

FIRE-SALE SPILLOVERS IN A NETWORK PERSPECTIVE *

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Abstract

I analyze correlation patterns of portfolio returns in an asset commonality network of financial institutions. 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. 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.

Keywords: Asset Commonality, Networks, Fire Sales, Portfolio Returns

JEL: C33, C55, E44, F36, G01, G12, G21, G33

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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 2 introduces the dataset and variable definitions. Section 3 explains the model and estimation methodology. Section 4 presents empirical results. And Section 5 concludes.

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.

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.

$$S_{it} = \overset{\circ}{S}_{it} \cup \check{S}_{it}$$

where S_{it} is a bank's total security portfolio, $\overset{\circ}{S}_{it}$ is the space of securities held only by bank i and no other bank in the system at time t , and \check{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 \check{S}_{ijt} for the space of securities which is held in common by bank i and j at time t . Note that $\check{S}_{it} \leq \sum_{j \neq i} \check{S}_{ijt}$ since \check{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.

2.1.1 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 \check{S}_{it} from the analysis and compute portfolio returns on $\overset{\circ}{S}_{it}$ 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

$$RI_{st} = RI_{st-1} \frac{P_{st} + A_{st} + NC_{st} + CP_{st}}{P_{st-1} + A_{st-1} + NC_{st-1}},$$

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.

$$\Delta\epsilon_{st} = RI_{st} - \beta\Delta PC_{(1)t}$$

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 $\overset{\circ}{R}_{it}$ is then defined

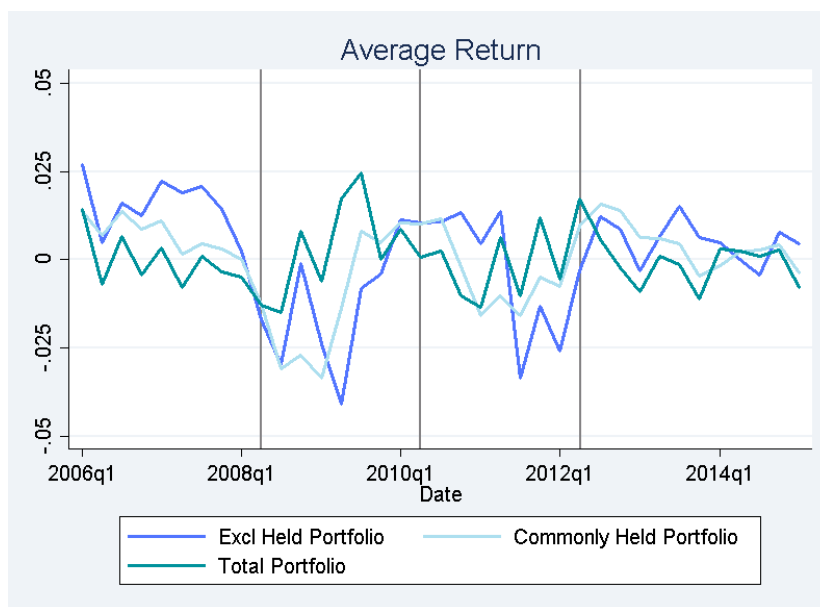
as a weighted portfolio of excess returns for all securities exclusively held by bank i at time t

$$\mathring{R}_{it} = \sum_{s \in S_{it}^{\circ}} \omega_{ist} \Delta \epsilon_{st},$$

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 shows the time variation in said returns, calculated as a time-varying mean for the entire sample of banks.

Figure 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{R}_{it} and R_{it} are tightly linked, hinting

towards securities contained in \mathring{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.

2.1.2 Commonality Index

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

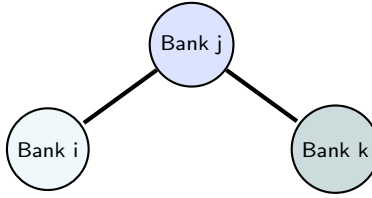
In particular, for each bank pair ij in each quarter t I extract the security space held in common \check{S}_{ijt} . In order to measure the potential impact of contagion at the pair level, I compute for each bank i the share of its portfolio, which is made up by assets held in common with bank j .

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

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.

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



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 , $\mathcal{E} = \{(i, j, t) : \check{S}_{ijt} \neq 0\}$, 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 $\text{deg}_{it} = \sum_{j \neq i} \mathbf{1}_{\Omega_{ijt} \neq 0}$. In the above example, $\text{deg}_{it} = \text{deg}_{kt} = 1$ whereas $\text{deg}_{jt} = 2$.

2.2 Descriptive Statistics

Descriptive statistics for the degree and commonality index are depicted in Table 1.

Table 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

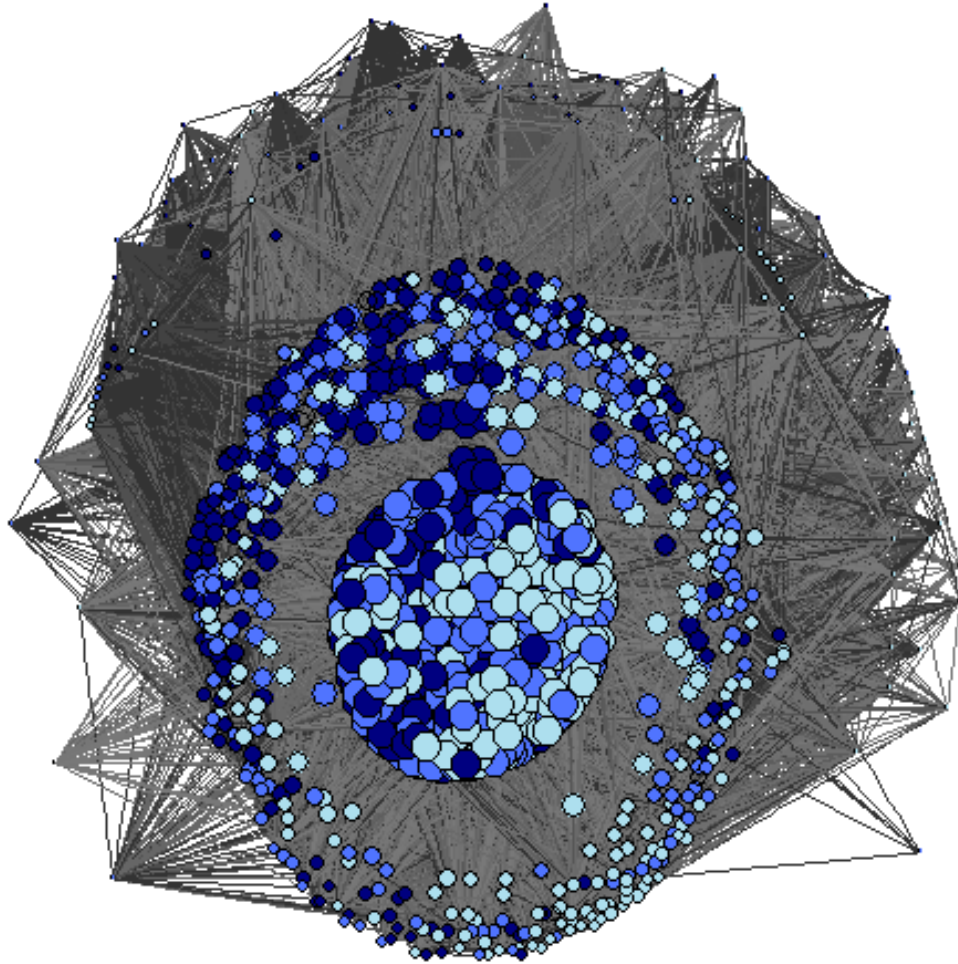
made up by a single interconnection, amounts to 34.55%. That is, on average, 34.55 % of bank i 's portfolio is also held by bank j at time t , taking into account a concentration at the level of the securities' issuer. Again, the commonality index varies considerably in the cross-section, with common 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.

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 3 contains the same network representation of the second quarter of 2007, but the color of nodes is chosen according

Figure 2: ASSET COMMONALITY NETWORK 06/2007 - COLORING BY BANK SIZE

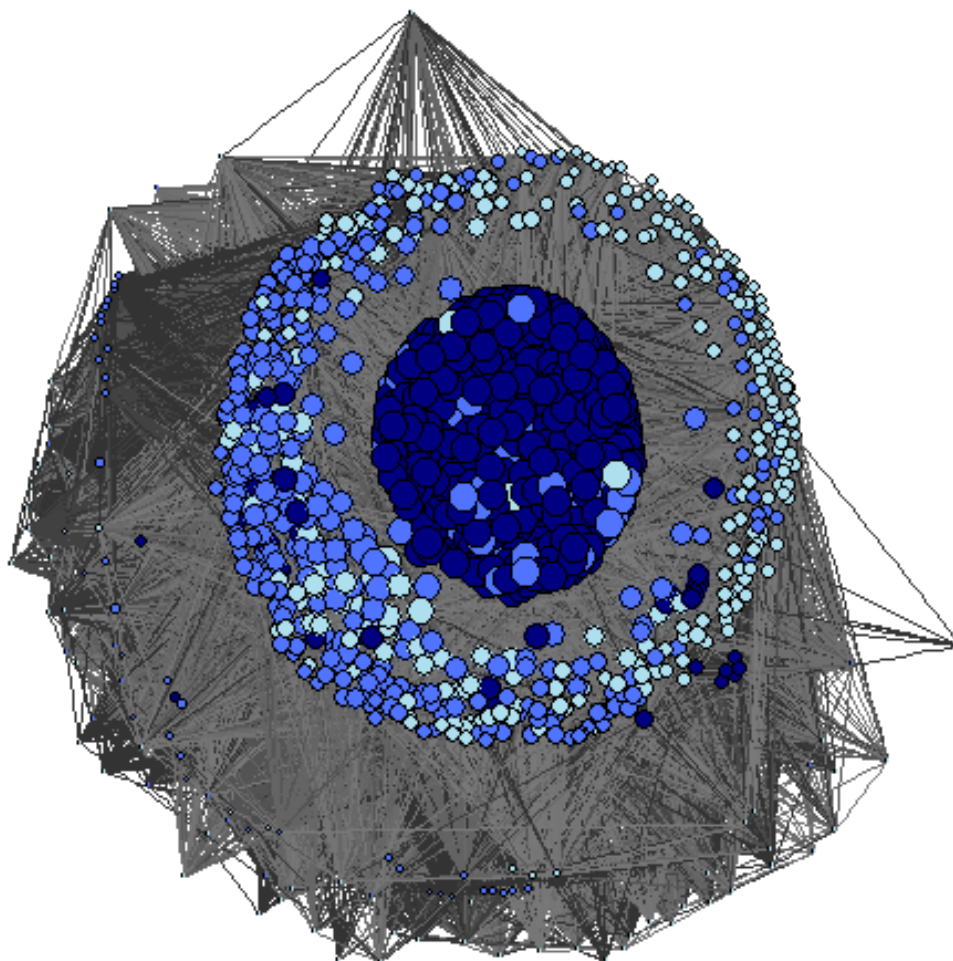


This figure shows the asset commonality network defined through overlap in security portfolios at the level of the issuer in the second quarter of 2007. Nodes are colored according to bank size by total assets: light blue represents small banks, dark blue are large banks. The node size is determined 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.

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 as-

Figure 3: ASSET COMMONALITY NETWORK 06/2007 - COLORING BY DEGREE



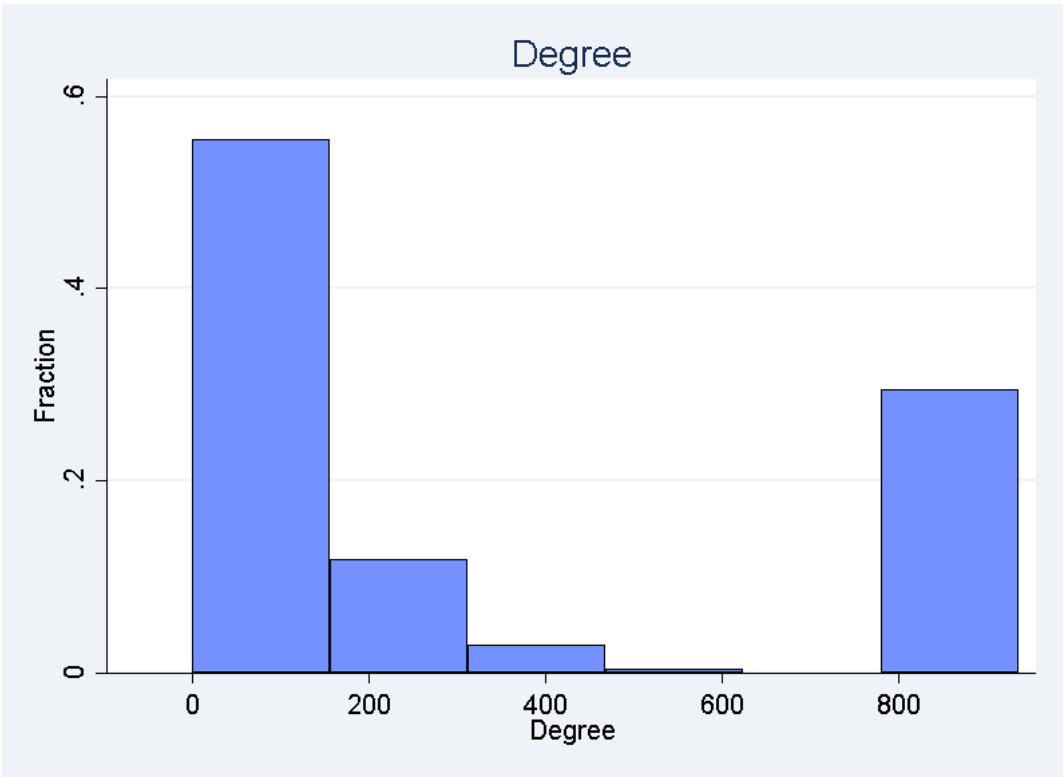
This figure shows the asset commonality network defined through overlap in security portfolios at the level of the issuer in the second quarter of 2007. Nodes are colored according to the degree: light blue represents a low degree, dark blue represents a high degree. The node size is also determined 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.

sortative 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 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 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.

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{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

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

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 .

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 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

$$\begin{aligned} \mathring{R}_{it} = & \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t) \in \mathcal{E}} \mathring{R}_{jt-1} \mathbf{1}_{\text{TA1}} + \beta_2 \frac{1}{c} \sum_{(i,j,t) \in \mathcal{E}} \mathring{R}_{jt-1} \mathbf{1}_{\text{TA2}} \\ & + \beta_3 \frac{1}{c} \sum_{(i,j,t) \in \mathcal{E}} \mathring{R}_{jt-1} \mathbf{1}_{\text{TA3}} + \beta_4 \frac{1}{u_i} \sum_{(i,k,t) \notin \mathcal{E}} \mathring{R}_{kt-1} + \epsilon_{it}, \end{aligned} \quad (2)$$

where \mathring{R}_{it} is the return on the exclusively held portfolio of bank i at time t . $\mathbf{1}_{\text{TA1}}$ 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 . 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

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

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 Ω_{ijT} is the value of the commonality index in the second quarter of 2007.

4 Empirical Analysis

4.1 Baseline Specification

I begin by estimating the baseline regression model of Equation 1 introduced in Section 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 2 contains the regression results for the baseline regression model.

Table 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*** (.0026) | .0234*** (.0040) | .0195*** (.0042) | .0182*** (.0046) |
| Uncon Portfolios _{it-1} | -.0112*** (.0021) | -.0050 (.0036) | .0040 (.0039) | .0006 (.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

$$\begin{aligned} \hat{R}_{it} = & \alpha_i + \alpha_t + \beta_1 \frac{1}{c_i} \sum_{(i,j,t) \in \mathcal{E}} \hat{R}_{jt-1} + \beta_2 \frac{1}{u_i} \sum_{(i,k,t) \notin \mathcal{E}} \hat{R}_{kt-1} \\ & + \beta_3 \text{NFL}_{it} + \beta_4 \text{FL}_{it} + \beta_5 \text{CR}_{it} \\ & + \beta_6 \text{DEP}_{it} + \beta_7 \text{WF}_{it} + \beta_8 \text{EQ}_{it} + \epsilon_{it}, \end{aligned} \quad (3)$$

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 3.

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

Table 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*** (.0045) | 0179*** (.0045) | .0171*** (.0047) |
| Uncon Portfolios _{it-1} | 1.09e-10 (9.67e-11) | .0007 (.0042) | -.0018 (.0043) |
| Loans to Fin. Sector _{it-1} | -1.96 e-11 (1.25 e-10) | | 2.16e-10 (1.74e-10) |
| Loans to Non-Fin. Sector _{it-1} | -2.09e-13 (1.34e-10) | | -2.32e-11 (2.92e-10) |
| Cash Reserves _{it-1} | -1.10e-08 (1.75e-08) | | 5.58e-09 (2.48e-08) |
| Deposits _{it-1} | | -6.20e-10 (1.20e-09) | 2.43e-10 (1.55e-09) |
| Wholesale Funding _{it-1} | - | 2.35e-11 (1.92e-10) | -3.04e-10 (.227e-10) |
| Equity _{it-1} | | -1.30e-10 (5.86e-10) | 1.39e-09 (.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

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

where NFL_{it} is the logarithm of value of bank i 's loans to the non-financial sector at time t , FL_{it} is the logarithm of value of bank i 's loans to the financial sector at time t and DEP_{it} is the logarithm of value of bank i 's 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 4.

Table 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*** (.0048354) | .0181515*** (.0045572) | .0181515*** (.0029874) |
| Uncon Portfolios _{it-1} | .0005877 (.0043757) | .0005877 (.0042277) | .0005877 (.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

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

where \hat{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.

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 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 2 with bank size as defined by total assets. Results are shown in Table 5.

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

Table 5: SUBSAMPLE SPECIFIC EFFECTS BY TOTAL ASSETS

| VARIABLES | Exc Portfolio _{it} |
|--|-----------------------------|
| Con Portfolio _{it-1} $\mathbf{1}_{TA1}$ | .0128** (.0045) |
| Con Portfolio _{it-1} $\mathbf{1}_{TA2}$ | .0131** (.0047) |
| Con Portfolio _{it-1} $\mathbf{1}_{TA3}$ | .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

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

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. $\mathbf{1}_{TA1}$ 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 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, $\text{deg}_{it} = \sum_{j \neq i} \mathbf{1}_{\Omega_{ijt} \neq 0}$. Results are shown in Table 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 6: SUBSAMPLE SPECIFIC EFFECTS BY LEVERAGE RATIO

| VARIABLES | Exc Portfolio _{it} |
|--|-----------------------------|
| Con Portfolio _{it-1} 1 _{LEV1} | .0146** (.0048) |
| Con Portfolio _{it-1} 1 _{LEV2} | .0189*** (.0050) |
| Con Portfolio _{it-1} 1 _{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

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

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. $\mathbf{1}_{LEV1}$ 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 7: SUBSAMPLE SPECIFIC EFFECTS FOR DEGREE

| VARIABLES | Exc Portfolio _{it} |
|---|-----------------------------|
| Con Portfolio _{it-1} 1 _{DEG1} | .0116* (.0051) |
| Con Portfolio _{it-1} 1 _{DEG2} | .0151** (.0050) |
| Con Portfolio _{it-1} 1 _{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

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

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. $\mathbf{1}_{\text{DEG1}}$ 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 of 2009. I then run an extended specification of the baseline model where observations are split into two time periods. Precisely, I run

$$\begin{aligned} \mathring{R}_{it} = & \alpha_i + \alpha_i + \beta_1 \frac{1}{c_i} \sum_{(i,j,t) \in \mathcal{E}} \mathring{R}_{jt-1} \mathbf{1}_{\text{CRISIS}} \\ & + \beta_2 \frac{1}{c} \sum_{(i,j,t) \in \mathcal{E}} \mathring{R}_{jt-1} (1 - \mathbf{1}_{\text{CRISIS}}) + \epsilon_{it}, \end{aligned} \tag{4}$$

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 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 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 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

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

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. $\mathbf{1}_{\text{CRISIS}}$ 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.

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,

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

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

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

where \mathring{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 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{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 .

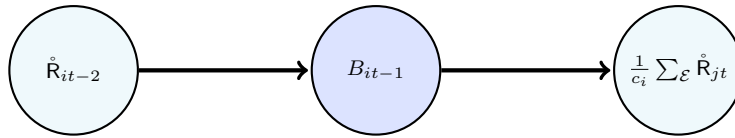


Table 9: SUBSAMPLE SPECIFIC EFFECTS FOR PORTFOLIO SELL-OFFS

| VARIABLES | Exc Portfolio _{it} |
|--|-----------------------------|
| Con Portfolio _{it-1} $\mathbf{1}_{B_{it}=0}$ | -0.0030 (.0046) |
| Con Portfolio _{it-1} $\mathbf{1}_{B_{it}<\bar{B}_t}$ | .0188*** (.0045) |
| Con Portfolio _{it-1} $\mathbf{1}_{B_{it}\geq\bar{B}_t}$ | .0212*** (.0049) |
| Uncon Portfolio _{it-1} | -0.0017 (.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

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

where \mathring{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 $\mathbf{1}_{B_{it}<\bar{B}_t}$ and $\mathbf{1}_{B_{it}\geq\bar{B}_t}$, 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

$$\begin{aligned}
 B_{it-1} &= \alpha_i + \alpha_t + \beta_1 \mathring{R}_{it-2} + \epsilon_{it} \\
 \frac{1}{c_i} \sum_{(i,j,t) \in \mathcal{E}} \mathring{R}_{jt1} &= \alpha_i + \alpha_t + \beta_2 \mathring{R}_{it-2} + \beta_3 B_{it-1} + \epsilon_{it},
 \end{aligned} \tag{5}$$

where \mathring{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 10.

Table 10: PATH ANALYSIS

| VARIABLES | Portfolio Sell-Offs _{it} | Con Portfolios _{it} |
|-----------------------------------|-----------------------------------|------------------------------|
| Exc Portfolio _{it-2} | -96001.54* (38974.52) | .0155766* (.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

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

where \mathring{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.

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 occurred 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, $|\dot{R}_{it} - \dot{R}_{jt}|$. 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 11.

Table 11: DIFFERENCE-IN-DIFFERENCE REGRESSION

| VARIABLES | (1) Return Distance ijt | (2) Return Distance ijt | (3) Return Distance ijt |
|-------------------------------|------------------------------|------------------------------|------------------------------|
| Strength of Portfolio Overlap | -0.0010 *** (.00002) | -0.0011* (.0005) | -0.0011* (.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.

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.

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