattern greatly differs for similarity in lending practices to the real economy. Both in the pre-crisis and in the banking crisis period, we find a negative effect: two banks with less similar lending practices are perceived as less interconnected by the market, and this is significant at the 1 % level. In the pre-crisis period, during

Table 3.11: Differential effects in subsample periods

VARIABLES	(1) ρ	(2) ρ	(3) ρ	(4) ρ	(5) ρ
IBpre	-0.213				2.110
	(2.047)				(1.425)
IBban	5.956*				6.760***
	(2.402)				(1.304)
IBsov	5.111**				5.288**
	(1.927)				(1.614)
IBpost	7.318**				8.154***
	(2.800)				(1.511)
LDpre		-0.136***			-0.137**
		(0.0294)			(0.0419)
LDban		-0.0845**			-0.0818*
		(0.0279)			(0.0334)
LDsov		-0.0407			-0.0465
		(0.0354)			(0.0413)
LDpost		-0.0116			-0.0270
		(0.0526)			(0.0563)
TEpre			0.00566***		0.00888***
			(0.00138)		(0.00217)
TEban			0.00502*		0.00609*
			(0.00255)		(0.00269)
TEsov			0.00911***		0.00500*
			(0.00225)		(0.00211)
TEpost			0.00453+		-0.000689
			(0.00270)		(0.00500)
SEpre				-0.00996**	-0.00871+
				(0.00308)	(0.00443)
SEban				-0.00403	-0.00303
				(0.00577)	(0.00599)
SEsov				0.00410	0.00479
				(0.00356)	(0.00585)
SEpost				0.000842	0.00425
				(0.00309)	(0.00305)
Number of Banks	13	13	13	13	13
Observations	20779	20779	20779	20779	20779
Adj. R-squared	0.157	0.162	0.157	0.161	0.188
Control Variables	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes

Two-way cluster robust standard errors in parenthesis
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

This table shows coeffient estimates and standard errors for a variant of the baseline regression model with sub-sample specific effects. For the example of Interbank Lending,

$$\rho_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta_0 + \beta_1 \mathsf{IB}_{ijt} \mathbf{1}_{pre} + \beta_2 \mathsf{IB}_{ijt} \mathbf{1}_{ban} + \beta_3 \mathsf{IB}_{ijt} \mathbf{1}_{sov} + \beta_4 \mathsf{IB}_{ijt} \mathbf{1}_{post} + \gamma' z_{ij,t-1} + \epsilon_{ijt}$$

The binary variables $\mathbf{1}_{pre}, \mathbf{1}_{ban}, \mathbf{1}_{sov}, \mathbf{1}_{post}$ indicate whether the observation lies in the specific sub-sample period pre-crisis, banking crisis, sovereign debt crisis or post crisis. The regression model is specified for Lending Distance, Troubled Exposures and Safe Exposures analogously. Standard errors are based on two-dimensional clustering along both banks contained in the dyad.

calm times, a percentage point increase in the distance between two banks is associated with a 13.6 percentage point drop in partial correlation. In the banking crisis period the magnitude of the coefficient approximately halves. With the beginning of the sovereign debt crisis period, significance of the effect vanishes. We conclude that, as overall turmoil in financial system increases, other factors such as interbank lending and commonality in securities investments become more important in the view of market participants and dominate the effect of similar lending practices to the real economy.

Last, we investigate the effect of commonality in securities investments related to troubled and safe securities. In the pre-crisis period, we find opposing significant coefficients for both security classes: higher pair-wise exposures to troubled securities are related to higher realized interconnectedness, whereas higher exposures to safe security classes are associated with lower realized interconnectedness. This points towards market participants perceiving troubled securities as a potential source of contagion, whereas safe securities should induce stability in financial markets and hence lead to lower interconnectedness in credit risk.

For safe security classes, this effect vanishes with the start of the banking crisis. We conclude that, during turmoil in financial markets, the definition of safe security classes becomes unclear, and market participants do not perceive any type of common holdings as inducing stability. Note that these results are in line with Table 3.11 where we find a significant negative effect for exposures to non-troubled securities when focusing on the time-varying part of variation within the same pair.

For troubled securities, we see a second, quantitatively stronger effect emerging during the sovereign debt crisis: following the Greek filing for sovereign bailout, market participants perceive a strong relation between exposures to securities issued in any of the GIIPS countries and realized interconnectedness: an increase in said holdings by one of the counterparties by 1% is associated with a 0.9 percentage point increase in partial correlations, and this effect is significant at the 0.1 % level. We conclude that this strong effect is related to the greater riskiness which was induced by holdings of securities issued in the GIIPS countries specifically during this period when these securities were most troubled.

3.5 Conclusion

The identification and quantification of the systemic component of financial risk requires an in-depth understanding of the channels through which shocks can spread and amplify, thereby jeopardizing the stability of a financial system. Our understanding of these links as a whole is, however, hampered by the absent comprehension of the key determinants of financial institutions' interconnections. This has been due to the lack of comprehensive datasets that are sufficient for analyses of this kind. The contribution of this paper is to study the relationship between market information-based credit risk interconnectedness and *actual* common exposures of banks through their actual funding and securities holding (liability-asset structure). We measure empirical bank interconnectedness of a partial correlation measure that relies solely on market-based information proposed in Brownlees *et al.* (2016).

Two main results emerge from our analysis. First, we find that realized interconnectedness strongly reflects both bank exposure vis-a-vis the wholesale funding market and assets associated with securities investments and credit supply. We find that bank pairs where both counterparties have higher Core Tier 1 capital-weighted interbank exposure show higher realized interconnectedness. On the asset allocation side, we document that both banks' exposure to the real economy and their securities investments have an impact on realized network connections. Bank pairs with more similar lending practices to the real economy show up as more interconnected. Moreover, we find higher realized interconnections among bank pairs with higher exposures to risky securities.

Second, we show that the relation between realized interconnectedness and the balance sheet positions exhibits asymmetries both cross-sectionally and over time. We find that interbank lending is a relevant driver of realized interconnectedness during crisis times as other sources of financing become hard to obtain. On the asset allocation side, we show that banks' securities investments have asymmetric effects in the cross-section: bank pairs with higher exposures to the troubled security classes show up as more interconnected. On the contrary, commonality in securities investments related to crisis-unaffected security classes does not induce higher dependency.

These results show that banks' wholesale funding exposure, securities investment and credit supply affect the interdependency in bank credit risk. Moreover, they show that market information-based measures of interdependence can serve well as risk monitoring tools in the absence of disaggregated high-frequency bank fundamental data.

3.6 Appendix: Estimating the Bank Credit Risk Network

We follow Ang and Longstaff (2013) in modelling credit events as jumps of a Poisson process with stochastic intensity, and consider two different types of credit events which can trigger default.

The first event is a systematic shock which affects all entities in the economy, modelled as the jump of a Poisson process $M(t)$ with stochastic intensity λ that follows a standard square root process,

$$d\lambda(t) = a(m - \lambda(t))dt + b\sqrt{\lambda(t)}dW(t)$$

where $W(t)$ denotes a Brownian motion. Following a systematic shock, entity i will default with conditional probability γ_i,

$$\gamma_i = \text{Prob}(\text{default}_i | \text{ systematic default}) \ ,$$

The second event is an idiosyncratic triggering default of entity i with certainty, modelled accordingly as the first jump of a Poisson process $N_i(t)$ with stochastic intensity ξ_i that follows a standard square root process,

$$d\xi_i(t) = \alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t) \text{ with } i = 1, ..., n \ ,$$

where again $B_i(t)$ denotes an entity specific Brownian motion with $B_i \perp W_i \forall i$.

For entities $1, ..., n$, the Brownian motions $(B_1(t), ..., B_n(t))'$ are assumed to be correlated with covariance matrix Σt. Following a well established result by () the conditional independence network can be fully characterized by the sparsity structure of K_t, the inverse of Σ_t: two entities i and j are conditionally independent if and only if the $i-j-th$ entry $k_{ij}=0$.

The probability that an entity has not defaulted by time t is

$$P\left(\text{no default}_i \text{ occurs by time t}\right) = \exp\left(-\int_0^t (\gamma_i\lambda(s)+\xi_i(s))ds\right)$$

We refer to $\lambda_i(s) = \gamma_i\lambda(s)+\xi_i(s)$ as the marginal default intensity of entity i. We can now use the standard framework for valuing credit derivatives as established in Duffie and Singleton (1999) setting the default probability equal to the marginal default intensity for each entity. Following this, we can express the protection leg of a CDS contract as

$$CDS_i^{pro} = \mathsf{E}^Q\left(\int_0^T \exp\left[-\int_0^t (r(s)+\gamma_i\lambda(s)+\xi_i(s))(1-\omega)ds\right]dt\right)$$

and its premium leg as

$$CDS_i^{pre} = \mathsf{E}^Q\left(s_i\int_0^T \exp\left[-\int_0^t (r(s)+\gamma_i\lambda(s)+\xi_i(s))ds\right]dt\right)$$

where s_i is the CDS spread and $1-\omega$ is the recovery fraction. For no arbitrage, those two must be equal, and we get

$$s_i = \frac{\omega\mathsf{E}^Q\left(\int_0^T D(t)(\gamma_i\lambda(t)+\xi_i(t))\exp\left[-\int_0^t(\gamma_i\lambda(s)+\xi_i(s))ds\right]dt\right)}{\mathsf{E}^Q\left(\int_0^T D(t)\exp\left[-\int_0^t(\gamma_i\lambda(s)+\xi_i(s))ds\right]dt\right)}$$

where $D(t)=\mathsf{E}^Q\left(\exp-\int_0^t r(s)ds\right)$

The estimation then proceeds as follows: For each institution i, we identify the systematic intensity as the default intensity of Germany. Applying a bootstrapping algorithm to make use of the full term structure of CDS spreads, we back out systematic default intensity λ and n marginal default intensities λ_i. In order to filter out the systematic component, idiosyncratic intensity differences are estimated as the residual of the regression of marginal intensity differences $\Delta\hat{\lambda}_i$ on systematic intensity differences $\Delta\hat{\lambda}$. The interconnectedness measured used in this work is the partial correlation among banks obtained from the residuals of this regression.

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