Intermediation in the Interbank Lending Market*

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Abstract

This paper studies systemic risk in the interbank market. We first establish that in the German interbank lending market, a few large banks intermediate funding flows between many smaller periphery banks and that shocks to these intermediary banks in the financial crisis spill over to the activities of the periphery banks. We then develop a network model in which banks trade off the costs and benefits of link formation to explain these patterns. The model is structurally estimated using banks' preferences as revealed by the observed network structure in the pre-crisis period. It explains why the interbank intermediation arrangement arises, estimates the frictions underlying the arrangement, and quantifies how shocks are transmitted across the network. Model estimates based on pre-crisis data successfully predict changes in network-links and in lending arising from the crisis in out-of-sample tests. Finally, we quantify the systemic risk of a single intermediary and the impact of ECB funding in reducing this risk through model counterfactuals.

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1 Introduction

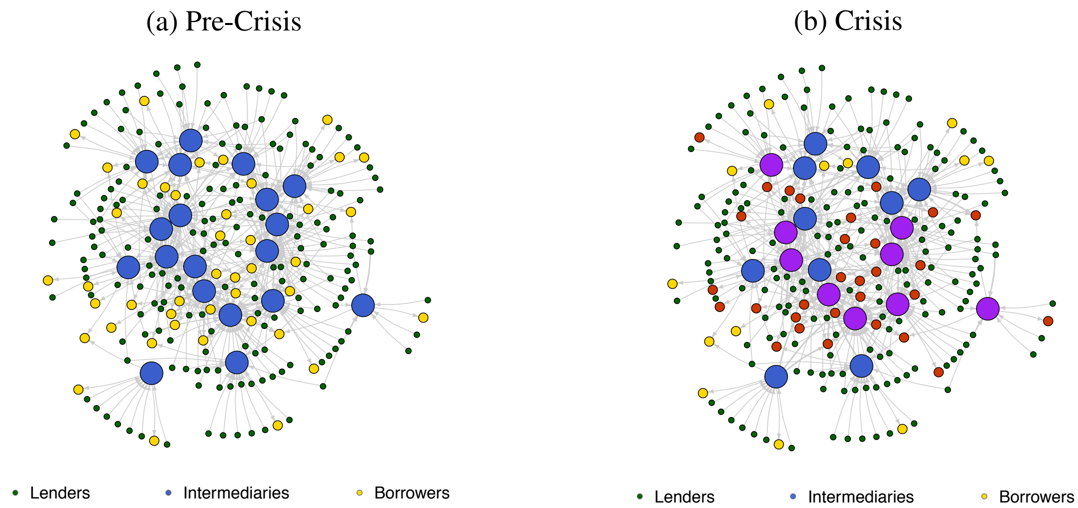
The interbank market is an important source of financing for banks. In Germany, the total volume of interbank loans outstanding in 2007 was €0.61 trillion, which makes up around 8% of the banking sector's total asset size. In this large over-the-counter market, trading between more than 2300 banks resembles Figure 1(a), where a small subset of large banks channel funds between a large number of smaller commercial banks without direct connections.[1] At the center, in blue circles, are some of the largest banks in the German economy. In the recent financial crisis, some of these banks were directly exposed to losses from U.S. subprime assets (see purple circles in Figure 1(b)). Notably, these losses spilled over through the interbank network to a large number of connected borrowing banks, who collectively contracted their loan supply to the real economy (see red circles in Figure 1(b)) by a total of €69.7 billion.[2] On average, this is 4.9% more than the mean change across all banks.

This paper studies systemic risk in the interbank market. We first present and estimate a novel model of the interbank network. The model is based on Diamond (1984), and the economics of the model turn on minimizing the duplication of monitoring costs. We estimate the model structurally from pre-crisis data using a revealed preference estimator based on Manski (1975). The estimation uncovers the nature of monitoring costs that gives rise to the pre-crisis network structure. Second, we use the model and estimates to quantify systemic risk. We predict the effects of the crisis shock described earlier using the model's pre-crisis estimates. The model does quite well in capturing the spillovers that were present in the crisis. Then we consider counterfactuals. We selectively shock individual banks and trace out the real impact of the shock as it is propagates through the network, thus quantifying systemic risk of that bank. We also show how ECB policy can ameliorate these systemic effects.

[1] This figure is a visual representation based on a simulated interbank network. For the pre-crisis period from 2005Q1 to 2007Q2, it matches the total number core banks, periphery lenders and periphery borrowers and the average number of links formed by borrowing and lending banks in the periphery but is otherwise randomly generated. The definitions of core and periphery will be explained in the paper as well as in Appendix B3.

[2] This refers to the aggregate change in loans to the real economy by banks who are not directly exposed to but borrow from other banks that are exposed to the losses in asset-backed commercial paper through their off-balance sheet conduits as identified by Acharya et al. (2013). More specific estimates of the loan supply changes will be detailed in the paper.

Figure 1: The German Interbank Lending Network



The model we present is new to the interbank literature. Much of the existing work on interbank markets rationalizes these markets as an arrangement to smooth the idiosyncratic liquidity needs of banks (Allen and Gale, 2000). But this explanation does not square with the facts of the German interbank market, where interbank loans balance persistent funding needs between banks that always lend and those that always borrow. That is, the set of banks that borrow and those that lend are remarkably stable over time, which is not consistent with a liquidity smoothing motive. Moreover, borrowing banks delegate their borrowing from lending banks to a small subset of large and well diversified intermediary banks. We argue that this arrangement arises in order to reduce inefficiencies from duplicated monitoring. As in Diamond (1984), delegating monitoring through diversified intermediaries results in less economy-wide monitoring costs.

After developing our model, we structurally estimate the unobserved monitoring costs through revealed preferences of the observed network structure. Monitoring costs are crucial in determining the magnitude of systemic risk. Intuitively, when monitoring costs are low, borrowing banks that were originally connected to exposed intermediaries can easily form new interbank credit relationships to avoid being affected by shocks to these intermediaries. As monitoring becomes more expensive, the rigidity of adjusting credit relationships increases, and borrowing banks are more exposed to shocks of their connected intermediaries. This was evident in the recent crisis, when only some borrowing banks that were connected to exposed intermediaries could "afford" to form new credit relationships. As an out-of-sample check, we show that our pre-crisis model estimates of monitoring cost predict 86% of the post-crisis credit relationships formed. They also predict the spillover of losses from crisis-affected intermediary banks to the firm-loans of borrowing banks. Finally, our estimates allow us to predict the effect of counterfactual shocks, in which a small impact to intermediary bank capital can curtail lending to firms by a large number of *borrowing* banks, thereby quantifying how credit risk shocks to a few banks spill over through increases in funding costs along a network of sticky interbank relationships. The network amplification of funding cost increases for borrowers identifies a new source of systemic risk relative to the current interbank networks literature, which has primarily focused on default cascades of lenders.[3]

We obtain these findings by taking a varied structural approach to a proprietary dataset of German interbank loans from 2005Q1 to 2009Q4. We begin by making a number of empirical observations that motivate our notion of interbank intermediation. First, there is a subset of banks that always borrows while the remaining ones always lend. The identity of these borrowing and lending banks is highly stable. The direction of loan flow through any given interbank relationship also remains constant throughout our sample period of four years. This is inconsistent with the existing liquidity insurance literature, which started from the seminal model of Allen and Gale (2000). According to this view, the direction of loan flows should fluctuate depending on the realization of idiosyncratic liquidity shocks. Second, borrowing banks are larger than lending banks and require four times the amount that these banks can provide. If they directly borrow from lending banks, costly monitoring would have to be duplicated an average of four times. Third, the interbank market structure and the distribution of loan flows avoid this inefficiency — borrowers only link to a few large banks who then borrow from lenders on their behalf. This effectively turns the large banks into interbank intermediaries, similar to the emergence of financial intermediaries for the real economy in Diamond (1984).

Based on our empirical observations, we develop and estimate a structural model to uncover unobserved monitoring costs and to empirically assess Diamond (1984) through the interbank lending market. In the model, borrowers can choose to form credit relationships with intermediaries. This reduces duplication in monitoring of direct lending but requires sharing part of the surplus with the intermediary. The surplus split is determined by bilateral Nash bargaining with renegotiable contracts. Borrowers can capture more of the total surplus by investing in more costly monitor-

[3] Refer to Hüser (2015) for a literature review. One criticism of the present literature has been that “no bank ever failed because of losses on the interbank market (alone).” (Upper, 2011).

ing relationships. At the same time, intermediaries' funding cost is affected by which borrowers they link and lend to. Since lending banks monitor intermediaries through a standard costly state verification technology (Townsend, 1979), improved diversification requires less monitoring and incurs lower funding costs. As banks consider these tradeoffs when deciding on their links, any observed link must have yielded a net surplus while any link not in the data must have been too costly relative to its benefits.

The above logic implies a series of inequality restrictions on monitoring costs equivalent to a pairwise stable equilibrium.[4] Using balance sheet information on bank profitability and applying a variant of the Manski maximum score estimator, we identify monitoring cost parameters that best rationalize the preferences revealed by the observed interbank network. Intuitively, since borrowers' share of surplus increases with the number of linked intermediaries, more profitable borrowers establish more links. Hence, the number of links formed by different borrowing banks with the same set of intermediaries uncover monitoring costs relative to the value of loans. Further, since lenders' costly state verification (CSV) cost decreases as the intermediary becomes more diversified, links formed by the same borrower with different sets of intermediaries reveal the relative magnitude of these CSV costs.

We find that the average borrower invests in two links with intermediaries at a total cost of €2.33 million while lenders' monitoring costs are at €0.20 million. Without intermediation, direct borrowing of the same bank would require the formation of about four monitoring relationships at double the cost. Aggregating across banks in the economy, interbank intermediation leads to a significant reduction in monitoring costs from €1.57 billion to €1.10 billion per year. Relatively speaking, the monitoring costs are quite large and are almost a quarter of borrowers' loan value net of funding costs. The high cost of forming new credit relationships gives rise to the stickiness of the network, which exposes borrowing banks to shocks of their initially linked intermediaries.

These forces were evident in the recent financial crisis, which we utilize as an out-of-sample test to verify our model mechanism and estimates. In Germany, the main direct exposure to the US crisis was through losses in asset-backed commercial paper conduits by a few internationally

[4]Pairwise stability is a seminal concept first introduced by Jackson and Wolinsky (1996). In the context of our structural estimation, pairwise stability implies pairwise Nash stability, which allows for severing multiple links at one time. This equilibrium concept is relatively conservative. More specific equilibrium selection processes are not necessary because our baseline estimation is conditioned on the single observed equilibrium.

exposed banks, which comprised a subset of the intermediaries. In the data, we observe that borrowers linked to more exposed intermediaries formed more new links. Viewed through the lens of our model, when intermediaries suffer a spike in credit risk, their cost of funding rises and they pass these costs on to borrowing banks. Borrowing banks decide between paying the cost of a new credit relationship versus continuing funding at the increased rates of the previous credit links (that require no reinvestment in monitoring). Our pre-crisis estimates allow us to quantify this tradeoff. We verify the pairwise stability conditions for all new links, whether formed or not formed, using computations based on pre-crisis parameter estimates. Indeed, we find that 86% of the link switches post-crisis were correctly predicted.

The exposure to intermediary banks spilled over to many dependent borrowing banks, who subsequently contracted loan supply to the real economy. Using the estimated cost parameters and observing new links formed after the crisis, we calculate the total change in funding cost for each bank. We find that borrowing banks' observed decline in lending are highly correlated with their model-implied rise in funding costs. Quantitatively, a 100 basis point increase in a borrowing bank's funding cost reduced its firm loan supply by 5.8%.[5] This shows that interbank loans are an important source of funding that cannot be substituted away. Note that if new links could be formed frictionlessly, borrowing banks could have fully substituted funding to new and unexposed intermediaries. Hence, costly interbank monitoring relationships allowed shocks to highly connected intermediary banks to affect both funding costs and loan supply by a large number of unexposed borrowing banks, revealing the systemic risk in interbank intermediation.

We enrich our baseline model with two realistic features to check for robustness and to generate counterfactual predictions. First, we allow banks to choose funding volumes together with their links. Banks are assumed to face downward sloping demand curves so that network structures providing lower funding costs increase the fundable volumes. At the same time, we allow borrowers and intermediaries to tap the European Central Bank's Long Term Refinancing Operation (LTRO) as an outside option to interbank funding.[6] With sufficient collateral, banks can borrow from the ECB to lower their average funding costs to fund more assets. We find that results from the exten-

[5]Note that this is the change in total firm loans due to a shock to interbank funding cost. Since interbank loans on average make up 8% of borrowing banks' total liabilities, this is a relatively large magnitude.

[6]The ECB also provides shorter term financing through its Main Refinancing Operation. We use the Long Term Refinancing Operation because its maturity is closer to that of interbank loans and because it comprises the vast majority of total central bank borrowing on bank balance sheets.

sion specification do not differ much from the baseline estimates and the model fit is only slightly improved.

Finally, we estimate the systemic risk of interbank intermediation in various counterfactual scenarios. First, we consider the effect of a 50 basis point increase in the funding cost of each intermediary. For highly connected intermediaries, the drop in loans fundable through the interbank market is 5.8%, equivalent to €15.74 billion.[7] In comparison, a 50 basis point drop in ECB funding rates to all banks increases loans fundable by only 2.96%. Thus, shocks to a single intermediary can lead to larger loan volume losses than economy-wide interest rate cuts of the same magnitude can ameliorate. This is in part because banks' limited collateral and binding allotment quotas limit the scope of access to ECB funding. More importantly, shocks to single intermediaries can extend to curtail funding volume by a large number of banks because of amplification of funding cost increases through a concentrated and costly-to-adjust interbank network. This highlights and quantifies a new and important notion of systemic risk in interbank markets, which has previously been attributed to either default cascades from interbank liabilities or correlated defaults from common asset holdings.[8] Indeed, one criticism of the present literature is that "no bank ever failed because of losses on the interbank market (alone)." (Upper, 2011). The channel that we propose does not rely on chains of bank defaults. Instead, es evident from the financial crisis and our counterfactual predictions, even moderate increases in credit risk to a single highly connected intermediary bank can trigger substantial aggregate declines in loan supply due to spillovers of funding cost increases through sticky monitoring relationships.

Literature Review

Identifying and quantifying this new source of systemic risk relies on a number of steps, each of which contributes to the literature. First, we provide a new explanation for the existence of interbank markets, which has previously been predominantly attributed to mutual insurance of liquidity shocks as in Allen and Gale (2000). Many papers followed to expand on their idea.[9]

[7]This is the average decrease in loans fundable through the interbank market for intermediary banks above the third quartile of connectivity. Predictions for specific intermediaries in this range cannot be reported for confidentiality reasons.

[8]Refer to Hüser (2015) for a literature review.

[9]For theory, recent examples include Brusco and Castiglionesi (2007), Castiglionesi and Wagner (2013) and Ladley (2013). Empirical studies include Cocco et al. (2009) for the Portuguese market and Afonso et al. (2013) for the U.S. market.

Persistence in the direction of lending between bank pairs and hence the identity of interbank borrowers and lenders suggests that interbank markets mainly serve to balance persistent funding needs, which bears important systemic implications.

At the same time, we are the first to empirically assess and rationalize Diamond (1984)'s seminal theory of intermediation, which is the first coherent theory to explain the existence of intermediation (Gorton and Winton, 2003). We show that similar to Diamond (1984)'s conjecture about the existence of banks in the real economy, intermediation in the interbank market arises to reduce duplication in monitoring of borrowers and that delegation costs are minimized through diversification of the intermediary's portfolio.

Further, the development of a structural model contributes to the literature on financial networks. On the theory front, a recent set of papers have examined the drivers of core-periphery structures in OTC markets (Farboodi, 2014, Wang, 2016, Hendershott et al., 2016, Babus and Hu, 2017, Chang and Zhang, 2016, Afonso and Lagos, 2015, Hugonnier et al., 2014).[10] We provide a new motivation for the emergence of core-periphery structures in the interbank lending market based on delegated monitoring as in Diamond (1984) coupled with network-contingent bargaining. The presence of monitoring in networks has been identified by a number of empirical papers but they are mostly reduced form in nature and cannot quantify the magnitude of monitoring costs nor explain the emergence of the network structure, e.g., Cocco et al. (2009), Furfine (2001), Affinito (2012), Afonso et al. (2013). Blasques et al. (2014) simulate a dynamic model of the overnight interbank market for 50 banks and recover parameters by matching characteristics of the network between 50 large banks in the Netherlands. While they focus on banks meeting liquidity shocks in the overnight market, we estimate monitoring between a disjoint set of lenders and borrowers in meeting persistent funding needs, which is consistent with the full sample of interbank loans. Also, our revealed preferences estimation takes the entire observed network with theheterogenous characteristics of banks into consideration. This improves the estimation accuracy while allowing for bank-specific predictions about how a given shock amplifies along the network.

Finally, we contribute to the discussion of interbank funding shortages during financial crisis by incorporating the underlying network structure. A number of theoretical papers have shown how

[10]A number of empirical papers have documented core-periphery structures in OTC markets, including the federal funds market (Bech and Atalay, 2010) and (Afonso et al., 2013); the Austrian interbank market (Boss et al., 2004), the Brazilian interbank market (Chang et al., 2008) and the Dutch interbank market (van Lelyveld et al., 2014).

increases in counterparty risk can raise the cost of external financing and reduce banks' access to funding in the presence of asymmetric information, e.g., Flannery (1996), Freixas and Jorge (2008) and Heider et al. (2015).[11] We extend the analysis to a network context, which bears important implications for systemic risk. In our model, monitoring can resolve asymmetric information for *connected* intermediary banks, for whom increases in default risk implies more intense monitoring by lenders and in turn higher funding costs. These higher funding costs spill over to its connected borrower network, with more concentrated intermediaries causing a larger amplification. Empirical evidence for interbank funding shortages in the recent financial crisis is provided by Afonso et al. (2011) for the overnight Fed Funds market, Kuo et al. (2014) for the term Fed Funds market, Iyer et al. (2013) for the Portuguese market and Gabrieli and Georg (2014) for the Eurozone market. Similar to these papers, we also find stressed interbank funding conditions in the aftermath of the crisis but we demonstrate that the significance of these effects stems from the underlying network structure in which a few banks are highly connected and in which relationships are sticky to adjust. Based on the network, we develop a structural model to predict borrowing banks' funding cost and funding volumes based on their network connectivity and that of the initially exposed bank.

The paper is arranged as followed. Section 2 explains the empirical evidence for interbank intermediation. Section 3 introduces a model of interbank intermediation which is structurally estimated in Section 4. The estimated parameters are checked using link switches following the recent financial crisis in Section 5. Section 6 explores the effect on the real economy by estimating the disruption in firm loan supply. Section 7 enriches the baseline model by endogenizing loan volumes and by introducing the ECB funding facility. Section 8 predicts the impact of counterfactual scenarios and Section 9 concludes.

2 The German Interbank Lending Market

This section introduces a number of new empirical facts about interbank networks that inform our model and estimation in subsequent sections. We use the German credit registry database, which

[11] There is also a literature about banks hoarding liquidity in anticipation of future funding conditions, e.g., Allen et al. (2009), Caballero and Krishnamurthy (2008), Gale and Yorulmazer (2013), Acharya and Skeie (2011). Although our network model is static in nature, it does predict a decrease in lending from intermediaries to borrowers. This results from lending banks charging higher funding costs to intermediaries, which is then passed on to increase funding cost for banks borrowing from intermediaries.

records, on a bilateral basis, loans between firms and financial institutions of at least € 1.5 million. [12] This covers around 95% of all interbank loans and 70% of loans extended to nonfinancial firms. Although the data only contains loan volumes and not loan rates, our revealed preference approach allows us to circumvent the use of price data. We match the credit registry with bank balance sheets collected monthly by the Bundesbank Statistics Department, referred to as the BISTA. These variables shed light on the characteristics of banks in different network positions.

2.1 Persistence of Interbank Lending and Borrowing

Consolidating by banking group, we find that 454 banks consistently borrow from the interbank market while the remaining 1882 banks consistently lend in the interbank market during our sample period from 2005Q1 to 2009Q4.[13] The identity of interbank borrowers and interbank lenders is stable and invariant over time. As illustrated in Figure 2(a), the percentage of overall net borrowers (lenders) that borrow (lend) in a given quarter is consistently between 91% to 96%. Figure 2(b) confirms that the stability persists at a link level. Specifically, more than 95% of bilateral interbank relationships are unidirectional over the course of our sample.[14]

The use of interbank loans to balance systematic funding needs between banks is surprising in light of the consensus explanation in the literature, which maintains that interbank markets smooth short-term liquidity shocks. In the seminal model by Allen and Gale (2000), interbank relationships offer insurance against idiosyncratic liquidity shocks so that banks alternate between lending and borrowing with their counterparties depending on the realization of liquidity needs. This notion of liquidity insurance has been examined in a number of empirical papers.[15] In the U.S. for example, Afonso et al. (2013) argue that banks hedge unexpected idiosyncratic liquidity shocks by linking with banks of negatively correlated and arguably unexpected net customer transfers. Using Portuguese data, Cocco et al. (2009) show that banks form relationships with banks that

[12] If the threshold is exceeded at any time during the quarter, banks report outstanding claims by counterparty as they stand at the end of the quarter, and these are then recorded in the credit registry.

[13] We augment the data with the historical mergers database to account for mergers and acquisitions during our sample period.

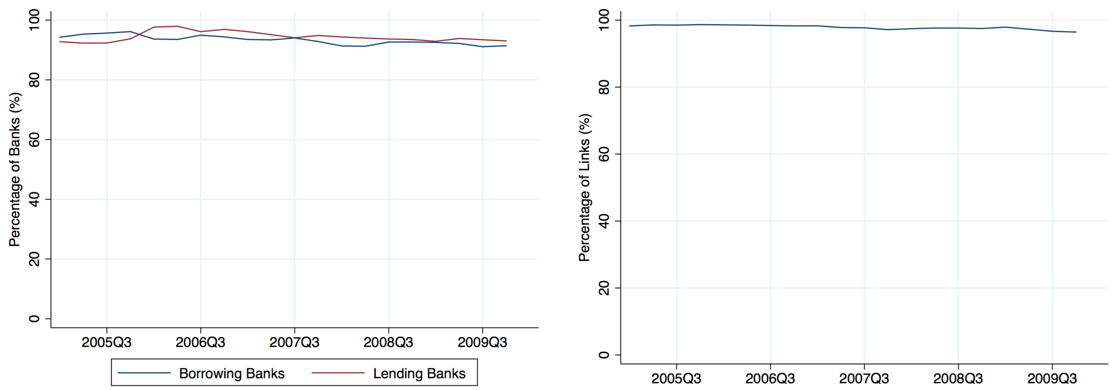
[14] This is calculated conditioning on the presence of bilateral relationships. The network is very stable before the recent financial crisis. When a link is observed in a given quarter, the likelihood of it reappearing in the next quarter is 88%. It increases to 96% if we exclude links of volumes below the 10th percentile. This is because low volume links tend to dip below the reporting threshold and artifically appear absent in some quarters.

[15] This is in addition to a large number of theoretical papers. See literature review.

Figure 2: Persistence of Interbank Lending and Borrowing

This figure reports the bank and link level persistence of interbank loans. Figure 2a plots the percentage of net lenders (net borrowers) that lend (borrow) in each quarter from 2005Q1 to 2009Q4. Figure 2b plots the percentage of links that have loan flows in the same direction as their overall direction in each quarter from 2005Q1 to 2009Q4. *Source: Research Data and Service Centre of the Deutsche Bundesbank, Credit Registry, 2005Q1 - 2009Q4, own calculations.*

(a) Bank Level Persistence (b) Link Level Persistence



have less correlated reserve deposit shocks.[16]

Differences in results likely stem from the use of different datasets. Most analysis on interbank markets are based on loans deduced from payments data (e.g., Fedwire in the U.S. and TARGET2 in Europe) using the Furfine algorithm. This is limited to identifying overnight loans because "extending the Furfine matching algorithm to maturities beyond overnight introduces a number of methodological and computational challenges" (Kuo et al., 2014).[17] We use credit registry data that covers close to the universe of all interbank loans. In this sample, overnight loans account for only around 15% of total loan volumes so the vast majority of interbank loans are of longer maturities (Figure 3).[18] Since medium- and long-term loans are more likely used in financing assets of similar maturities, e.g., firm loans, rather than as a buffer against liquidity shocks, the maturity breakdown lends further support for the notion that interbank markets balance persistent

[16]Specifications assuming fixed lending and borrowing banks are included in the aforementioned papers but the implications are not discussed with the main results on liquidity insurance.

[17]Cocco et al. (2009) also use credit registry data but drop non-overnight loans from their sample.

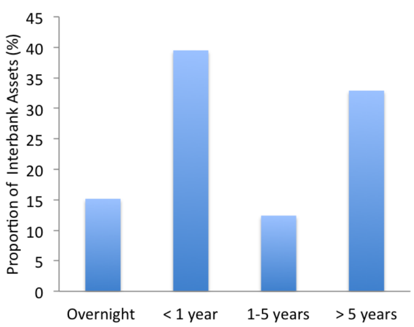
[18]Maturity brackets are not available for the credit registry data. The graphs were constructed using bank level interbank assets and liabilities from bank balance sheets, where maturity brackets for assets and liabilities differ.

funding needs.

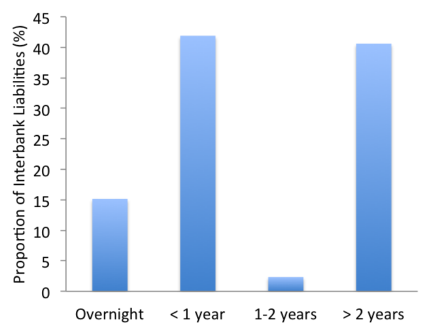
Figure 3: Breakdown of Maturities

This figure reports the distribution of interbank assets and loans by maturity brackets. It is calculated by first collapsing to the time series average for each bank from 2005Q1 to 2009Q4 and then taking the average over the cross section of banks. *Source: Research Data and Service Centre of the Deutsche Bundesbank, Monthly Balance Sheet Statistics, 2005Q1 - 2009Q4, own calculations.*

(a) Interbank Assets



(b) Interbank Liabilities



Based on the above evidence, we focus on the bulk of the interbank market and examine banks' incentive to build monitoring relationships to meet structural funding needs. Monitoring is especially relevant for loans of longer maturity because of asymmetric information about the borrower's credit risk.[19]

2.2 Loan Volumes of Borrowing and Lending Banks

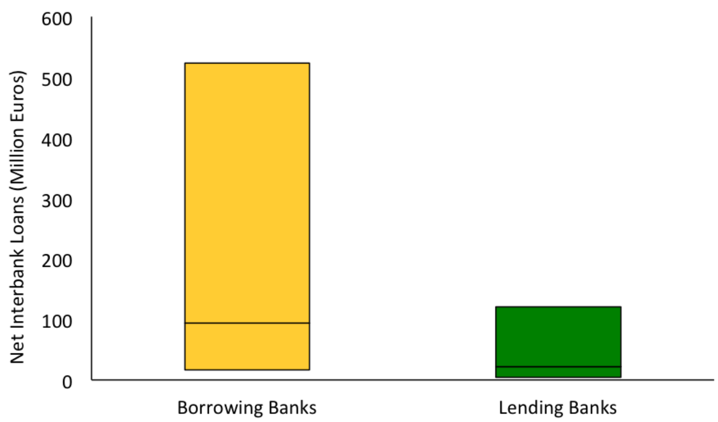
The average net outstanding loan volume for borrowing banks is €598 million, which is more than four times that provided by the average lender. Figure 4 displays the first three quartiles of interbank loans for borrowing and lending banks, respectively. The medians are smaller than the means due to heavily right skewed distributions but the relative distribution of loan sizes follow a similar trend. This implies that if borrowing banks were to borrow directly from lending banks, the average borrower would link to and be monitored by approximately four different lending banks.

[19]Unfortunately, the credit registry does not have maturity brackets on a bilateral basis so we cannot explicitly exclude overnight loans. However, given the skewed volume distributions and the significance of monitoring for longer term loans, this may not be a bad approximation. Based on discussions with market participants, banks often first form credit (monitoring) relationships to satisfy their structural funding needs and then use the existing links to smooth liquidity shocks in the interbank market.

As a consequence, monitoring costs would have to be duplicated four times. The next subsection will show how instead of suffering the inefficiencies of directly borrowing from each other, banks delegate monitoring and borrowing to a small subset of intermediary banks. [20]

Figure 4: Net Interbank Loans of Borrowing and Lending Banks (Quartiles)

This figure reports quartiles of the net volume of interbank loans for net borrowing and net lending banks respectively. Within net borrowers (lenders), quartiles are defined by ranking banks in increasing order of their average net volume borrowed (lent) from 2005Q1 to 2007Q4. *Source: Research Data and Service Centre of the Deutsche Bundesbank, Monthly Balance Sheet Statistics and Credit Registry, 2005Q1 - 2009Q4, own calculations.*



2.3 Existence of Intermediary Banks

Examining the distribution of lending relationships, we find that instead of directly borrowing from lending banks, interbank borrowers exclusively channel funding from a few banks that in turn borrow from a large set of lending banks. A core-periphery structure emerges, in which a small subset of banks, denoted as the core, connect with each other and all remaining banks, while the remaining banks, denoted as the periphery, connect only with the core and not among themselves. We are not the first to discover this structure but the function and explanation of the

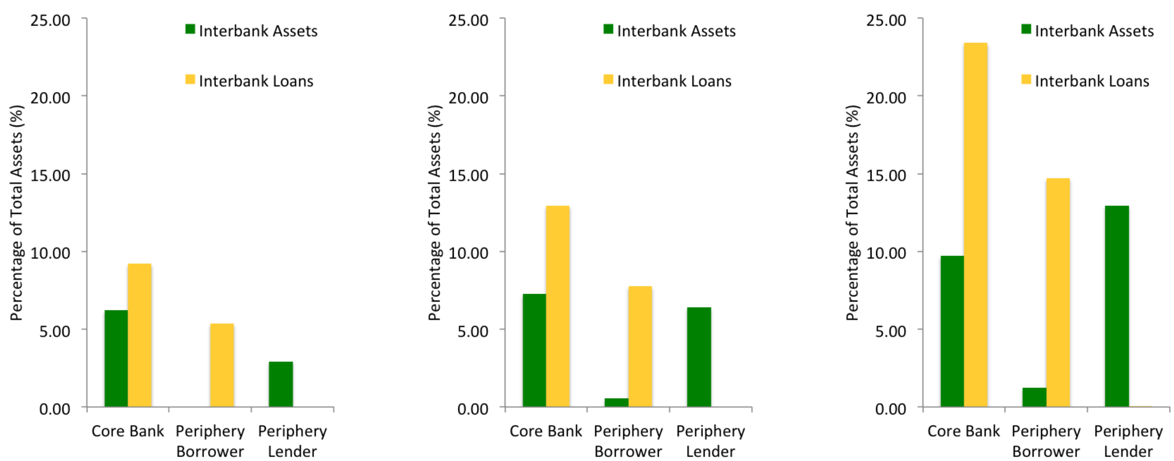
[20] Such duplication in monitoring resembles the inefficiency of direct borrowing by firms described in Diamond (1984). In this paper, firms must be monitored because information asymmetry renders project realizations unobservable by lenders, i.e., retail depositors. Since the average loan demanded by borrowing firms exceeds each individual depositor's available funding, duplication in monitoring would occur if firms borrow directly from retail depositors. This leads to the emergence of a financial intermediary, i.e., a bank, which centralizes monitoring of the borrower on behalf of the lenders to reduce duplication.

core and periphery that we provide through delegated monitoring as in Diamond (1984) is novel. [21]

Figure 5: Net and Intermediated Interbank Loans (Quartiles)

This figure reports, by quartiles, interbank loans and asset of core banks, periphery borrowers and periphery lenders. Within each category, quartiles are defined by ranking banks in increasing order of their average intermediated volume from 2005Q1 to 2007Q4, where intermediated volume is defined as the overlap between interbank assets and liabilities, i.e., min(interbank assets, interbank loans). *Source: Research Data and Service Centre of the Deutsche Bundesbank, Credit Registry, 2005Q1 - 2009Q4, own calculations.*

(a) First Quartile (b) Median (c) Third Quartile



The distribution of loan flows across the core-periphery structure is consistent with core banks acting as delegated interbank intermediaries and monitors. We first identify a core of 19 banks and the remaining banks as periphery following the standard optimization technique in the literature (Craig and Von Peter, 2014).[22] Then, we rank core and periphery banks by increasing degrees of intermediation, i.e., overlap between interbank assets and liabilities, and plot interbank assets and liabilities normalized by total assets. As displayed in Figure 5, only core banks have a significant fraction of intermediation while periphery lenders and borrowers almost exclusively lend or borrow across all three quartiles.[23] Since periphery banks only connect to the 19 core banks and not with

[21] Similar structures have been documented in interbank markets around the world, including the federal funds market (Bech and Atalay, 2010) and (Afonso et al., 2013); the Austrian interbank market (Boss et al., 2004), the Brazilian interbank market (Chang et al., 2008) and the Dutch interbank market (van Lelyveld et al., 2014).

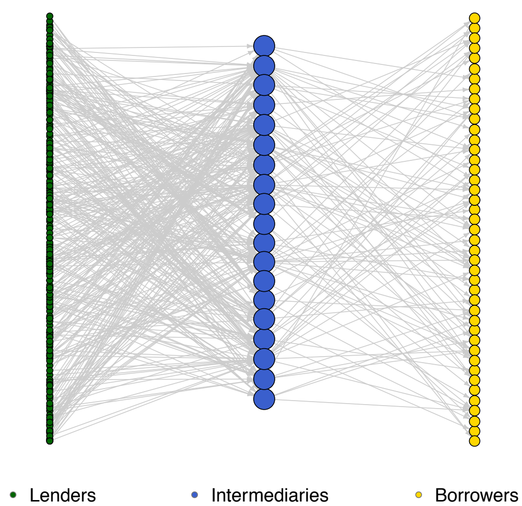
[22] Appendix B3 provides further details about the selection algorithm.

[23] Normalizing by total assets ensures that these figures are not mechanically driven by bank asset size. Core banks

each other, we can deduce that core banks act as intermediaries to channel funds from a large number of periphery lenders to a large number of periphery borrowers. Visually, this arrangement is represented in Figure 6. The median intermediary forms a total of 376 links, while the median borrowing bank connects to only two intermediaries.

Figure 6: Interbank Intermediation Structure

This figure depicts a reshaped version of the simulated interbank network in Figure 1. It matches the total number core banks, periphery lenders and periphery borrowers and the average number of links formed by borrowing and lending banks in the periphery but is otherwise randomly generated. *Source: Research Data and Service Centre of the Deutsche Bundesbank, Credit Registry, 2005Q1 - 2007Q2, own calculations.*



Intermediaries, periphery lenders, and periphery borrowers also differ along other dimensions. Consistent with their high interbank connectivity, intermediary banks are some of the largest banks in the economy. As seen from Table 1, the median intermediary has a total asset size of €99.32 billion compared to €1.58 billion of the median borrowing banks and €0.44 billion of the median lender. Intermediary banks also hold more diversified portfolios and invest less in firm loans, which we will show is beneficial for their role as delegated monitors in the interbank market. Consistent with their interbank loan volumes, borrowing banks are on average larger in size than lending banks. Nevertheless, both periphery borrowers and lenders are traditional commercial banks focused on lending to firms and funding from retail deposits. Banks with extra deposits become interbank lenders, while those with additional investment opportunities borrow from the

are much larger in size than periphery banks so differences in the absolute volume of intermediation, i.e., overlaps between interbank assets and liabilities, are much more pronounced than those normalized by total assets.

interbank market.

One concern is that the network structure follows mechanically from the institutional set-up of the German banking system, which consists of private banks, savings banks and cooperatives. For example, savings banks in each German state were originally designed to trade with their respective state bank (Landesbank) only. In the data however, the vast majority of savings banks now trade with a variety of counterparties and are no longer confined to the historical set up. To remove any remaining potential counfounding, we will explicitly account for institutional details and demonstrate robustness in Appendix B4. For now, we proceed with the baseline model for the ease of exposition.

3 A Model of Interbank Intermediation

This section builds on the empirical observations and develops a structural model of interbank intermediation. The model formulates network-contingent benefits and costs from link formation, which are then juxtaposed against each other to identify monitoring costs through structural estimation. Monitoring costs determine the magnitude of adjustment frictions and ultimately the extent of potential shock amplifications in the interbank market.

3.1 Model Set Up

Consider an economy with a set of borrowing banks $\mathbb{B}$ and lending banks $\mathbb{L}$. We take banks' interbank funding needs as an outcome of their interaction with the real economy. Intuitively, borrowing banks can be thought of as operating in areas with more investment opportunities than available retail deposits. Conversely, banks in areas with retail deposits in excess of lending opportunities become lenders in the interbank market.[24]

[24]Another plausible explanation is that banks lend to firms in their geographic proximity and invest in specialized assets. When deciding on the optimal funding structure, banks choose between investing in a fixed cost to set up a retail deposit base and saving on the fixed cost and relying on others' retail deposit base through interbank borrowing. As long as it is not optimal for all banks to invest in collecting deposits, e.g., there are economies of scale, some banks will opt to "borrow deposits" from other banks. In the presence of costly monitoring between banks, it is optimal for banks with more transparent assets to borrow from the interbank market and for those with more opaque assets to invest in retail deposits and become interbank lenders. This is consistent with the characteristics of borrowing and lending banks displayed in Table 1.

Borrowing banks $b = 1, ..., \mathscr{B}$ have risky loan portfolios of volume V_b and return x_b distributed with CDF $F_b(x_b)$. The distribution of returns is common knowledge but there is asymmetric information about the realization: only borrower b can freely observe the realization of its own return x_b.

Lending banks $l = 1, ..., \mathscr{L}$ participate in the interbank market and have excess funds to be lent out. Let the average size of lenders' excess funds be L. Assume that individual lenders' loan volume on the interbank market is capped due to inelastic retail deposit bases. For borrowing to take place, lending banks must resolve the asymmetric information issue and ensure repayment of borrowers' loans.[25]This can be achieved through monitoring. Let there be an ex ante monitoring technology of cost $k(\delta_b)$, which allows sufficient understanding of the borrower's project to credibly observe outcomes after their realization and subsequently enforce payment.[26] Monitoring costs depend on a vector of borrower statistics, δ_b, including asset opacity and balance sheet size because more complex assets and larger banks require higher monitoring effort. Soft information obtained through monitoring is difficult to transfer so we take monitoring to be exclusive.

Direct lending duplicates monitoring. Given inelastic retail deposits of individual lenders, when a borrowing bank of funding volume V_b expects to borrow from an average lender, it borrows from $\lceil \frac{V_b}{L} \rceil$ of them, where $\lceil \frac{V_b}{L} \rceil$ stands for the smallest integer equal or greater to $\frac{V_b}{L}$. Because monitoring by each lender is exclusive, total monitoring costs are subject to duplication and amount to $\lceil \frac{V_b}{L} \rceil k(\delta_b)$.[27] Based on the distribution of funding volumes from the previous section, monitoring for the average borrower would be expected to be repeated four times under direct borrowing.

[25]Another friction related to OTC markets are search frictions. However, because the identity of banks as lenders and borrowers is stable and publicly known from balance sheets, locating lending and borrowing banks is unlikely very costly. While dealer networks with high-frequency inventory fluctuations of different securities have higher search frictions, they become much less relevant when there is only one asset, i.e. interbank loans, whose trading is very persistent. In contrast, it is the persistent, long term and unsecured nature of the interbank loan contract that renders the return of borrowing banks the most important statistic for lenders and hence our focus on monitoring to overcome asymmetric information about borrowers' return realization.

[26]Anecdotally, bank examiners of the lending bank go to the borrowing bank's premises to talk to loan officers, examine the loan book etc. Monitoring cost can be understood as the time and effort required to conduct this due diligence.

[27]For tractability and computational purposes, we abstract from details in the matching process between borrowing and lending banks in the hypothetical case of direct borrowing and assume that borrowing banks expect to contact lenders of the average size in the economy.

Interbank intermediation can avoid this duplication in monitoring. We first provide an overview of the sequence of events to illustrate the main economic forces. Details of contracts will be specified in the following subsections.

$\underline{t = 0}$

To benefit from intermediated access to lenders, borrowers can first designate a subset of intermediaries to borrow on their behalf at $t = 0$. Denote intermediaries as $i \in \mathbb{I}$. Since the asymmetric information problem persists between borrowers and their designated intermediaries, monitoring at the same cost, $k(\delta_b)$, is required for a credit relationship.[28] Monitoring costs are split between borrowers and intermediaries consistent with the anticipated bargaining power in the next stage.[29] Forming credit relationships is costly, but it can also (1) tilt the division of surplus during bargaining in $t = 1$ and (2) affect the amount of surplus by changing the cost of monitoring the intermediary in $t = 2$.

$\underline{t = 1}$

The network of credit relationships affects surplus division. Based on monitoring relationships formed in $t = 0$, borrowing banks and intermediary banks engage in bilateral bargaining with renegotiable contracts at $t = 1$. Renegotiable contracts allow borrowing banks to switch funding volume between their connected intermediaries and award a larger share of the surplus to borrowing banks with more links, effectively endogenizing bargaining with respect to the entire network structure. When deciding on which links to form, the key tradeoff for borrowing banks is between securing a higher surplus split and incurring additional monitoring costs.

$\underline{t = 2}$

At the same time, credit relationships formed in $t = 0$ affect intermediaries' funding cost when borrowing from lenders at $t = 2$. Let lending banks monitor the intermediary via a costly state verification technology (CSV) as in Townsend (1979), where they expend effort to verify the outcome only when repayments fall below the face value of debt. As a result, the expected CSV cost scales with the default probability of the intermediary, which depends not only on its own assets but also

[28]Hence, intermediary banks do not mechanically become intermediaries because of any specialized skills in monitoring.

[29]Realistically, this comes in the form of an upfront fee paid by the borrower to the intermediary, which is separate from the interest rate of the loan itself. Similar fees are observed in other markets such as the U.S. syndicated loans market.

on those of its connected borrowing banks.

For tractability reasons, we abstract away from explicitly modeling the choice of monitoring and let lenders adopt a costly state verification technology to ensure repayment from intermediaries. This is consistent with the observation that large banks, e.g., Deutsche Bank, have more access to transaction-based loans for borrowing than small and medium sized banks. Intuitively, while lenders conduct on-site due diligence and form relationships with smaller periphery borrowers, it is implausible to imagine them doing the the same with entire asset portfolio of large and complex banks like Deutsche bank. Viewed through the model, this dichotomy arises because intermediaries are large diversified banks whose low default risk allows for a low expected cost of verification. Periphery borrowers are smaller commercial banks specialized in lending to particular industries. The lack of diversification subjects them to higher volatility and increases default risk so that CSV technology is less efficient. Finally, we check for the consistency of this assumption after obtaining the bank-specific parameters in Section 4.3, and find that the choice of monitoring is incentive compatible for all intermediary banks and 87 % of all borrowing banks in the periphery.

Also at time $t = 2$, any standalone borrowers not linked to intermediaries have the outside option of directly borrowing from lending banks. This is subject to the inefficiencies of direct borrowing as described before.

$\underline{t = 3}$

Finally, at $t = 3$, returns realize, lenders carry out CSV where necessary, and payments are exchanged accordingly.

To recap, we have sketched a model of interbank intermediation in which asymmetric information about portfolio realizations have to be resolved through costly monitoring. Forming more credit relationships requires higher monitoring costs but yields diversification benefits and improved bargaining power for the borrowing bank. The equilibrium network of links is determined as banks optimize between these tradeoffs.

We now proceed to formally define the contracts formed between intermediaries and lenders at $t = 2$ as well as those between intermediaries and borrowers at $t = 1$ before solving for the equilibrium network chosen at $t = 0$. In terms of notation, when a monitoring relationship is established between intermediary i and borrower b in $t = 0$, denote link $\{i,b\}$ to be part of network g, i.e., $\{i,b\} \in g$, while b and i become each others' counterparties, i.e., $b \in N_i(g)$ and $i \in N_b(g)$.

3.2 Contracting between Intermediaries and Lending Banks

When lenders borrow from intermediaries in $t = 2$, funding costs depend on the default risk of the intermediary balance sheet, which includes loans to its connected borrowers under the formed network. Formally, given a network g in which intermediary i forms credit relationships with a set of borrowers, $N_i(g)$, the average return of intermediary i's portfolio is the weighted average of its own portfolio and that of its monitored borrowers:

$$y_i = \frac{1}{\sum\limits_{b \in N_i(g)} V_b + V_i} (V_i x_i + \sum_{b \in N_i(g)} V_b^i x_b),$$

where x_i is the intermediary's return distributed with CDF $F_i(x_i)$, V_i is the intermediary's funding volume, x_b is borrower b's return distributed with CDF $F_b(x_b)$, and V_b^i is the portion of V_b allocated to intermediary i.

Stemming from the same asymmetric information issue, intermediary banks cannot credibly communicate the realization of their return, y_i, to lending banks. To enforce repayment, lending banks adopt a CSV technology to check up on and find out the intermediary banks' true return if the reported value does not meet the face value of debt. Verification is costly but allows the lender to obtain the full value of the realized y_i. As shown in Townsend (1979), it is incentive compatible for the intermediary to truthfully report the return if it falls below the face value of debt.[30] Otherwise, it will report and transfer the face value of debt to the lender.[31] The per unit face value of debt $R_i(g)$ is determined such that lending banks obtain their outside option value of funding, r, plus their expected verification costs.[32] Formally, for a lender of size L:

$$\underbrace{L\left\{\int_{\underline{R}}^{R_i(g)} y_i \, \mathrm{d}F_i^g(y_i) + \int_{R_i(g)}^{\overline{R}} R_i(g) \, \mathrm{d}F_i^g(y_i)\right\}}_{\text{Expected Return of Debt Contract}} = Lr + \underbrace{\int_{\underline{R}}^{R_i(g)} C(\delta_i) \, \mathrm{d}F_i^g(y_i)}_{\text{Expected CSV cost}},$$

[30]Different from Townsend (1979), we assume that the observed signal is privately revealed only to the lender who requested the verification. This is to be consistent with reality where soft information about banks cannot be easily transferred.

[31]It is never optimal to report anything above the face value of debt because the lender would not verify the true return.

[32]For tractability purposes, we have abstracted away from the bargaining power of lending banks relative to intermediaries. This is an arguably realistic assumption because (1) there are many more lending banks relative to borrowing banks and intermediary banks; (2) contracts under costly state verification are faster to form relative to ex ante monitoring, which takes much time and effort at the onset, rendering lending banks more substitutable for intermediaries.

where $F_i^g(y_i)$ is the CDF of intermediary's return y_i under network g, $C(\delta_i)$ is the per state cost of verification and δ_i is a vector of intermediary characteristics.

In words, lending banks verify and obtain the full realization in each state equal to or smaller than the face value of debt $R_i(g)$. Above $R_i(g)$, intermediaries are not verified and pay back the lowest amount possible without verification. As intermediaries become more diversified, the left tail of $F_i^g(y_i)$ decreases so that guaranteeing the same expected return r requires verification of fewer states. For the ease of notation, normalize $c(\delta_i) = \frac{C(\delta_i)}{L}$ and denote $\lambda_i(g,c) = \int_{\underline{R}}^{R_i(g)} c(\delta_i)\,\mathrm{d}F_i^g(y_i)$. Under general distributional assumptions, as the intermediary sets up credit lines with more borrowing banks, diversification decreases the tail risk of y_i, which lowers monitoring costs when funding is sought from lending banks at $t = 2$.

3.3 Contracting between Intermediaries and Borrowing Banks

In addition to affecting the intermediary's balance sheet and hence the efficiency of lenders' monitoring, the network structure also determines the distribution of surplus when borrowing banks and intermediary banks bargain over the terms of trade in $t = 1$. We assume a bilateral Nash bargaining game with renegotiable contracts as in Stole and Zwiebel (1996), which effectively yields a multilateral bargaining outcome contingent on the network structure.

Bargaining frictions between intermediary and borrowing banks are relevant because after monitoring is conducted in $t = 0$, new credit lines cannot be formed during negotiation at $t = 1$ and borrowers become non-substitutable. In reality, credit relationships also take a long time to build up so that active switching between borrowers is rather unlikely and rarely observed in the data. Hence, when bargaining breaks down between i and b under network g, both banks cannot form new links and are left to receive their outside options under the network $g' = g - \{i,b\}$. Outside options update accordingly when any pair of bilateral bargaining breaks down through renegotiation of contracts in the sense of Stole and Zwiebel (1996). When negotiations break down across link $\{i,b\}$, borrowers can renegotiate and switch their borrowing to other connected intermediaries in g.[33] With respect to these outside options, the surplus is split between counterparties if negotiations are successful.

[33] We can think of credit relationships as credit lines where once monitoring is conducted, it is relatively easy to increase the amount borrowed. This also seems consistent with the data, where loan volumes from different intermediaries to the same borrower are negatively correlated, indicating substitutability.

Formally, given network g, bilateral Nash bargaining determines the shares of the loan value retained by connected borrowing banks and intermediary banks, $\gamma_{ib}(g)$.[34] That is,

$$U_b(g) - U_b(g') = U_i(g) - U_i(g') \qquad \forall g' = g - \{i,b\}, \tag{1}$$

where $\forall N_b(g) \neq \emptyset$,

$$\begin{cases} U_b(g) = \sum_{i \in N_b(g)} \overbrace{(1-\gamma_{ib}(g))V_b^i E[x_b]}^{\text{Share of Own Value}} \\ U_i(g) = \sum_{b \in N_i(g)} \underbrace{\left[\gamma_{ib}(g)V_b^i E[x_b] - V_b^i(r+\lambda_i(g,c))\right]}_{\text{Share of Borrower Value - Funding Cost}} + \underbrace{V_i(E[x_i]-\lambda_i(g,c)-r)}_{\text{Own Value - Funding Cost}}. \end{cases} \tag{2}$$

Intermediary banks not connected to any borrowers fund their own portfolio, while borrowing banks without any links resort to direct borrowing from lenders. They will still be able to fund their loans, but they are exposed to duplication in monitoring costs and share surplus with lending banks. In other words, $U_b(g) = \frac{1}{2}V_b\big(E[x_b]-r\big) - \lceil \frac{V_b}{L} \rceil k(\delta_b)$ when $N_b(g) = \emptyset$.

A simple example will demonstrate the intuition behind the general formula. When bargaining breaks down with only one connected intermediary as in network g', borrowing banks are left to directly borrow from lending banks at $t = 2$ as illustrated in network g''. Denote the outside option value of direct borrowing for bank b as $\underline{W}_b$. In this case, the intermediary would walk away without the borrowing banks' loans on its books. Solving $U_b(g') - U_b(g'') = U_i(g') - U_i(g'')$, the borrower obtains half of the surplus, which is comprised of its loan value net of funding costs, $V_b\left[E[x_b]-r\right]$, the contribution to the intermediary's CSV funding costs, and the borrowers' outside option $\underline{W}_b$. Effectively, we can write borrower b's utility under network g' as:

$$U_b(g') = \underbrace{\frac{1}{2}V_b\left[E[x_b]-r\right] - \frac{1}{2}V_b\lambda_i(g',c)}_{\text{Share of Own Value - Share of Own Funding Cost}} + \underbrace{\frac{1}{2}V_i[\lambda_i(g'',c)-\lambda_i(g',c)]}_{\text{Contribution to Intermediary Funding Cost}} + \underbrace{\frac{1}{2}\underline{W}_b}_{\text{Outside Option Reward}}.$$

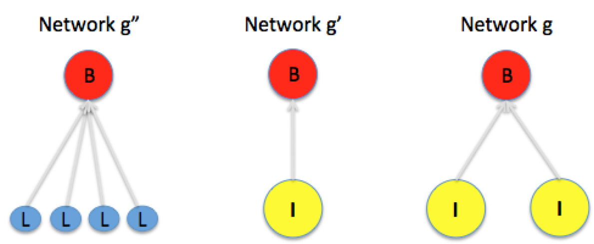
Instead, if the borrowing bank splits its funding volume and forms two credit relationships as in network g, then it could threaten any of its intermediaries by sending all its funds to the other one when bargaining breaks down, i.e., $V_b^1 = V_b$ when bargaining with $i = 2$, and $V_b^2 = V_b$ when bargaining with $i = 1$. That is,

[34] This can be reformulated into a debt contract, where $\gamma_{ib}(g)$ maps into a link specific interest rate.

$$\begin{cases} U_b(g) - U_b(g') = U_i(g) - U_i(g'') \\ U_b(g) - U_b(g') = U_i(g) - U_i(g''). \end{cases}$$

Since the borrower's outside option in each bilateral bargaining improves from $U_b(g'')$ to $U_b(g')$, it can eventually secure two-thirds of the total value of loans net of funding costs as shown in the equation below:

$$U_b(g) = \underbrace{\frac{2}{3}V_b\big[E[x_b] - r\big] - \frac{1}{3}V_b\big[\lambda(g,c) + \lambda(g',c)\big]}_{\text{Share of Own Value - Share of Own Funding Cost}} - V_i\underbrace{\big[\frac{2}{3}\lambda(g,c) + \frac{1}{3}\lambda(g',c) - \lambda(g'',c)\big]}_{\text{Contribution to Intermediary Funding Cost}} + \underbrace{\frac{1}{3}\underline{W}_b}_{\text{Outside Option Reward}}.$$



Hence, borrowing banks can form more links to tilt surplus division in their favor. Realistically, interbank lending links can be viewed as credit lines so that borrowers are able to credibly (threaten to) substitute between lines of credit from different intermediaries. The contribution to intermediary diversification is now a weighted average of $\lambda(g,c)$, $\lambda(g',c)$ and $\lambda(g'',c)$ because contracts are renegotiable along each link and are thus functions of funding costs in all three subnetworks.

As the above example illustrates, the value for borrowers and intermediaries under any network will depend on the values of all possible subnetworks through the renegotiation of contracts. The number of subnetworks increases drastically with the number of banks and renders direct calculation of $\gamma_{ib}(g)$ infeasible given the size of our network. Instead, we solve our model by proving equivalence to Shapley values, which is one of the most commonly used solution concepts in cooperative game theory. Intuitively, Shapley values assign a unique distribution of a total surplus generated by the coalition of all players according to the average contribution of each player. Specific to our context, letting the set containing all intermediary banks and borrowing banks be $\mathbb{N}$, we can show that

Proposition I *For any network g, there exists a cooperative game between banks in $\mathbb{N}$ with characteristic function $v_g(\cdot)$ for which the Shapley values $\phi(v_g)$ are equivalent to the solutions of the non-cooperative bargaining game as defined by equations (1) and (2). That is,*

$$\begin{cases} U_b(g) = \phi_b(v_g) = \dfrac{1}{|\mathbb{N}|!} \sum_R [v_g(P_b^R \cup \{b\}) - v_g(P_b^R)] \\ U_i(g) = \phi_i(v_g) = \dfrac{1}{|\mathbb{N}|!} \sum_R [v_g(P_i^R \cup \{i\}) - v_g(P_i^R)], \end{cases} \tag{3}$$

where P_b^R (P_i^R) is the set of players in $\mathbb{N}$ which precede b (i) in the order R and $v_g(S)$ is the characteristic function for a subset of banks S under network g,

$$v_g(S) = \underbrace{\sum_{i \in S} V_i \left[E[x_i] - r - \lambda_i(g^S, c)\right]}_{\text{Value - Funding Cost of Intermediaries}} + \underbrace{\sum_{b \in S} \sum_{i \in S} V_b^i \left[E[x_b] - r] - \lambda_i(g^S, c)\right]}_{\text{Value - Funding Cost of Connected Borrowers}} + \underbrace{\sum_{b \in S, N_b(g) \cap S = \emptyset} \underline{W}_b}_{\text{Outside Option of Stand-alone Borrowers}} .$$

The characteristic function $v_g(S)$ defines the total value created by the subset of banks S under network g. The first two summations respectively correspond to the value of loans by intermediaries and connected borrowing banks less the opportunity cost of deposits r and monitoring cost $\lambda(g^S, c)$. The last term adds up outside option values of borrowing banks not linked to any intermediaries when a subset of banks S is chosen from all banks in network g. Now imagine that banks are drawn one by one into a sequence R, then bank b (i) would demand its marginal contribution as a fair compensation, which is the difference in value created by the preceding subset of banks P_b^R (P_i^R) with and without bank b (i), i.e., $v_g(P_b^R \cup \{b\}) - v_g(P_b^R)$ ($v_g(P_i^R \cup \{i\}) - v_g(P_i^R)$). Shapley values are the expected marginal contribution as shown in equation (2). Since the average is taken over all possible permutations, there is a unique solution of the game independent of the sequence in which banks are arranged. This embodies the spirit of our bargaining game for which the order of contracting does not matter because existing contracts can be renegotiated upon the addition of new contracts.

In addition to providing a tractable closed-form solution for our bargaining game, Shapley values also have a number of appealing properties and satisfy a series of natural axioms. We apply one of them, the axiom of balanced contributions by Myerson (1980), to prove our equivalence result. This builds on the work of Stole and Zwiebel (1996), who show that wages determined in intrafirm bargaining with renegotiable contracts can be mapped into Shapley values of a correponding cooperative game. We extend their analysis by allowing for a more general network structure with more than one essential agent, which in our case are the intermediary banks. For details, please refer to the proof in Appendix B1.

3.4 Equilibrium Definition

Weighing the higher share in surplus from forming more links against the increase in monitoring costs, banks optimally choose their set of counterparties $i \in N_b(g)$ and $b \in N_i(g)$ at time $t = 0$. We adopt the equilibrium concept of pairwise stability. First introduced by Jackson and Wolinsky (1996), this is a standard concept in the networks literature by which forming a link, i.e., cooperation requires the consent of both borrowing and intermediary banks whereas links can be dropped once either party wishes to do so. Formally,

Pairwise Stability *In a pairwise stable network g^*, no bank i or b wants to unilaterally sever any link and no pairs of banks i and b want to jointly form any new links. That is,*

$$\begin{cases} U_b(g^*) - U_b(g') \geq \frac{1}{2}k(\delta_b) & \forall g' = g^* - \{i,b\} \\ U_b(g'') - U_b(g^*) < \frac{1}{2}k(\delta_b) & \forall g'' = g^* + \{i,b\}. \end{cases} \tag{4}$$

In our context, the idea of pairwise cooperation naturally follows from bilateral Nash bargaining with renegotiable contracts. It is a relatively weak concept prone to generating multiple equilibria. Nevertheless, as the next section will detail, our structural estimation technique does not require imposing further restrictions on equilibrium selection.

While bilateral cooperation is essential in link formation, one might ask why banks cannot choose to sever any number of their own links. Indeed, this corresponds to a pairwise Nash stable equilibrium condition at the intersection of pairwise stability and Nash stability, where the latter is built on Myerson (1991)'s non-cooperative game of network formation. Under general parameter restrictions, the convexity of our value function ensures that pairwise stability suffices for pairwise Nash stability. Please see Appendix B2 for a more formal discussion of this correspondence.

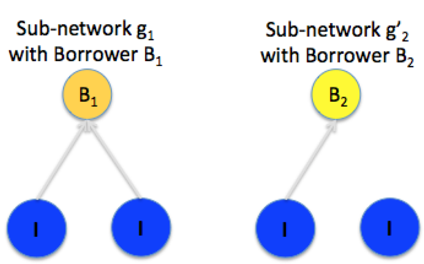
4 Structural Estimation

Based on the tradeoff between the benefits and costs of link formation, this section adopts a revealed preferences approach to uncover cost parameters $C(\delta_i)$ and $k(\delta_b)$, which are not directly observable. They determine adjustment frictions that will be important in estimating the aggregate systemic exposure to initial bank-specific shocks.

4.1 Revealed Preference Approach

We identify unobservable monitoring costs and CSV costs by structurally estimating the pairwise stable equilibrium implied by the model. This is done by taking the observed network as the equilibrium outcome and finding parameter values that best rationalize inequality conditions of observed matches in a given market. If the observed equilibrium in the data is g^*, then the true cost parameters c and k must have been such that equations (4) are satisfied. In other words, for every observed link, we know that the cost saved from deleting that link is smaller than the benefit obtained, $U_b(g^*) - U_b(g')$. Similarly, for every link that we do not observe, the cost of an additional link must have exceeded the improvement in welfare, $U_b(g'') - U_b(g^*)$.

Before introducing the general form of our structural estimator, we illustrate how variations along two dimensions in the data allow inequality constraints to determine k and c. First, links formed by borrowing banks of different profitability unveil the magnitude of total costs. As in the figure below, if we see borrowing bank B_1 forming two links while its less-profitable counterpart B_2 forms only one link to one of the same intermediaries, we know that the borrower's value from the second link was higher than the cost only in the first case. Using the coefficients derived from bargaining and $E[x_1]$ and $E[x_2]$ from the data, we can put a bound on the sum of monitoring costs using inequalities (5):

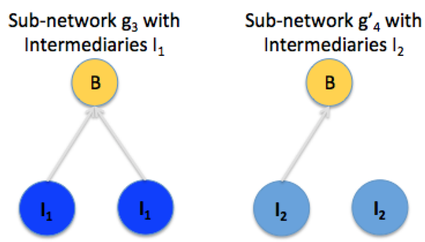


$$\begin{cases} \frac{1}{12}\left[E[x_1] - r\right] \geq \kappa(c) + \frac{1}{2}(1 - \frac{V}{6L})k \\ \frac{1}{12}\left[E[x_2] - r\right] < \kappa(c) + \frac{1}{2}(1 - \frac{V}{6L})k, \end{cases} \tag{5}$$

where CSV costs are denoted as $\kappa(c) = V_b\left[\frac{1}{3}\lambda(g,c) - \frac{1}{6}\lambda(g',c)\right] + V_i\left[\frac{2}{3}\lambda(g,c) - \frac{1}{6}\lambda(g',c) -\right.$

$\frac{1}{2}\lambda(g'',c)\big]$.[35]

Second, the density of links between differentially diversified intermediaries with the same borrower disentangles the relative magnitude of ex ante monitoring cost and CSV cost. In the figure below, I_2s are less diversified than I_1s; hence $\lambda(g_4,c) > \lambda(g_3,c)$. Since the borrower only forms one link with I_2, the increase in CSV cost for I_2 relative to I_1 must have made the link not profitable. Hence, we can deduce the relative magnitude of c from k since the respective CSV costs, $\kappa_3(c)$ and $\kappa_4(c)$, satisfy inequalities (6):



$$\begin{cases} \frac{1}{12}\big[E[x]-r\big] - \frac{1}{2}(1-\frac{V}{6L})k \geq \kappa_3(c) \\ \frac{1}{12}\big[E[x]-r\big] - \frac{1}{2}(1-\frac{V}{6L})k < \kappa_4(c), \end{cases} \tag{6}$$

where $\kappa_3(c) = V_b\big[\frac{1}{3}\lambda(g_3,c) - \frac{1}{6}\lambda(g_3',c)\big] + V_1\big[\frac{2}{3}\lambda(g_3,c) - \frac{1}{6}\lambda(g_3',c) - \frac{1}{2}\lambda(g_3'',c)\big]$ and $\kappa_4(c) = V_b\big[\frac{1}{3}\lambda(g_4,c) - \frac{1}{6}\lambda(g_4',c)\big] + V_2\big[\frac{2}{3}\lambda(g_4,c) - \frac{1}{6}\lambda(g_4',c) - \frac{1}{2}\lambda(g_4'',c)\big]$.

Generalizing to the actual observed network, we embed our model-implied inequality conditions within a maximum score estimator. To do so, we first parameterize inequalities in (3) to write the net value of deleting link $\{i,b\}$ from network g as a linear function of the unknown parameters c and k plus a link specific error: $W_{ib}(c,k) = U_b(g,c,k) - U_b(g',c,k) - \frac{1}{2}k + \varepsilon_{ib}$. Then, define the objective function as a sum of indicators for whether a given inequality is correctly predicted given values of c and k:

$$Q(c,k) = \sum_{i\in\mathbb{I}}\Big\{\sum_{b\in N_i(g^*)} \mathbb{1}\big[U_b(g^*,c,k) - U_b(g',c,k) \geq \frac{1}{2}k\big] + \sum_{b\notin N_i(g^*)} \mathbb{1}\big[U_b(g'',c,k) - U_b(g^*,c,k) < \frac{1}{2}k\big]\Big\}.$$

Finally, we find the c^* and k^* that best rationalize the observed equilibrium network g^* as the ones that satisfy the highest fraction of inequalities to maximize $Q(c,k)$. For identification, we assume that the unobserved match errors, ε_{ib}, are independently and identically distributed with mean zero. Then, in the limit, as more banks are sampled and the size of the market grows, estimates c^*

[35] In the case of large diversified intermediary banks, loans of a single borrower cause little perturbation to its portfolio diversification. Hence we approximate them by $\kappa(c)$ in both cases. Also, in this example, we assume $\lceil\frac{V_b}{L}\rceil = \frac{V_b}{L}$ for the ease of exposition

and k^* should converge to their true values.[36] Mean zero match errors can include measurement error in the data and other shocks to match values realized after the formation of links. However, they do not allow for information relevant for link formation that are ex ante known to the agent but unobserved to the econometrician. If intermediary banks have prior information about potential borrowing banks before the formation of links through, for example, a social network between bankers or other types of business relationships with borrowing banks, our estimates would be biased. The latter is less of a concern because borrowing banks are small and relatively simple institutions, who are not active in trading with other banks outside of the interbank lending market. The former is more of a concern, especially when geographic proximity increases the probability of bankers knowing each other. Appendix B4 repeats the analysis conditioning on geographic distance and yields similar quantitative predictions. We also verify our parameters estimates using an out-of-sample test in Section 5 and extend the model to account for loan demand and actions by the central bank in Section 7. The economic and statistical significance of the results remain throughout.

The maximum score estimator was introduced by Manski (1975) and has been extended to matching markets by Fox (2008). [37] It allows us to estimate the model using information from every link and non-link in the network, and avoids a potentially arbitrary choice of specific moments as in other indirect-inference approaches. It is also computationally efficient for a large network like ours and does not suffer from the curse of dimensionality as other maximum likelihood estimators do. While we apply it to estimate the cost of interbank lending relationships, previous papers have adopted a similar estimation approach to other contexts, e.g. Akkus et al. (2015), Chen and Song (2013), and Schwert (2018).

For computation, we adopt the differential evolution algorithm proposed by Storn and Price (1997) that randomizes movements across the parameter space to ensure a global maximum.[38] We

[36] The asymptotic argument is that as we are drawing from a continuum of banks, more agents from the limiting game are observed and we are learning more about the underlying equilibrium.

[37] Fox (2008) provides a rank order condition for identification. Intuitively, it requires the likelihood of seeing a link to be higher when the observable component of the match value is higher. It is satisfied under our assumption of mean zero iid errors.

[38] In general, the maximum score estimator only allows for set identification. However, all 20 runs of the optimization procedure with different initial populations yield the same value of the objective function and the same point estimates up to three decimal figures. As explained in Fox (2008), it is therefore reasonable to assume the model to be point identified in the limit.

follow Delgado et al. (2001) and Politis and Romano (1992) to generate confidence intervals by drawing 100 random subsamples of a quarter of the full sample. Then, letting n_s be the fraction of the subsample, the empirical sampling distribution is given by

$$\tilde{\beta}_s = (n_s)^{\frac{1}{3}}(\hat{\beta} - \hat{\beta}_s) + \hat{\beta},$$

where $\hat{\beta}_s = [\hat{c}_s \ \hat{k}_s]'$ and $\hat{\beta} = [\hat{c} \ \hat{k}]'$ refer to the subsample and full sample estimates, respectively. The 2.5$^{\text{th}}$ and 97.5$^{\text{th}}$ percentile of this empirical sampling distribution are used to compute the 95% confidence interval.

4.2 Data Matching

To uncover unobservable monitoring costs, we first estimate the following variables from balance sheet and credit registry data as an input to the structural model.

For estimating the baseline model, we obtain V_i^b from the average bilateral loan volumes in the observed network from 2005Q1 to 2007Q2.[39] Let $x = (x_1, ..., x_i, ..., x_N)$ follow a joint normal distribution with x_b of mean μ_b and variance σ_b^2. Take μ_b and σ_b^2 as the time series sample average and sample variance of each bank's gross return. The gross return is calculated as a weighted average of the interest income from nonfinancial corporations and noninterest income, where weights are taken as the balance sheet sizes. We estimate our model for different asset correlations, ρ, between 0.12 to 0.24, which are the lower and upper bounds guided by the analysis in Basel III. [40] Lending banks' outside option, r, is taken to be the German Bund yield extrapolated to match the average maturity of interbank loans. Finally, monitoring costs vary proportionately with the borrowing banks' asset size and fraction of firm loans, where the latter has been used as a proxy for opacity in the literature. Table 2 shows average values for the above parameters.

[39]The distribution of loan volumes between a borrower's intermediaries is determined by relative preferences not observable to the econometrician. Assuming that they arise after link formation, we use the bilateral loan volumes observed in the data in our estimation.

[40]Estimating the time series correlation of bank asset portfolios in our data, we find it to be 0.22, which is within the bounds. However, since asset correlations can change during different stages of the business cycle and given our relatively short time series, we estimate the model for the range of correlation values outlined by the Basel regulation.

4.3 Estimation Results

According to the estimation results in Table 3, k is estimated to be between €1.28 and €1.41 million while C ranges from €0.21 to €0.24 million for the range of correlations. All estimates are statistically significant at the 95% level. Equivalently, the average borrowing bank forming two links has 23.1% of its value generated lost on CSV and monitoring, where value is the spread between the gross return less lenders' outside option funding rate r scaled by the total volume of loans. Ex ante monitoring accounts for the vast majority of the total monitoring costs expended on borrowers.

Aggregating across banks in the economy, the interbank lending network yields an annual net value of €5.63 billion in the present network. This is after deducting lenders' outside option funding rate, r, ex ante monitoring costs, and CSV costs. The latter two costs are €1.10 billion and €0.12 billion respectively, showing that the main investment in the interbank network is for establishing long-term credit relationships to monitor borrowing banks. The small share of CSV costs is consistent with "monitoring the monitor" costs being sufficiently low. Absent interbank intermediation, many more long-term credit relationships have to be set up due to the limited deposit base of the average lending bank. The total value created would drop mainly due to an increase in total ex ante monitoring cost from €1.10 billion to €1.57 billion.

5 Verification of Model Parameters

During the recent financial crisis, intermediary banks were differentially affected.[41] We utilize this unexpected cut in profitability and the subsequent changes in the interbank network as an out-of-sample test to verify the accuracy of our model and estimation.

After the onset of the crisis, the main observable changes were a drop in funding volume through existing links and a series of new links added to the existing network, which had been very stable. Viewed through the lens of our model, these changes reflect an increase in the default risk for some intermediaries, which increased the CSV cost charged by their lenders. The increase in funding cost is passed on to connected borrowing banks, who attempted to form new credit links to unaffected intermediaries in search of less expensive alternative funding sources.

[41] One of the main exposures was due to losses from asset-backed commercial paper held by their conduits (Acharya et al., 2013).

Since investments in new credit relationships is costly, not all exposed borrowers could avoid the initial exposure, resulting in an overall increase in total funding cost for borrowing banks and a subsequent decline in their loans fundable.

In other words, borrowing banks decide between paying the cost of investing in new credit relationships or continuing funding at the increased rates of their established credit links. If our model is correct, then the larger the funding cost increase from connected intermediaries in the pre-crisis network, g^*, the larger the borrower's incentive to form new links. Plotting the average number of new links for buckets of borrowing banks with different predicted changes in funding costs, Figure 7 lends support for this hypothesis. As the model-implied funding cost increases by 100 basis points, the expected number of new links formed also increases by 1. The change in funding costs is calculated using post-crisis balance sheets and returns as shown in Table 4 and the monitoring and CSV technology parameters obtained from the pre-crisis sample. Note that this only assumes no changes to the technologies of monitoring, while monitoring intensity and hence funding costs increase because the returns on investment relative to the outside option r decrease significantly for exposed intermediary banks.

Note that the drop in mean returns in Table 4 results from different intermediary banks being exposed to a different extent.[42] Heterogeneity in intermediary exposure provides the necessary variation for our out-of-sample test. Intuitively, the larger the crisis exposure of the intermediary bank, the more its funding costs increase, and the less likely for it to form new links to borrowing banks. Plotting the number of new links formed against quartiles of intermediaries sorted in increasing order of crisis exposure, all new links were formed with less affected intermediary banks with most of them concentrated in the first quartile as shown in Figure 8.

Knowing that the direction of predictions are aligned, we proceed to a more formal out-of-sample test of our model estimates estimated using pre-crisis data by checking whether they can accurately quantify the cost and benefits of link formation in the post crisis period. Specifically, if the model estimates of $c(\hat{\delta}_i)$ and $k(\hat{\delta}_b)$ were accurate, they shoudl be able predict the formation of new links and absences thereof. To check, we verify the pairwise stability conditions for all new links formed and not formed by again using cost parameter estimates from the pre-crisis period and updated balance sheet characteristics and returns from the crisis period. We denote the post-crisis

[42]Due to confidentiality constraints, we are unable to display the full distribution for all intermediaries. The quartile breakdown is the most granular breakdown allowed.

network as g^*_{post} and compute the fraction of successful predictions as $\frac{Q(\hat{c},\hat{k})}{Q(c,k)}$, where

$$Q(\hat{c},\hat{k}) = \sum_{i\in\mathbb{I}} \Bigg\{ \sum_{b\in N_i(g^*_{post}),\, b\notin N_i(g^*)} \mathbb{1}\left[U_b(g^*_{post},\hat{c},\hat{k}) - U_b(g'_{post},\hat{c},\hat{k}) \geq \frac{1}{2}\hat{k}\right] + \sum_{b\notin N_i(g^*),\, b\notin N_i(g^*)} \mathbb{1}\left[U_b(g''_{post},\hat{c},\hat{k}) - U_b(g^*_{post},\hat{c},\hat{k}) < \frac{1}{2}\hat{k}\right] \Bigg\}.$$

and $Q(c,k)$ is the total number of new links that could have been formed. To not overinflate our results, we do not include links already present in the pre-crisis network. We can think of their cost of formation as sunk so that continued usage does not require additional monitoring.

We correctly predict around 86% of post-crisis inequalities of potential links between borrowing and intermediary banks (Table 5). Although we identified a smaller fraction of links that were formed versus those that were not formed - 66.5% to 71.9% versus 85.4% to 86.7% — the overall accuracy is high. Note that these numbers are not due to a vast overprediction or underprediction of the number of links - we predict between 177 and 207 new links while the data shows 185 new links. Without the model, if we took the same number of new links predicted and assumed a random formation, the predictive accuracy would be between 2.9% to 3.4% and 83.2% to 83.8% for new links formed and not formed respectively. Even if we were to limit the matching to links between intermediaries with below median exposure and borrowing banks only funding from intermediaries with above median exposure, expected predictability would be improved to between 11.6% to 13.7% and 85.7% to 86.1% for links formed and not formed. Overall predictability ranges between 81.1% to 82.5% for the fully randmomized benchmark case and 83.9% to 84.7% for the one restricted to less exposed intermediaries and more (indirectly) exposed borrowers.

Conceptually, our predictability stems from a few factors. On the borrowers' end, those with more exposed intermediaries are more likely to form new links. Consistent predictions along this dimension were already evident from Figure 7. For intermediaries, the number of new links formed is highly negatively correlated with the exposure suffered during the crisis, which is captured by changes in balance sheet profitability, in line with the results in Figure 8. The model structure does well at weighing the effect of these different components to accurately predict the quantity and identity of new links formed.

6 Effect of Interbank Funding Cost on Lending to the Real Economy

The quantity of loans from borrowing banks to firms provides further evidence for our model and demonstrates the real impact of disruptions in interbank intermediation. Figure 9 plots the average change in firm loan supply for borrowing banks for borrowing banks in different buckets of model-implied funding cost changes after the formation of new links. For each bucket, the average change in firm loans by all banks is subtracted to control for shifts in aggregate loan demand. The negative trend is consistent with banks facing a downward-sloping demand for firm loans, where the number of positive NPV projects decreases as funding costs increase. Quantitatively, for every 100 basis point increase in bank funding cost, firm loans extended decrease by 4.2%.

To address concerns of bank-specific loan demand, we examine changes in loans at the bank-firm level and condition borrowing by the same firm. From Column 3 in Table 6, firm loans drop by 5.5% for every 100 basis point increase in funding cost, which is only slightly below the unconditioned result in column (2). Column (4) repeats the same specification by also including firm loans extended by lending banks, assuming that lending banks did not suffer direct impacts to funding costs for their firm loans. This checks whether lending banks, which lend less to exposed intermediaries post crisis, can fully substitute lending lost by interbank borrowers. The coefficients slightly change in magnitude but remain significantly negative, demonstrating that a breakdown of interbank intermediation impacted aggregate funding supply to the real economy. This likely results from sticky bank-firm credit relationships as well as the irreplaceability of interbank funding.

7 Extension: Central Bank Liquidity Facilities and Endogenous Loan Volumes

This section extends the baseline model by allowing banks to optimize on their funding volume when choosing interbank relationships and by granting them access to central bank funding. The inclusion of these realistic elements verifies the robustness of the baseline model and offers the capacity for testing counterfactuals.

7.1 Endogenous Loan Volume

So far, we have assumed that banks generate a fixed funding need from their interaction with the real economy, and they seek to obtain this funding from the interbank market. The recent crisis has illustrated how changes in the network such as the default risk of intermediary banks can influence the cost of intermediated borrowing and affect the volume of loans. Hence, we relax this assumption by allowing banks to adjust the extensive margin of loans together with their choice of interbank links.

Let borrowing banks b and intermediary banks i face a downward sloping demand curve for interbank funding with marginal revenue, $\alpha_{1b} - \alpha_{2b}V_b$ and $\alpha_{1i} - \alpha_{2i}V_i$, respectively. Then, when deciding over links at $t = 0$, they simultaneously opt for the optimal volume of borrowing, V_b^* and V_i^*. This yields modified Shapley values dependent on the chosen volumes:

$$\begin{cases} U_b(g,V) = \phi_b(v_{V,g}) = \dfrac{1}{|\mathbb{N}|!}\sum_R [v_{V,g}(P_b^R \cup \{b\}) - v_{V,g}(P_b^R)] \\ U_i(g,V) = \phi_i(v_{V,g}) = \dfrac{1}{|\mathbb{N}|!}\sum_R [v_{V,g}(P_i^R \cup \{i\}) - v_{V,g}(P_i^R)], \end{cases}$$

where P_b^R (P_i^R) is the set of players in $\mathbb{N}$ which precede b (i) in the order R and $v_{V,g}(S)$ is the characteristic function for a subset of banks S with volumes V under network g,

$$\begin{aligned} v_{V,g}(S) = \quad & \sum_{i\in S}\int_0^{V_i} \alpha_{1i} - \alpha_{2i}V_i - r - \lambda_i(g^S,c)dV_i + \sum_{b\in S}\sum_{i\in S}\frac{V_b^i}{V_b}\int_0^{V_b} \alpha_{1b} - \alpha_{2b}V_b - r - \lambda_i(g^S,c)dV_b \\ & + \sum_{b\in S, N_b(g)\cap S=\emptyset} \underline{W}_b \end{aligned}$$

.

Given equilibrium network g^*, a necessary condition is for funding volumes to satisfy the following first order conditions:

$$\begin{cases} \left.\dfrac{\partial U_b(V,g)}{\partial V_b}\right|_{\substack{V=V^* \\ g=g^*}} = 0 \\ \left.\dfrac{\partial U_i(V,g)}{\partial V_i}\right|_{\substack{V=V^* \\ g=g^*}} = 0. \end{cases} \tag{7}$$

Furthermore, we know that the gross return on assets observed in the data, ROA_b and ROA_i, map into the average return on assets in equilibrium:

$$\begin{cases} ROA_b = \alpha_{1b} - \frac{1}{2}\alpha_{2b}V_b^* \\ ROA_i = \alpha_{1i} - \frac{1}{2}\alpha_{2i}V_i^*. \end{cases} \tag{8}$$

This yields two equations (6) and (7) to deduce the unknown demand parameters α_1 and α_2 for each bank. Then, we proceed to estimate the model as in the baseline case.

7.2 Central Bank Funding Facilities

In addition to obtaining funding from the interbank market, banks can also borrow from the central bank to fulfill their liquidity needs. In the German context, the European Central Bank regularly conducts longer-term refinancing operations (LTROs) in which banks can borrow for a duration of three months against eligible collateral.[43] We extend the model by allowing for this outside option of secured borrowing from the ECB. [44]

Specifically, let borrowing and intermediary banks borrow from the ECB in $t = 2$ with probability P_b and P_i respectively. Otherwise, they continue to borrow from lending banks. Since ECB loans are secured, the likelihood of borrowing varies with the amount of available collateral. We use the proportion of ECB borrowing as a fraction of the total balance sheet size as a proxy because balance sheet data cannot directly distinguish which assets are eligible as collateral. To map the proxy variable into the actual borrowing likelihoods, we further allow for a scaling parameter, p.[45] Thus, we parameterize $P = p\frac{ECBBorrowing}{TotalAssets}$.

The distribution of $\frac{ECBBorrowing}{TotalAssets}$ is displayed in Table 7. We observe that the vast majority of borrowing and lending banks do not fund through the ECB. Intermediary banks borrow much more

[43] 3-year LTROs were introduced at the end of 2011, which is beyond our sample period.

[44] The ECB also conducts week-long liquidity providing operations called the main refinancing operation. The MRO mainly affects short-term rates, which signal the monetary policy stance. Since it is not meant for providing longer-term refinancing to the financial sector, the MRO is unlikely to be a substitute for persistent interbank loans. Hence, we set them aside in our analysis. In fact, even if considered, the average volume of MROs in our sample period is extremely small because banks access the MROs very infrequently. This is further evidence for the claim that MROs are not used to satisfy systematic liquidity needs.

[45] This scaling parameter also accounts for the fact that not all bids were honored given the fixed allotment quota.

on average, which is likely because their business model requires more liquid assets that can also serve as collateral.

7.3 Estimation and Results

We estimate the extension model by finding parameters that maximize the maximum score estimator. Compared to the baseline model, bilateral deviations from g^* to g' and g'' are now associated with respective changes in funding volume from V^* to V' and V'', which reflect endogenous changes in funding volume given network contingent diversification. There is also a third parameter p to capture the outside option of obtaining funding from the ECB.

$$
\begin{aligned}
Q(c,k,p) = \quad & \sum_{i \in \mathbb{I}} \Bigg\{ \sum_{b \in N_i(g^*)} \mathbb{1}\left[U_b(g^*,V^*,c,k,p) - U_b(g',V',c,k,p) \geq \frac{1}{2}k\right] \\
& + \sum_{b \notin N_i(g^*)} \mathbb{1}\left[U_b(g'',V'',c,k,p) - U_b(g^*,V^*,c,k,p) < \frac{1}{2}k\right] \Bigg\}
\end{aligned}
$$

We add the amount and cost of ECB borrowing to the previous data to obtain parameter values. Since LTRO auction bids are not announced, we resort to using the 3-month repo rate provided by the European Money Market Institute, which has been shown to closely track the LTRO rate by Linzert et al. (2004). The average rate for the pre-crisis and crisis period are 2.83% and 2.61% respectively.

Comparing the results in Table 8 with those in the baseline model, we find that both the monitoring cost parameter, k, and the costly state verification parameter, C, slightly increased in magnitude. On one hand, new links provide the additional gain of increasing funding volume. At the same time, ECB funding provisions lower the average funding cost for intermediaries. The benefits from interbank lending relationships are therefore higher relative to the baseline model. Hence, to rationalize the same equilibrium network, monitoring costs increase accordingly. The estimates for p imply that the median intermediary borrows about 9.1% to 11.2% of its interbank funding from the ECB before the crisis. This value increases to around 21.5% to 26.6% after the crisis. Similar conversions show that ECB funding tapped by periphery banks is largely negligible.

7.4 Verification of Model Parameters

We verify our model estimates with the crisis predictions. Similar to the baseline case, Figure 10 shows a clear positive relationship between predicted increases in funding cost and the number of new links formed. The highest funding cost increases are slightly reduced compared to the baseline model, showing that the ECB helped to partially alleviate surges in funding cost. Nevertheless, ECB funding provision was unable to fully compensate for the increase in monitoring. This stems from low Ps induced by limited collateral and allotment quotas.

Compared to the baseline model, the accuracy of link change predictions is also slightly improved for all three correlation cases. As shown in Table 9, the percentage of correct predictions is now between 86.8% and 89.0% compared to the previous 85.0% to 86.2%.

Finally, we relate changes in predicted funding costs with loans supplied to the real economy in Figure 11. As before, net increases in funding costs imply that most borrowing banks could not afford to form new links to substitute away from their intermediaries' credit risk exposure. Since ECB funding was unable to fully offset spikes in intermediary funding cost, the adjustment frictions of costly monitoring relationships remained significant and trickled down to affect lending to the real economy. Hence, the systemic importance of interbank intermediation persists in the presence of the ECB.

8 Counterfactual Scenarios

The recent financial crisis demonstrated how shocks to a few intermediary banks can affect the funding cost of a large number of borrowing banks. To shed light on the extent of shock amplification through increased CSV costs and sticky monitoring relationships, we shock intermediary banks one at a time and measure the aggregate impact on the banking system. Then, we examine whether and to what extent the provision of central bank funding can lower funding cost in the interbank market and increase the volume of fundable loans.

8.1 Credit Risk Shocks to Intermediary Banks

Consider a 50 basis point increase in funding cost to each intermediary's own balance sheet.[46] Given higher CSV costs under downward-sloping demand curves, loans to the real economy funded through the interbank market should fall. To alleviate the surge in funding cost, borrowing banks consider forming new monitoring relationships that provide alternative funding sources. Assuming that agents behave optimally, we allow for the formation of new links and select the socially efficient pairwise stable equilibrium network.[47]

Intermediary banks' connectivity plays a crucial role in determining the aggregate impact of a given shock. Figure 12 shows that the decrease in total loans fundable is 4.3 times higher for the intermediary at the third versus first quartile of loans intermediated. On average, the drop in total loans for intermediaries above the third quartile reaches 12.3 times that of the first quartile intermediary, showing a highly skewed right tail of intermediary connectivity.[48] Most of this wedge is driven by contractions in borrowers' loans. This demonstrates the systemic importance of intermediary banks, who pass on shocks to their own funding to a large number of dependent borrowing banks.

In absolute terms, a 50 basis point shock to the median intermediary decreases fundable loans by a total of €2.46 billion. For the third quartile intermediary, this number more than doubles to €5.50 billion. Above the third quartile, the average value is at €15.74 billion. These make up 0.9%, 2.1% and 5.8% of the aggregate respectively.

[46] The estimation is based on the pre-crisis network, where we decrease the average return on assets for one intermediary at a time corresponding to a 50 basis point increase in funding cost required by the lending banks. All other loan values and balance sheet characteristics remain unchanged. For the unobservable portion of the match values, we draw from a truncated mean zero normal distribution to rationalize the observed linking decisions. That is, for every link that is formed, we draw the match errors conditional on it being larger than the negative of the predicted match value. Similarly, for every link that is not formed, we draw the match errors conditional on it being smaller than the negative of the predicted match value. The variance of the normal distribution is estimated by matching the sample covariance between the predicted values and the observed links. All counterfactual outcomes are computed for and averaged over ten draws of the unobserved match errors.

[47] In practice, this corresponds to the new network with the least number of new links formed by affected borrowers to intermediaries of the lowest funding cost. Although the range of outcomes for other pairwise stable equilibria could be computed, the socially efficient one seems to be a reasonable benchmark given network changes in the recent financial crisis.

[48] Due to data restrictions, we are unable to disclose the exact values for banks in the right tail

8.2 Changes in Central Bank Funding Policy

In the first scenario, we consider a 50 basis point interest rate drop of the ECB's funding facility. Given constraints from allotment quotas and collateral availability, we also increase P by 25% while lowering interest rates by 50 basis points in the second scenario.[49] In reality, this can be achieved through a variety of policy measures such allowing for a wider range of eligible collateral and reducing haircuts.

The results are shown in Figure 13. A 50 basis point drop in ECB funding rates increases loans fundable by 2.96%. Combined with more accommodative collateral policy, the effect improves to 4.18%. Again, this shows that banks' collateral availability and the allotment quotas were binding constraints for accessing ECB funding.

Interestingly, even after allowing for the formation of new links, shocks to a single intermediary can lead to larger loan volume losses than economy-wide interest rate cuts of the same magnitude can ameliorate. This is in part because banks' limited collateral and binding allotment quotas limit the scope of access to ECB funding. More importantly, shocks to single intermediaries can extend to curtail funding volume by a large number of borrowers because costly monitoring induces credit relationships to be highly sticky. This highlights and quantifies the systemic risk in interbank markets.

9 Conclusion

This paper establishes a novel notion of interbank intermediation. In balancing persistent funding needs, borrowing and lending banks rely on a small subset of intermediary banks to channel funds on their behalf. As monitoring of borrowers is concentrated on a few intermediaries instead of a

[49]Both scenarios are based on the pre-crisis network, where we drop the borrowing cost from the ECB for all banks, and for the second scenario, also increase the supply of collateral by 25%. All other loan values and balance sheet characteristics remain unchanged. For the unobservable portion of the match values, we draw from a truncated mean zero normal distribution to rationalize the observed linking decisions. That is, for every link that is formed, we draw the match errors conditional on it being larger than the negative of the predicted match value. Similarly, for every link that is not formed, we draw the match errors conditional on it being smaller than the negative of the predicted match value. The variance of the normal distribution is estimated by matching the sample covariance between the predicted values and the observed links. All counterfactual outcomes are computed for and averaged over ten draws of the unobserved match errors.

large number of lending banks, duplication in monitoring is alleviated. Meanwhile, intermediary banks' diversified portfolios minimize the cost of monitoring the monitor. We develop a model of this intermediation arrangement in which banks trade off the costs of forming credit relationships with (1) changes in surplus division from bargaining and (2) effects on intermediary diversification. Banks' consideration of this tradeoff is revealed by their choice of links observed in the data. From this choice, we structurally estimate unobservable monitoring costs. We verify our model through an out-of-sample test of the recent crisis and predict effects of similar crisis events, when shocks to a few interbank intermediary banks can spill over to contract lending to the real economy by a large number of their borrowing banks.

Knowing the magnitude of monitoring costs is essential in determining the degree of systemic risk in interbank markets. In a frictionless world, shocks to intermediary banks would be contained on their own balance sheets because dependent borrowers can costlessly form new links to circumvent any increases in funding cost. If costly state verification of the intermediary balance sheet were also costless, there would be no initial change in expected funding cost. Under the same initial shock, larger CSV costs raise the sensitivity of lenders' monitoring intensity and this amplifies the increase in funding costs. Also, when monitoring of the borrower is more costly, switching to new intermediaries becomes more expensive and less likely to be feasible. The rigidity of adjustment determines the extent to which an initial shock to intermediary funding cost is passed on to connected borrowing banks, who subsequently curtail their lending to the real economy.

This is an important channel of systemic risk. A 50 basis point shock to an intermediary with median connectivity can already trigger an aggregate cut in interbank funded firm loan supply of 0.9% with the additional effect from borrowers accounting for 0.73%. Using pre-crisis estimates of monitoring cost, our model mechanism predicts 86% of network structure changes and successfully matches observed trends in banks' firm loan supply. This demonstrates that the spillover of funding cost changes through sticky interbank intermediation networks provides a highly relevant source of systemic risk.

An interesting avenue for future research is how implicit and explicit government guarantees affect systemic risk. If expected guarantees increases, lending banks would be less inclined to charge higher funding costs when intermediaries suffer capital shocks. This would better insure against loan supply contractions not only by the intermediary but also by its dependent borrowers. Nevertheless, the system-wide effects of potential incentive issues, e.g., moral hazard, would also increase. Taken together, examining bail-out guarantees through the lens of interbank intermediation will offer a more complete view on the costs and benefits of government subsidies to the banking sector.

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A Tables and Figures

Results in all tables and figures of this section are based on data from the Research Data and Service Centre of the Deutsche Bundesbank, Monthly Balance Sheet Statistics and Credit Registry, 2005Q1 - 2009Q4, and our own calculations.

Table 1: Characteristics of Borrowing, Lending and Intermediary Banks

This table reports balance sheet characteristics for banks that borrow, lend and intermediate on the interbank market respectively. In a core-periphery structure, lending and borrowing banks are in the periphery while intermediaries are in the core. The statistics correspond to the first, second and third quartile of the distribution for each variable during the sample period from 2005Q1 to 2009Q4.

	Borrowing Banks			Lending Banks			Intermediary Banks		
	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
Total Assets (Billion Euro)	0.59	1.58	3.93	0.21	0.44	1.08	53.44	99.32	321.35
Equity Ratio (%)	4.85	5.59	6.02	4.77	5.45	6.58	4.11	5.12	5.61
Ratio of Firm Loans (%)	60.15	66.30	71.52	70.30	79.54	85.42	31.64	39.11	49.76
Gross Return (%)	4.85	5.59	6.02	4.98	5.67	6.13	5.01	5.43	5.99
Loan Loss Reserves (%)	2.14	2.75	3.02	2.06	2.51	2.89	2.57	2.61	3.98
Number of Banks	435			1882			19		

Table 2: Pre-Crisis Period Average Parameter Values

This table reports average parameter values for borrowing banks and intermediary banks in the pre-crisis period from 2005Q1 to 2007Q2. r corresponds to the average 2 year German bund yield. All remaining variables are obtained from bank balance sheets.

	Borrowing Banks	Intermediaries
Gross Return (%)	5.54	5.32
r (%)	3.26	3.26
S.D.(Gross Return) (%)	1.28	0.42
Ratio of Firm Loans (%)	66.02	38.98
Total Assets (bn)	1.37	229.1

Table 3: Estimation Results (Baseline Model)

This table reports results from the maximum score estimation of the baseline model. Estimates correspond to monitoring cost parameter k and costly state verification parameter C under different correlation coefficients ρ. 95% confidence intervals, based on subsampling, are included in brackets, with the double asterisk ** indicating that the confidence interval does not include zero. Inequalities satisfied is the fraction of correctly predicted links using the vector of parameter estimates.

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
Monitoring cost k	1.408^{**}	1.354^{**}	1.283^{**}
CSV cost C	0.240^{**}	0.224^{**}	0.212^{**}
Inequalities Satisfied (%)	90.2	89.1	88.9
Number of Inequalities		8265	

Table 4: Pre-Crisis and Crisis Period Average Parameter Values

This table reports average parameter values for borrowing banks and intermediary banks in the pre-crisis period from 2005Q1 to 2007Q2 and in the crisis period from 2007Q3 to 2009Q4. r corresponds to the average 2 year German bund yield. All remaining variables are obtained from bank balance sheets.

	Borrowing Banks		Intermediaries	
	Pre-Crisis	Crisis	Pre-Crisis	Crisis
Gross Return (%)	5.54	5.34	5.32	4.89
r (%)	3.26	3.17	3.26	3.17
S.D.(Gross Return) (%)	1.28	1.31	0.42	0.61
Ratio of Firm Loans (%)	66.02	68.61	38.98	37.25
Total Assets (bn)	1.37	1.28	229.1	219.5

Table 5: Percentage of Correctly Predicted Inequalities (Baseline Model)

This table reports the percentage of correctly predicted inequalities in the out of sample test of the recent financial crisis for the baseline model. ρ refers to the correlation coefficient between borrowing banks. Each inequality corresponds to a link between a borrowing and an intermediary bank. "New Links Formed" and "No New links formed" refer to the fraction of correct predictions given that a new link was and was not observed in the post crisis network.

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
New links formed (%)	66.5	70.3	71.9
No new links formed (%)	86.7	86.0	85.4
Overall (%)	86.2	85.6	85.0

Table 6: Impact on Firm Loans

This table reports regressions of changes in firm loan supply by borrowing banks on model predicted changes in funding costs for borrowing banks. Columns (1) to (3) focuses on the sample of firm loans from borrowing banks only. In addition to firm loans by borrowing banks, Column (4) further includes all firm loans by lending banks, whose change in funding cost is taken to be zero. The dependent variable measures the log change in loans between a bank firm pair before and after the crisis. The main explanatory variable is the change in funding cost for borrowing banks before and after the crisis. It is calculated using model implied monitoring cost and costly state verification costs from the pre-crisis period coupled with changes in bank balance sheet characteristics after the onset of the crisis. Remaining explanatory variables reflect average balance sheet characteristics of borrowing banks in the pre-crisis period. They are expressed in percentages of total assets except for Log(Total Assets). Standard errors are clustered at the bank level.

	Δ Log(Bank-Firm Loans)			
	(1)	(2)	(3)	(4)
Δ Funding Cost (%)	-0.063**	-0.066**	-0.055**	-0.059*
	(-3.20)	(-1.99)	(-2.09)	(-2.34)
Cash (%)		0.046*	0.041*	0.031
		(1.76)	(1.82)	(1.08)
Log(Total Assets)		0.009	0.001	0.008*
		(1.08)	(0.77)	(2.09)
Equity (%)		0.315	0.233	0.198*
		(1.33)	(1.49)	(1.71)
Constant	-0.029**	-0.031**	-0.030**	-0.015**
	(-2.22)	(-1.99)	(-2.00)	(-2.34)
Firm FE	No	No	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 7: Ratio of ECB Funding to Total Asset Size

This table reports summary statistics for the amount of non overnight borrowing from the ECB as a fraction of total assets. Quartiles and means reported are for borrowing banks, lending banks and intermediary banks in the pre-crisis and crisis period respectively. Values are in percentage.

	Pre-Crisis				Crisis			
	Q1	Q2	Q3	Mean	Q1	Q2	Q3	Mean
Borrowers	0.00	0.00	0.32	0.76	0.00	0.18	0.86	0.75
Intermediaries	0.30	1.63	7.93	2.81	1.22	3.85	9.82	3.56
Lenders	0.00	0.00	0.00	0.26	0.00	0.15	0.87	0.89

Table 8: Estimation Results (Extension Model)

This table reports results from the maximum score estimation of the extension model. Estimates correspond to monitoring cost parameter k and costly state verification parameter C under different correlation coefficients between borrowing banks. 95% confidence intervals, based on subsampling, are included in brackets, with the double asterisk ** indicating that the confidence interval does not include zero. Inequalities satisfied is the fraction of correctly predicted links using the vector of parameter estimates.

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
Monitoring cost k	1.293^{**}	1.412^{**}	1.451^{**}
CSV cost C	0.286^{**}	0.239^{**}	0.279^{**}
ECB funding p	5.590^{**}	6.053^{**}	6.897^{**}
Inequalities Satisfied (%)	91.8	90.9	89.5
Number of Inequalities		8265	

Table 9: Percentage of Correctly Predicted Inequalities (Extension)

This table reports the percentage of correctly predicted inequalities in the out of sample test of the recent financial crisis for the extension model. ρ refers to the correlation coefficient between borrowing banks. Each inequality corresponds to a link between a borrowing and an intermediary bank. "New Links Formed" and "No New links formed" refer to the fraction of correct predictions given that a new link was and was not observed in the post crisis network.

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
New links formed (%)	72.4	76.2	75.1
No New links formed (%)	88.7	89.3	87.1
Overall (%)	88.3	89.0	86.8

Figure 7: Number of New Links versus Funding Cost Changes (Baseline Model)

This figure shows bucket plots of the number of new links formed by borrowing banks against model predicted changes in their funding cost (basis points) for the baseline model. It is obtained by first sorting borrowing banks into 44 bins according to their model implied funding cost change from the recent crisis. This yields bins of about 10 borrowing banks. Then, for each bin, the average number of new links formed is plotted against the change in funding cost.

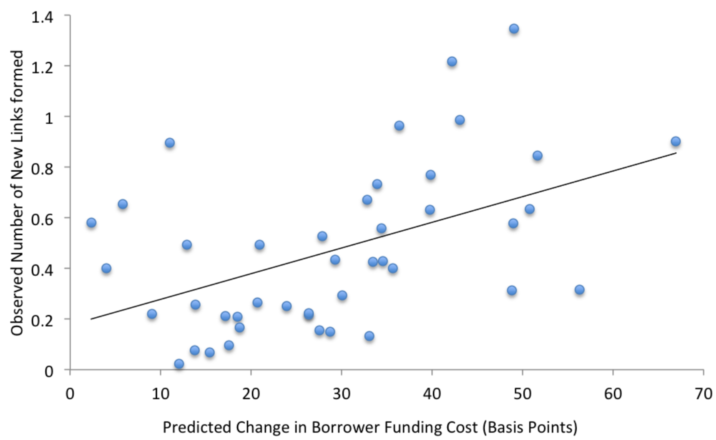


Figure 8: Number of New Links versus Intermediary Funding Cost Increases (Baseline Model)

This figure shows bucket plots of the number of new links formed by intermediary banks for quartiles of intermediaries sorted by their model implied increase in funding cost in the post-crisis sample. Q1 intermediaries have the smallest increase while Q4 intermediaries have the largest increase.

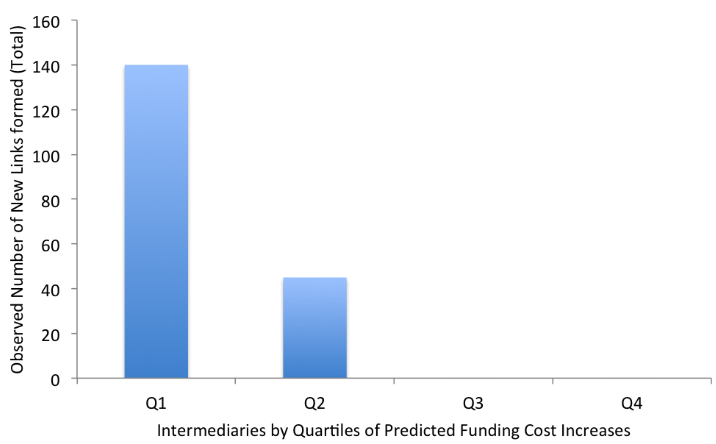


Figure 9: Loan Supply to Firms versus Funding Cost Changes (Baseline Model)

This figure shows bucket plots of changes in firm loan supply against model predicted changes in borrower funding cost for the baseline model. It is obtained by first sorting borrowing banks into 44 bins according to their model implied funding cost change from the recent crisis after the formation of new links. This yields bins of about 10 borrowing banks. We control for changes in aggregate loan demand by subtracting the market average change in firm loans from the average change in firm loans for each bin. Finally, for each bin, we plot the effective change in firm loan supply against the average change in funding cost.

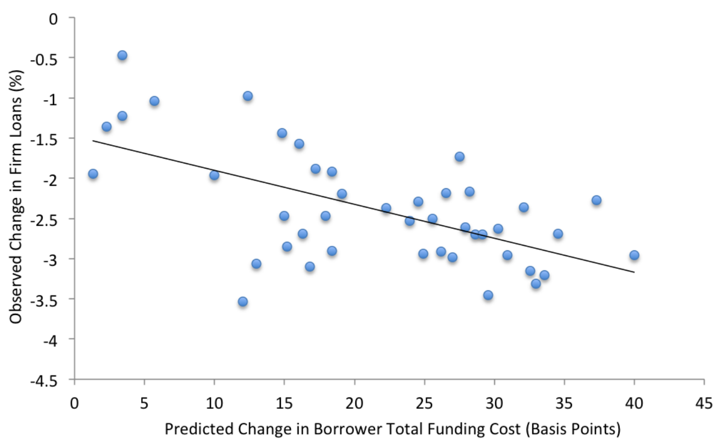


Figure 10: Number of New Links versus Funding Cost Changes (Extension Model)

This figure shows bucket plots of the number of new links formed against model predicted changes in borrower funding cost (basis points) for the extension model. It is obtained by first sorting borrowing banks into 44 bins according to their model implied funding cost change from the recent crisis. This yields bins of about 10 borrowing banks. Then, for each bin, the average number of new links formed is plotted against the average change in funding cost.

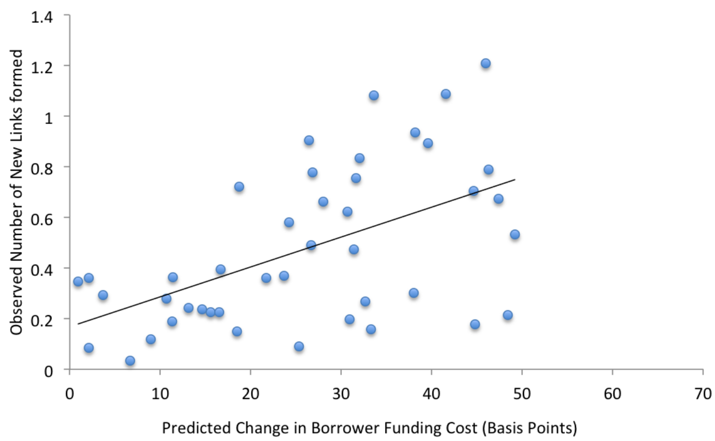


Figure 11: Loan Supply to Firms versus Funding Cost Changes (Extension Model)

This figure shows bucket plots of changes in firm loan supply against model predicted changes in borrower funding cost for the extension model. It is obtained by first sorting borrowing banks into 44 bins according to their model implied funding cost change from the recent crisis after the formation of new links. This yields bins of about 10 borrowing banks. We control for changes in aggregate loan demand by subtracting the market average change in firm loans from the average change in firm loans for each bin. Finally, for each bin, we plot the effective change in firm loan supply against the average change in funding cost.

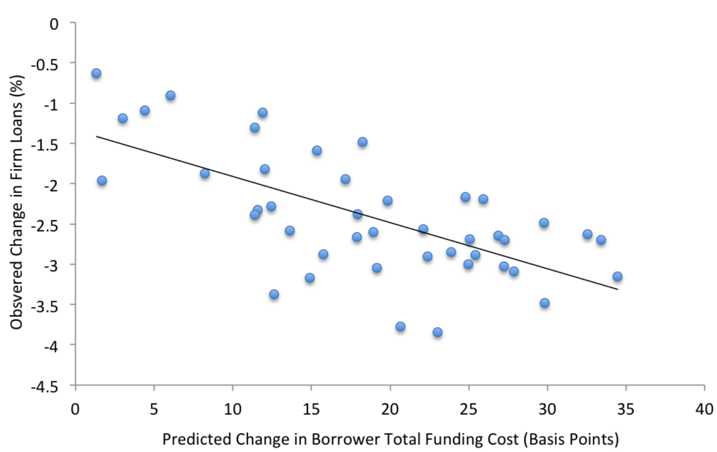


Figure 12: Effect of Intermediary Capital Shocks on Total Loans Fundable

This figure reports the effect of a hypothetical 50 basis point increase in intermediary funding cost on loan supply. Results are shown for the first, second and third quartile intermediary ranked in increasing order of intermediated loan volume. The dark blue bar corresponds to the loan supply contraction from the intermediary's own balance sheet whereas the light blue bar corresponds to that of its dependent borrowing banks. Estimates are based on the pre-crisis network. Values are graphed as a percentage of total loan volume funded through the interbank market. Nominal volumes are displayed on top of the bars.

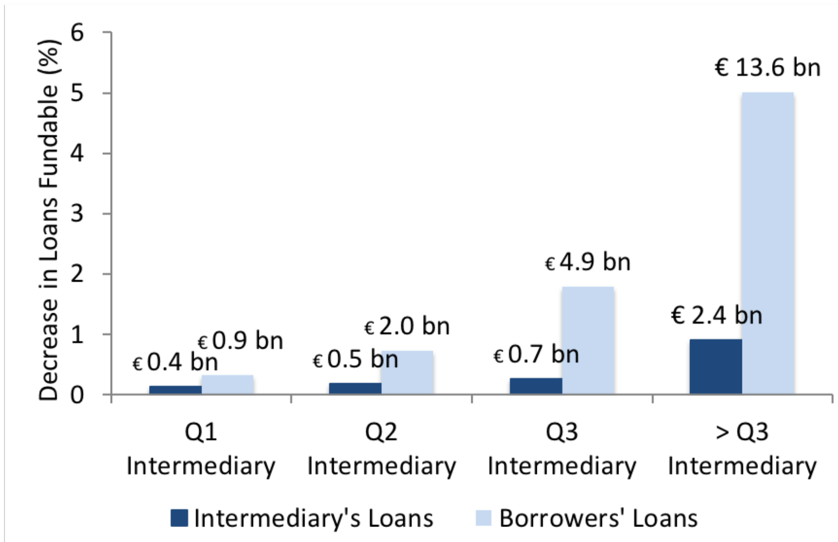
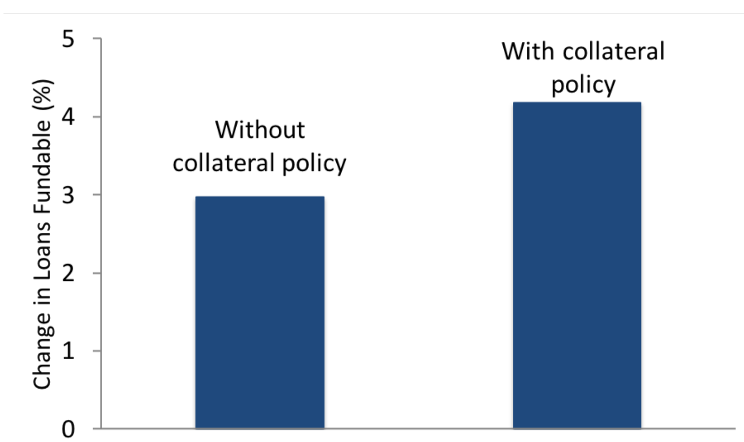


Figure 13: Effect of Lower ECB Funding Cost on Loans Fundable

This figure reports the effect of a hypothetical accommodative ECB funding policy on loan supply. The left column shows the effect of a 50 basis point decrease in the funding rate. The right column shows the combined effect with a 25% increase in allotment volume or collateral cost. Estimates are based on the pre-crisis network. Values are graphed as a percentage of total loan volume funded through the interbank market.



B Internet Appendix (For Online Publication)

B.1 Proof for Proposition I

Applying Myerson (1980) and Hart and Mas-Colell (2000), we verify the sufficient condition that bargaining payoffs given by equation (1) are part of a payoff structure over all subsets that induces balanced contribution and efficiency. That is,

$$\psi_j(v_g, S) - \psi_j(v_g, S-q) = \psi_q(v_g, S) - \psi_q(v_g, S-j) \qquad \forall S \subseteq \mathbb{N}, \forall j \in S, \forall q \in S, \tag{9}$$

and

$$\sum_{j \in S} \psi_j(v_g, S) = v_g(S) \qquad \forall S \subseteq \mathbb{N}, \tag{10}$$

where $\psi_j(v_g, S)$ is the payoff to j when the cooperative game is restricted to coalition S.

Define $g^S \subseteq g$ as the subnetwork such that $\{i, b\} \in g^S$ if $\{i, b\} \in g$, $b \in S$ and $i \in S$. To verify the balanced contribution condition, we will show that for any $j \in S$, letting

$$\begin{aligned} \psi_j(v_g, S) &= U_i(g^S) \qquad \forall j = i \in \mathbb{I} \cap S, \\ \psi_j(v_g, S) &= U_b(g^S) \qquad \forall j = b \in \mathbb{B} \cap S, \end{aligned}$$

equation (9) is satisfied. If the two equalities above hold, (10) will follow trivially from the specification of utilities in (2) and the characteristic function $v_g(S)$.

The case when at least one of j and q is not connected to any other bank in set S under network g is trivial. When a bank is not connected to any other bank, its payoff equals its stand-alone value. Borrowing banks would obtain their outside option of directly borrowing from lenders while intermediary banks would only finance their own projects. WLOG, let j be a stand-alone bank. When any other bank is removed from S, j still yields its stand-alone value while its removal from the set does not impact the payoff of any other bank because it was not connected to begin with. Hence, $\forall q \in S$, equation (9) is satisfied because $\psi_j(v_g, S) - \psi_j(v_g, S-q) = 0$ and $\psi_q(v_g, S) - \psi_q(v_g, S-j) = 0$.

If j and q are directly connected under network g, one must be an intermediary and the other must be a borrower. Then, WLOG,

$$U_i(g^S) - U_i(g^{S-q}) = U_i(g^S) - U_i(g^S - \{i,b\})$$
$$U_b(g^S) - U_b(g^{S-j}) = U_b(g^S) - U_b(g^S - \{i,b\})$$

Since equation (1) maintains $U_i(g^S) - U_i(g^S - \{i,b\}) = U_b(g^S) - U_b(g^S - \{i,b\})$, equation (9) is satisfied.

If j and q are not directly connected but each connects to at least one other bank in S under network g, then they could be (i) two borrowers; (ii) two intermediaries; and (iii) one borrower and one non-connected intermediary. We will consider each of these cases individually.

Case 1: $j = b$ and $q = b'$

The goal is to show that:

$$U_b(g^S) - U_b(g^{S-b'}) = U_{b'}(g^S) - U_{b'}(g^{S-b}).$$

Let $\mathbb{I}^c$ be the set of intermediaries both b and b' are linked to and denote them as $i^c = i^c_1, ..., i^c_M$. Using equation (1), we can write down the following equations:

$$U_b(g^S) - U_b(g^S - \{i^c_1, b\}) = U_{i^c_1}(g^S) - U_{i^c_1}(g^S - \{i^c_1, b\})$$
$$U_b(g^S - \{i^c_1, b\}) - U_b(g^S - \{i^c_1, b\} - \{i^c_2, b\}) = U_{i^2_M}(g^S - \{i^c_1, b\}) - U_{i^c_2}(g^S - \{i^c_1, b\} - \{i^c_2, b\})$$
$$\vdots$$
$$U_b(g^S - ... - \{i^c_{M-1}, b\}) - U_b(g^S - ... - \{i^c_M, b\}) = U_{i^c_M}(g^S - ... - \{i^c_{M-1}, b\}) - U_{i^c_M}(g^S - ... - \{i^c_M, b\})$$

Denoting the sum of the right hand sides as $\Omega_b(g^S)$, we have:

$$U_b(g^S) - U_b(g^S - ... - \{i^c_M, b\}) = \Omega_b(g^S). \tag{11}$$

Similarly,

$$U_b(g^{S-b'}) - U_b(g^{S-b'} - \{i^c_1, b\}) = U_{i^c_1}(g^{S-b'}) - U_{i^c_1}(g^{S-b'} - \{i^c_1, b\})$$
$$U_b(g^{S-b'} - \{i^c_1, b\}) - U_b(g^{S-b'} - \{i^c_1, b\} - \{i^c_2, b\}) = U_{i^2_M}(g^{S-b'} - \{i^c_1, b\}) - U_{i^c_2}(g^{S-b'} - \{i^c_1, b\} - \{i^c_2, b\})$$
$$\vdots$$
$$U_b(g^{S-b'} - ... - \{i^c_{M-1}, b\}) - U_b(g^{S-b'} - ... - \{i^c_M, b\}) = U_{i^c_M}(g^{S-b'} - ... - \{i^c_{M-1}, b\}) - U_{i^c_M}(g^{S-b'} - ... - \{i^c_M, b\})$$

Denoting the sum of the right hand sides as $\Omega_b(g^{S-b'})$, we have:

$$U_b(g^{S-b'}) - U_b(g^{S-b'} - ... - \{i^c_M, b\}) = \Omega_b(g^{S-b'}). \tag{12}$$

Since borrowing banks not connected to any common intermediaries do not affect each other's payoff, $U_b(g^S) - U_b(g^S - ... - \{i^c_M, b\}) = U_b(g^{S-b'} - ... - \{i^c_M, b\})$. Hence, deducting equation (12) from equation (11) yields:

$$U_b(g^S) - U_b(g^{S-b'}) = \Omega_b(g^S) - \Omega_b(g^{S-b'}.) \tag{13}$$

Repeating the above steps for borrower b' in place of borrower b,

$$U_{b'}(g^S) - U_{b'}(g^{S-b}) = \Omega_{b'}(g^S) - \Omega_{b'}(g^{S-b}). \tag{14}$$

With some algebra, we can show that:

$$\Omega_b(g^S) - \Omega_b(g^{S-b'}) = \Omega_{b'}(g^S) - \Omega_{b'}(g^{S-b}).$$

Therefore,

$$U_b(g^S) - U_b(g^{S-b'}) = U_{b'}(g^S) - U_{b'}(g^{S-b}).$$

Case 2: $j = i$ and $q = i'$

The goal is to show that:

$$U_i(g^S) - U_i(g^{S-i'}) = U_{i'}(g^S) - U_{i'}(g^{S-i}).$$

Let $\mathbb{B}^c$ be the set of intermediaries both i and i' are linked to and denote them as $b^c = b^c_1, ..., b^c_W$. Using equation (1), we can write down the following equations:

$$U_i(g^S) - U_i(g^S - \{i, b^c_1\}) = U_{b^c_1}(g^S) - U_{b^c_1}(g^S - \{i, b^c_1\})$$

$$U_i(g^S - \{i, b^c_1\}) - U_i(g^S - \{i, b^c_1\} - \{i, b^c_2\}) = U_{b^c_2}(g^S - \{i, b^c_1\}) - U_{b^c_2}(g^S - \{i, b^c_1\} - \{i, b^c_2\})$$

$$\vdots$$

$$U_i(g^S - ... - \{i, b^c_{W-1}\}) - U_i(g^S - ... - \{i, b^c_W\}) = U_{b^c_W}(g^S - ... - \{i, b^c_{W-1}\}) - U_{b^c_W}(g^S - ... - \{i, b^c_W\})$$

Denoting the sum of the right hand sides as $\Omega_i(g^S)$, we have:

$$U_i(g^S) - U_i(g^S - ... - \{i, b^c_W\}) = \Omega_i(g^S). \tag{15}$$

Similarly,

$$U_i(g^{S-i'}) - U_i(g^{S-i'} - \{i, b_1^c\}) = U_{b_1^c}(g^{S-i'}) - U_{b_1^c}(g^{S-i'} - \{i, b_1^c\})$$
$$U_i(g^{S-i'} - \{i, b_1^c\}) - U_i(g^{S-i'} - \{i, b_1^c\} - \{i, b_2^c\}) = U_{b_2^c}(g^{S-i'} - \{i, b_1^c\}) - U_{b_2^c}(g^{S-i'} - \{i, b_1^c\} - \{i, b_2^c\})$$
$$\vdots$$
$$U_i(g^{S-i'} - \ldots - \{i, b_{W-1}^c\}) - U_i(g^{S-i'} - \ldots - \{i, b_W^c\}) = U_{b_W^c}(g^{S-i'} - \ldots - \{i, b_{W-1}^c\}) - U_{b_W^c}(g^{S-i'} - \ldots - \{i, b_W^c\})$$

Denoting the sum of the right hand sides as $\Omega_i(g^{S-i'})$, we have:

$$U_i(g^{S-i'}) - U_i(g^{S-i'} - \ldots - \{i, b_W^c\}) = \Omega_i(g^{S-i'}). \tag{16}$$

Since intermediary banks not connected to any common borrowing banks do not affect each other's payff, $U_i(g^{S-i'} - \ldots - \{i, b_W^c\}) = U_i(g^S - \ldots - \{i, b_W^c\})$. Hence, deducting equation (16) from equation (15) yields

$$U_i(g^S) - U_i(g^{S-i'}) = \Omega_i(g^S) - \Omega_i(g^{S-i'}). \tag{17}$$

Repeating the above steps for intermediary i' in place of intermediary i,

$$U_{i'}(g^S) - U_{i'}(g^{S-i'}) = \Omega_{i'}(g^S) - \Omega_{i'}(g^{S-i'}). \tag{18}$$

With some algebra, we can show that:

$$\Omega_i(g^S) - \Omega_i(g^{S-i'}) = \Omega_{i'}(g^S) - \Omega_{i'}(g^{S-i'}).$$

Therefore,

$$U_i(g^S) - U_i(g^{S-i'}) = U_{i'}(g^S) - U_{i'}(g^{S-i}).$$

Case 3: $j = i$ and $q = b$

The goal is to show that:

$$U_i(g^S) - U_i(g^{S-b}) = U_b(g^S) - U_b(g^{S-i}).$$

Let $\mathbb{B}^{c'}$ be the set of borrowers both i and intermediaries connected to b are connected to and denote them as $b^{c'} = b_1^{c'}, \ldots, b_1^{c'}, \ldots, b_W^{c'}$. Similarly, let $\mathbb{I}^{c'}$ be the set of intermediaries both b and borrowers connected to i are connected to and denote them as $i^{c'} = i_1^{c'}, \ldots, i_M^{c'}$. Further, define common intermediaries that common borrower $b_w^{c'}$ is connected to as $i_w^{c'} = i_{w1}^{c'}, \ldots, i_{wm_w}^{c'}$.

Based on equation (1), we can write down the conditions for bargaining between intermediary i and its borrowers in $\mathbb{B}^{c'}$:

$$U_i(g^S) - U_i(g^S - \{i, b_1^{c'}\}) = U_{b_1^{c'}}(g^S) - U_{b_1^{c'}}(g^S - \{i, b_1^{c'}\})$$
$$U_i(g^S - \{i, b_1^{c'}\}) - U_i(g^S - \{i, b_1^{c'}\} - \{i, b_2^{c'}\}) = U_{b_2^{c'}}(g^S - \{i, b_1^{c'}\}) - U_{b_2^{c'}}(g^S - \{i, b_1^{c'}\} - \{i, b_2^{c'}\})$$
$$\vdots$$
$$U_i(g^S - ... - \{i, b_{W-1}^{c'}\}) - U_i(g^S - ... - \{i, b_W^{c'}\}) = U_{b_W^{c'}}(g^S - ... - \{i, b_{W-1}^{c'}\}) - U_{b_W^{c'}}(g^S - ... - \{i, b_W^{c'}\})$$

Denoting the sum of the right hand sides as $\Omega_i'(g^S)$, we have:

$$U_i(g^S) - U_i(g^S - ... - \{i, b_W^{c'}\}) = \Omega_i'(g^S). \tag{19}$$

Similarly,

$$U_i(g^{S-b}) - U_i(g^{S-b} - \{i, b_1^{c'}\}) = U_{b_1^{c'}}(g^{S-b}) - U_{b_1^{c'}}(g^{S-b} - \{i, b_1^{c'}\})$$
$$U_i(g^{S-b} - \{i, b_1^{c'}\}) - U_i(g^{S-b} - \{i, b_1^{c'}\} - \{i, b_2^{c'}\}) = U_{b_2^{c'}}(g^{S-b} - \{i, b_1^{c'}\}) - U_{b_2^{c'}}(g^{S-b} - \{i, b_1^{c'}\} - \{i, b_2^{c'}\})$$
$$\vdots$$
$$U_i(g^{S-b} - ... - \{i, b_{W-1}^{c'}\}) - U_i(g^{S-b} - ... - \{i, b_W^{c'}\}) = U_{b_W^{c'}}(g^{S-b} - ... - \{i, b_{W-1}^{c'}\}) - U_{b_W^{c'}}(g^{S-b} - ... - \{i, b_W^{c'}\})$$

Denoting the sum of the right hand sides as $\Omega_i'(g^{S-b})$, we have:

$$U_i(g^{S-b}) - U_i(g^{S-b} - ... - \{i, b_W^{c'}\}) = \Omega_i'(g^{S-b}). \tag{20}$$

When an intermediary i is not connected to any borrowing banks that connect to other intermediaries a given borrowing bank is connected to, that borrowing bank does not affect i's payoff. Thus, $U_{b_W^{c'}}(g^S - ... - \{i, b_W^{c'}\}) = U_{b_W^{c'}}(g^{S-b} - ... - \{i, b_W^{c'}\})$, and deducting equation (21) from equation (20) yields:

$$U_i(g^S) - U_i(g^{S-b}) = \Omega_i'(g^S) - \Omega_i'(g^{S-b}). \tag{21}$$

Next, we again apply equation (1) to set up conditions for bargaining between borrower b and its intermediaries in $\mathbb{I}^{c'}$:

$$U_b(g^S) - U_b(g^S - \{i_1^{c'}, b\}) = U_{i_1^{c'}}(g^S) - U_{i_1^{c'}}(g^S - \{i_1^{c'}, b\})$$
$$U_b(g^S - \{i_1^{c'}, b\}) - U_b(g^S - \{i_1^{c'}, b\} - \{i_2^{c'}, b\}) = U_{i_2^{c'}}(g^S - \{i_1^{c'}, b\}) - U_{i_2^{c'}}(g^S - \{i_1^{c'}, b\} - \{i_2^{c'}, b\})$$
$$\vdots$$
$$U_b(g^S - ... - \{i_{M-1}^{c'}, b\}) - U_b(g^S - ... - \{i_M^{c'}, b\}) = U_{i_M^{c'}}(g^S - ... - \{i_{M-1}^{c'}, b\}) - U_{i_M^{c'}}(g^S - ... - \{i_M^{c'}, b\})$$

Denoting the sum of the right hand sides as $\Omega_b'(g^S)$, we have:

$$U_b(g^S) - U_b(g^S - ... - \{i_M^{c'}, b\}) = \Omega_b'(g^S). \tag{22}$$

Similarly,

$$U_b(g^{S-i}) - U_b(g^{S-i} - \{i_1^{c'}, b\}) = U_{i_1^{c'}}(g^{S-i}) - U_{i_1^{c'}}(g^{S-i} - \{i_1^{c'}, b\})$$
$$U_b(g^{S-i} - \{i_1^{c'}, b\}) - U_b(g^{S-i} - \{i_1^{c'}, b\} - \{i_2^{c'}, b\}) = U_{i_2^{c'}}(g^{S-i} - \{i_1^{c'}, b\}) - U_{i_2^{c'}}(g^{S-i} - \{i_1^{c'}, b\} - \{i_2^{c'}, b\})$$
$$\vdots$$
$$U_b(g^{S-i} - ... - \{i_{M-1}^{c'}, b\}) - U_b(g^{S-i} - ... - \{i_M^{c'}, b\}) = U_{i_M^{c'}}(g^{S-i} - ... - \{i_{M-1}^{c'}, b\}) - U_{i_M^{c'}}(g^{S-i} - ... - \{i_M^{c'}, b\})$$

Denoting the sum of the right hand sides as $\Omega_b'(g^S)$, we have:

$$U_b(g^{S-i}) - U_b(g^{S-i} - ... - \{i_M^{c'}, b\}) = \Omega_b'(g^{S-i}). \tag{23}$$

When a borrowing bank b does not connect to any intermediaries that share borrowing banks with an intermediary, that intermediary does not affect b's payoff. Thus, $U_b(g^S - ... - \{i_M^{c'}, b\}) = U_b(g^{S-i} - ... - \{i_M^{c'}, b\})$, and deducting equation (23) from equation (22) yields:

$$U_b(g^S) - U_b(g^{S-i}) = \Omega_b'(g^S) - \Omega_b'(g^{S-i}). \tag{24}$$

Distinct from the previous two cases, note that $\Omega_b'(g^S) - \Omega_b'(g^{S-i})$ is expressed in terms of payoffs for common intermediaries in $\mathbb{I}^{c'}$ while $\Omega_i'(g^S) - \Omega_i'(g^{S-b})$ is in terms of payoffs for common borrowers in $\mathbb{B}^{c'}$. With some algebra, it is easy to show that $\Omega_b'(g^S) - \Omega_b'(g^{S-i}) = \Omega_i'(g^S) - \Omega_i'(g^{S-b})$ when substituting either side with the conditions guiding bargaining between common borrowers and their respective common intermediaries. That is,

$$U_{b_1^{c'}}(g^S) - U_{b_1^{c'}}(g^S - \{i_{11}^{c'}, b_1^{c'}\}) = U_{i_{11}^{c'}}(g^S) - U_{i_{11}^{c'}}(g^S - \{i_{11}^{c'}, b_1^{c'}\})$$
$$\vdots$$
$$U_{b_1^{c'}}(g^S - \ldots - \{i_{1m_1-1}^{c'}, b_1^{c'}\}) - U_{b_1^{c'}}(g^S - \ldots - \{i_{1m_1}^{c'}, b_1^{c'}\}) = U_{i_{1m_1}^{c'}}(g^S - \ldots - \{i_{1m_1-1}^{c'}, b_1^{c'}\}) - U_{i_{1m_1}^{c'}}(g^S - \ldots - \{i_{1m_1}^{c'}, b_1^{c'}\})$$
$$\vdots$$
$$U_{b_W^{c'}}(g^S) - U_{b_W^{c'}}(g^S - \{i_{W1}^{c'}, b_W^{c'}\}) = U_{i_{W1}^{c'}}(g^S) - U_{i_{W1}^{c'}}(g^S - \{i_{W1}^{c'}, b_W^{c'}\})$$
$$\vdots$$
$$U_{b_W^{c'}}(g^S - \ldots - \{i_{Wm_W-1}^{c'}, b_W^{c'}\}) - U_{b_W^{c'}}(g^S - \ldots - \{i_{Wm_W}^{c'}, b_W^{c'}\}) = U_{i_{Wm_W}^{c'}}(g^S - \ldots - \{i_{Wm_W-1}^{c'}, b_W^{c'}\}) - U_{i_{Wm_W}^{c'}}(g^S - \ldots - \{i_{Wm_W}^{c'}, b_W^{c'}\})$$

and,

$$U_{b_1^{c'}}(g^{S-b}) - U_{b_1^{c'}}(g^{S-b} - \{i_{11}^{c'}, b_1^{c'}\}) = U_{i_{11}^{c'}}(g^{S-b}) - U_{i_{11}^{c'}}(g^{S-b} - \{i_{11}^{c'}, b_1^{c'}\})$$
$$\vdots$$
$$U_{b_1^{c'}}(g^{S-b} - \ldots - \{i_{1m_1-1}^{c'}, b_1^{c'}\}) - U_{b_1^{c'}}(g^{S-b} - \ldots - \{i_{1m_1}^{c'}, b_1^{c'}\}) = U_{i_{1m_1}^{c'}}(g^{S-b} - \ldots - \{i_{1m_1-1}^{c'}, b_1^{c'}\}) - U_{i_{1m_1}^{c'}}(g^{S-b} - \ldots - \{i_{1m_1}^{c'}, b_1^{c'}\})$$
$$\vdots$$
$$U_{b_W^{c'}}(g^{S-b}) - U_{b_W^{c'}}(g^{S-b} - \{i_{W1}^{c'}, b_W^{c'}\}) = U_{i_{W1}^{c'}}(g^{S-b}) - U_{i_{W1}^{c'}}(g^{S-b} - \{i_{W1}^{c'}, b_W^{c'}\})$$
$$\vdots$$
$$U_{b_W^{c'}}(g^{S-b} - \ldots - \{i_{Wm_W-1}^{c'}, b_W^{c'}\}) - U_{b_W^{c'}}(g^{S-b} - \ldots - \{i_{Wm_W}^{c'}, b_W^{c'}\}) = U_{i_{Wm_W}^{c'}}(g^{S-b} - \ldots - \{i_{Wm_W-1}^{c'}, b_W^{c'}\}) - U_{i_{Wm_W}^{c'}}(g^{S} - \ldots - \{i_{Wm_W}^{c'}, b_W^{c'}\})$$

B.2 Correspondence between Pairwise Stability and Pairwise Nash Stability

In this subsection, we first prove a case in which pairwise stability implies pairwise Nash stability and then discuss to what extent the assumptions are in line with our empirical setting.

First, we simplify Shapley values given by equation (3). Recall that the set of intermediaries linked to borrower b is $N_b(g)$, it can be shown that:

$$\begin{aligned} U_b(g) = \phi_b(v_g) &= \frac{1}{|\mathbb{N}|!}\sum_R [v_g(P_b^R \cup \{b\}) - v_g(P_b^R)] \\ &= \frac{V_b|N_b(g)|}{|N_b(g)|+1}\left[E[x_b] - r + \underline{W}_b + \Lambda_b(g)\right]. \end{aligned}$$

with

$$\Lambda_b(g) = \frac{|N_b(g)|+1}{V_b|N_b(g)|}\frac{1}{|\mathbb{N}|!}\sum_R [v'_g(P_b^R \cup \{b\}) - v'_g(P_b^R)],$$

where P_b^R (P_i^R) is the set of players in N which precede b (i) in the order R and $v'_g(S)$ is the function below for a subset of banks S under network g,

$$v'_g(S) = -\sum_{i\in S} V_i \lambda_i(g^S, c) - \sum_{b\in S}\sum_{i\in S} V_b^i \lambda_i(g^S, c).$$

In words, we have separated out and simplified the portion of the Shapley values corresponding to the value of the loan, while leaving CSV dependent costs in the original form as $\Lambda_b(g)$.

Gilles and Sarangi (2005) show that a sufficient condition for pairwise stability implying pairwise Nash staility is a convex network in which for any set of links, h, by a player, the sum of the marginal benefits from links in h being non-negative implies that the marginal benefit from the link set h is also non-negative. Applied to borrowing bank b, this condition is equivalent to showing:

$$\frac{|N_b(g)|}{|N_b(g)|+1} - \frac{|N_b(g)|-1}{|N_b(g)|} \leq \frac{|N_b(g)|}{|N_b(g)|+1} - \frac{|N_b(g)|-|h|}{|N_b(g)|-|h|+1} \tag{25}$$

$$\frac{1}{|N_b(g)|(|N_b(g)|+1)} \leq -\frac{|h|}{(|N_b(g)|-|h|+1)(|N_b(g)|+1)}, \tag{26}$$

if $\Lambda_b(g)$ is constant across any network g. When $\Lambda_b(g)$ is indepdendent of g, then the inequalities are satisfied with certainty as $|h| \geq 1$. For example, this corresponds to a case when intermediaries have the same $\lambda_i(g)$ and which is not affected by its connected borrowers in the network.

Intuitively, when diversification is unchanged across network structures, marginal benefits from link formation are solely attributed to obtaining a larger share of the surplus. As evident from the above inequalities, this share declines as the number of links increases.

Perfect symmetry of intermediaries is not a necessary condition. In fact, everything can be asymmetric as long as the convexity of the marginal returns in equation (25) dominates CSV cost changes when links are dropped. This is not a very binding condition in our context. Intermediaries are in general highly diversified banks so that the effective CSV costs and variations in such are relatively low.[50] Further, intermediaries have much larger balance sheet sizes as their dependent borrowing banks. Hence, the effect of additional borrower connections will have limited effect.

[50]This applies in normal times and can become less valid in crisis, when intermediaries are differentially exposed. Nevertheless, since our crisis test only checks for link formation, it does not rely on this sufficiency result for pairwise Nash stability.

The intermediary's condition is then trivial. Since it obtains an equal share of the surplus that depends on the number of links *borrowers* form, the intermediary's convexity condition holds with equality.

B.3 Core-Periphery Selection

We follow the iterative algorithm by Craig and Von Peter (2014) to identify core and periphery banks based on the network structure. This is the standard procedure in the literature and has been adopted by a number of papers (van Lelyveld et al., 2014, Gabrieli and Georg, 2014, Fricke and Lux, 2015).

In our context, the model tries to fit banks on the interbank market into two distinct subsets based on their network position - a core and a periphery. Ideally, the core comprises a subset of bank that is linked among themselves and the periphery represent the remaining banks that connect to the core banks but not with each other. This can be seen as a generalization of the star network, in which case there would be a single bank in the center of the network connecting all other banks, where the latter are not connected to each other.

We can form a square matrix of dimension equal to the number of banks to represent the interbank network. The element (i, j) is set to zero and one in the absence and presence of a credit relationship where bank i lends to bank j. Similarly, when bank j lends to bank i, element (j,i) is set equal to one. In block modeling terms, an ideal core-periphery structure maps into an adjacency matrix M, such that connections between cores are represented by a region containing only ones (CC), whereas connections between periphery banks is represented by a region of the matrix with only zeros PP. Off-diagonal regions in the matrix CP and PC are represented by a row-regular and column regular matrix respectively. That is,

$$M = \begin{pmatrix} 1 & CP \\ PC & 0 \end{pmatrix}. \tag{27}$$

To identify the core and periphery in the data, the authors derive an optimization technique to find the partition that most resembles M of the same dimension. They first define a measure of distance between the observed network and the ideal pattern M and then solve for the optimal partition of banks into core and periphery that minimizes the error term. Formally, for a given partition of core banks, G, the error score is

$$e(G) = \frac{E_{cc} + E_{pp} + (E_{cp} + E_{pc})}{\text{Number of Links}}. \tag{28}$$

where E_{cc}, E_{pp}, E_{cp} and E_{pc} represent the number of inconsistencies in the four matrix regions generated by partition G with respect to the ideal core-periphery structure.

We apply this algorithm to our quarterly network data to identify core and periphery banks. Banks that are more than 50% of the time in the core in both pre and crisis periods are defined as core banks in our sample. Note that this is robust to increasing the threshold value to 90% and altering penalty scores, consistent with a high persistence in the structure of the network.

B.4 Effect of Geography and Bank-type on Monitoring Costs (For Online Publication)

One complexity not captured in the baseline estimation is whether the intermediation structure is affected by institutional design or geographical proximity.

Historically, the German banking system has followed a tiered structure, in which the Landesbanken, which are big public banks in each state, were set up to trade with the Sparkassen or Savings banks of their state, which are smaller public banks. In reality, the network structure now no longer resembles the historical set up such that both Landesbanken and Sparkassen do not exclusively trade with each other but also public banks in other states and commercial banks across the country. Nevertheless, one may still be worried that the current interbank relationships have been influenced by the bank type. Relatedly, banks located closer to each other may have a lower cost of establishing monitoring relationships. This is especially likely if the links were formed some time ago when telecommunication technology was less advanced.

To address these concerns, we further allow for variation in the monitoring cost coefficient k according to the bank-types and geographical proximity of the intermediary and borrowing bank pair. When the two banks satisfy the Landesbank and Savings bank criterion for the same state, we let the monitoring coefficient be k_1. If they are not public banks but located in the same state, then let the coefficient be k_2. Finally, for bank pairs in different states, assume the monitoring technology parameter to be k_3.

Repeating the estimation of the baseline model with heterogeneous cost parameters yields the results in Table E1. As expected, for the same bank characteristics, the monitoring cost among public banks in the same state is the lowest while those for banks located in different states are the highest, where all estimates are significant at the 95% level. In terms of magnitude, the annual net value remains largely unchanged with a slight drop by 3.8%. Intuitively, this is because k_1 is smaller than the original k and balances the increase from the original k to k_2 and k_3. For the average bank, 24.2% of its value generated are now spent on monitoring and CSV costs, almost unchanged from the original 23.1%.

Even with the two additional degrees of freedom, the fit of the model is not significantly improved. In the estimation, the number of inequalities satisfied increased slightly from between 88.9% and 90.2% to 92.7% and 93.1%. In the out-of-sample test of the recent financial crisis, the fraction of correctly predicted links goes up by 0.3% to 2.2% relative to the baseline levels at around 85%. Results are shown in Table E2.

Overall, we find that the qualitative results are as expected for bank-type and location but that the quantitative predictions and the fit of the model are not significantly changed by the additional heterogeneity.

Table E1: Estimation Results

This table reports results from the maximum score estimation of the baseline model after accounting for monitoring costs by geography and bank type. Estimates correspond to monitoring cost parameters k_1, k_2, and k_3, and costly state verification parameter C under different correlation coefficients between borrowing banks. k_1, k_2, and k_3 apply respectively when the intermediary and borrowing bank are state/savings banks in the same state, non-state/savings banks in the same state, and banks in different states. 95% confidence intervals, based on subsampling, are included in brackets, with the double asterisk ** indicating that the confidence interval does not include zero. Inequalities satisfied is the fraction of correctly predicted links using the vector of parameter estimates. *Source: Research Data and Service Centre of the Deutsche Bundesbank, Monthly Balance Sheet Statistics and Credit Registry, 2005Q1 - 2007Q2, own calculations.*

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
Monitoring cost (state banks) k_1	1.180^{**}	1.351^{**}	1.367^{**}
Monitoring cost (same state) k_2	1.301^{**}	1.420^{**}	1.488^{**}
Monitoring cost (other) k_3	1.321^{**}	1.476^{**}	1.503^{**}
CSV cost C	0.279^{**}	0.242^{**}	0.277^{**}
Inequalities Satisfied (%)	93.1	92.9	92.7
Number of Inequalities		8265	

Table E2: Percentage of Correctly Predicted Inequalities

This table reports the percentage of correctly predicted inequalities in the out of sample test of the recent financial crisis for the baseline model after accounting for monitoring costs by geography and bank type. ρ refers to the correlation coefficient between borrowing banks. Each inequality corresponds to a link between a borrowing and an intermediary bank. “New Links Formed” and “No New links formed” refer to the fraction of correct predictions given that a new link was and was not observed in the post crisis network. *Source: Research Data and Service Centre of the Deutsche Bundesbank, Monthly Balance Sheet Statistics and Credit Registry, 2005Q1 - 2009Q4, own calculations.*

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
New links formed (%)	70.3	68.6	72.4
No new links formed (%)	88.9	87.7	85.7
Overall (%)	88.4	87.2	85.3