Intermediation in the interbank lending market*

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We examine 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. We then develop a network model in which banks trade off the costs and benefits of link formation. The model is structurally estimated using banks' preferences as revealed by the observed network structure before the Great Financial Crisis. In out-of-sample tests, model estimates based on pre-crisis data successfully predict changes in the network structure and lending to firms during the Great Financial Crisis. Finally, for each of the intermediaries, we quantify systemic risk and the impact of European Central Bank funding in reducing this risk.

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1. Introduction

The interbank market is an important but fragile source of financing for banks. In Germany, domestic interbank claims outstanding at the end of 2007 make up around 14% of the banking sector's total asset size.[1] In this large over-the-counter market, trading between banks resembles Fig. 1(a), wherein a small subset of large banks (blue circles) serves as interbank intermediaries by borrowing from a large number of lending banks (green circles) and then lending the funds to a large number of borrowing banks (yellow circles). During the Great Financial Crisis, some of these large intermediary banks were directly exposed to losses from subprime assets in the United States (purple circles in Fig. 1(b)). Notably, these losses triggered funding cost shocks that spilled over through the interbank network to a large number of connected borrowing banks, which collectively contracted their loan supply to the real economy (red circles in Fig. 1(b)).

In this paper, we show that funding shocks to one bank can amplify along a sticky and concentrated interbank network to contract lending to firms by a large number of other banks. The amplification of a funding shock that affects one bank to a collective reduction in loan supply by a large number of other banks is a newly identified form of systemic risk.

We first present and estimate a novel model of the interbank network. Much of the 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, in which the bulk of interbank loans are longer-term in nature to balance persistent funding needs between banks that consistently lend and those that consistently borrow. Moreover, borrowing banks delegate their borrowing from lending banks to a small set of large and well-diversified intermediary banks. We argue that this arrangement arises to reduce inefficiencies from duplicated monitoring. As in Diamond (1984), delegating monitoring to diversified intermediaries can lower 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 are 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 become more exposed to the shocks of their connected intermediaries. This was evident in the Great Financial Crisis, when only some of the 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

[1] The volume of interbank loans is calculated as the sum of consolidated domestic interbank positions.

estimates of monitoring costs predict 86% of the changes in credit relationships during the post-crisis period. They also predict the spillover of intermediary banks' funding-cost shocks to the loans that borrowing banks make to firms.

Finally, we conduct counterfactuals, which show that a small impact to intermediary bank capital can curtail lending to a large number of borrowing banks. We selectively shock individual banks and trace how the heightened credit risk at one bank increases funding costs through a network of sticky interbank relationships to ultimately contract lending by a large number of connected banks.

We obtain these findings by taking a structural approach to a dataset consisting of all interbank loans in Germany from 2005:Q1 to 2009:Q4. We begin by making several 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. This pattern cannot be fully explained by the liquidity insurance literature, which originates in the 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, on average, require four times the amount that a given lending bank can provide. If they directly borrowed from lending banks, costly monitoring would have to be duplicated an average of four times.[2] Third, the interbank market structure and the distribution of loan flows avoid this inefficiency—borrowers link to only a few large banks, which then borrow from lenders on their behalf. These observations suggest that the large banks act as interbank intermediaries similar to the intermediaries in Diamond (1984).

Based on our empirical observations, we develop and estimate a structural model to uncover unobserved monitoring costs through the interbank lending market. In the model, borrowers can choose to form credit relationships with intermediaries. This arrangement reduces the duplication of monitoring under direct lending but requires that borrowers share 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 monitoring relationships. At the same time, intermediaries' funding costs are affected by which borrowers they choose to link and lend to. Since lending banks monitor intermediary banks through a standard state verification technology (Townsend, 1979), improved diversification of an intermediary's portfolio lowers its probability of default and thus its expected funding cost. 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 more costly than its benefits.

The above logic implies a series of inequality restrictions on monitoring costs equivalent to

[2] Although monitoring is conducted by lending banks, a share of the monitoring cost is passed on to borrowing banks through loan rates and fees.

a pairwise stable equilibrium. Using balance sheet information on bank profitability and characteristics, we apply a variant of the Manski maximum score estimator to identify monitoring cost parameters that best rationalize the preferences revealed by the observed interbank network. Intuitively, since borrowers' share of the surplus increases with the number of linked intermediaries, borrowers with higher returns and thus a higher surplus benefit the most from choosing to establish more links. Hence, the number of links formed by differentially profitable borrowing banks with the same set of intermediaries uncover monitoring costs relative to the value of loans. Further, since lenders' expected state verification cost decreases as the intermediary becomes more diversified, links formed by the same borrower with different sets of intermediaries reveal the relative magnitude of the state verification cost parameter.

We find that the average borrower invests in two links with intermediaries and incurs monitoring costs of 48.5 bps per euro out of a loan spread of 228 bps per euro. In comparison, expected state verification costs for the same borrower are much less, at 4.6 bps per euro. Without intermediation, direct borrowing of the same bank would, on average, require the formation of four monitoring relationships at double the monitoring cost. 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 during the Great 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 exposed banks that comprised a subset of the intermediary banks. In the data, we observe that borrowers linked to more-exposed intermediaries formed more new links. Viewed through the lens of our model, when an intermediary suffers a spike in credit risk, its cost of funding rises, and the increase is then passed on to its connected borrowing banks. Borrowing banks decide between continuing funding at the increased rates with the previous credit links and paying the cost of a new credit relationship with an unexposed intermediary. 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 post-crisis link switches from 2007:Q3 to 2009:Q4 were correctly predicted.

The exposure to intermediary banks spilled over to many dependent borrowing banks, which subsequently contracted their loan supply to the real economy. Using the estimated cost parameters, we calculate the total change in funding costs for each bank. We find that borrowing banks' observed decline in lending to firms is highly correlated with their model-implied rise in funding costs. Quantitatively, a 100 bps increase in a borrowing bank's funding costs reduced its loan supply to firms by 5.5%, which shows that interbank loans are an important source of funding that cannot be substituted away. If new links could be formed frictionlessly, borrowing banks could have fully switched to borrowing from new and unexposed intermediaries. Hence, costly interbank monitoring relationships allowed shocks to highly connected intermediary banks to spill over to affect the cost and volume of funding for a large number of borrowing banks, which collectively curtailed their lending to the real economy.

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 such that lower funding costs increase their loans fundable. At the same time, we allow borrowers and intermediaries to use the European Cental Bank's (ECB's) Long Term Refinancing Operation (LTRO) as an outside option for interbank funding.[3] With sufficient collateral, banks can borrow from the ECB to lower their average funding costs to fund more assets.

Finally, we analyze various counterfactual scenarios. First, we consider the effect of a 50 bps increase in the funding cost that a given intermediary pays to its lending banks. For highly connected intermediaries, the resulting drop in loans fundable through the interbank market is 5.9% of the aggregate interbank loan volume. Meanwhile, access to ECB funding had a limited effect during our sample period due to collateral constraints at borrowing banks and binding allotment quotas. An economy-wide 50 bps drop in ECB funding rates increases loans fundable by only 2.96%. Thus, shocks to one highly connected intermediary can lead to larger loan volume losses than what economy-wide interest rate cuts of the same magnitude can ameliorate.

The network amplification of funding shocks that intensifies loan contractions highlights a new source of systemic risk in interbank markets. Although the specific definition of systemic risk varies, one common theme is how a shock to an institution can spill over to have a large system-wide impact. For example, Billio et al. (2012), Adrian and Brunnermeier (2016), and Acharya et al. (2017) take a global approach to measure how losses and poor performance at a given institution coincide and contribute to system-wide distress.[4] When the mechanism of contagion is examined in interbank networks, the focus has mostly been on how the default of one institution propagates along its interbank liabilities to cause the default of other institutions (e.g., Eisenberg and Noe, 2001; Elliott et al., 2014; Acemoglu et al., 2015). Our channel of systemic risk does not require default cascades.[5] Rather, some banks are systemically important because an idiosyncratic funding

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

[4]Please refer to Benoit et al. (2017) for a literature review on systemic risk.

[5]Our perspective is in part motivated by the empirical observation has been that no bank ever failed because of losses on the interbank market (Upper, 2011).

shock to them can increase funding costs at a large number of other banks that then collectively contract their lending to the real economy. As we show, this amplification of funding shocks arises because a large number of borrowing banks form costly-to-adjust monitoring relationships with a concentrated set of intermediary banks to obtain funding in the interbank market.

This paper makes a number of contributions to the literature. First, we provide a new explanation for the existence of interbank markets, which has previously been attributed to mutual insurance against liquidity shocks, as in Allen and Gale (2000). Many papers followed to expand on their idea. 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 US market. Persistence in the identity of interbank borrowers and lenders suggests that a key function of interbank markets lies in balancing persistent funding needs, which bears important systemic implications.

Our structural model also contributes to the literature on financial networks. On the theory front, a recent set of papers examined the drivers of core-periphery structures in over-the-counter (OTC) markets (Farboodi, 2014; Hugonnier et al., 2014; Afonso and Lagos, 2015; Wang, 2016; Chang and Zhang, 2018; Babus and Hu, 2017; Hendershott et al., 2020).[6] 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). The presence of monitoring in networks has mostly been identified in a number of reduced-form empirical papers (e.g., Furfine, 2001; Cocco et al., 2009; Affinito, 2012; Afonso et al., 2013). More recently, Gofman (2017), Blasques et al. (2018), and Denbee et al. (2021) take a structural approach to study interbank markets. Our structural model is novel in applying the maximum scores estimator to quantify interbank monitoring costs, which captures the stickiness for the network structure to adjust and the potential for funding shocks to amplify.

We also contribute to the discussion of interbank funding shortages during financial crises by incorporating the underlying network structure. There are a number of theories on how increases in counterparty risk raise the cost of external financing (e.g., Flannery, 1996; Freixas and Jorge, 2008; Heider et al., 2015). Empirical evidence for interbank funding shortages in the Great Financial Crisis is also provided by Afonso et al. (2011), Iyer et al. (2013), Kuo et al. (2014), and Gabrieli and Georg (2014). We extend the analysis to a network context, in which increases in default risk at intermediary banks imply higher funding costs that spill over to their connected borrowing banks. We also find stressed interbank funding conditions following the Great Financial Crisis and further

[6]A number of empirical papers have documented core-periphery structures in OTC markets, including the federal funds market (Bech and Atalay, 2010; 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 (in't Veld and van Lelyveld, 2014).

demonstrate the importance of the underlying network structure.

Finally, we add to the literature on the transmission of bank liquidity shocks to firms (e.g., Paravisini, 2008; Khwaja and Mian, 2008; Schnabl, 2012; Iyer et al., 2013). We highlight that increases in interbank funding costs may not be solely the result of the increased credit risk of a bank itself. A large number of banks may suffer hikes in funding costs and cuts in funding volume if they are borrowing from an intermediary bank that has suffered credit-risk shocks. Our structural model quantifies the systemic importance of this amplification mechanism and the transmission to firm loan supply.

The paper is arranged as follows. In Section 2, we explain the empirical evidence for interbank intermediation. In Section 3, we introduce a model of interbank intermediation and this model is structurally estimated in Section 4. In Section 5, the estimated parameters are used to check out-of-sample changes in the network following the Great Financial Crisis. In Section 6, we explore the effect of disruptions in interbank markets on the supply of loans to nonfinancial firms. In Section 7, we extend the baseline model and conduct counterfactuals. We conclude in Section 8.

2. The German interbank lending market

We use the German credit registry database, which records, on a bilateral basis, loans between firms and financial institutions on the last business day of each quarter that amounted to at least €1.5 million at some point during the quarter. Almost 100% of interbank loans and about 60% of loans to nonfinancial firms are covered (Schmieder, 2006).[7] Although the data contain only loan volumes and no loan rates, our revealed preference approach allows us to circumvent the lack of price data. To provide insight on the characteristics of banks in different network positions, we match the credit registry with bank balance sheets and consolidate by banking group. The banking groups are consolidated to eliminate funding flows within the group.

We next present a set of facts that are central to motivating our structural model. We then review relevant results in the literature and describe our findings regarding the persistence, characteristics, and network connectivity of lending and borrowing banks.

[7]Despite the high coverage of interbank loans, a few low volume links may temporarily disappear from the data because loan volumes in some quarters fall below the reporting threshold. To this end, we count a link as present whenever it exists for at least 90% of the quarters. This threshold was chosen because the number of counted links stabilizes around it, i.e., when the threshold is further reduced, the number of links remains relatively constant.

2.1. *Persistence of interbank lending and borrowing*

We find a stable set of borrowers and lenders in the German interbank market. During our sample period from 2005:Q1 to 2009:Q4, 454 banks consistently borrow and 1,882 banks consistently lend. The percentage of both overall net borrowers that borrow and net lenders that lend in a given quarter is consistently between 91% and 96% (Fig. 2).[8] This pattern suggests that interbank loans are used to balance systematic funding surpluses and shortages. This finding is novel to the interbank literature, which has primarily focused on smoothing short-term liquidity shocks. In the model of Allen and Gale (2000), interbank relationships offer insurance against idiosyncratic liquidity shocks so that banks alternate between lending and borrowing depending on the realization of their liquidity needs. Liquidity insurance has also been examined in a number of contexts; Afonso et al. (2013) for the US federal funds market and Cocco et al. (2009) for the Portuguese interbank market.[9]

The differences in results stem from the use of interbank loan data of different maturities. Most analyses on interbank markets employ the Furfine algorithm to infer loans from payments data, which is mostly limited to identifying overnight loans. We use credit registry data that covers close to the universe of interbank loans in Germany across all maturity brackets. Consistent with Upper and Worms (2004), Gabrieli and Georg (2014), and Craig and Von Peter (2014), the interbank loans in our sample have maturities above one year, and overnight loans account for around only 10% of total loan volumes (Fig. 3).

The use of medium- and long-term interbank loans bears important economic implications. It lends support for the notion that interbank markets balance persistent funding needs because longer-term loans are more likely used in financing assets of similar maturities (e.g., firm loans) rather than as a buffer against liquidity shocks. Monitoring is also especially relevant and costly for loans of longer maturities due to asymmetric information about the borrower's credit risk. Therefore, we focus on the bulk of the interbank market and examine banks' incentives to build monitoring relationships to meet structural funding needs.

2.2. *Loan volumes of borrowing and lending banks*

We further examine the interbank loan volumes outstanding. We find that the net loan volume taken up by the average borrowing bank is more than four times that provided by the average

[8]The persistence in borrower and lender identities complements the finding that links in the German interbank network are stable over time (Bluhm et al., 2016; Craig and Von Peter, 2014).

[9]One exception is Bluhm et al. (2016), who use balance sheet data to study the role of interbank loans in reducing banks' duration gap.

lender. Fig. 4 displays the first three quartiles of interbank loans for borrowing and lending banks, respectively. The medians are smaller than the means because of right-skewed distributions, but the relative distribution of loan sizes follows a similar trend. In other words, 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. As a consequence, monitoring costs would be incurred four times. Such duplication in monitoring resembles the inefficiency of direct borrowing described in Diamond (1984). In Diamond (1984), the inefficiency from duplicated monitoring is based on the use of unsecured loans that incentivizes every lender to monitor the credit quality of the borrower. The credit registry does not contain direct information on the use of collateral. Nevertheless, we infer from bank balance sheet data that the vast majority of the interbank loans in our sample is unsecured (see Internet Appendix B.1 for details).

2.3. *Existence of intermediary banks*

Instead of directly borrowing from lending banks, we find that interbank borrowers exclusively seek funding from a few intermediary banks that in turn borrow from a large set of lending banks. We argue that banks delegate borrowing and monitoring to a small set of intermediary banks to prevent the inefficiencies of duplicated monitoring under direct borrowing. Our finding is consistent with the trading between core and periphery banks within a core-periphery network. In core-periphery networks, a small subset of banks, denoted as the core, connect with each other and all remaining banks, while these remaining banks, denoted as the periphery, connect only with the core and not among themselves. Nevertheless, our main model does not explain the trading between core banks, which appear to serve important but different functions that we detail in Internet Appendix B.2.

We identify a core of 19 banks and a periphery of the remaining banks following Craig and Von Peter (2014). Please refer to Appendix C for details about the core-selection algorithm and its fit to the data. We find that only core banks have a significant fraction of intermediation, while periphery lenders and borrowers almost exclusively lend or borrow (Fig. 5). Hence, core banks effectively act as intermediaries to channel funds from a large number of periphery lenders to a large number of periphery borrowers. Fig. 6 presents a visual representation of this intermediation arrangement.

Intermediaries, periphery lenders, and periphery borrowers also differ along other dimensions. Intermediary banks are some of the largest banks in the German economy. The median intermediary has a total asset size of €99.32 billion compared to €1.58 billion for the median borrowing bank and €0.44 billion for the median lending bank (Table 1). Intermediary banks also hold more highly diversified portfolios and invest less in firm loans, which we show are beneficial features for their role as delegated monitors.

One concern with our approach is that the network structure follows mechanically from the institutional setup of the German banking system, which consists of private banks, savings banks, and cooperatives. In the data, however, the vast majority of savings banks now trade with a range of counterparties and seem no longer confined to the historical setup. To remove any remaining potential confounding, we explicitly account for institutional details and demonstrate robustness in Internet Appendix B.3.

Network characteristics consistent with the core-periphery intermediation structure are not unique to the German interbank market. In the Netherlands, for example, in't Veld and van Lelyveld (2014) show that the interbank market also follows a core-periphery structure. In the US federal funds market, Bech and Atalay (2010) find that the minimum number of links connecting two banks, i.e., the average distance, is 2.4 for borrowing links and 2.7 for lending links, while in the Austian interbank market, Boss et al. (2004) find an average distance of 2.26. The average distance in our sample is very similar at 2.3. These small average distances imply that funds from lenders can travel through very few intermediaries to reach an ultimate borrower. This is consistent with our intermediation structure, in which a concentrated set of core banks intermediate on behalf of the vast majority of banks in the economy.

3. A model of interbank intermediation

In this section, we build on our empirical observations and develop a structural model of interbank intermediation. The goal of the model is to formulate network-contingent benefits and costs from link formation so that the costs and benefits can then be juxtaposed against each other to identify monitoring costs in Section 4. In Section 3.1, we introduce the model setup. In Section 3.2, we detail the contracting between intermediary banks and periphery lenders before explaining in Section 3.3 the monitoring and bargaining between intermediary banks and periphery borrowers. Finally, in Section 3.4, we define pairwise stability as the equilibrium concept.

3.1. Model setup

Consider an economy with a set of borrowing banks $\mathbb{B}$ and a set of lending banks $\mathbb{L}$. We take the sets of interbank borrowers and lenders as an outcome of banks' structural funding needs arising from firm-lending and deposit-taking, which is their main line of business. For example, banks in areas with fewer economic developments have more limited lending opportunities and an excess of retail deposits, which they then lend out on the interbank market. In our baseline model, we focus on banks' interaction in the interbank lending market, taking as given their business model with the real economy.

Each borrowing bank b, where $b = 1, ..., \mathscr{B}$, has its own risky loan portfolio 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. In the baseline model, we take V_b as given, but we extend the model and allow V_b to vary with the interbank funding cost and network structure in Section 7.1.

Lending banks $l = 1, ..., \mathscr{L}$ participate in the interbank market and have excess funds to be lent out. We let the size of lenders' excess funds take on the average value of L and abstract away from heterogeneities in individual lenders' network connectivity.

Lenders must resolve the asymmetric information about borrowers' returns to ensure the repayment of their loans. One way to resolve asymmetric information is by monitoring the borrower. Let there be an ex-ante monitoring technology of cost $k\delta_b$ that allows for sufficient understanding of the borrower's project to credibly observe return realizations and subsequently enforce payment.[10] Monitoring costs consist of a common monitoring technology parameter, k, multiplied by a borrower-specific parameter, δ_b. Monitoring is exclusive because the soft information obtained is difficult to transfer. Thus, when a borrowing bank of funding volume V_b borrows from an average lender, it requires $\lceil \frac{V_b}{L} \rceil$ of them, where $\lceil \frac{V_b}{L} \rceil$ stands for the smallest integer equal to or greater than $\frac{V_b}{L}$. Based on the distribution of funding volumes from Section 2, monitoring for the average borrower would be repeated four times under direct borrowing from the average lender.

Such duplication in monitoring can be avoided by interbank intermediation. We first provide an overview of the sequence of events and then explain each stage in detail.

To benefit from intermediated access to lenders, borrowers first form credit relationships with a subset of intermediary banks at $t = 0$, where these intermediaries are denoted as $i \in \mathbb{I}$. Since asymmetric information also exists between borrowers and their designated intermediaries, their monitoring relationships also cost $k\delta_b$. We let monitoring costs be split equally between borrowers and intermediaries consistent with their equal bargaining power. As we discuss in Section 3.4, this is the economically meaningful case that allows all links with total benefits exceeding total costs to be formed.[11] Forming credit relationships is costly, but the formation of more credit relationships

[10] 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 costs can be understood as the time and effort required to conduct this due diligence.

[11] Realistically, this comes in the form of an upfront fee paid by the borrower to the intermediary that is separate from the interest rate of the loan itself.

can tilt the division of surplus during bargaining in $t = 1$.

Based on the monitoring relationships formed in $t = 0$, borrowing banks and intermediary banks engage in bilateral bargaining with renegotiable contracts at $t = 1$. Renegotiable contracts award a larger share of the surplus to borrowing banks with more links, effectively endogenizing the bargaining outcome with respect to the network structure. When deciding on which links to form, the key tradeoff for borrowing banks is between securing a larger split of the surplus and incurring additional monitoring costs.

Credit relationships formed in $t = 0$ also affect intermediaries' funding costs when they borrow from lenders at $t = 2$. Let lending banks resolve asymmetric information about the intermediaries' return via a state verification technology as in Townsend (1979), i.e., they pay a cost to have the outcome verified when repayments fall below the face value of debt. As a result, the expected state verification cost scales with the default probability of the intermediary.

For tractability, we let lenders use state verification to ensure repayment from intermediaries. This assumption is consistent with the observation that large banks have more access to transaction-based loans than do small- and medium-sized banks. Intuitively, while lenders conduct on-site due diligence and form relationships with smaller periphery borrowers, it is less plausible for them to do the same with the entire asset portfolio of large and complex banks.[12]

At $t = 3$, returns realize, lenders carry out state verification where necessary, and payments are exchanged.

To recap, we have sketched a model of interbank intermediation in which asymmetric information about portfolio realizations has to be resolved through costly monitoring. Forming more credit relationships requires higher monitoring costs but improves bargaining power. The equilibrium network of links is determined as banks optimize between these tradeoffs. We now proceed to solve the game backwards by first defining the contracts formed between intermediaries and lenders at $t = 2$ and then those between intermediaries and borrowers at $t = 1$ before solving for the equilibrium network at $t = 0$. In terms of notation, when a monitoring relationship is established between intermediary i and borrower b in $t = 0$, we 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 $i \in N_b(g)$.

[12] After obtaining the bank-specific parameters in Section 4.4, we verify that the choice of monitoring is incentive compatible for all intermediary banks and 87% of all borrowing banks in the periphery.

3.2. *Contracting between intermediaries and lending banks*

When an intermediary borrows from lenders at $t = 2$, its interbank funding costs depend on the default risk of its asset portfolio, which is in turn affected by both its investments outside of the interbank market and its interbank loans to connected borrowers. Formally, given 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 the intermediary's portfolio return outside of the interbank market, x_i, and that of its connected interbank borrowers, x_b:

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

where the weights vary with the volume of intermediary i's own projects outside of the interbank market, A_i, and the volume lent out to its borrowing banks in the interbank market, $V_b^i(g)$. $H(y_i)$ denotes the cumulative distribution function (CDF) of y_i and is jointly dependent on the connected borrowers' return CDF, $F(x_b)$, and the intermediary's own return CDF, $F(x_i)$. Notice that the functional form in Eq. (1) is an approximation to allow for a feasible estimation of $H(y_i)$. In practice, intermediaries lend to borrowers via debt contracts, so their returns may not be fully proportional to borrowers' returns. We show in Internet Appendix B.4 that this approximation has limited effects on our results.

Intermediary banks cannot credibly communicate the realization of their return, y_i, to lenders, i.e., the realization of y_i is private information to intermediary i. Absent any monitoring or verification, intermediary i always has an incentive to report a low realization at the time of loan repayment to keep more of the return for itself. Let there be a state verification technology as in Townsend (1979) through which the true realization of y_i can be verified. Townsend (1979) shows that the optimal incentive-compatible contract in this case is a debt contract, wherein lending banks pay a cost to verify and obtain the entire y_i if it was claimed to fall below the promised value, i.e., the loan defaults. Otherwise, if the realization of y_i exceeds the face value of debt, no verification takes place, and lending banks receive the promised amount.

In practice, state verification technology can be thought of as arising in transaction-based loans, where the costs incurred resemble bankruptcy costs that are shared among creditors. For example, these could involve fees paid to a third-party to determine the true value of assets. These costs are especially relevant for large and complex financial institutions, such as intermediary banks, whose lenders are unlikely to monitor every detailed component of their balance sheets in normal times. We let each lender's share of the verification costs in the case of default be $C\delta_i$, where C is a common technology parameter and δ_i is the product of the asset size and opacity of intermediary

i that affect the difficulty of verification. The lending bank's expected verification cost is then the probability of default multiplied by $C\delta_i$.

To allow for a feasible estimation of intermediaries' cost of funding, we let intermediary banks have full bargaining power over lending banks. This approximation is likely reasonable in our context because there is a large number of lending banks and because transaction-based loans do not ex-ante lock in any particular lender so that intermediaries can relatively easily switch between lenders. This ease of switching between lenders is in contrast to the sticky monitoring relationships between intermediary and borrowing banks, relationships that give rise to the bargaining frictions we discuss in the next subsection.

Formally, we let the expected verification cost for a lender of size L lending to intermediary i be determined by:

$$\underbrace{\int_{\underline{R}}^{R_i(g)} C\delta_i \, dH(y_i)}_{\text{Expected State Verification Cost}} + Lr = \underbrace{L\left\{ \int_{\underline{R}}^{R_i(g)} y_i \, dH(y_i) + \int_{R_i(g)}^{\overline{R}} R_i(g) \, dH(y_i) \right\}}_{\text{Expected Return of Debt Contract}}, \tag{2}$$

where r is the lending bank's outside option return, $H(y_i)$ is the CDF of the intermediary's return y_i, and $C\delta_i$ is the per state verification cost. The right-hand side denotes the standard expected return of a loan contract with a promised repayment of $R_i(g)$. In other words, the intermediary is verified when y_i falls below the promised $R_i(g)$, and this comes at a cost but allows the lending bank to claim the full return. When y_i falls above $R_i(g)$, the intermediary is not verified and pays back $R_i(g)$. Notice that the promised repayment, $R_i(g)$, and the expected state verification cost depend on network g because the distribution of returns of banks borrowing from intermediary i affects the distribution y_i as in Eq. (1).

We make one final simplification by letting all lenders be of the same size, L. Lender size heterogeneity has limited significance in the absence of their bargaining. Abstracting away from it greatly benefits our estimation efficiency by eliminating the need to keep track of individual lenders.[13] Normalizing Eq. (2) by lender size, we obtain:

$$\underbrace{\int_{\underline{R}}^{R_i(g)} c\delta_i \, dH(y_i)}_{\text{Expected State Verification Cost}} + r = \underbrace{\int_{\underline{R}}^{R_i(g)} y_i \, dH(y_i) + \int_{R_i(g)}^{\overline{R}} R_i(g) \, dH(y_i)}_{\text{Expected Return of Debt Contract}}, \tag{3}$$

where $c = \frac{C}{L}$ is the normalized technology parameter capturing the state verification cost efficiency

[13] One assumption is that if a lender lends to multiple intermediary banks, then the state verification of one intermediary does not reduce the need for state verification of another connected intermediary. In practice, this can be thought of as bankruptcy proceedings being conducted separately for different intermediaries.

per unit loan. Going forward, we denote the per-unit expected state verification cost for intermediary bank i under network g, $\int_{\underline{R}}^{R_i(g)} c\delta_i \, dH(y_i)$, as $\lambda_i(g,c)$.

3.3. Contracting between intermediaries and borrowing banks

The network structure determines the surplus distribution when borrowing banks and intermediary banks bargain over the terms of trade in $t = 1$. We assume bilateral Nash bargaining with renegotiable contracts, as in Stole and Zwiebel (1996).

Bargaining frictions between intermediary and borrowing banks are relevant because after monitoring is conducted at $t = 0$, new credit lines cannot be spontaneously formed during negotiation at $t = 1$. If bargaining breaks down between intermediary i and borrower b under network g, both are left to receive their outside options under the remaining network, $g' = g - \{i,b\}$. Thus, we let each pair of connected borrowers and intermediaries bargain over the surplus with equal bargaining power relative to their respective outside options. We use the bilateral loan volumes from the observed network and set the redistribution of loans in bargaining to be proportional to borrowers' existing funding volumes to best match the data. That is, when borrower b's negotiation with a given intermediary i breaks down, its borrowing from all other connected intermediaries i' under $g' = g - \{i,b\}$ becomes:

$$V_b^{i'}(g') = V_b \frac{V_b^{i'}(g)}{\sum\limits_{i' \in N_b(g')} V_b^{i'}(g)}. \tag{4}$$

Formally, letting $U_b(g)$ and $U_i(g)$ be borrower b and intermediary i's utilities derived from the interbank market under network g, bilateral Nash bargaining between borrowing bank b and intermediary bank i of equal bargaining power implies:

$$U_b(g) - U_b(g') = U_i(g) - U_i(g') \qquad \forall g' = g - \{i,b\}, \tag{5}$$

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

$$\begin{cases} U_b(g) = \sum\limits_{i \in N_b(g)} \overbrace{(1-\gamma_{ib}(g))V_b^i(g)E[x_b]}^{\text{Share of Own Value}} \\ U_i(g) = \sum\limits_{b \in N_i(g)} \underbrace{\left[\gamma_{ib}(g)V_b^i(g)E[x_b] - V_b^i(g)(r+\lambda_i(g,c))\right]}_{\text{Share of Borrower Value - Funding Cost}} + \underbrace{V_i(E[x_i] - \lambda_i(g,c) - r)}_{\text{Own Value - Funding Cost}}. \end{cases} \tag{6}$$

In words, borrower b's utility under network g is the sum of its own loan value less the share paid to intermediaries, $\gamma_{ib}(g)$. Notice that $\gamma_{ib}(g)$ is not equal to the bargaining weight but will adjust so that the bargaining weights are equalized.[14] Intermediary i's utility is composed of two parts. First, it obtains the remaining share of connected borrowers' loan value but incurs the cost of funding in terms of the risk-free rate, r, and the expected state verification costs, $\lambda_i(g,c)$. Second, it derives value from funding its own projects in the interbank market amounting to V_i. These projects offer an expected return of $E[x_i]$ and a per-unit funding cost of $r+\lambda_i(g,c)$. In practice, banks also have assets outside of the interbank market. Our focus on interbank utilities does not imply that banks derive no value from non-interbank assets. As we discuss in Section 3.4, we only assume that changes in an intermediary bank's interbank connections with borrowing banks do not change its non-interbank asset returns and funding costs.[15]

When bargaining with their last connected intermediary breaks down, borrowing banks resort to direct borrowing from lenders. Just as intermediaries monitor borrowing banks, lenders need to monitor borrowing banks. However, due to lenders' limited size, borrowers may need to borrow from multiple lenders to fulfill their funding needs. Formally, we have $U_b(g) = \frac{1}{2}V_b\big(E[x_b]-r\big) - \frac{1}{2}\lceil \frac{V_b}{L} \rceil k\delta_b$ when $N_b(g)=\emptyset$, where the cost for forming a monitoring relationship, $k\delta_b$, depends on the common monitoring technology parameter, k, and the borrowing bank characteristics, δ_b.

We demonstrate the intuition behind the general formula with a simple example.[16] We illustrate the tradeoff from borrowing banks' point of view, which is without loss of generality due to equal bargaining power. When there is only one connected intermediary as in network g^1 (Fig. 7(b)) and bargaining breaks down, borrowing banks are left to directly borrow from lending banks as in network g^0 (Fig. 7(a)). Denote the outside option value of direct borrowing for bank b as $\underline{W}_b$. Solving $U_b(g^1)-U_b(g^0)=U_i(g^1)-U_i(g^0)$, the borrower in network g^1 obtains half of the surplus. Because monitoring costs have already been incurred when bargaining takes place, the surplus includes the borrower's loan value net of funding costs, its contribution to the intermediary's funding costs, and its outside option, $\underline{W}_b$. That is,

$$U_b(g^1) = \underbrace{\frac{1}{2}V_b\big[E[x_b]-r\big]-\frac{1}{2}V_b\lambda_i(g^1,c)}_{\text{Share of Own Value - Share of Own Funding Cost}} + \underbrace{\frac{1}{2}V_i[\lambda_i(g^0,c)-\lambda_i(g^1,c)]}_{\text{Contribution to Intermediary Funding Cost}} + \frac{1}{2}\underline{W}_b. \quad (7)$$

If the borrowing bank has two credit relationships as in network g'' (Fig. 7(c)), it could threaten

[14]This expression can be reformulated into a debt contract, where $\gamma_{ib}(g)$ maps into a link-specific interest rate. We use the current formulation for ease of notation.

[15]This decision was made in part because of the lack of data for other types of bank funding. Nevertheless, as we show in Internet Appendix B.4, this assumption seems reasonable because the large size of intermediary banks' aggregate balance sheets render their asset returns less dependent on changes in interbank connections.

[16]For a step-by-step derivation, please refer to Appendix A.

to redistribute its funding through the other intermediary if bargaining with any one intermediary breaks down. That is, the borrower's outside option in each bilateral bargaining improves from $U_b(g^0)$ to $U_b(g^1)$, while the intermediary would no longer be connected to any borrowing banks as in g^0 if bargaining breaks down. Hence, bargaining between each borrower-intermediary pair becomes $U_b(g^2) - U_b(g^1) = U_i(g^2) - U_i(g^0)$. Assuming symmetric intermediaries and bilateral loan volumes, we obtain borrower b's utility under network g^2 (Fig. 7(c)):

$$U_b(g^2) = \underbrace{\frac{2}{3}V_b\big[E[x_b] - r\big] - \frac{1}{3}V_b\big[\lambda(g^1,c) + \lambda(g^2,c)\big]}_{\text{Share of Own Value - Share of Own Funding Cost}} - \underbrace{V_i\big[\frac{2}{3}\lambda(g^2,c) + \frac{1}{3}\lambda(g^1,c) - \lambda(g^0,c)\big]}_{\text{Contribution to Intermediary Funding Cost}} + \frac{1}{3}\underline{W}_b. \quad (8)$$

Borrowing banks with two connected intermediaries (i.e., borrowers in network g^2) can secure two-thirds of the total value of loans net of funding costs compared to one-half in the case with only one intermediary (i.e., borrowers in network g^1). This gain illustrates how borrowing banks can tilt the surplus in their favor by forming more links with intermediaries. The additional links improve their outside option value in bargaining. Notice that the contribution to intermediary diversification is now a weighted average of $\lambda(g^0,c)$, $\lambda(g^1,c)$, and $\lambda(g^2,c)$ 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 subnetworks through the renegotiation of contracts. The number of subnetworks increases quickly 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. Shapley values assign a unique distribution of the total surplus generated by a coalition of players according to the average marginal contribution of each player. Formally, Shapley values are defined as follows.

Definition I *Let $\mathbb{N}$ be a finite set of players, indexed by j, and v a characteristic function that associates with each coalition $S \subseteq \mathbb{N}$ a real-valued payoff $v(S)$ that coalition members can jointly generate. Then, for a coalitional game $(\mathbb{N}, v)$, the Shapley value of player j is given by:*

$$\phi_j(v) = \frac{1}{|\mathbb{N}|!}\sum_R [v(P_j^R \cup \{j\}) - v(P_j^R)], \quad (9)$$

where P_j^R is the set of players in $\mathbb{N}$ that precede j in the order R.

Intuitively, imagine that when players are drawn one by one into a sequence R, each player j demands its marginal contribution as fair compensation, which is the value created by the preceding subset of players P_j^R with player j, $v(P_j^R \cup \{j\})$, minus the value created by the preceding set of players without j, $v(P_j^R)$. The Shapley value for player j is then j's average marginal contribution over all possible permutations in which the coalition of players can be formed. Averaging contributions over permutations produces a unique solution of the game independent of the sequence in which players are arranged. This feature embodies the spirit of our bargaining game for which the order of negotiations between borrowing and intermediary banks does not matter. The following proposition shows that the payoffs for borrowing and intermediary banks can be expressed as Shapley values.

Proposition I *Let the set containing all intermediary and borrowing banks be $\mathbb{N}$ and the characteristic function v_g assign a payoff $v_g(S)$ for a subset of banks $S \subseteq \mathbb{N}$ under network g:*

$$v_g(S) = \underbrace{\sum_{i \in S} V_i \left[E[x_i] - r - \lambda_i(g^S, c)\right]}_{\text{Value - Funding Cost of Intermediaries}} + \underbrace{\sum_{b \in S} \sum_{i \in S} V_b^i(g^S) \left[E[x_b] - r\right] - \lambda_i(g^S, c)\Big]}_{\text{Value - Funding Cost of Connected Borrowers}} + \underbrace{\sum_{b \in S, N_b(g) \cap S = \emptyset} \underline{W}_b}_{\text{Stand-alone Value}}. \tag{10}$$

Then, borrowing and intermediary banks' utilities in Eqs. (5) and (6) are given by the Shapley values $\phi(v_g)$ of the underlying coalitional game $(\mathbb{N}, v_g)$:

$$\begin{cases} U_b(g) = \phi_b(v_g) = \dfrac{1}{|\mathbb{N}|!} \displaystyle\sum_R [v_g(P_b^R \cup \{b\}) - v_g(P_b^R)] \\ U_i(g) = \phi_i(v_g) = \dfrac{1}{|\mathbb{N}|!} \displaystyle\sum_R [v_g(P_i^R \cup \{i\}) - v_g(P_i^R)], \end{cases} \tag{11}$$

where P_b^R (P_i^R) is the set of banks in $\mathbb{N}$ that precede b (i) in the order R.

The characteristic function, $v_g(S)$, denotes the total value created by the subset of banks S under network g. The first summation corresponds to the value of loans by intermediaries and connected borrowing banks less the opportunity cost of r and the expected state verification cost of $\lambda(g^S, c)$. The last term is the sum of the 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. The Shapley value for a given bank is then its average marginal contribution to the total payoff, $v_g(S)$, over all possible permutations in which the coalition of banks can be formed.

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. In Appendix B, we apply the axiom of balanced contributions by Myerson (1980) to prove our equivalence result.[17]

[17] We follow Theorem 4 in Stole and Zwiebel (1996), which shows that payoffs satisfying a stability condition can be mapped to Shapley values. Our analysis does not involve the specific non-cooperative game proposed by Stole and Zwiebel (1996). For a non-cooperative game with payoffs equal to Shapley values, see Brügemann et al. (2019).

3.4. *Pairwise stable equilibrium*

Having derived the division of surplus given a network g at $t = 1$, we define which links are chosen in equilibrium at $t = 0$. At $t = 0$, banks optimally choose to form links by weighing the larger share of surplus against the increase in monitoring costs. We adopt the equilibrium concept of pairwise stability. First introduced by Jackson and Wolinsky (1996), pairwise stability is a standard concept in the networks literature. It requires that links that are part of an equilibrium network have a benefit of link formation exceeding the cost of link formation for both counterparties, whereas links that are not part of the equilibrium network incur a cost of link formation larger than the benefit for at least one counterparty. Because of equal bargaining weights and equal splits in monitoring costs, the borrower's decision is symmetric to the intermediary's decision so that we can consider the borrower's perspective without loss of generality. Formally, a pairwise stable network is defined as follows.

Definition II *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,*

$$\begin{cases} U_b(g^*) - U_b(g') \geq \frac{1}{2}k\delta_b & \forall g' = g^* - \{i,b\} \\ U_b(g'') - U_b(g^*) < \frac{1}{2}k\delta_b & \forall g'' = g^* + \{i,b\}. \end{cases} \tag{12}$$

Pairwise stability is a relatively weak concept prone to multiple equilibria. Nevertheless, as we discuss next, it is sufficient for our structural estimation approach, which takes the observed network as being pairwise stable to infer the unknown cost parameters. Notice that pairwise stability only focuses on changes in utilities from one-link deviations. In other words, benefits and costs from a bank's non-interbank activities that do not interact with its interbank connections do not affect pairwise stability of the interbank network.

4. Structural estimation

In this section, we structurally estimate the monitoring cost parameter k and state verification cost parameter c using the preferences revealed by pairwise stability of the observed network. In our revealed preferences approach, we take the observed network as the equilibrium outcome, apply loan volumes and returns observed from the data, and find parameter values that best rationalize the conditions of observed and unobserved matches provided by Eq. (12).

We explain our estimation in a few steps. First, we use a simple example to provide insight on the empirical variations that inform the parameter estimates in Section 4.1. In Section 4.2, we explain the data used for the estimation strategy in Section 4.3. Finally, we present our baseline results in Section 4.4. In Internet Appendix A, we provide further details about the computation of Shapley values and the estimation procedure.

4.1. Example

We first illustrate how variations along two dimensions in the data generate inequality constraints to determine k and c. First, links formed by borrowing banks with different profitability inform the magnitude of total costs. In Example II, when borrowing bank B_1 forms two links and its less-profitable counterpart B_2 forms only one link with the same intermediaries (Fig. 8), we know that B_1's value from the second link is higher than the cost, whereas B_2's value from the second link fell short of its cost. Formally, pairwise stability implies that:

$$U_{b_1}(g^2) - U_{b_1}(g^1) \geq \frac{1}{2}k\delta_{b_1} \tag{13}$$

$$U_{b_2}(g^2) - U_{b_2}(g^1) < \frac{1}{2}k\delta_{b_2}. \tag{14}$$

Assuming symmetric intermediaries and plugging in Eqs. (7) and (8) derived in Example I for $U_b(g^1)$ and $U_b(g^2)$, we have:

$$\frac{1}{12}V_b\big[E[x_1] - r\big] \geq \kappa(c) + \frac{1}{2}(1 - \frac{V_b}{6L})k\delta_b \tag{15}$$

$$\frac{1}{12}V_b\big[E[x_2] - r\big] < \kappa(c) + \frac{1}{2}(1 - \frac{V_b}{6L})k\delta_b, \tag{16}$$

where $\kappa(c) = V_b\big[\frac{1}{3}\lambda(g^2,c) - \frac{1}{6}\lambda(g^1,c)\big] + V_i\big[\frac{2}{3}\lambda(g^2,c) - \frac{1}{6}\lambda(g^1,c) - \frac{1}{2}\lambda(g^0,c)\big]$ captures the expected state verification costs.[18] Applying loan volumes V_b and V_i, parameters δ_{b_1} and δ_{b_2}, and returns $E[x_1]$ and $E[x_2]$ from the data to Eqs. (15) and (16), we can put a bound on the sum of monitoring and expected state verification costs.

Second, variation in link density for differentially diversified intermediaries with the same borrower distinguishes the relative magnitude of monitoring costs and expected state verification costs. In Example III (Fig. 9), intermediaries I_2 are less diversified than intermediaries I_1, so that $\lambda_1(g^2,c) < \lambda_2(g^2,c)$. Since the borrower forms a second link with I_1 but not with I_2, the increase in expected state verification costs must have rendered the second link not profitable for I_2. Hence,

[18]In the case of a large diversified intermediary bank, loans of a single borrower cause little perturbation to the intermediary's 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 ease of exposition.

similar to Example II, pairwise stability of the observed network in Example III implies that:

$$\frac{1}{12}V_b\big[E[x]-r\big]-\frac{1}{2}(1-\frac{V_b}{6L})k\delta_b \geq \kappa_1(c) \tag{17}$$

$$\frac{1}{12}V_b\big[E[x]-r\big]-\frac{1}{2}(1-\frac{V_b}{6L})k\delta_b < \kappa_2(c), \tag{18}$$

where the expected state verification costs for I_1 and I_2 are captured by $\kappa_1(c) = V_b\big[\frac{1}{3}\lambda_1(g^2,c) - \frac{1}{6}\lambda_1(g^1,c)\big] + V_1\big[\frac{2}{3}\lambda_1(g^2,c) - \frac{1}{6}\lambda_1(g^1,c) - \frac{1}{2}\lambda_1(g^0,c)\big]$ and $\kappa_2(c) = V_b\big[\frac{1}{3}\lambda_2(g^2,c) - \frac{1}{6}\lambda_2(g^1,c)\big] + V_2\big[\frac{2}{3}\lambda_2(g^2,c) - \frac{1}{6}\lambda_2(g^1,c) - \frac{1}{2}\lambda_2(g^0,c)\big]$, respectively. Loan volumes V_b and V_i, parameters δ_{b_1} and δ_{b_2}, and returns $E[x]$ are again obtained from the data, so that we can deduce the relative magnitudes of c from k from Eqs. (17) and (18).

4.2. Data

As the previous two examples illustrate, we use balance sheet and credit registry data as inputs for the structural model to estimate the unknown cost parameters k and c. We explain the inputs we use below and summarize their magnitudes in Table 2.

Loan volumes. We obtain equilibrium loan volumes between each borrower b and intermediary i, $V_b^i(g^*)$, from the average bilateral loan volumes in the observed network g^* from 2005:Q1 to 2007:Q2. In the baseline model, each borrowing bank's total loan volume, V_b, is fixed and equal to the sum of its bilateral loan volumes, $V_b^i(g^*)$. When the network changes, we set the redistribution of a borrower's bilateral interbank loans proportional to that borrower's funding volumes as in Eq. (4). We relax the assumption of fixed total loan volumes and allow aggregate loans fundable to vary with the network in the extension model in Section 7.1. Intermediary banks' interbank funding volumes, V_i, are obtained by deducting the total interbank lending volume from the total interbank borrowing volume for intermediary i.

Expected returns. We obtain bank-level expected returns, $E[x_b]$ and $E[x_i]$, by averaging gross returns on bank balance sheets for the pre- and post-crisis periods from 2005:Q1 to 2007:Q2 and 2007:Q3 to 2009:Q4, respectively. We use income from nonfinancial corporations to avoid confounding by income from interbank loans.

State verification costs. To parameterize the expected state verification costs, $\lambda_i(g,c)$, we need the distribution of each intermediary bank's effective return, y_i, which is a weighted average of its own project return and that of its connected borrowing banks as stated in Eq. (1). We assume that the returns of borrowing banks and intermediary banks follow a joint normal distribution. The mean return for each bank is its average gross return as in $E[x_b]$ and $E[x_i]$. The variance is the sample variance in gross returns over the same time period. We let the correlation in returns across banks be ρ, and estimate our model for values of ρ between 0.12 and 0.24, which are the lower and upper bounds of asset correlations provided by the guidelines in Basel III.[19] Together with interbank loan volumes from the credit registry and intermediary asset size from balance sheets, we can then use Eq. (1) to calculate the mean and variance of y_i. For ease of computation, we use a Taylor expansion to simplify $\lambda_i(g,c) = \int_{\underline{R}}^{R_i(g)} c\delta_i \, dH(y_i)$. We refer the reader to Internet Appendix A for details of this approximation.

Bank asset size and opacity. Recall that monitoring and expected state verification costs are parameterized by the characteristics of the borrowing bank, δ_b, and intermediary bank, δ_i. δ_b and δ_i are the product of bank asset size and asset opacity, where asset opacity is proxied by the ratio of firm loans divided by total assets on bank balance sheets because there tends to be less public information available for firm loans than for more liquid securities.

Risk-free rate. Lending banks' outside option, r, is taken to be the German bund yield matching the average maturity of interbank loans.

4.3. Estimation strategy

Generalizing from our simple examples, we estimate the cost parameters c and k that best satisfy the set of model-implied pairwise stability conditions of the observed network as in Eq. (12).

Recall from Section 3.3 that borrowing and intermediary banks' utilities can be expressed in terms of the unknown parameters c and k for any given network g using Shapley values. All other inputs for Shapley values are directly obtained from the data, as described in Section 4.2. Hence, we can derive the borrower's value for both a given network g and one-link deviations from network g. Further noting that the borrower's cost of link formation is $\frac{1}{2}k\delta_b$, we can express the net value of one-link additions as a function of c and k plus a link-specific error: $W_{ib}(c,k) = U_b(g,c,k) - U_b(g',c,k) - \frac{1}{2}k\delta_b + \varepsilon_{ib}$. Finally, we apply $W_{ib}(c,k)$ to all one-link deviations from the observed network g^*, i.e., $g' = g^* - \{i,b\}$ and $g'' = g^* + \{i,b\}$, to construct the maximum score

[19]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 III regulation.

function $Q(c,k)$:

$$Q(c,k) = \underbrace{\sum_{i\in\mathbb{I}}\sum_{b\in N_i(g^*)} \mathbb{1}\left[U_b(g^*,c,k) - U_b(g',c,k) - \frac{1}{2}k\delta_b \geq 0\right]}_{\text{Inequality Conditions Satisfied for Observed Links}} + \underbrace{\sum_{i\in\mathbb{I}}\sum_{b\notin N_i(g^*)} \mathbb{1}\left[U_b(g'',c,k) - U_b(g^*,c,k) - \frac{1}{2}k\delta_b < 0\right]}_{\text{Inequality Conditions Satisfied for Unobserved Links}}.$$

Given a set of parameters c and k, the score function, $Q(c,k)$, counts the number of times Eq. (12) is satisfied for the observed network g^*. For links that are observed to be part of network g^*, pairwise stability is satisfied when parameters c and k imply that the net benefits from forming the link are positive. Similarly, for links not part of the observed network g^*, pairwise stability is satisfied when parameters c and k imply that the net benefits from forming the link are negative. Finally, we can find the values of c and k that correctly predict the largest number of inequalities to be the maximum score estimator of the score function. Notice that following the definition of pairwise stability, $W_{ib}(c,k)$ contains an implicit tie-breaking assumption in which links are formed when the net benefit is zero. We find that this assumption does not affect our main results in Section 4.4.

To find parameter estimates that maximize the score function, we adopt the differential evolution algorithm proposed by Storn and Price (1997) to ensure that a global maximum of $Q(c,k)$ is reached.[20] We further follow Delgado et al. (2001) and Politis and Romano (1994) 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^{th} and 97.5^{th} percentile of this empirical sampling distribution are used to compute the 95% confidence interval.

For identification, we assume that the unobserved match errors, ε_{ib}, are independently and identically distributed with mean zero. 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 is ex-ante known to the agent but

[20] In general, the maximum score estimator allows only for set identification. To this end, we repeat the optimization procedure 20 times with different initial populations and find the same point estimates up to three decimal places.

unobserved by 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, our estimates would be biased. These channels may especially be of concern when the geographic proximity increases the probability that bankers know each other. We repeat the analysis conditioning on geographic distance and generate similar quantitative predictions (see Internet Appendix B.3).

The maximum score estimator was introduced by Manski (1975) and has been extended to matching markets by Fox (2008). 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, which is satisfied under our assumption of mean zero errors. This method 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. It is also computationally efficient for large networks and does not suffer from the curse of dimensionality as other maximum likelihood estimators do. While we estimate the cost of interbank lending relationships, previous studies have adopted a similar estimation approach in other contexts (e.g., Chen and Song, 2013; Akkus et al., 2015; Schwert, 2018).

4.4. *Estimation results*

Our estimation results for the baseline model are presented in Table 3. All estimates are statistically significant at the 95% level. The monitoring cost parameter, k, is estimated between 1.28 and 1.41 for the range of correlations considered. For an easier comparison, we present the state verification cost parameter in terms of C, which is the per-unit parameter c scaled by the average lender size, L. C lies between 0.21 and 0.24 for the range of correlations considered, which implies that when facing a hypothetical borrower of the same size and asset opacity, the state verification cost incurred by the average lender in a default state is 15% to 20% of the cost for forming one monitoring relationship.

Notice, however, that the simple ratio between the cost parameters does not directly map into the ratio of the actual monitoring costs and expected verification costs due to differences in asset size and asset opacity across banks and because state verification costs are incurred only when lenders cannot pay the face value of debt. Considering these heterogeneities in the data, we calculate the monitoring cost and expected state verification cost for an average euro of interbank funding obtained by borrowing banks. We find that the per-euro monitoring costs and expected state verification costs for a borrowing bank with two monitoring links are on average 48.5 bps and 4.6 bps, respectively. Therefore, ex–ante monitoring accounts for the vast majority of the total costs for interbank borrowers in the pre-crisis period.

Aggregating across all banks, we find the interbank lending network yields an annual net value of €5.63 billion in the pre-crisis network. This is after deducting lenders' outside option funding rate, *r*, ex–ante monitoring costs, and expected state verification costs. The latter two costs are €1.10 billion and €0.12 billion, respectively, showing again that the main investment in the interbank network is for establishing long-term credit relationships to monitor borrowing banks. The small share of expected state verification costs is consistent with "monitoring-the-monitor" costs being very low, as conjectured by Diamond (1984). Absent interbank intermediation, many more long-term credit relationships would have to be set up, and doing so would increase the costs of obtaining interbank loans.

However, the present network is not the most efficient one. As Jackson and Wolinsky (1996) show, pairwise stable networks are often not efficient, and the star network is the only efficient outcome in a range of settings. In our context, the surplus could be further improved if every borrowing bank formed only one link with a single intermediary. Fewer links would be formed in this case, and the further reduction in duplicated monitoring would make up the main welfare improvement. The additional benefit from diversification—a drop in the expected state verification cost—is relatively small because the level of diversification in the present network is already quite high.

Intuitively, we can understand deviations from the first-best outcome to be driven by banks' private incentives. On the one hand, borrowing banks connect to more than one intermediary to leverage their outside options in bargaining and thereby obtain a larger share of the surplus for themselves. At the same time, banks with relatively diversified portfolios establish themselves as intermediaries to partake in obtaining intermediation profits. From this perspective, a social planner would find it optimal to reorganize the interbank market through a central intermediary that monitors on behalf of all borrowers.

5. Verification of model parameters

During the Great Financial Crisis, intermediary banks were differentially affected. One of the main exposures was losses from asset-backed commercial paper held by conduits (Acharya et al., 2013). We utilize the unexpected cut in profitability and the subsequent changes in the interbank network from 2007:Q3 to 2009:Q4 as an out-of-sample test to verify the accuracy of our model and estimates, which are based on pre-crisis data from 2005:Q1 to 2007:Q2.

After the onset of the crisis, the main observable changes in the interbank market were a drop in funding volume through existing links and a number of links added to the existing network. Viewed through the lens of our model, these changes reflect an increase in the default risk for some intermediaries, which increased the expected state verification cost charged by their lenders. This increase in funding costs is passed on to connected borrowing banks, which attempted to form new credit links to unaffected intermediaries in search of less expensive funding sources. Forming new credit relationships is costly, however, so not all exposed borrowers could avoid the initial exposure. As a result, total funding costs for borrowing banks increased, and their fundable loans declined.

In other words, borrowing banks decide between paying the cost of investing in new credit relationships and continuing funding at the increased rates of their established credit links. If our model is accurate, 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. This conjecture is confirmed in Fig. 10, which shows that the average number of new links formed by borrowing banks increases with their predicted change in funding costs. The change in funding costs is calculated using post-crisis balance sheets and returns, as shown in Table 2. Only the monitoring and state verification technology parameters, k and c, respectively, are based on their pre-crisis estimates. The implicit assumption is that there are no changes to the technologies of monitoring and state verification as a result of the onset of the Great Financial Crisis, while monitoring intensity and the expected funding costs are allowed to change according to the post-crisis data.

Note that the drop in mean returns in Table 2 stems from heterogenous exposure across intermediary banks.[21] Heterogeneity in intermediary exposure provides the cross-sectional variation for our out-of-sample test. Intuitively, the larger the exposure to an intermediary bank, the more its funding costs increase, and the less likely it is to form new links with borrowing banks. Indeed, we find that all new links were formed with intermediary banks with below-median exposure.

We conduct a more formal out-of-sample test of our parameter estimates based on pre-crisis data from 2005:Q1 to 2007:Q2 by checking whether they can accurately quantify the costs and benefits of link formation in the post-crisis period from 2007:Q3 to 2009:Q4. If the model estimates of k and c are accurate, they should be able to predict the formation of new links and absences thereof in the post-crisis period. Specifically, we use pre-crisis estimates $\hat{k}$ and $\hat{c}$ and post-crisis balance sheet and network characteristics to calculate the predicted benefit and cost for each link that could have been formed (i.e., links that did not exist in the pre-crisis period). Pairwise stability conditions are computed one link at a time while holding the remaining network constant. For each new link observed in the post-crisis network, g^*_{post}, the pairwise stability condition is satisfied when the predicted benefit of link formation exceeds the cost of link formation. Similarly, for each

[21] Due to data confidentiality requirements, we are unable to display the full distribution for all intermediaries.

link absent in the post-crisis network, the pairwise stability condition is satisfied when the predicted benefit falls short of the cost. Then, we evaluate the number of pairwise stability conditions satisfied among all potential links in the post-crisis network and compute the fraction of successful predictions as $\frac{Q(\hat{c},\hat{k})}{Q_{max}}$, 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_{max} is the total number of new links that could have been formed. We focus on new links that could have been formed so as not to overinflate our results with links already present in the pre-crisis network. One can think of their formation cost as sunk, so that continued usage does not require additional monitoring.

We correctly predict around 86% of the potential links between borrowing and intermediary banks (Table 4). Among the links that were formed versus those that were not formed, we predict 66.5% to 71.9% and 85.4% to 86.7%, respectively. Predicting the identity of the formed links is especially challenging because consistent with a sticky interbank network, the vast majority of links that could have been formed were not formed. Our model effectively captures the relatively low-level of link formation—we predict between 177 and 207 new links. Out of the formed links, we further predict at an accuracy between 66.5% and 71.9% which pair of borrowing and intermediary banks formed a new link.

Without the model, if we took the same number of new links predicted and assumed a random formation, the predictive accuracy would be 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 funding from intermediaries with above-median exposure, the expected predictability would only be improved to 11.6% to 13.7% and 85.7% to 86.1% for links formed and not formed, respectively. Notice that in both of these scenarios, the predictive accuracy drops substantially for links that were formed relative to our model performance. As mentioned above, pinpointing which borrower-intermediary pair formed links is especially challenging given the small number of links formed. The improvement in predictability for formed links is thus an especially strong indicator for our model's out-of-sample performance.[22]

[22] If the monitoring cost parameter, k, were 25% higher than the estimated value, forming new links would be costlier, and fewer links would be formed. The smaller number of predicted links would only match 43.2% of formed links when $\rho = 0.18$, while the match for links that are not formed slightly improves to 88.3%.

Our model's predictability stems from two dimensions. On the borrowers' end, cross-sectional variation in intermediary banks' exposure gives rise to cross-sectional variation in borrowing banks' exposure and their likelihood of forming new links. Those with the most concentrated exposure to the most affected intermediary banks (e.g., borrowers with only one link to the most impacted intermediary bank) gain the most from forming new links. Our parameter estimates allow us to quantify these benefits, compare them against the estimated costs of link formation, and thereby pin down which borrowing banks form new links.

The benefits of link formation also depend on with which intermediary bank a borrowing bank chooses to form a new link. Using our parameter estimates, we can calculate the funding cost for each intermediary to determine which one would offer a low enough funding cost (i.e., $\lambda_i(g^*_{post}, c)$) for there to be a net benefit from link formation. In the end, we find that all new links formed by borrowing banks are concentrated in intermediaries that have lower funding costs in the pre-crisis period and that are unexposed during the crisis.

6. Effect of interbank funding costs on lending to the real economy

The quantity of loans extended by borrowing banks to firms provides further evidence for our model and demonstrates the real impact of disruptions in interbank intermediation. Fig. 11 is a binned scatter plot of changes in borrowing banks' loan supply to firms against changes in borrowing banks' model-implied interbank funding costs. For each bin, the average change in loans to firms 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 loans to firms, wherein the number of fundable projects decreases as funding costs increase. On average, when a borrowing bank's funding increases by 100 bps, the loans it extends to firms decrease by 4.2%.

To address concerns of bank-specific loan demand, we examine changes in loans at the bank-firm level and condition on borrowing by the same firm. Column (3) in Table 5 shows that loans to firms drop by 5.5% for every 100 bps increase in funding costs, which is only slightly below the unconditioned result in Column (2). Column (4) repeats the same specification and also includes firm loans extended by lending banks, assuming that lending banks did not suffer direct impacts to funding costs for their firm loans. The coefficients slightly change in magnitude but remain significantly negative, demonstrating that lending banks could not fully compensate for the contraction in firm loan supply by borrowing banks. Therefore, the breakdown of interbank intermediation during the Great Financial Crisis impacted the aggregate funding supply to the real economy.

7. Counterfactual analysis

The Great Financial Crisis demonstrated how shocks to a few intermediary banks can affect the funding costs and volume of a large number of borrowing banks. To shed light on the extent of shock amplification through an increase in expected state verification costs in a network of sticky monitoring relationships, we first extend our baseline model to allow for endogenous loan volumes and borrowing from the central bank in Section 7.1. Then, we shock intermediary banks one at a time and measure the aggregate impact on the banking system in Section 7.2. Finally, we examine to what extent the provision of central bank funding can increase the volume of fundable loans in the interbank market in Section 7.3.

7.1. Extension: central bank liquidity facilities and endogenous loan volumes

We extend the baseline model by allowing banks to choose their funding volume and by granting them access to central bank funding. The inclusion of these realistic elements serves as a robustness check of the baseline model and allows for a richer set of counterfactuals. In this section, we focus on explaining the additions to the baseline framework and their implications. The estimation and verification of the extension model are very similar to the baseline case and are detailed in Appendix D.

First, we relax the assumption of fixed funding volumes and allow changes in interbank funding costs to affect the volume of interbank loans fundable. We let borrowing banks and intermediary banks face downward-sloping demand curves for interbank funding. Then, at $t = 0$, they opt for the optimal volume of interbank borrowing, V_b^* and V_i^*.

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 ECB regularly conducts LTROs in which banks can borrow for three months against eligible collateral.[23] We extend the model by letting borrowing and intermediary banks access ECB loans with probabilities P_b and P_i at a rate r_{ECB}. These probabilities capture banks' constraints in accessing central bank loans because of their insufficient collateral and ECB allotment quotas. We use the proportion of ECB borrowing as a fraction of the total balance sheet size as a proxy for collateral constraints because balance

[23] In the wake of the European sovereign debt crisis, the ECB further introduced longer-term LTROs, broadened the scope of eligible collateral, and carried out asset purchase programs. These measures occur after our sample period. The ECB also conducts week-long liquidity-providing operations called the main refinancing operation (MRO). The MRO mainly affects short-term rates that signal the monetary policy stance. Since it is not meant to provide 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.

sheet data cannot directly distinguish which assets are eligible as collateral. We parameterize $P_b = p\frac{ECBBorrowing_b}{TotalAssets_b}$ and $P_i = p\frac{ECBBorrowing_i}{TotalAssets_i}$, where p is a common scaling coefficient to be estimated. We use the 3-month repo rate for the cost of central bank borrowing, r_{ECB}, because this rate closely tracks the LTRO rate (Linzert et al., 2004).

Re-estimating the model, we find that the overall magnitude of parameters and the model fit remain largely unchanged. Please refer to Appendix D for detailed results. From the estimates for p, we infer that the median intermediary borrowed 21.5% to 26.6% of its interbank funding from the ECB in the crisis period. Similar conversions show that ECB funding tapped by periphery banks is largely negligible. One potential explanation is that intermediary banks' business model involves the use of liquid assets, which are also eligible as collateral at the ECB. In contrast, smaller periphery banks hold much less in securities and were likely more constrained in tapping secured funding from the central bank.

7.2. *Credit risk shocks to intermediary banks*

The first set of counterfactuals examines how increases in funding costs to individual intermediary banks spill over through the interbank network to affect the funding volume of borrowing banks. To compare how the amplification of funding-cost increases varies with network connectivity, we shock intermediary banks one at a time by increasing the effective interbank funding costs of the shocked intermediary by 50 bps based on the pre-crisis network. Specifically, we decrease the average return of the shocked intermediary bank's own projects such that the funding costs required by lending banks increase by 50 bps. The variance of returns and all other balance sheet characteristics are kept the same.

When an intermediary bank's funding costs increase, the interbank funding volume for its own projects decreases because of the downward-sloping demand curve. At the same time, the increase in funding costs is passed on to connected borrowing banks, whose interbank funding volume also contracts.

We find that intermediary banks' connectivity to borrowing banks plays a crucial role in determining the aggregate impact of the initial shock. As shown in Fig. 12, the drop in aggregate interbank loans when an intermediary above the third quartile experiences a 50 bps funding cost shock is 12.3 times that of a first-quartile intermediary. This difference in loan contractions is predominantly driven by cuts in funding volumes at connected borrowing banks because more connected intermediaries pass on shocks to a larger number of dependent borrowing banks. In absolute terms, a 50 bps shock to intermediaries above the third quartile decreases total interbank loans by 5.9%, in which 5% of the 5.9% stems from the contraction in borrowing banks' loans.

Network connectivity also matters from the perspective of borrowing banks. When a given intermediary bank experiences increases in funding costs, the impact on its borrowers depends on how many other intermediary banks they have loan relationships with. Additional links can diversify shocks to individual intermediaries and dampen the overall impact on a borrowing bank's loans fundable. Fig. 13 shows the average changes in interbank funding volumes for connected borrowing banks when intermediaries at the first, second, and third quartiles of loans intermediated are shocked with a 50 bps increase in funding costs one at a time. On average, borrowing banks with only one link suffer a 15.6% decline in interbank loans, while borrowers with two and three links experience 9.8% and 6.6% in loan contractions, respectively. Notice, though, that these results are obtained by shocking individual intermediary banks. The benefit of having more links may diminish when funding shocks at intermediary banks are more systematic.

7.3. Changes in central bank funding policy

Our second set of counterfactuals examines how more accomodative central bank funding policies can improve funding volumes in the interbank market. As described in Section 7.1, the central bank provides an outside option to funding from interbank markets at a rate r_{ECB} that borrowing banks and intermediary banks can access with probabilities P_b and P_i, which reflect constraints in collateral availability and allotment quotas. We consider two scenarios. The first one involves lowering the ECB's funding facility rate, r_{ECB}, by 50 bps. The second one combines a 50 bps drop in r_{ECB} with a 25% increase in access probabilities P_b and P_i, which can be achieved through policy measures such as allowing for a wider range of eligible collateral. Both scenarios are based on the pre-crisis network, and balance sheet characteristics are kept unchanged.

Fig. 14 shows the effect of easing central bank funding policies on the interbank market. A 50 bps drop in ECB funding rates increases aggregate interbank loans by 2.96%. Combined with a more accommodative collateral policy, the effect improves to 4.18%. The difference between these two estimates is significant and arises from relaxing collateral constraints and allotment quotas for accessing ECB funding. Indeed, both the eligibility criteria for collateral and allotment quotas were relaxed later during the European sovereign debt crisis.

Comparing the results across counterfactuals, we find that funding-cost shocks to an individual intermediary can lead to even larger reductions in loan volumes than a same-magnitude interest rate cut at the ECB funding facility can ameliorate. This is in part because banks' limited collateral and binding allotment quotas constrain their access to ECB funding. At the same time, shocks to individual intermediaries not only affect the intermediaries' own interbank loans, they also amplify through a concentrated and costly-to-adjust interbank network and curtail funding to a large number of connected borrowing banks. These results highlight the systemic importance of intermediary banks in interbank markets.

8. Conclusion

In this paper, we establish 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. Because the monitoring of borrowers is concentrated in a few intermediaries instead of a 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 the changes in surplus division from bargaining. Banks' consideration of this tradeoff is revealed by the links they choose to form. We structurally estimate the unobserved monitoring costs based on the observed links in the German interbank lending market before the Great Financial Crisis. We verify our model through an out-of-sample test of the Great Financial Crisis. We also predict effects of similar crisis events, when shocks to a single interbank intermediary bank can spill over to the rest of the banking system and contract lending by a large number of borrowing banks to the real economy.

Knowing the magnitude of monitoring costs is essential for 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 would costlessly form new links to circumvent increases in funding costs. When monitoring of the borrower is more costly, switching to new intermediaries becomes more expensive. The rigidity of adjustment determines the extent to which an initial shock to intermediary funding costs is passed on to connected borrowing banks and their lending to firms in the real economy.

This channel of systemic risk is quantitatively important. A 50 bps increase in the funding costs of a highly connected intermediary can trigger an aggregate cut in interbank loans of 5.9%, with the add-on effect from borrowing banks accounting for 5%. Using pre-crisis estimates of monitoring costs, our model mechanism predicts 86% of the changes in network structure and successfully matches observed trends in banks' supply of loans to firms during the Great Financial Crisis. These results demonstrate and verify that the spillover of funding-cost changes through sticky interbank intermediation networks is 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 increase, 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 government interventions through the lens of interbank intermediation will offer a more complete view of the subsidies to the banking sector.

References

Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A., 2015. Systemic risk and stability in financial networks. American Economic Review 105, 564–608.

Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M., 2017. Measuring systemic risk. Review of Financial Studies 30, 2–47.

Acharya, V.V., Schnabl, P., Suarez, G., 2013. Securitization without risk transfer. Journal of Financial Economics 107, 515–536.

Adrian, T., Brunnermeier, M.K., 2016. Covar. American Economic Review 106, 1705.

Affinito, M., 2012. Do interbank customer relationships exist? And how did they function in the crisis? Learning from Italy. Journal of Banking & Finance 36, 3163–3184.

Afonso, G., Kovner, A., Schoar, A., 2011. Stressed, not frozen: The federal funds market in the financial crisis. Journal of Finance 66, 1109–1139.

Afonso, G., Kovner, A., Schoar, A., 2013. Trading partners in the interbank lending market. Unpublished working paper. Federal Reserve Bank of New York.

Afonso, G., Lagos, R., 2015. Trade dynamics in the market for federal funds. Econometrica 83, 263–313.

Akkus, O., Cookson, J.A., Hortacsu, A., 2015. The determinants of bank mergers: A revealed preference analysis. Management Science 62, 2241–2258.

Allen, F., Gale, D., 2000. Financial contagion. Journal of Political Economy 108, 1–33.

Babus, A., Hu, T.W., 2017. Endogenous intermediation in over-the-counter markets. Journal of Financial Economics 125, 200–215.

Bech, M.L., Atalay, E., 2010. The topology of the federal funds market. Physica A: Statistical Mechanics and its Applications 389, 5223–5246.

Benoit, S., Colliard, J.E., Hurlin, C., Pérignon, C., 2017. Where the risks lie: A survey on systemic risk. Review of Finance 21, 109–152.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104, 535–559.

Blasques, F., Bräuning, F., Van Lelyveld, I., 2018. A dynamic network model of the unsecured interbank lending market. Journal of Economic Dynamics and Control 90, 310–342.

Bluhm, M., Georg, C.P., Krahnen, J.P., 2016. Interbank intermediation. Unpublished working paper. Deutsche Bundesbank.

Boss, M., Elsinger, H., Summer, M., Thurner, S., 2004. Network topology of the interbank market. Quantitative Finance 4, 677–684.

Brügemann, B., Gautier, P., Menzio, G., 2019. Intra firm bargaining and shapley values. Review of Economic Studies 86, 564–592.

Brusco, S., Castiglionesi, F., 2007. Liquidity coinsurance, moral hazard, and financial contagion. Journal of Finance 62, 2275–2302.

Castiglionesi, F., Wagner, W., 2013. On the efficiency of bilateral interbank insurance. Journal of Financial Intermediation 22, 177–200.

Chang, B., Zhang, S., 2018. Endogenous market making and network formation. Unpublished working paper. London School of Economics and Political Science.

Chang, E.J., Lima, E.J.A., Guerra, S.M., Tabak, B.M., 2008. Measures of interbank market structure: An application to Brazil. Brazilian Review of Econometrics 28, 163–190.

Chen, J., Song, K., 2013. Two-sided matching in the loan market. International Journal of Industrial Organization 31, 145–152.

Cocco, J.F., Gomes, F.J., Martins, N.C., 2009. Lending relationships in the interbank market. Journal of Financial Intermediation 18, 24–48.

Craig, B.R., Von Peter, G., 2014. Interbank tiering and money center banks. Journal of Financial Intermediation 23, 322–347.

Delgado, M.A., Rodriguez-Poo, J.M., Wolf, M., 2001. Subsampling inference in cube root asymptotics with an application to Manski's maximum score estimator. Economics Letters 73, 241–250.

Denbee, E., Julliard, C., Li, Y., Yuan, K., 2021. Network risk and key players: A structural analysis of interbank liquidity. Journal of Financial Economics 141, 831–859.

Diamond, D.W., 1984. Financial intermediation and delegated monitoring. Review of Economic Studies 51, 393–414.

Eisenberg, L., Noe, T.H., 2001. Systemic risk in financial systems. Management Science 47, 236–249.

Elliott, M., Golub, B., Jackson, M.O., 2014. Financial networks and contagion. American Economic Review 104, 3115–53.

Farboodi, M., 2014. Intermediation and Voluntary Exposure to Counterparty Risk. Unpublished working paper. Princeton University.

Flannery, M.J., 1996. Financial crises, payment system problems, and discount window lending. Journal of Money, Credit and Banking 28, 804–824.

Fox, J.T., 2008. Estimating Matching Games with Transfers. Unpublished working paper. National Bureau of Economic Research.

Freixas, X., Jorge, J., 2008. The role of interbank markets in monetary policy: A model with rationing. Journal of Money, Credit and Banking 40, 1151–1176.

Fricke, D., Lux, T., 2015. Core–periphery structure in the overnight money market: Evidence from the e-Mid trading platform. Computational Economics 45, 359–395.

Furfine, C.H., 2001. Banks as monitors of other banks: Evidence from the overnight federal funds market. Journal of Business 74, 33–57.

Gabrieli, S., Georg, C.P., 2014. A Network View on Interbank Market Freezes. Unpublished working paper. Deutsche Bundesbank.

Gofman, M., 2017. Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. Journal of Financial Economics 124, 113–146.

Hart, S., Mas-Colell, A., 1989. Potential, value, and consistency. Econometrica , 589–614.

Heider, F., Hoerova, M., Holthausen, C., 2015. Liquidity hoarding and interbank market rates: The role of counterparty risk. Journal of Financial Economics 118, 336–354.

Hendershott, T., Li, D., Livdan, D., Schürhoff, N., 2020. Relationship trading in over-the-counter markets. Journal of Finance 75, 683–734.

Hugonnier, J., Lester, B., Weill, P.O., 2014. Heterogeneity in Decentralized Asset Markets. Unpublished working paper. National Bureau of Economic Research.

Iyer, R., Peydró, J.L., da-Rocha-Lopes, S., Schoar, A., 2013. Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis. Review of Financial Studies 27, 347–372.

Jackson, M.O., Wolinsky, A., 1996. A strategic model of social and economic networks. Journal of Economic Theory 71, 44–74.

Khwaja, A.I., Mian, A., 2008. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. American Economic Review 98, 1413–42.

Kuo, D., Skeie, D.R., Vickery, J.I., Youle, T., 2014. Identifying Term Interbank Loans from Fedwire Payments Data. Unpublished working paper. Federal Reserve Bank of New York.

Ladley, D., 2013. Contagion and risk-sharing on the inter-bank market. Journal of Economic Dynamics and Control 37, 1384–1400.

Linzert, T., Nautz, D., Bindseil, U., 2004. The Longer Term Refinancing Operations of the ECB. Unpublished working paper. European Central Bank.

Manski, C.F., 1975. Maximum score estimation of the stochastic utility model of choice. Journal of Econometrics 3, 205–228.

Myerson, R.B., 1980. Conference structures and fair allocation rules. International Journal of Game Theory 9, 169–182.

Paravisini, D., 2008. Local bank financial constraints and firm access to external finance. Journal of Finance 63, 2161–2193.

Politis, D.N., Romano, J.P., 1994. Large sample confidence regions based on subsamples under minimal assumptions. The Annals of Statistics , 2031–2050.

Schmieder, C., 2006. The Deutsche Bundesbank's large credit database (BAKIS-M and MiMiK). Schmollers Jahrbuch : Journal of Applied Social Science Studies / Zeitschrift für Wirtschafts- und Sozialwissenschaften 126, 653–663.

Schnabl, P., 2012. The international transmission of bank liquidity shocks: Evidence from an emerging market. Journal of Finance 67, 897–932.

Schwert, M., 2018. Bank capital and lending relationships. Journal of Finance 73, 787–830.

Stole, L.A., Zwiebel, J., 1996. Intra-firm bargaining under non-binding contracts. Review of Economic Studies 63, 375–410.

Storn, R., Price, K., 1997. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. Journal of Global Optimization 11, 341–359.

Townsend, R.M., 1979. Optimal contracts and competitive markets with costly state verification. Journal of Economic Theory 21, 265–293.

Upper, C., 2011. Simulation methods to assess the danger of contagion in interbank markets. Journal of Financial Stability 7, 111–125.

Upper, C., Worms, A., 2004. Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? European Economic Review 48, 827–849.

in't Veld, D., van Lelyveld, I., 2014. Finding the core: Network structure in interbank markets. Journal of Banking & Finance 49, 27–40.

Wang, C., 2016. Core-Periphery Trading Networks. Unpublished working paper. Stanford Institute for Economic Policy Research.

Table 1
Characteristics of Borrowing, Lending, and Intermediary Banks. This table reports balance sheet characteristics for banks that borrow, lend, and intermediate in the interbank market. 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 2005:Q1 to 2009:Q4.

	Borrowing Banks			Lending Banks			Intermediary Banks
	Q1	Q2	Q3	Q1	Q2	Q3	Q2
Total Assets (billion euro)	0.59	1.58	3.93	0.21	0.44	1.08	99.32
Equity Ratio (%)	4.85	5.59	6.02	4.77	5.45	6.58	5.12
Ratio of Firm Loans (%)	60.15	66.30	71.52	70.30	79.54	85.42	39.11
Gross Return (%)	4.85	5.59	6.02	4.98	5.67	6.13	5.43
Loan Loss Reserves (%)	2.14	2.75	3.02	2.06	2.51	2.89	2.61

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

	Borrowing Banks		Intermediaries	
	Pre-crisis	Post-crisis	Pre-crisis	Post-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 3

Estimation Results (Baseline Model). This table reports results from the maximum score estimation of the baseline model. k represents the monitoring cost technology parameter for each link between intermediaries and borrowing banks. C represents the state verification cost parameter for each link between intermediaries and the average lender. ρ is the correlation of returns across banks. The 95% confidence interval bounds, based on subsampling, are in parentheses. ** indicates that the 95% 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^{**}
	$(0.876, 2.198)$	$(0.658, 1.991)$	$(0.641, 1.816)$
State Verification Cost C	0.240^{**}	0.224^{**}	0.212^{**}
	$(0.076, 0.389)$	$(0.055, 0.402)$	$(0.040, 0.441)$
Inequalities Satisfied (%)	90.2	89.1	88.9
Number of Inequalities		8,265	

Table 4

Percentage of Correctly Predicted Inequalities (Baseline Model). This table reports the percentage of correctly predicted inequalities in the out-of-sample test of the Great 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

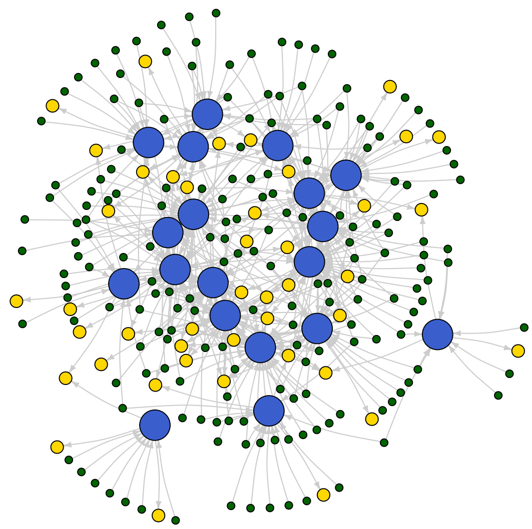
Table 5

Impact on Firm Loans. This table reports the regression results of changes in firm loan supply by borrowing banks on model-predicted changes in funding costs for borrowing banks. Columns 1 to 3 focus on the sample of firm loans from borrowing banks only. In addition to firm loans by borrowing banks, The regression for column 4 further includes all firm loans by lending banks. The dependent variable measures the log change in loans between a bank-firm pair before and after the Great Financial Crisis. The main explanatory variable is the change in funding cost for borrowing banks before and after the Great Financial Crisis. The remaining explanatory variables reflect the 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 and shown in parentheses. * and ** indicate statistical significance at the 10% and 5% levels, respectively.

	Δ Log(Bank-Firm Loans)			
	(1)	(2)	(3)	(4)
Δ Funding Cost (%)	-0.063**	-0.066**	-0.055**	-0.059**
	(0.019)	(0.033)	(0.026)	(0.025)
Cash (%)		0.046*	0.041*	0.031
		(0.026)	(0.022)	(0.029)
Log(Total Assets)		0.009	0.001	0.008**
		(0.008)	(0.001)	(0.004)
Equity (%)		0.315	0.233	0.198*
		(0.237)	(0.156)	(0.116)
Constant	-0.029**	-0.031**	-0.030**	-0.015**
	(0.013)	(0.016)	(0.015)	(0.006)
Firm FE	No	No	Yes	Yes

Figure 1
This figure is a visual representation of a simulated interbank network based on the German interbank market. For the pre-crisis period from 2005:Q1 to 2007:Q2, the simulated data matches the total number of core banks (blue circles), periphery lenders (green circles), and periphery borrowers (yellow circles) to the German interbank data. It also matches the average number of links formed by borrowing and lending banks in the periphery with intermediary banks. Each big circle represents one core bank, and each smaller circle represents 8 to 10 periphery banks. In Panel (b), the purple circles represent intermediary banks with direct exposure to the Great Financial Crisis, and the red circles represent borrowing banks that were indirectly exposed through their connected intermediary banks.

(a) Pre-crisis



(b) Post-crisis

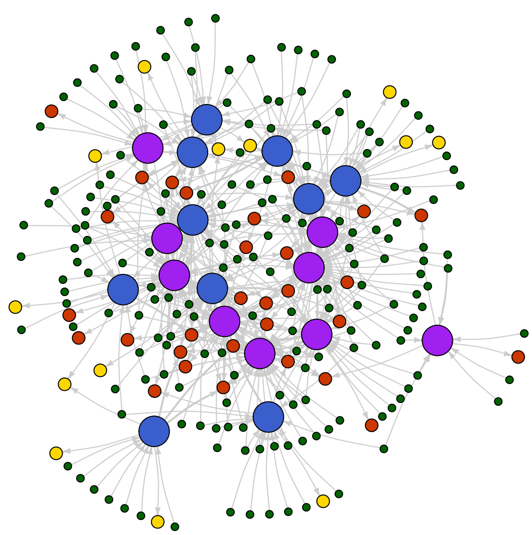


Figure 2
This figure reports the bank-level persistence of interbank loans. It shows the percentage of net lenders (net borrowers) that lend (borrow) in each quarter.

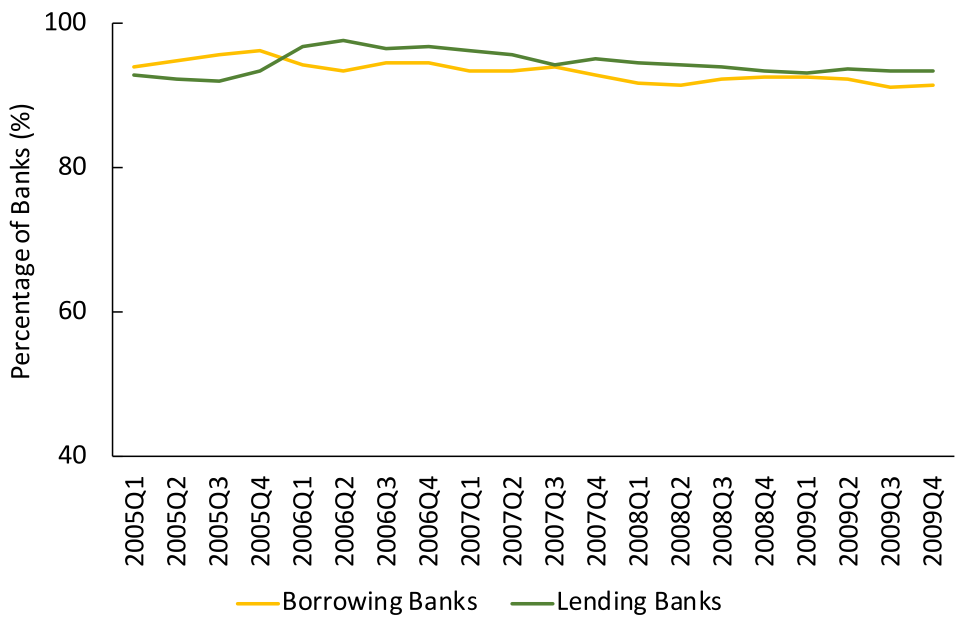


Figure 3
This figure reports the distribution of domestic interbank loans by maturity bracket. It is calculated by first collapsing to the time-series average for each periphery bank from 2005:Q1 to 2009:Q4 and then taking the average over the cross-section of banks.

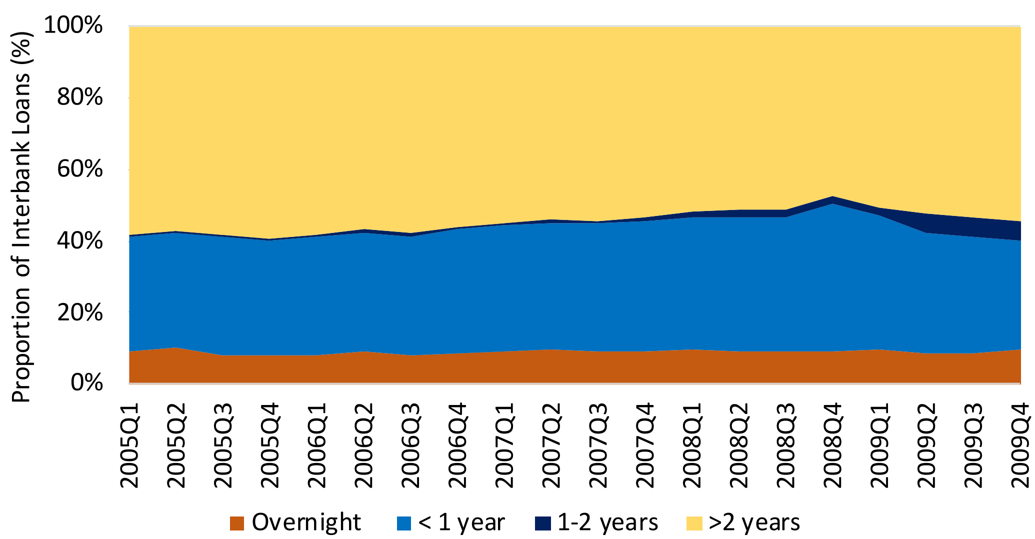


Figure 4
This figure reports quartiles of the net volume of interbank loans for net borrowing and net lending banks. Within net borrowers (lenders), quartiles are defined by ranking banks in increasing order of their average net volume borrowed (lent) from 2005:Q1 to 2007:Q2.

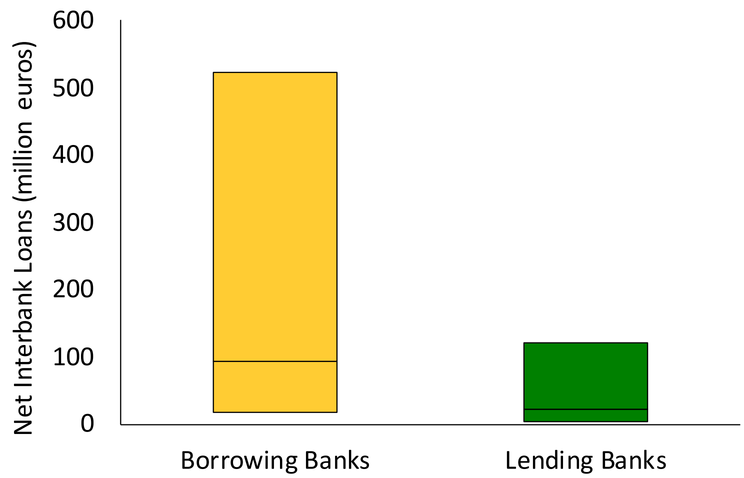


Figure 5
This figure reports, by quartiles, interbank liabilities and assets of core banks, periphery borrowers, and periphery lenders. The green and yellow bars represent the proportion of interbank assets and liabilities as a percentage of total assets, respectively. Within each category, quartiles are defined by ranking banks in increasing order of their average intermediated volume from 2005:Q1 to 2007:Q2, where intermediated volume is defined as the overlap between interbank assets and liabilities.

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

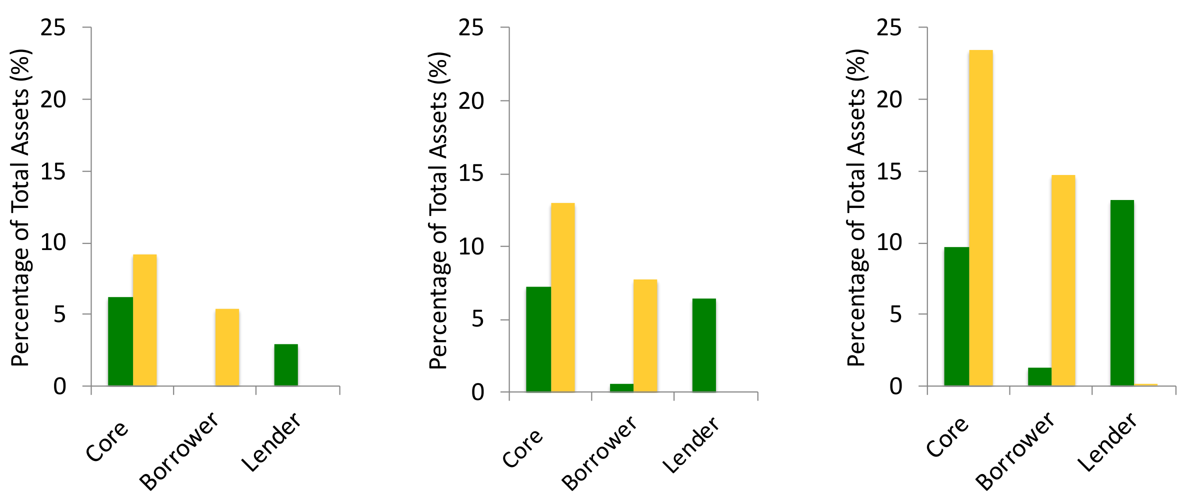


Figure 6
This figure depicts a reshaped version of the simulated interbank network in Figure 1. We match the total number of core banks (blue circles), periphery lenders (green circles), and periphery borrowers (yellow circles) to the corresponding numbers in the German interbank market. We also match the average number of links formed between borrowing and lending banks in the periphery with intermediary banks. Each big circle represents one intermediary bank, and each smaller circle represents 8 to 10 periphery banks.

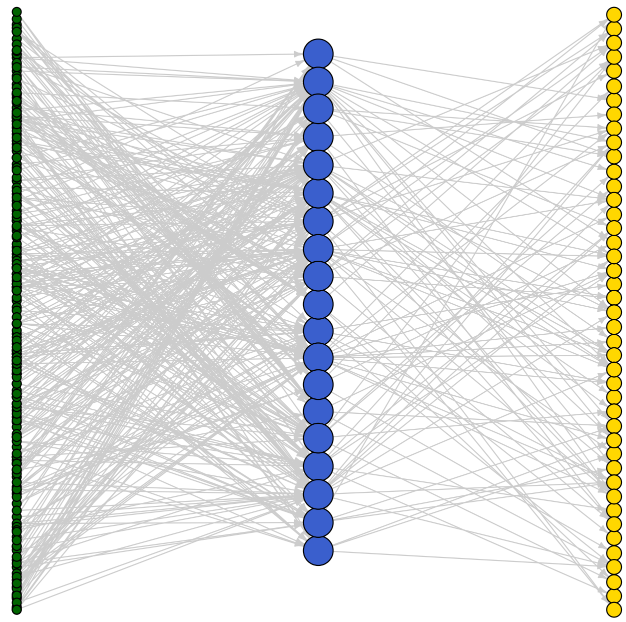


Figure 7
Example I

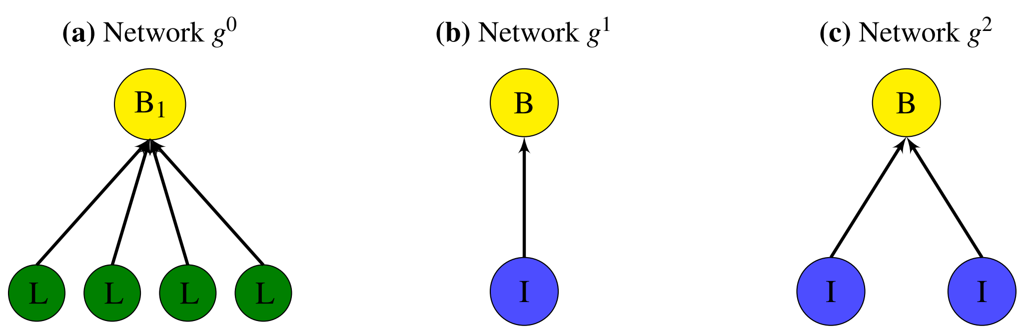


Figure 8
Example II

(a) Network g^2 with Borrower B_1 **(b)** Network g^1 with Borrower B_2

Figure 9
Example III

(a) Network g^2 with Intermediaries I_1 **(b)** Network g^1 with Intermediaries I_2

Figure 10

This is a binned scatter plot of the number of new links formed by borrowing banks against model-implied changes in their funding costs (bps) in the baseline model. It is obtained by first sorting borrowing banks into 44 bins according to their model-implied funding-cost change during the Great Financial Crisis. Each bin consists of about 10 borrowing banks. Then, the average number of new links formed is plotted against the change in funding costs for each bin.

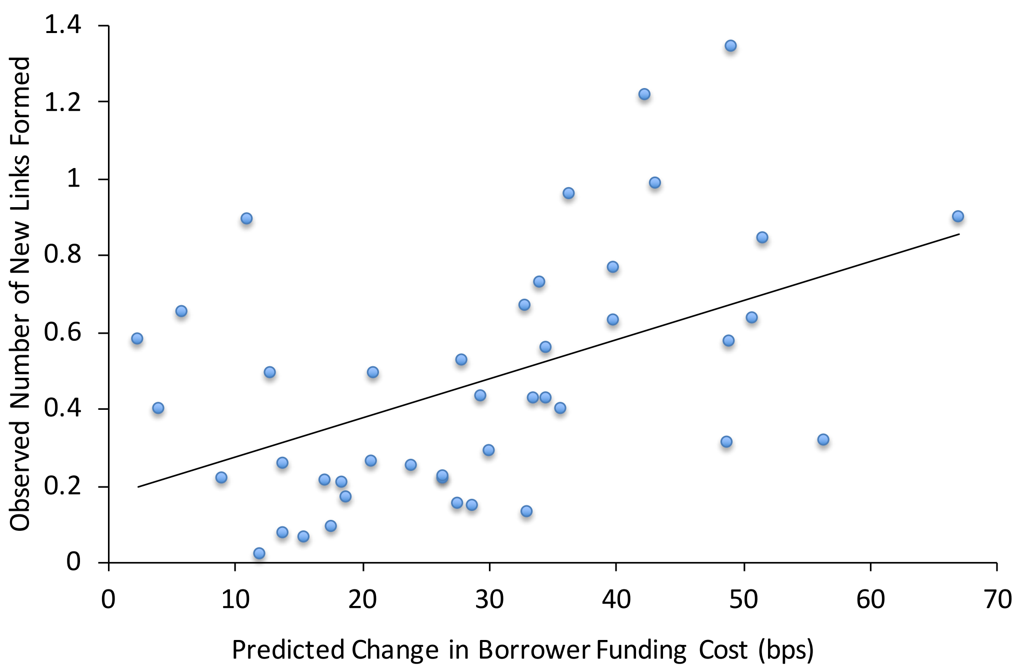


Figure 11

This is a binned plot of changes in firm loan supply against model-implied changes in borrowers' funding costs in the baseline model. It is obtained by first sorting borrowing banks into 44 bins according to their model-implied funding-cost change from the Great Financial Crisis. Each bin comprises 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, we plot the effective change in firm loan supply against the average change in funding cost for each bin.

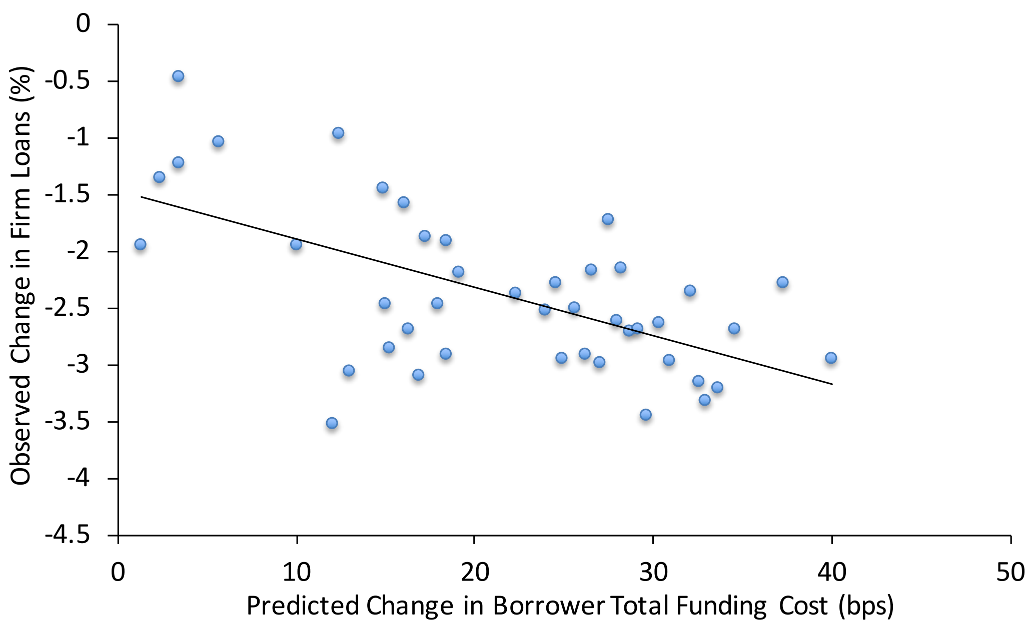


Figure 12
This figure reports the effect of a hypothetical 50 bps increase in a given intermediary's funding costs on the volume of interbank loans. Q1, Q2, and Q3 correspond to results for the first-, second-, and third-quartile intermediary bank ranked in increasing order of their intermediated loan volume. >Q3 indicates the average for intermediaries above the third quartile. The dark bar corresponds to the loan volume contraction from the intermediary's own balance sheet, whereas the light bar corresponds to that of its dependent borrowing banks. Estimates are based on the pre-crisis network and pre-crisis interbank loan volumes.

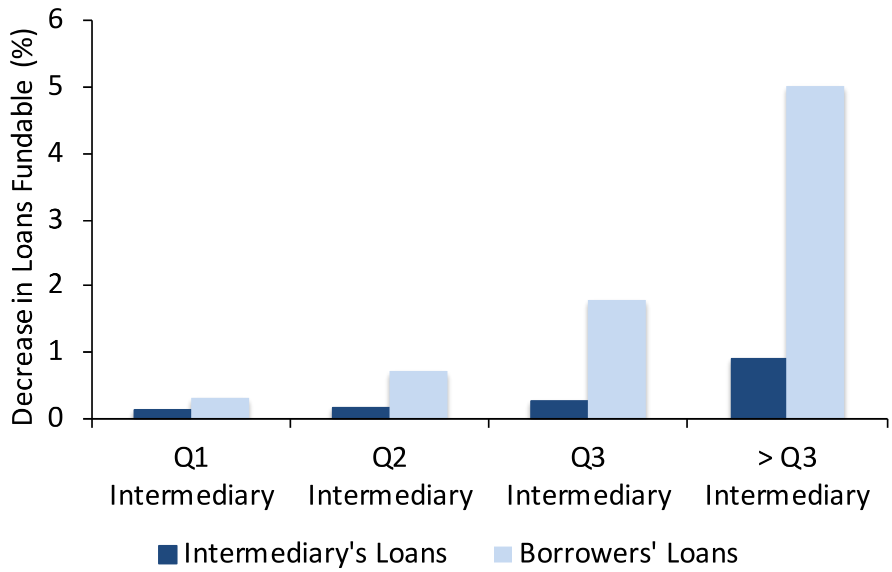


Figure 13
This figure reports the effect of a hypothetical 50 bps increase in a given intermediary's funding costs on the volume of interbank funding for borrowing banks of different connectivity. Q1, Q2, and Q3 correspond to borrowing banks connected to the first-, second-, and third-quartile intermediary ranked in increasing order of their intermediated loan volume. >Q3 corresponds to borrowing banks connected to intermediaries above the third quartile. Borrowing banks in each group are divided by the number of links they form with an intermediary bank. Estimates are based on the pre-crisis network and pre-crisis interbank loan volumes.

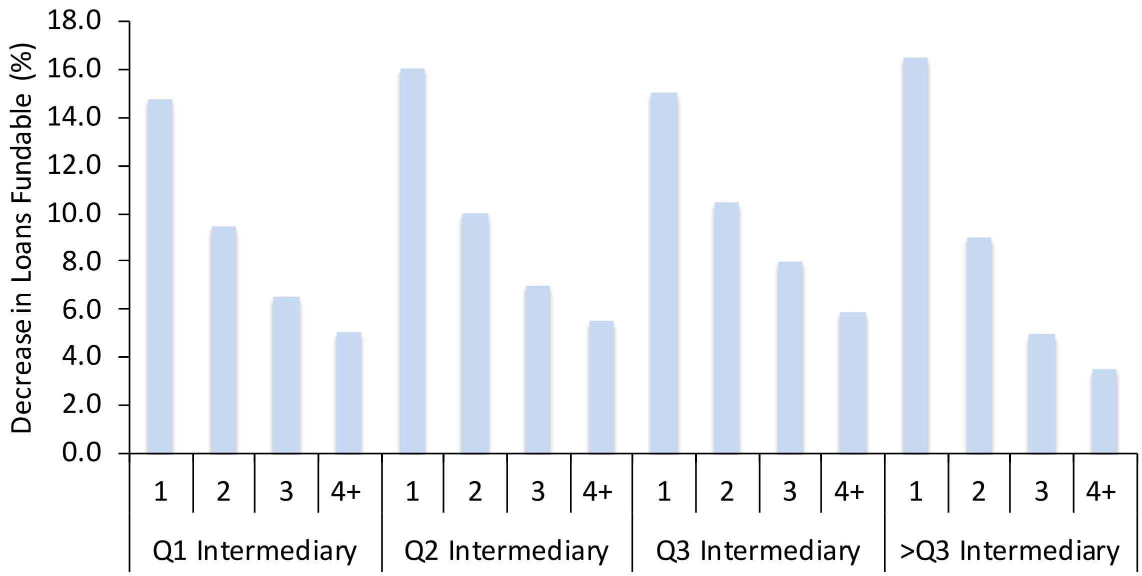
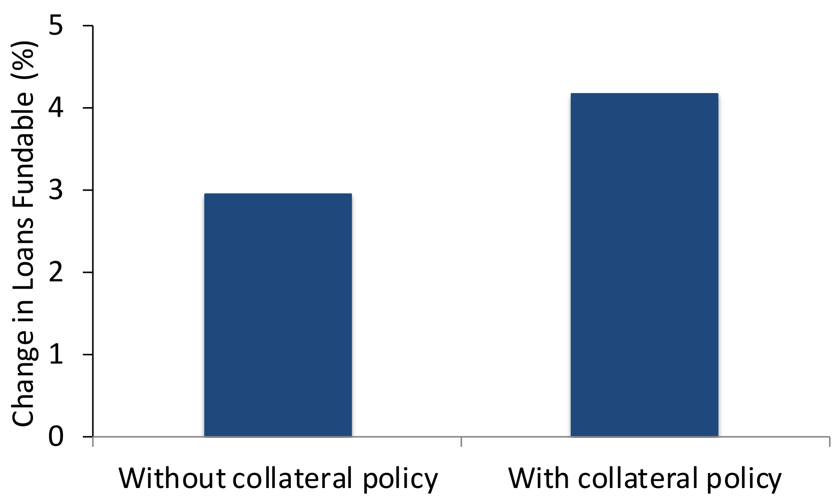


Figure 14
This figure reports the effect of a hypothetical accommodative ECB funding policy on loan supply. The left bar shows the effect of a 50 bps decrease in the ECB funding rate. The right bar shows the combined effect with a 25% increase in allotment volume or collateral availability. Estimates are based on the pre-crisis network and pre-crisis interbank loan volumes.



Appendix

A. Example

In this Appendix, we provide a step-by-step solution of the bargaining outcome of networks g^1 and g^2 as stated in Eqs. (7) and (8). Recall that borrowing bank b is connected to one intermediary in network g^1 (Fig. 7(b)) and two intermediaries in network g^2 (Fig. 7(c)). In network g^0 (Fig. 7(a)), the borrowing bank is not connected to any intermediary and relies on direct lending. Due to equal bargaining power, we consider the borrowing bank's utility without loss of generality.

When the borrowing bank bargains with its only connected intermdiary i in g^1, we have:

$$U_b(g^1) - U_b(g^0) = U_i(g^1) - U_i(g^0). \tag{A.1}$$

$U_b(g^0)$ is the utility of borrower b when bargaining with i breaks down and b is no longer connected to any other intermediary, as in g^0. In that case, it resorts to direct borrowing from $\lceil \frac{V_b}{L} \rceil$ lending banks with cost $k\delta_b$. Given equal bargaining power between the borrowing bank and the lending banks, the borrowing bank b would obtain half of its expected return, $E[x_b]$, minus the risk-free rate and incur half of the monitoring costs. That is,

$$U_b(g^0) = \frac{1}{2} V_b\big(E[x_b] - r\big) - \frac{1}{2} \lceil \frac{V_b}{L} \rceil k\delta_b. \tag{A.2}$$

Similarly, $U_i(g^0)$ is the utility of intermediary i when bargaining with b breaks down and i is no longer connected to any other borrower, as in g^0. In that case, intermediary i funds its own interbank loan volume, V_i, with expected return, $E[x_i]$, and pays the risk-free rate and expected state verification costs. That is,

$$U_i(g^0) = V_i\big(E[x_i] - r - \lambda_i(g^0, c)\big). \tag{A.3}$$

Now, under g^1, both the borrower and the intermediary can fund their projects at the expected (per-unit) state verification cost, $\lambda_i(g^1, c)$. Hence, their combined surplus is:

$$U_b(g^1) + U_i(g^1) = V_b\big(E[x_b] - r - \lambda_i(g^1, c)\big) + V_i\big(E[x_i] - r - \lambda_i(g^1, c)\big). \tag{A.4}$$

Note that monitoring costs are not part of the surplus because they have been incurred at $t = 0$ before bargaining takes place.

Substituting Eqs. (A.2) and (A.3) into Eq. (A.1), we have:

$$U_b(g^1) - U_i(g^1) = \underline{W}_b - V_i\big(E[x_i] - r - \lambda_i(g^0, c)\big), \tag{A.5}$$

where we used $\underline{W}_b$ to denote $U_b(g^0)$.

Then, adding Eqs. (A.4) and (A.5), we have:

$$U_b(g^1) = \frac{1}{2}V_b\big(E[x_b] - r - \lambda_i(g^1, c)\big) + \frac{1}{2}V_i\big(\lambda_i(g^0, c) - \lambda_i(g^1, c)\big) + \frac{1}{2}\underline{W}_b, \tag{A.6}$$

which is the same as in Eq. (7) of the main text.

We can obtain $U_b(g^2)$ in a similar way. Notice that in g^2, there are two symmetric intermediaries $i = 1, 2$ connected to borrower b. When the borrowing bank bargains with any one intermdiary in g^2, we have:

$$U_b(g^2) - U_b(g^1) = U_i(g^2) - U_i(g^0), \tag{A.7}$$

where the borrower's utility when bargaining breaks down is $U_b(g^1)$, as in Eq. (A.6), and the utility for the intermediary that bargains is just its stand-alone value without any connected borrowers as in Eq. (A.3). Hence, substituting Eqs. (A.3) and (A.6) into Eq. (A.7), we have:

$$U_b(g^2) - U_i(g^2) = \frac{1}{2}V_b\big(E[x_b] - r - \lambda_i(g^1, c)\big) + \frac{1}{2}V_i\big(\lambda_i(g^0, c) - \lambda_i(g^1, c)\big) + \frac{1}{2}\underline{W}_b - V_i\big(E[x_i] - r - \lambda_i(g^0, c)\big). \tag{A.8}$$

At the same time, the borrower and the two intermediaries fund their projects at the expected (per unit) state verification cost, $\lambda_i(g^2, c)$. Hence, given symmetric intermediaries, the combined surplus is:

$$U_b(g^2) + 2U_i(g^2) = V_b\big(E[x_b] - r - \lambda_i(g^2, c)\big) + 2V_i\big(E[x_i] - r - \lambda_i(g^2, c)\big). \tag{A.9}$$

Solving Eqs. (A.8) and (A.9) for $U_b(g^2)$, we have:

$$U_b(g^2) = \frac{2}{3}V_b\big(E[x_b] - r\big) - \frac{1}{3}V_b(\lambda_i(g^1, c) + \lambda_i(g^2, c)) - V_i\Big(\frac{2}{3}\lambda_i(g^2, c) + \frac{1}{3}\lambda_i(g^1, c) - \lambda_i(g^0, c)\Big) + \frac{1}{3}\underline{W}_b, \tag{A.10}$$

which is the same as Eq. (8) in the main text.

B. Proofs

B.1. *Proof of Proposition I*

Proof. Applying Myerson (1980), we verify the sufficient condition that bargaining payoffs given by Eqs. (5) and (6) are part of a payoff structure over all subsets that induce balanced contribution and efficiency.[24] That is,

$$\psi_j(v_g,S)-\psi_j(v_g,S-q)=\psi_q(v_g,S)-\psi_q(v_g,S-j) \qquad \forall S\subseteq\mathbb{N},\forall j\in S,\forall q\in S, \tag{B.1}$$

and

$$\sum_{j\in S}\psi_j(v_g,S)=v_g(S) \qquad \forall S\subseteq\mathbb{N}, \tag{B.2}$$

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 show that for any $j\in S$, letting

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

Eq. (B.1) is satisfied. If the two equalities above hold, Eq. (B.2) follows trivially from the specification of utilities in Eq. (6) and the characteristic function $v_g(S)$.

The case in which 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 finance only 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, $\forall q\in S$, Eq. (B.1) 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

[24] Alternatively, we could have also shown that the bargaining payoffs given by Eqs. (5) and (6) correspond to the first difference of the potential function P proposed by Hart and Mas-Colell (1989).

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 Eq. (5) maintains that $U_i(g^S) - U_i(g^S - \{i,b\}) = U_b(g^S) - U_b(g^S - \{i,b\})$, Eq. (B.1) 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, or (iii) one borrower and one non-connected intermediary. We 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 Eq. (5), we can write 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:

$$U_b(g^S) - U_b(g^S - ... - \{i^c_M, b\}) = \Omega_b(g^S). \tag{B.3}$$

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:

$$U_b(g^{S-b'}) - U_b(g^{S-b'} - ... - \{i^c_M, b\}) = \Omega_b(g^{S-b'}). \tag{B.4}$$

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 Eq. (B.4) from Eq. (B.3) yields:

$$U_b(g^S) - U_b(g^{S-b'}) = \Omega_b(g^S) - \Omega_b(g^{S-b'}). \tag{B.5}$$

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

$$U_{b'}(g^S) - U_{b'}(g^{S-b}) = \Omega_{b'}(g^S) - \Omega_{b'}(g^{S-b}). \tag{B.6}$$

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 Eq. (5), we can write 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:

$$U_i(g^S) - U_i(g^S - ... - \{i, b^c_W\}) = \Omega_i(g^S). \tag{B.7}$$

Similarly,

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

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

$$U_i(g^{S-i'}) - U_i(g^{S-i'} - ... - \{i, b_W^c\}) = \Omega_i(g^{S-i'}). \tag{B.8}$$

Since intermediary banks not connected to any common borrowing banks do not affect each other's payff, $U_i(g^{S-i'} - ... - \{i, b_W^c\}) = U_i(g^S - ... - \{i, b_W^c\})$. Hence, deducting Eq. (B.8) from Eq. (B.7) yields:

$$U_i(g^S) - U_i(g^{S-i'}) = \Omega_i(g^S) - \Omega_i(g^{S-i'}). \tag{B.9}$$

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

$$U_{i'}(g^S) - U_{i'}(g^{S-i'}) = \Omega_{i'}(g^S) - \Omega_{i'}(g^{S-i'}). \tag{B.10}$$

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

Based on Eq. (5), we can write the conditions for bargaining between intermediary i and its borrowers in $\mathbb{B}^{c'}$ as:

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

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

$$U_i(g^S) - U_i(g^S - ... - \{i, b_W^{c'}\}) = \Omega_i'(g^S). \tag{B.11}$$

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:

$$U_i(g^{S-b}) - U_i(g^{S-b} - ... - \{i, b_W^{c'}\}) = \Omega_i'(g^{S-b}). \tag{B.12}$$

When an intermediary i is not connected to any borrowing banks that connect to other intermediaries to which a given borrowing bank is connected, 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 Eq. (B.12) from Eq. (B.11) yields:

$$U_i(g^S) - U_i(g^{S-b}) = \Omega_i'(g^S) - \Omega_i'(g^{S-b}). \tag{B.13}$$

Next, we again apply Eq. (5) 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:

$$U_b(g^S) - U_b(g^S - ... - \{i_M^{c'}, b\}) = \Omega_b'(g^S). \tag{B.14}$$

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:

$$U_b(g^{S-i}) - U_b(g^{S-i} - ... - \{i_M^{c'}, b\}) = \Omega_b'(g^{S-i}). \tag{B.15}$$

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 Eq. (B.15) from Eq. (B.14) yields:

$$U_b(g^S) - U_b(g^{S-i}) = \Omega_b'(g^S) - \Omega_b'(g^{S-i}). \tag{B.16}$$

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 $\mathbb{B}^{c'}$. We can then 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.

□

C. Core and 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 a standard procedure in the literature and has been adopted in a number of papers (e.g., Gabrieli and Georg, 2014; in't Veld and van Lelyveld, 2014; Fricke and Lux, 2015).

In our context, the model tries to fit banks into two distinct subsets based on their network position—a core and a periphery. Ideally, the core comprises a subset of banks that are linked among themselves, and the periphery represents the remaining banks that connect to the core banks but not with each other. This structure can be seen as a generalization of the star network, in which a single bank in the center of the network connects all other banks that are not connected to each other.

To represent the interbank network, we can form a square matrix of dimensions equal to the number of banks. 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, where connections between cores are represented by a region containing only ones, (CC), whereas connections between periphery banks are represented by a region with only zeros, (PP). Off-diagonal regions in the matrix are represented by a row-regular and column-regular matrix, respectively. That is,

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

To identify the core and periphery in the data, Craig and Von Peter (2014) derive an optimization technique to find the partition that most resembles M. They first define a measure of the 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 determined as follows:

$$e(G) = \frac{E_{cc} + E_{pp} + (E_{cp} + E_{pc})}{\text{Number of Links}}, \tag{C.2}$$

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 in the core more than 50% of the time in both the pre- and post-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 high persistence in the network structure.

D. Estimation of the extension model

In this section, we extend the baseline model by allowing banks to optimize 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 richer counterfactuals.

D.1. Endogenous loan volume

In the baseline model, we assume that banks generate a fixed funding need from their interaction with the real economy, which they then seek to fulfill from the interbank market. We now relax this assumption by allowing banks to adjust the extensive margin of their interbank loans.

Let borrowing banks and intermediary banks face downward-sloping demand curves 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 also 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,

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

.

We use two conditions to pin down the bank-level demand parameters, α_1 and α_2. First, banks break even on the margin, so that funding volumes satisfy the following first-order condition:

$$\begin{cases} \left.\dfrac{\partial U_b(V,g)}{\partial V_b}\right|_{\substack{V=V^* \\ g=g^*}} = 0, \\ \left.\dfrac{\partial U_i(V,g)}{\partial V_i}\right|_{\substack{V=V^* \\ g=g^*}} = 0. \end{cases} \tag{D.1}$$

Second, the gross return on assets observed in the data map into the average return on assets in equilibrium:

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

D.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 ECB regularly conducts LTROs in which banks can borrow for a duration of three months against eligible collateral. We extend the model by allowing for the outside option of secured borrowing from the ECB.

In the wake of the European sovereign debt crisis, the ECB further introduced longer-term LTROs, broadened the scope of eligible collateral, and carried out asset purchase programs. These measures occur after our sample period, which focuses on the Great Financial Crisis. The ECB also conducts week-long liquidity-providing operations called the MRO. The MRO mainly affects short-term rates, which signal the monetary policy stance. Since it is not meant to provide longer-term refinancing for 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.

Specifically, we let borrowing and intermediary banks borrow from the ECB in $t = 2$ with probabilities P_b and P_i, respectively. Otherwise, they continue to borrow from the interbank market. 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. This scaling parameter also accounts for the fact that not all bids were honored given the fixed allotment quota. Thus, we parameterize $P = p\frac{ECBBorrowing}{TotalAssets}$.

The distribution of $\frac{ECBBorrowing}{TotalAssets}$ is displayed in Table D.1. We observe that the vast majority of borrowing and lending banks do not borrow from the ECB.[25] Intermediary banks borrow much more on average, which is likely because their business model requires more liquid assets that can also serve as collateral.

We use the 3-month repo rate provided by the European Money Market Institute to proxy for the cost of borrowing from the ECB because LTRO auction bids are not publicly avilable. Neverthless, the 3-month repo rate has been shown to closely track the LTRO rate (Linzert et al., 2004). The average rates for the pre- and post-crisis periods are 2.83% and 2.61%, respectively.

D.3. Estimation and results

Similar to the baseline model's estimation, we find the extension model parameters that maximize the maximum score estimator. Compared to the baseline case, 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 adjustments in funding volume given network contingent diversification. There is also an additional parameter p to capture the outside option of obtaining funding from the ECB. Specifically, the score function becomes:

$$\begin{aligned} Q(c,k,p) = \quad & \sum_{i\in\mathbb{I}} \sum_{b\in N_i(g^*)} \mathbb{1}\left[U_b(g^*,V^*,c,k,p) - U_b(g',V',c,k,p) - \frac{1}{2}k\delta_b \geq 0\right] \\ & + \sum_{i\in\mathbb{I}} \sum_{b\notin N_i(g^*)} \mathbb{1}\left[U_b(g'',V'',c,k,p) - U_b(g^*,V^*,c,k,p) - \frac{1}{2}k\delta_b < 0\right]. \end{aligned}$$

The estimation results are shown in Table D.2. Compared to the baseline model results, both the monitoring cost parameter, k, and the state verification parameter, C, slightly increased in magnitude. On the one hand, new links provide the additional gain of increasing funding volume. On the other hand, the ECB's funding provision lowers the average funding cost for intermediaries. The benefits from interbank lending relationships are therefore higher relative to the baseline model's. 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.

We verify the extension model's parameter estimates with data from the post-crisis period. Compared to the baseline model's, the accuracy of the out-of-sample prediction is slightly im-

[25] Borrowing from the ECB increased in later years during the European sovereign debt crisis, which is not part of our sample period.

proved for all three correlation cases. As shown in Table D.3, the percentage of correct predictions is between 86.8% and 89.0% compared to the previous 85.0% to 86.2%.

Table D.1
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- and post-crisis periods. Values are in percentages.

	Pre-crisis				Post-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 D.2
Estimation Results (Extension Model). This table reports results from the maximum score estimation of the extension model. k represents the monitoring cost technology parameter for each link between intermediaries and borrowing banks. C represents the state verification cost parameter for each link between intermediaries and the average lender. ρ is the correlation of returns across banks. The 95% confidence interval bounds, based on subsampling, are in parentheses. ** indicates that the 95% 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**
	$(0.650, 1.999)$	$(0.527, 2.218)$	$(0.353, 1.731)$
State Verification Cost C	0.286**	0.239**	0.279**
	$(0.057, 0.397)$	$(0.081, 0.388)$	$(0.066, 0.455)$
ECB Funding p	5.590**	6.053**	6.897**
	$(3.112, 8.781)$	$(3.477, 8.913)$	$(2.678, 9.015)$
Inequalities Satisfied (%)	91.8	90.9	89.5
Number of Inequalities		8,265	

Table D.3

Percentage of Correctly Predicted Inequalities (Extension). This table reports the percentage of correctly predicted inequalities in the out-of-sample test of the Great 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

Internet Appendix

A. Computation and estimation

This Internet Appendix presents a step-by-step guide to estimating our structural model. It is divided into three main sections. First, we outline the preparation of the input data for our analysis in Section A.1. Then, we walk through the Shapley value calculation given any network in Section A.2. Finally, in Section A.3, we explain the estimation of our parameters using the maximum score estimator, which compares the Shapley values and monitoring costs in the observed network, g^*, against the Shapley values and monitoring costs for all one-link deviations from the observed network, i.e., $g' = g^* - \{i,b\}$ and $g'' = g^* + \{i,b\}$. The three sections can be followed to complete our estimation procedure. Individual steps may also serve as a guide for applications to other contexts. For example, Section A.3 can be applied for structural models using the maximum score estimator in general.

A.1. Data preparation

A.1.1. Network data

We start with a sample of quarterly bilateral loan volumes (stock) between all banks consolidated at the banking-group level. We obtain the average bilateral volumes from 2005:Q1 to 2007:Q2 for the pre-crisis period and the average bilateral volumes from 2007:Q3 to 2009:Q4 for the post-crisis period. We further sum the bilateral loan volumes at the bank level to classify them into interbank lenders and interbank borrowers. At the same time, the core-periphery selection procedure detailed in Appendix C sorts banks into a set of core and periphery banks. We denote banks in the core as intermediary banks, and those in the periphery as either periphery lenders or periphery borrowers.

Our model focuses on the detailed network structure between borrowing banks and intermediary banks. Intermediary banks' interbank funding volumes, V_i, are obtained by deducting the total interbank lending volume from the total interbank borrowing volume for intermediary i. We denote the observed bilateral volumes between intermediary bank i and borrowing banks b as $V_b^i(g^*)$, where g^* is the observed network. To simplify the analysis, we drop links in which borrowing banks are lending to intermediaries. In our sample, this procedure removes 4.1% of the total loans between intermediary banks and periphery borrowers. When $V_b^i(g^*) > 0$, we have $\{i,g\} \in g^*$, $i \in N_b(g^*)$, and $b \in N_i(g^*)$, where $N_b(g^*)$ denotes the set of intermediaries connected to borrower

b under network g^* and $N_i(g^*)$ denotes the set of borrowers connected to intermediary i under network g^*.

For lending banks, we obtain L as the average bank-level lending volume of all lending banks in the system.

A.1.2. Other data

We extract a number of variables from monthly bank balance sheets. Regarding the distribution of returns, we obtain the time-series sample mean, μ_b (μ_i), and sample standard deviation, σ_b (σ_i), of gross returns over assets for borrowing banks (intermediary banks). We exclude returns and assets from other banks (MFIs) as part of our calculation. For intermediary banks, we further record their nonbank assets as A_i.

We multiply the ratio of firm loans by the asset size to obtain δ_b and δ_i for borrowing and intermediary banks. As described in the text, δ_b and δ_i allow us to parameterize the monitoring and state verification cost parameters to reflect that larger and more opaque banks are more costly to monitor.

For the outside option rate, r, we use the average 2-year German bund yield.

A.2. Shapley value computation

In this section, we derive Shapley values given a network. We first set up the calculation of an intermediary's portfolio return, y_i, and the intermediary's state verification cost, $\lambda_i(g,c)$. Then, we go over the characteristic function, $v_g(S)$, which indicates the total value created by a set of banks in $S \subseteq \mathbb{N}$. The average contribution of a given bank is then obtained as its Shapley value. Finally, we provide a simple example as a demonstration.

A.2.1. Portfolio return y_i

From Eq. (1), we can write the distribution of an intermediary i's portfolio, which is the weighted average of the intermediary's own portfolio return and that of its connected borrowers under network g, as:

$$y_i = \frac{1}{A_i + \sum_{b \in N_i(g)} V_b^i(g)} (A_i x_i + \sum_{b \in N_i(g)} V_b^i(g) x_b) \equiv w_i^i(g) x_i + \sum_{b \in N_i(g)} w_i^b(g) x_b \equiv \mathbf{w_i}(\mathbf{g})' \mathbf{x}. \qquad \text{(A.1)}$$

Assuming that every borrower's return, x_b, and the intermediary's nonbank portfolio return, x_i, are jointly normally distributed with a common correlation parameter, ρ, we obtain the distribution of y_i as a normal distribution with mean $\mu_i^g = \mathbf{w_i}(\mathbf{g})'\mu$ and standard deviation $\sigma_i^g = \sqrt{\mathbf{w_i}(\mathbf{g})'\Sigma\mathbf{w_i}(\mathbf{g})}$, where:

$$\mu = \begin{bmatrix} \mu_i \\ \mu_1 \\ \ldots \\ \mu_b \\ \ldots \end{bmatrix} \text{ and } \Sigma = \begin{bmatrix} \sigma_i^2 & \rho\sigma_i\sigma_1 & \ldots & \rho\sigma_i\sigma_n \\ \rho\sigma_i\sigma_1 & \sigma_1^2 & \ldots & \rho\sigma_1\sigma_n \\ \ldots & \ldots & \ldots & \ldots \\ \rho\sigma_i\sigma_n & \rho\sigma_1\sigma_n & \ldots & \sigma_n^2 \end{bmatrix}.$$

All elements in μ and Σ are obtained from the data, except for the correlation parameter, ρ. In the data, we find the average time-series correlation to be 0.22. 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, which is between 0.12 and 0.24. Specifically, we repeat our analysis with the asset correlation parameter equal to 0.12, 0.18, and 0.24, respectively.

For the observed network, g^*, elements in $\mathbf{w_i}(\mathbf{g})$ can also be directly taken from the data, where:

$$w_i^i(g^*) = \frac{A_i}{A_i + \sum_{b \in N_i(g^*)} V_b^i(g^*)}, \tag{A.2}$$

$$w_i^b(g^*) = \frac{V_b^i(g^*)}{A_i + \sum_{b \in N_i(g^*)} V_b^i(g^*)}. \tag{A.3}$$

When a given network deviates from the observed network, g^*, the same equations apply but with $V_b^i(g^*)$ replaced by $V_b^i(g)$. We explain how $V_b^i(g)$ is determined in Section A.2.2.

A.2.2. State verification cost $\lambda_i(g,c)$

Based on the distribution of y_i, we can determine how each of the intermediary's funding costs depends on the network, g, and state verification parameter, c. Recall from Section 3.2 in the main text that the expected state verification cost for an intermediary bank i under a given network g is $\lambda_i(g,c) = \int_{\underline{R}}^{R_i(g)} c\delta_i \, dH(y_i)$, where:

$$\underbrace{\int_{\underline{R}}^{R_i(g)} c\delta_i \, dH(y_i)}_{\text{Expected State Verification Cost}} + r = \underbrace{\int_{\underline{R}}^{R_i(g)} y_i \, dH(y_i) + \int_{R_i(g)}^{\overline{R}} R_i(g) \, dH(y_i)}_{\text{Expected Return of Debt Contract}}.$$

Equivalently, we can write:

$$c\delta_i\Phi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})+r=\mu_i^g\Phi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})-\sigma_i^g\varphi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})+R_i(g)\left\{1-\Phi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})\right\}, \tag{A.4}$$

where φ and Φ are the PDF and CDF of the standard normal distribution, respectively.

The goal is to obtain $c\delta_i\Phi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})$ as a function of c. μ_i^g and σ_i^g can be directly calculated from the data given network g, as shown in the previous section. However, according to Eq. (A.4), $R_i(g)$ is a nonlinear function of g, μ_i^g, σ_i^g, δ_i, and c, which is the parameter to be estimated. For ease of computing Shapley values, we approximate $\Phi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})$ using a first-order Taylor expansion in c for a given network g. That is,

$$\lambda_i(g,c)=c\delta_i\Phi(\frac{R_i(g)-\mu_i^g}{\sigma_i^g})=\tau_{0i}(g)c+\tau_{1i}(g)c^2.$$

We check that our first-order Taylor expansion is an accurate approximation for a grid of μ_i^g, σ_i^g, and $R_i(g)$. If closer estimates are required, Taylor expansions of higher orders or iterative methods may be used.

A.2.3. Characteristic function

We next derive the characteristic function, v_g, in terms of the parameters c and k. Recall that the characteristic function assigns a payoff $v_g(S)$ for a subset of banks $S\subseteq\mathbb{N}$ under network g:

$$v_g(S)=\underbrace{\sum_{i\in S}V_i\big[E[x_i]-r-\lambda_i(g^S,c)\big]}_{\text{Value - Funding Cost of Intermediaries}}+\underbrace{\sum_{b\in S}\sum_{i\in S}V_b^i(g^S)\big[E[x_b]-r]-\lambda_i(g^S,c)\big]}_{\text{Value - Funding Cost of Connected Borrowers}}+\sum_{b\in S,N_b(g)\cap S=\emptyset}\underline{W}_b, \tag{A.5}$$

where $\underline{W}_b=V_b(g)\big(E[x_b]-r\big)-\lceil\frac{V_b}{L}\rceil k\delta_b$ is the value of stand-alone borrowers.

For a given network g and a subset of banks S, $v_g(S)$ calculates the total value generated by the banks in S from the links with other banks in S. Values generated by links in g wherein one or both counterparties are not part of S are not included. Hence, the first step after selecting a subset of banks S is to find the new network of links within the subset, g^S, where $\{i,b\}\in g^S$ if $i\in S$, $b\in S$, and $\{i,b\}\in g$.

Then, we calculate the bilateral volumes, $V_b^i(g^S)$, associated with g^S. When all banks are selected, then the bilateral volumes are simply the ones observed in the data, i.e., $V_b^i(g^S)=V_b^i(g^*)$. Otherwise, because of the bargaining described in Section 3.3 of the main text, a borrowing bank's funding volume, V_b, is proportionately redistributed to its existing links in g^S:

$$V_b^i(g^S) = V_b \frac{V_b^i(g^*)}{\sum_{i \in S} V_b^i(g^*)} \;\; \forall i \in S, \tag{A.6}$$

where $\frac{V_b^i(g^*)}{\sum_{i \in S} V_b^i(g^*)}$ is the proportion of loans in link $\{i, b\}$ when only intermediaries in S are selected. When all intermediaries are selected, $\sum_{i \in S} V_b^i(g^*) = V_b$ and $V_b^i(g^S) = V_b^i(g^*)$.

The bilateral volumes, $V_b^i(g^S)$, are used to obtain the volume of loans in Eq. (A.5). We also use the bilateral volumes to calculate an intermediary's funding cost, $\lambda_i(g^S, c)$, in Eq. (A.5). Thus, Eqs. (A.2) and (A.3) under network g^S are:

$$w_i^i(g^S) = \frac{A_i}{A_i + \sum\limits_{b \in N_i(g^*)} V_b^i(g^S)}, \tag{A.7}$$

$$w_i^b(g^S) = \frac{V_b^i(g^S)}{A_i + \sum\limits_{b \in N_i(g^*)} V_b^i(g^S)}. \tag{A.8}$$

The remaining inputs for $v(S)$ are V_i, $E[x_i] = \mu_i$, $E[x_b] = \mu_b$, r, L, δ_b, and δ_i, all of which are directly obtained from the data.

A.2.4. Average over permutations

Finally, we calculate the Shapley values for borrowing and intermediary banks:

$$\begin{cases} U_b(g) = \phi_b(v_g) = \dfrac{1}{|\mathbb{N}|!} \sum\limits_R [v_g(P_b^R \cup \{b\}) - v_g(P_b^R)] \\ U_i(g) = \phi_i(v_g) = \dfrac{1}{|\mathbb{N}|!} \sum\limits_R [v_g(P_i^R \cup \{i\}) - v_g(P_i^R)], \end{cases} \tag{A.9}$$

where P_b^R (P_i^R) is the set of banks in $\mathbb{N}$ that precede b (i) in the order R.

Recall that the Shapley value for a bank is defined as the average value it contributes to the coalition (i.e., the set of banks in $\mathbb{N}$). To calculate Shapley values for borrowing bank b, we first arrange the banks in our sample into a given permutation, i.e., an order, R. Then, we locate bank b in that permutation and calculate the value of the characteristic function including and excluding bank b, which are $v_g(P_b^R \cup \{b\})$ and $v_g(P_b^R)$, respectively. The difference between $v_g(P_b^R \cup \{b\})$ and $v_g(P_b^R)$ is the value that bank b contributes to the coalition given the permutation we have chosen. We repeat the calculation by permutation and take their average to be the Shapley value for borrowing bank b. The same can be done for all borrowing banks in the sample. Notice that Shapley values are also defined for intermediary banks i. However, our maximum score estimation can be obtained based on the borrowing banks' utilities only because of the symmetric bargaining power between borrowing and intermediary banks. Hence, we need to keep track of only the borrowing banks' Shapley values.

Since the characteristic function, $v(S)$, is expressed as a linear function in k, c, c^2, and a constant, the Shapley values for banks in the observed network g^* are linear functions of the same parameters.

A.2.5. An example

We provide a simple example to demonstrate the calculation of Shapley values for a given network. We re-use the networks in Example I of the main text, where g^2 has one borrower, $b = 1$, connected to two identical intermediaries, $i = 1$ and $i = 2$, and g^1 has one borrower connected to only one intermediary.

We first obtain variables from the data. For ease of exposition, let the intermediaries be symmetric such that the means and variances of their project returns and their own interbank funding volumes are $\mu_2 = \mu_1 = \mu_i$, $\sigma_2 = \sigma_1 = \sigma_i$, and $V_1 = V_2 = V_i$, respectively. Also, let intermediaries' non-interbank asset size be $A_1 = A_2 = A_i$. Let the borrower's project be equally funded by the two intermediaries in equilibrium, i.e., $V_b^1(g^2) = V_b^2(g^2) = \frac{1}{2}V_b$, and let the project return have mean and variance of μ_b and σ_b^2, respectively. The variables δ_i, δ_b, and r are also taken from the data.

Second, to obtain $\lambda_i(g^2, c)$, we prepare the distribution of intermediaries' effective portfolio returns and the associated state verification costs. In the observed network g^2, we have:

$$\begin{aligned}
\mu_i^{g^2} &= w_i^b \mu_b + w_i^i \mu_i, \\
\sigma_i^{g^2} &= (w_i^i)^2 \sigma_i^2 + 2\rho w_i^i w_i^b \sigma_b \sigma_i + (w_i^b)^2 \sigma_b^2,
\end{aligned}$$

where:

$$\begin{aligned}
w_i^i &= \frac{A_i}{A_i + V_b^i(g^2)} = \frac{A_i}{A_i + 0.5V_b}, \\
w_i^b &= \frac{V_b^i(g^2)}{A_i + V_b^i(g^2)} = \frac{0.5V_b}{A_i + 0.5V_b}.
\end{aligned}$$

Third, we derive the characteristic functions. When S includes all three banks, we have:

$$v_g(\{B,I_1,I_2\}) = 2V_i\left[\mu_i - r - \lambda_i(g^2,c)\right] + V_b\left[\mu_b - r - \lambda_i(g^2,c)\right].$$

When S includes the borrowing bank and only one intermediary as in network g', the borrowing bank's volume would be redistributed to the included intermediary, such that:

$$\begin{aligned}
V_b^i(g^1) &= V_b\frac{V_b^i(g^2)}{V_b^i(g^2)} = V_b, \\
w_i^i &= \frac{A_i}{A_i + V_b^i(g^1)} = \frac{A_i}{A_i + V_b}, \\
w_i^b &= \frac{V_b^i(g^1)}{A_i + V_b^i(g^1)} = \frac{V_b}{A_i + V_b}.
\end{aligned}$$

Then, the characteristic function is:

$$v_g(\{B,I_1\}) = v_g(\{B,I_2\}) = V_i\left[\mu_i - r - \lambda_i(g^1,c)\right] + V_b\left[\mu_b - r - \lambda_i(g^1,c)\right].$$

When only the borrower is selected, it has to resort to its outside option of borrowing directly from lending banks as in network g^0:

$$v_g(\{B\}) = \underline{W}_b.$$

At the same time, when only intermediary banks are selected without the borrowing bank, the portfolio return of intermediaries is just their own project as in network g^0, i.e., $\mu_i^{g^0} = \mu_i$ and $\sigma_i^{g^0} = \sigma_i$:

$$\begin{aligned}
v_g(\{I_1,I_2\}) &= 2V_i\left[\mu_i - r - \lambda_i(g^0,c)\right], \\
v_g(\{I_1\}) = v_g(\{I_2\}) &= V_i\left[\mu_i - r - \lambda_i(g^0,c)\right].
\end{aligned}$$

Finally, we can calculate the borrowing bank's Shapley values as its average contribution. Although there are six permutations of the three banks, the two intermediary banks are symmetric, so that only the position of the borrowing bank matters in determining the contribution of the borrowing bank. Specifically, when the borrowing bank is the first in the order, R, i.e., (B,I_1,I_2) or (B,I_2,I_1), we have:

$$v_g(\{B\}) - v_g(\{\}) = \underline{W}_b - 0 = \underline{W}_b. \tag{A.10}$$

When the borrowing bank is in the second position, i.e., (I_1,B,I_2) or (I_2,B,I_1), we have:

$$\begin{aligned} v_g(\{I_1,B\})-v_g(\{I_1\}) &= V_i\big[\mu_i-r-\lambda_i(g^1,c)\big]+V_b\big[\mu_b-r-\lambda_i(g^1,c)\big]-V_i\big[\mu_i-r-\lambda_i(g^0,c)\big], \\ &= V_i\big[\lambda_i(g^0,c)-\lambda_i(g^1,c)\big]+V_b\big[\mu_b-r-\lambda_i(g^1,c)\big]. \qquad (A.11) \end{aligned}$$

Intuitively, the borrower contributes its own value, $V_b\big[\mu_b-r-\lambda_i(g^1,c)\big]$, and changes the funding cost for the intermediary from $V_i\lambda_i(g^0,c)$ to $V_i\lambda_i(g^1,c)$. The gross return of the intermediary, $V_i[\mu_i-r]$, is not part of the borrower's contribution because it was already present when the intermediary alone was part of the selected agents. Similarly, when the borrower is in the third position, i.e., (I_1,I_2,B) or (I_2,I_1,B), its contribution becomes:

$$v_g(\{I_1,I_2,B\})-v_g(\{I_1,I_2\}) = 2V_i\big[\lambda_i(g^0,c)-\lambda_i(g^2,c)\big]+V_b\big[\mu_b-r-\lambda_i(g^2,c)\big]. \qquad (A.12)$$

The borrower contributes its own value, $V_b\big[\mu_b-r-\lambda_i(g^2,c)\big]$, and changes the per-unit funding cost of both intermediaries from $\lambda_i(g^0,c)$ to $\lambda_i(g^2,c)$.

The Shapley value of the borrowing bank is then simply the average of Eqs. (A.10), (A.11), and (A.12):

$$\phi_b(v_g)=\frac{2}{3}V_b\big[\mu_b-r\big]-\frac{1}{3}V_b\big[\lambda(g^2,c)+\lambda(g^1,c)\big]-V_i\Big[\frac{2}{3}\lambda(g^2,c)+\frac{1}{3}\lambda(g^1,c)-\lambda(g^0,c)\Big]+\frac{1}{3}\underline{W}_b,$$

which is the same as we derived in Eq. (8) of the main text.

A.3. *Maximum score estimation*

In the previous section, we expressed Shapley values for borrowing banks in the observed network, g^*. In this section, we first set up inequality conditions by comparing Shapley values in the observed network against Shapley values in networks with one-link deviations. Then, we explain the optimization of the score function and the computation of standard errors.

A.3.1. Inequality conditions

After expressing Shapley values for borrowing banks in the observed network, g^*, we express their Shapley values under the alternative networks $g' = g^* - \{i,b\}$, where $\{i,b\} \in g^*$, and $g'' = g^* + \{i,b\}$, where $\{i,b\} \notin g^*$.

Specifically, for each borrowing bank b, we repeat the Shapley value calculation by removing its links from network g^* one link at a time. That is, $U_b(g') = \phi_b(v_{g'})$, where $g' = g^* - \{i,b\}$

and $\{i,b\} \in g^*$. Inputs to the Shapley value calculation remain the same except for a proportional redistribution of the borrowing bank's funding volumes to the remaining links as in Eq. (A.6):

$$V_b^i(g') = V_b(g^*) \frac{V_b^i(g^*)}{\sum_{i \in N_b(g')} V_b^i(g^*)} \ \forall i \in N_b(g'), \tag{A.13}$$

where $N_b(g')$ is the set of intermediaries connected to borrowing bank b under network g'. Then, for each new network g', we can write the pairwise stability condition:

$$U_b(g^*) - U_b(g') - \frac{1}{2}\delta_b k \geq 0. \tag{A.14}$$

Similarly, for each borrowing bank b, we repeat the Shapley value calculation by adding one new link at a time to the existing network. That is, $U_b(g'') = \phi_b(v_{g''})$, where $g'' = g^* + \{i,b\}$ and $\{i,b\} \notin g^*$. The borrowing bank's funding volumes are also proportionally redistributed to the new link. Then, for each new network g'' formed by adding a new link to g^*, we can write the pairwise stability condition:

$$U_b(g^*) - U_b(g'') - \frac{1}{2}\delta_b k < 0. \tag{A.15}$$

We collect all inequalities to set up the score function:

$$\begin{aligned} Q(c,k) = \quad & \sum_{i \in \mathbb{I}} \sum_{b \in N_i(g^*)} \mathbb{1}\left[U_b(g^*,c,k) - U_b(g',c,k) - \frac{1}{2}k\delta_b \geq 0\right] \\ & + \sum_{i \in \mathbb{I}} \sum_{b \notin N_i(g^*)} \mathbb{1}\left[U_b(g'',c,k) - U_b(g^*,c,k) - \frac{1}{2}k\delta_b < 0\right], \end{aligned}$$

which computes the number of inequality conditions satisfied under the observed network, g^*, and the unknown parameters, c and k. The first part comprises inequality conditions for all observed links, and the second part comprises those for unobserved links. Since Shapley values are a function of c, c^2, and k, the value of the score function is determined by a set of c and k under the observed network g^*.

A.3.2. Optimization

We use the differential evolution algorithm proposed by Storn and Price (1997) to find parameter estimates c and k that maximize the score function, $Q(c,k)$. In general, the score function is not continuous with respect to the estimated parameters, so that it only allows for set identification. However, we repeat the optimization 20 times with different initial populations and obtain the same value for the objective function and the same point estimates of the parameters up to three decimal figures. Following Fox (2008), we therefore assume the model to be point identified in the limit. The precision of the estimates in our case arises from the relatively large number of inequality conditions and the relatively small number of parameters.

The differential evolution algorithm is computationally efficient for a large network like ours and does not suffer from the curse of dimensionality as other maximum likelihood estimators do. The challenge lies in making sure that the estimated parameters are attained at the global optimum rather than at one of the local optima. To this end, we first plot the score function over a wide grid of c and k to narrow down the region over which to apply the differential evolution algorithm. This step is made possible by having only two parameters in the baseline model. The understanding of the score function behavior developed from the baseline model was also very helpful in informing the selection of the optimization region for the extension models. Hence, even for models with a larger number of parameters, we encourage examining the score function based on a low-dimensional set of parameters first to better assess whether the computed optimum is a global maximum.

Finally, we generate confidence intervals by drawing 100 random subsamples of a quarter of the full sample. This approach follows Politis and Romano (1994) and Delgado et al. (2001). 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^{th} and 97.5^{th} percentile of this empirical sampling distribution are used to compute the 95% confidence interval.

B. Additional results and robustness

B.1. Effect of secured loans on monitoring costs

The use of collateral in interbank loans could affect the structure and reduce the intensity of monitoring. We first show that secured loans make up a small fraction of the total interbank loans in Germany during our sample period. Then, we re-estimate the model by deducting projected volumes of secured loans from the total volume of interbank loans.

Using bank balance sheet data, we find that the proportion of secured domestic interbank loans over total domestic interbank loans fluctuates between 3% and 5% in our sample period. This is in line with the magnitudes of secured interbank borrowing cited in Upper and Worms (2004). The balance sheet variable used is domestic liabilities to banks arising from repurchase agreements. It covers all maturity buckets and is available at the individual bank level from 2010Q2 onwards. Because the credit registry does not contain collateral information, we use the earliest available bank-level secured interbank loan ratio from 2010Q2 to approximate the volume of unsecured interbank loans for each borrowing bank and project the same ratio across all its links. We re-estimate the model with the adjusted data to obtain the results in Table IA.B.1, which remain statistically significant and are economically very similar to those from the baseline specification in Table 3.

The pre-crisis estimates also do well in the out-of-sample test, correctly predicting between 84.3% and 85.8% of overall link changes in the Great Financial Crisis, as shown in Table IA.B.2.

B.2. Trading between intermediary banks

One component of core-periphery networks that we have not included in our model and estimation are the links between core banks, i.e., intermediary banks in our case. These links also exist in our data, but they seem to serve an important yet distinct purpose from the intermediation of persistent funding needs.

First, we back out the maturity structure of loans between intermediary banks from bank balance sheet data. Specifically, we deduct the volume of loans by maturity bucket for periphery banks from the totals of intermediary banks so that the remainder must have arisen from trading within intermediary banks.[26] We find that trading between intermediary banks is dominated by

[26]The implicit assumption here is that all interbank loans for periphery banks arise from trading with intermediary banks. We use bank balance sheet data to infer the maturity of loans because the credit registry does not contain information on maturity.

overnight loans. This is in contrast to the small fraction of overnight loans between intermediary and periphery banks in our sample, which, as shown in Fig. 3 of the main text, is around 10%. With the high concentration of overnight loans, trading between intermediary banks is more in line with the smoothing of short-term liquidity shocks, as proposed by Allen and Gale (2000).

Although trading between intermediaries is likely focused on smoothing liquidity shocks over short horizons, it may still interplay with the intermediation of longer-term funding needs to affect our estimation results. To this end, we further check whether a given intermediary's ability to lend to its periphery borrowers is affected by its borrowing from and lending to other intermediaries. We regress intermediaries' lending to periphery borrowers on their borrowing from other intermediaries, borrowing from periphery lenders, and lending to other intermediaries. The results in Table IA.B.3 show that borrowing from periphery lenders translates into more lending to periphery borrowers, as expected. However, borrowing from other intermediaries does not have a statistically significant effect, although the negative point estimate suggests that borrowing from intermediaries is different from borrowing from periphery lenders. Similarly, lending to other intermediaries has a positive but largely insignificant coefficient. These results are robust across specifications and with the inclusion of intermediary and quarter fixed effects.

B.3. Effect of geography and bank–type on monitoring costs

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

Historically, the German banking system was designed according to a tiered structure, in which each state's separate Landesbank, a big public bank, was set up to trade with the Sparkassen, smaller savings banks within its state. Similarly, Genossenschaften, which are small cooperative banks, were meant to trade through their central cooperative bank. In reality, the network structure now no longer resembles the historical setup as public savings banks and cooperative banks also trade with public banks in other states and commercial banks across the country. Nevertheless, one may still worry that the current interbank network has been influenced by the historical setup. Relatedly, banks located closer to each other may have a lower cost of establishing monitoring relationships.

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

Repeating the estimation of the baseline model with heterogeneous cost parameters yields the results in Table IA B.6. As expected, for the same bank characteristics, the monitoring cost among public banks is the lowest and 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 of 4.1%. For the average bank, 24.5% of its value generated is now spent on monitoring and state verification costs, which is similar to the baseline result.

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 between 92.3% and 93.5%. In the out-of-sample test of the Great Financial Crisis, the fraction of correctly predicted links goes up by 0.2% to 2.9% relative to the baseline (see Table IA.B.7).

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

B.4. Funding costs of intermediary banks

The baseline model makes two simplifying assumptions regarding the calculation of funding costs for intermediary banks: (1) the functional form of intermediaries' effective average return, and (2) frictions in non-interbank funding sources.

An intermediary's effective average return, y_i, is calculated as the weighted average of its own return outside of the interbank market and the return of the borrowing banks it lends to. Recall Eq. (1), wherein the average return of intermediary i's portfolio given network g in which intermediary i forms credit relationships with a set of borrowers, $N_i(g)$, is:

$$y_i(g) = \frac{1}{A_i + \sum_{b \in N_i(g)} V_b^i(g)} \left(A_i x_i + \sum_{b \in N_i(g)} V_b^i(g) x_b\right),$$

where the weights vary with the volume of intermediary i's own projects, A_i; the volume lent out to its borrowing banks in the interbank market, $V_b^i(g)$; its own portfolio return, x_i, distributed with CDF $F_i(x_i)$; and borrower b's return, x_b, distributed with CDF $F_b(x_b)$.

This specification may overestimate the sensitivity of intermediaries' average return and hence the state verification cost, $\lambda(g,c)$, to changes in the network, g, in the Shapley value calculations. The reason is that interbank loans are debt contracts whose values are not directly proportional to borrowers' asset return as specified in the formula above unless in default. We resorted to this approximation because using the exact functional form would greatly complicate the Shapley value derviation and the intermediary funding cost estimation.

Nevertheless, we check the impact of this approximation by re-estimating the model using each intermediary's observed asset return under the observed network, g^*, to calculate state verification costs for all subnetworks g (instead of allowing the state verification cost, $\lambda(g,c)$, to vary with network g). That is, we let:

$$y_i(g) = y_i(g^*) = \frac{1}{A_i + \sum_{b \in N_i(g^*)} V_b^i(g^*)} (A_i x_i + \sum_{b \in N_i(g^*)} V_b^i(g^*) x_b).$$

Using intermediaries' equilibrium return to calculate funding costs for all subnetworks in the Shapley value removes the sensitivity of intermediaries' funding costs to changes in their connected borrowers and the returns of their connected borrowers in different subnetworks. This zero sensitivity case can be viewed as the opposite end of the spectrum relative to our baseline model. The true sensitivity should lie between the two cases.

Table IA.B.4 reports parameter estimates when we let $y_i(g) = y_i(g^*)$. Relative to the baseline results, we find a slight increase in the state verification cost parameter, c, and a small decrease in the monitoring cost parameter, k. Intuitively, gains from link formation no longer include diversification benefits for intermediaries so that the monitoring costs revealed through the same network are smaller. Table IA.B.5 suggests that the flexibility in intermediaries' return slightly improves the model's out-of-sample performance. Out of the new links that are formed and not formed in the post-crisis period, the re-estimated model correctly predicts 63.2% and 85.0%. The limited impact of fixing intermediaries' average return on the estimation results is likely because intermediaries' asset sizes are much bigger than the average amount borrowed by borrowing banks. This is why A_i bears the dominant weight in the results and why the functional form over borrowers' returns has limited influence.

The estimates above also alleviate our second concern regarding frictions from non-interbank funding sources. To maintain focus on the interbank market, we assumed that changes in the network structure g affect only intermediaries' funding costs from interbank lenders. This assumption requires that the frictions in intermediaries' other sources of funding are not directly impacted by marginal changes in interbank connections, which is satisfied when $y_i(g) = y_i(g^*)$. The limited change in the re-estimated model estimates and their out-of-sample predictive power lend support for this assumption.

Table IA B.1

Estimation Results (Secured Loans Adjustment). This table reports results from the maximum score estimation after deducting the proportion of secured loans. k represents the monitoring cost technology parameter for each link between intermediaries and borrowing banks. C represents the state verification cost parameter for each link between intermediaries and the average lender. ρ is the correlation of returns across banks. The 95% confidence interval bounds, based on subsampling, are in parentheses. ** indicates that the 95% 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 (state banks) k	1.465^{**}	1.411^{**}	1.314^{**}
	$(0.651, 2.050)$	$(0.499, 1.859)$	$(0.405, 2.014)$
State Verification Cost C	0.266^{**}	0.241^{**}	0.234^{**}
	$(0.055, 0.310)$	$(0.031, 0.389)$	$(0.022, 0.466)$
Inequalities Satisfied (%)	89.5	89.9	90.2
Number of Inequalities		8,265	

Table IA B.2

Percentage of Correctly Predicted Inequalities (Secured Loans Adjustment). This table reports the percentage of correctly predicted inequalities in the out-of-sample test of the Great Financial Crisis for the baseline model after deducting the proportion of secured loans. 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 (%)	65.4	69.2	68.7
No New Links Formed (%)	86.6	86.2	84.8
Overall (%)	85.8	85.6	84.3

Table IA B.3
Determinants of Lending to Periphery Borrowers. This table estimates the determinants of intermediary lending to periphery borrowers. The data is at the intermediary-quarter level and covers 2005:Q1 to 2009:Q4. The explanatory variables are intermediary borrowing from periphery banks, intermediary borrowing from core banks, and intermediary lending to core banks. Standard errors are clustered at the intermediary level and shown in pathentheses. * and ** indicate statistical significance at the 10% and 5% levels, respectively.

	Lending to Periphery Borrowers				
	(1)	(2)	(3)	(4)	(5)
Borrowing from Periphery Lenders	0.788**			0.614**	0.538**
	(0.168)			(0.120)	(0.116)
Borrowing from Intermediaries		-0.384		-0.371	-0.342
		(0.362)		(0.313)	(0.298)
Lending to Intermediaries			0.236*	0.182	0.299
			(0.129)	(0.158)	(0.196)
Observations	377	377	377	377	377
Intermediary FE	No	No	No	Yes	Yes
Time FE	No	No	No	No	Yes

Table IA B.4 Estimation Results (Fixed Intermediary Returns). This table reports estimation results from the baseline model using intermediaries' observed returns to calculate funding costs, $\lambda(g,c)$. k represents the monitoring cost technology parameter for each link between intermediaries and borrowing banks. C represents the state verification cost parameter for each link between intermediaries and the average lender. ρ is the correlation of returns across banks. The 95% confidence interval bounds, based on subsampling, are in parentheses. ** indicates that the 95% confidence interval does not include zero. Inequalities Satisfied is the fraction of correctly predicted links using the vector of parameter estimates.

Monitoring Cost k	1.235^{**}
	$(0.444, 2.316)$
State Verification Cost C	0.260^{**}
	$(0.023, 0.468)$
Inequalities Satisfied (%)	88.9
Number of Inequalities	8,265

Table IA B.5

Percentage of Correctly Predicted Inequalities (Fixed Intermediary Returns). This table reports the percentage of correctly predicted inequalities in the out-of-sample test of the Great Financial Crisis for the baseline model when using intermediaries' observed returns to calculate funding costs, $\lambda(g,c)$. 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.

New Links Formed (%)	63.2
No New Links Formed (%)	85.0
Overall (%)	84.3

Table IA B.6

Estimation Results (Bank Type and Geography). This table reports results from the maximum score estimation of the baseline model after accounting for monitoring costs by geography and bank type. k_1, k_2, and k_3 represent the monitoring cost technology parameter for each link between intermediaries and borrowing banks. k_1, k_2, and k_3 apply when the pair of intermediary and borrowing banks are same-state Landesbank and savings banks or central cooperative bank and cooperative banks, private banks in the same state, and banks in different states, respectively. C represents the state verification cost parameter for each link between intermediaries and the average lender. ρ is the correlation of returns across banks. The 95% confidence interval bounds, based on subsampling, are in parentheses. ** indicates that the 95% 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 (state banks) k_1	1.187**	1.349**	1.358**
	(0.178, 2.091)	(0.410, 1.883)	(0.227, 2.220)
Monitoring Cost (same state) k_2	1.312**	1.424**	1.476**
	(0.255, 2.787)	(0.396, 2.902)	(0.444, 2.583)
Monitoring Cost (other) k_3	1.329**	1.463**	1.490**
	(0.589, 1.840)	(0.470, 2.053)	(0.622, 2.374)
State Verification Cost C	0.271**	0.233**	0.261**
	(0.045, 0.419)	(0.058, 0.473)	(0.060, 0.455)
Inequalities Satisfied (%)	93.5	92.3	92.9
Number of Inequalities		8,265	

Table IA B.7

Percentage of Correctly Predicted Inequalities (Bank Type and Geography). This table reports the percentage of correctly predicted inequalities in the out-of-sample test of the Great 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.

	$\rho = 0.12$	$\rho = 0.18$	$\rho = 0.24$
New Links Formed (%)	70.5	68.9	72.7
No New Links Formed (%)	88.4	87.6	85.7
Overall (%)	87.9	87.1	85.2