Credit Market Spillovers: Evidence from a Syndicated Loan Market Network*

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December 11, 2017

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Abstract

A large theoretical literature emphasizes the importance of financial networks, but empirical studies remain scarce. Due to overlapping bank portfolios, the syndicated loan market provides a natural setting to study financial networks. We exploit the tiered structure of syndicated loans to construct such a network and characterize quantitatively its evolution over time. A spatial autoregressive model provides an ideal methodological framework to estimate spillovers from this financial network to lending rates and quantities. We find that these spillovers are economically large, time-varying and can switch sign after major economic shocks. Moreover, we find that network complexity and uncertainty rise after a large negative shock. Counterfactual experiments confirm the quantitative importance of spillovers and network structure on lending rates and quantities and can be used to disentangle the effects arising from spillovers versus changes in network structure.

Keywords: Financial networks, spillovers, cost of lending, spatial autoregression, syndicated loan market, complexity.

JEL Classification: G01, G21

*We thank Jorge Abad, Martin Brown, Hans Degryse, Manthos Delis, Jayant Ganguli, Raffaella Giacomini, Rajkamal Iyer, Jose-Luis Peydró, Raghuram Rajan, David Scharfstein, Amir Sufi, John Wilson and seminar participants at Imperial College London, University of Essex and University of Zurich, and conference participants at the World Finance Conference, Central Bank of Brazil Seminar on Risk, Financial Stability and Banking 2017, MMF 2017, CRETE 2017 and FINEST 2017.

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1 Introduction

A large theoretical literature is associated with understanding financial networks and how network interactions might affect the real economy (for instance, Allen and Gale (2000), Freixas, Parigi and Rochet (2000), Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)).[1] Despite the importance of this theoretical literature in understanding potential propagation channels of macroeconomic shocks through bank interconnectedness, empirical work investigating how network structure might affect lending rates and quantities is relatively scant.[2]

Empirical work is scant partly because of the difficulty in building an empirically plausible financial network.[3] One major obstacle arises from the confidentiality of bilateral bank exposure data from the inter-banking market (Elsinger, Lehar and Summer, 2006). We instead use publicly available data from the syndicated loan market to construct such a financial network. Our key insight is that the syndicated loan market, a dominant source of corporate credit, enables a natural interaction between financial institutions. Equivalently, banks interact not only directly through interbank connections, but also through indirect connections due to, for example, investment in common syndicated loans. This market provides a natural source of overlapping portfolios across banks and can be used to create a loan network that measures proximity in terms of similarity in sectoral investment exposure between individual banks.[4]

Even after addressing the data availability issues, mapping the syndicated loan market

[1]One major view in the literature is that diversification has a beneficial effect and more diversified (integrated) systems are more resilient. For instance, Allen and Gale (2000) theoretically analyze the implications of different network structures on financial stability and show that denser interconnections between banks can mitigate systemic risk. In contrast, Wagner (2010) and Tasca, Battiston and Deghi (2017) find conditions under which diversification may have undesired effects (U-shaped) on the propagation of financial contagion by making systemic crises more likely. Blume, Easley, Kleinberg, Kleinberg and Tardos (2011) also suggest that denser interconnections can act as a destabilizing force, illustrating that the details of network structure can be important in the propagation of shocks. In a similar spirit, Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) point out that the precise propagation depends on both network structure and the size of shocks hitting the economy.

[2]Benoit, Colliard, Hurlin and Perignon (2016) survey the literature on systemic risk with the aim of discussing the mapping between theories, empirical measures and regulatory reforms.

[3]Iyer and Peydro (2011) provide empirical evidence on interbank contagion, without using a network structure, from a large bank failure in India.

[4]The paper also contributes in part to the study of the problem of overlapping portfolios previously theoretically considered in the literature. Gai and Kapadia (2010), Gai, Haldane and Kapadia (2011), Allen, Babus and Carletti (2012) and Amini, Cont and Minca (2016), consider for instance the situation where one asset is held by banks engaged in interbank lending. In these models contagion occurs because of fire-sales (asset commonality) and/or counter-party loss.

data to quantitative measures of a financial network remains challenging. To this end, we use the fact that a syndicated loan is originated by one or more lead banks that sell portions of the loan to other participants. Therefore, by construction, the syndicate structure contains two different levels of decision making: one at the firm (loan) level and one at the bank level. By analogy, we create a loan network following a two-step approach that takes into account this syndication process. In the first step, we follow Cocco, Gomes and Martins (2009), Giannetti and Yafeh (2012), and Cai, Saunders and Steffen (2016) to calculate a bank's sectoral exposure in each area of specialization according to industry portfolio weights (the share of lending of each bank to different sectors). The bilateral distance between these bank sectoral exposures is used as a measure of banks' similarities. This distance measure accounts for the information overlap that influences lending practices. In the second step we rely on these bilateral bank distances to create the loan network as the loan "similarity" based on the banks that participate in the syndicated loan. We thus incorporate private information spillovers that can cause lending rates and quantities to be different from those determined by fundamentals alone. The focus on loan interconnectedness is a distinguishing feature of our approach, i.e. we conduct a loan level, rather than bank level, analysis.

An example can illustrate the intuition underlying the loan network construction. Suppose we are in an economy with only three loans, ℓ_1, ℓ_2 and ℓ_3, and three banks, say Citibank (C), JP Morgan (JPM) and Bank of America (BoA). The three banks have different sectoral loan exposures as a proportion of their balance sheet. Loans ℓ_1 and ℓ_3 are both shared by C and JPM, while ℓ_2 is shared by JPM and BoA. An intuitive network construction procedure should realize that loans ℓ_1 and ℓ_3 must have a stronger link than the other pairs (ℓ_1, ℓ_2) and (ℓ_2, ℓ_3), because they are shared by the same bank pair (C, JPM). Moreover, stronger bank similarity through higher exposure to the same sector should also be taken into account when constructing the loan network. Our two-step procedure is built on this idea. In the first step, we compute pairwise distance measures between C, JPM and BoA based on their sectoral specializations, before the loan issuance in the syndicated loan market. As a result, banks with higher specializations in the same sector (as a proportion of their total loan exposure) are more similar, a feature that can arise from common soft information channels. In the second step, we use both the observed syndicated loan participation decision and the sectoral exposures from the first step to construct a measure of loan similarities. The resulting loan network presents a direct measure of interconnectedness; more interconnected loans have more similar banks (across sectors) and more common exposures (participation in syndicated loans). The decision to participate in different loans per industry is a source of information about the firm and industry cash flows, and plays an important role in assessing the behaviour of other rival banks.[5]

This two-step approach in constructing the loan network offers crucial advantages. First, aggregation at the loan level (within loan) replicates the syndicate structure and can be directly mapped to our data set. Second, by aggregating from the bank-level to the loan-level, measurement error is averaged out. Third, the second step can also reduce the bias introduced by the endogeneity of the bank's participation decision (Hanushek, Rivkin and Taylor, 1996). This aggregation step reduces omitted variable bias because omitted variables have their clearest effects on estimates when the data are not aggregated to the level of the omitted factors (such as when factors affecting a bank's participation decision are neglected).

To implement our empirical analysis we use data from three different sources. Specifically, we use the syndicated loan market that includes corporate loans to US firms in the 30 years between 1987 and 2016. To enrich the information at the bank level, we match the loan-level data from Dealscan with Call Reports, with the help of coding from Call Reports and a hand-matching process. We can do the same for firms, by matching our end sample with Compustat. Our final sample consists of large US corporate loans from specific US banks (lead arrangers and participants) to specific US firms (excluding utilities and financial companies).

A key question of interest is whether loan rates and quantities are correlated with loan interconnectedness. A natural way to empirically test for the presence of spillover externalities is to estimate a spatial autoregressive (SAR) model with simultaneous network interactions. The syndicated loans market, with its overlapping portfolios through connected banks, is uniquely suited to the application of such techniques. This framework has been used widely in other areas like geography, trade, regional science and urban economics (Case, 1991; Conley and Ligon, 2002; Pinkse, Slade and Brett, 2002; Conley and Dupor, 2003). A political economy application is given in König, Rohner, Thoenig and Zilibotti (2017), who implement empirically a model of networks using conflict data and estimate a

[5] Helwege and Zhang (2016) observe that interconnectedness causes negative externalities through counterparty and information contagion and highlight the role of exposures to common shocks. They find that externalities that arise from counterparty exposures are small, especially among banks that face diversification regulations, and do not typically cause a cascade of failures.

SAR model with network interactions given by allegiances of participants. However, to the best of our knowledge it has never been used with syndicated loans data.[6] Our aim is to assess the role of loan similarity in cross-loan linkages in the syndicated loan market. Spatial models offer the advantage of allowing us to directly detect patterns of co-movements in lending rates and quantities. Consequently, we can assess whether co-movements, on top of fundamental characteristics, are economically significant and time-varying in determining lending rates and quantities.

What are our main empirical findings? First, we characterize the evolution of the financial network and find a noticeable variation in network density over time. This is visible in both the number of syndicated loans arranged, as well as the number of connections that form between these loans. Moreover, during large crisis periods like the 2007-09 recession, we observe a sizeable drop in the number of connections and the number of loans arranged. This offers a visual validation of the two-step procedure in constructing the network since the density of connections rises as 2007 approaches and markedly decline during the Great Recession, and rises again thereafter. Quantitative measures of network density confirm these visual impressions.

Second, we find strong evidence for the economically important existence of spillovers in lending rates and quantities, beyond the effect of fundamentals. These spillovers can be interpreted as capturing the complex interactions across banks, which are reflected in their lending decisions in the syndicated loan market. Moreover, our empirical specification uses a particular linear parameterization of Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and how spillovers might arise from the actions of other network members. Our results provide empirical support for such a specification.

Third, we characterize the evolution of spillovers over time. We find an economically and statistically significant positive co-movement in lending rates during expansionary periods. This co-movement becomes zero at the peak of the 2007-09 financial crisis, and after the crisis we observe a switch in the sign of the co-movement. During good times, when shocks are fewer and smaller, we find that a one standard deviation increase in the rates charged by a loan's neighbours in the network leads to an increase in its own rate by 7.32 basis points (bps), amounting to a nearly 4% increase in the average loan rate in our sample. On the other hand, during bad times, with large and numerous shocks,

[6] The model that we use is similar to those used in the social interactions literature (Sacerdote, 2001; Topa, 2001; Durlauf and Ioannides, 2010), but is less likely to suffer from the 'reflection problem', see e.g. Lee (2007), Pinkse and Slade (2010) and de Paula (2017) and the more detailed discussion in footnote 17.

a one standard deviation increase in the rates charged by a loan's neighbours leads to a fall in its own lending rates of 3.95 bps, around a 2.1% drop for the average loan. We also analyze loan quantity spillovers. We find that in good times banks that participate in more interconnected loan networks increase their lending quantities, while in bad times the response is economically very weak.

Fourth, we explicitly test and find supportive evidence for an increase in network complexity and/or uncertainty during the financial crisis of 2007-09. In our model, unobserved spatial heterogeneity between loans can be interpreted as a measure of network complexity and our framework allows us to explicitly test for the presence of network spillovers in unobserved characteristics. We find evidence for an increase in network complexity and/or uncertainty during large recessions, consistent with recent theoretical predictions of increase in network complexity (Caballero and Simsek, 2013) and empirical results of increases in counterparty uncertainty (Ivashina and Scharfstein, 2010) during recessions.

In interpreting these empirical findings, a policy maker would be interested to know whether lending rates change due to loan network evolution or due to the evolution of spillover effects. In a counterfactual experiment using our constructed network and estimated spillovers, we find that a networked economy with time evolving network structure has lending rates and quantities that are significantly different from non-networked economies. Our largest estimated positive spillover suggests that the networked economy has lending rates (quantities) that are 5.54% (20.59%) higher, on average, than the non-networked economy. If, on the other hand, the network is assumed to stay the same over time and remains always the same as during the peak of the financial crisis in 2008, we find that the difference between lending rates and quantities in networked versus non-networked economies is no longer as large. For the same estimated spillover that led to 5.54% (20.59%) higher lending rates when the network evolves over time, the lending rates (quantities) are only 1.18% (4.02%) higher on average in the static 2008-networked economy. This empirical finding supports the theoretical findings relating to collapse of financial networks during major crises, e.g. Acemoglu, Ozdaglar and Tahbaz-Salehi (2015).

To control for unobserved heterogeneity, we use the multi-level structure of our data set (multiple loans by the same lender and to the same borrower) to mitigate omitted-variable bias in a fashion similar to Jiménez, Ongena, Peydró and Saurina (2014, 2017) and Delis, Kokas and Ongena (2017). We acknowledge that it is challenging to control for all (observed and unobserved) firm and bank heterogeneity, which stems from banks' participation decisions and firms' exposure to systemic and idiosyncratic risk. However, our sample allows the inclusion of firm, bank, year and bank $\times$ year fixed effects. These fixed effects saturate our analysis from other within firm (time invariant demand side), year (common shocks) and within bank-year (supply-side) effects. We find that including bank or bank $\times$ year fixed effects does little to change either our parameter estimates or the goodness-of-fit, thus further supporting the claim that observed or unobserved supply fundamentals are uncorrelated with the financial-loan network. More precisely, we analyze whether the estimated spillover is different from one estimated in a regression without bank fixed effects to verify that unobserved bank-specific credit supply shocks are not correlated with the loan interconnectedness (Altonji, Elder and Taber, 2005; Khwaja and Mian, 2008). This provides a safeguard that variation in the co-movement of the lending rates and quantities is due to the loan network's structure rather than any heterogeneity in size, leverage, fundamentals, among other variables.

The paper is organized as follows. In Section 2, we describe data sources and the construction of the final sample used in our analysis. Section 3 details the construction of the bank distances and loan network that we have discussed above. As the loan network we construct is dynamic, we devote Section 4 to study its evolution over time. Section 5 introduces the econometric model that we employ and describes the estimation procedure. The key empirical results are presented and discussed in Section 6, clearly demonstrating both the effect of spillovers in lending rates and quantities and their time-varying nature. In addition, in Section 7, we show that network complexity and uncertainty rises after major economic shocks. In Section 8 we conduct a counterfactual simulation study that combines the networks created in Section 3 and the spillovers estimated in Section 6 to examine the quantitative difference in lending rates and quantities between networked and non-networked economies, as well as static and dynamic networks. Section 9 concludes the paper. Three appendices illustrate the financial network construction, provide more details about the econometric model that we use and further examine the implications of the estimates that we obtain.

2 Data

We begin with a brief description of the syndicated loan market (see, for instance, Sufi (2007); Delis, Kokas and Ongena (2017) for further details). Syndicated loans are granted by a group of banks to a single borrower. Loan syndication allows banks to compete with capital markets in the generation of relatively large transactions that a sole lender would not otherwise be able (or willing) to undertake due to internal and regulatory restrictions. These loans combine features of relationship and transactional lending (Dennis and Mullineaux, 2000) and apportion credit risk between financial institutions without the disclosure and marketing burden that bond issuers face.

The syndication process works as follows. The borrowing firm signs a loan agreement with the lead arranger specifying the loan characteristics (collateral, loan amount, covenant, a range for the interest rate, etc.). The members of the syndicate fall into three groups: the lead arranger or co-leads, the co-agents, and the participant lenders. The first group consists of senior syndicate members and is led by one or more lenders, typically acting as mandated arrangers, arrangers, lead managers or agents. If two or more lead arrangers are identified, they are then co-leads. Lead arrangers coordinate the documentation process, choose whom to invite to participate in the loan syndicate and may delegate certain tasks to the co-agents. In addition, the lead arranger receives a fee (paid by the borrower) for arranging and managing the syndicated loan.

The co-agents collaborate with the lead arranger in administrative responsibilities as well as in screening and monitoring efforts. The lenders with neither lead nor co-agent roles are classified as participant lenders. These lenders can provide comments and suggestions when the syndication occurs prior to closing. However, they are not generally involved in the negotiations or the information sharing between the borrower and the lead arrangers (or the co-agents if applicable). The price and the structure of the loans are determined in a bargaining process that takes place between the lead bank and the potential participants after the non-price characteristics of the loan are set.

We obtain data on syndicated loan deals from Dealscan. This database provides detailed information on the loan deal's characteristics (amount, maturity, collateral, borrowing spread, performance pricing, etc.), as well as more limited information for the members of the syndicate, the lead bank, the share of each bank in the syndicate (which is important in the construction of the loan network) and the firm that receives the loan.[7]

[7] We apply two selection rules to avoid bias in our sample. This is an essential part of the sample-selection process that is absent from most empirical studies using the Dealscan database (for a similar strategy see Lim, Minton and Weisbach (2014)). First, we disentangle banks from non-banks. We consider a loan facility to have a non-bank institutional investor if at least one institutional investor that is neither a commercial nor an investment bank is involved in the lending syndicate. Non-bank institutions include hedge funds, private equity funds, mutual funds, pension funds and endowments, insurance companies, and finance companies. To identify commercial bank lenders, we start from lenders whose type in Dealscan is *US Bank*, *African Bank*, *Asian-Pacific Bank*, *Foreign Bank*, *Eastern Europe/Russian Bank*, *Middle Eastern Bank*, *Western European Bank*, or *Thrift/S&L*. We manually exclude the observations that are classified

To obtain information for the financial statements of the banks we match these data with the Call Reports. We hand-match Dealscan's lender ID with the commercial bank ID (RSSD9001) from the Call Reports. This process yields a unique identity for each lender. In turn, we link the lenders at their top holding company level (RSSD9348) to avoid losing observations. Because these reports are available on a quarterly basis, we match the origination date of the loan deal with the relevant quarter. For example, we match all syndicated loans that were originated from April 1st to June 30th with the second quarter of that year of the Call Reports. Similarly, we obtain annual information for the financial statements of firms from Compustat.

The matching process yields a maximum of 52,810 loans originated by 823 banks involving 7,511 non-financial firms spanning 1987-2016. This sample is a so-called 'multi-level' data set, which has observations on banks and firms (lower level) and loan deals (higher level). Table 1 formally defines all variables used in the empirical analysis and Table 2 offers summary statistics. The all-in-spread drawn (AISD) is one of our main dependent variables and is defined as the sum of the spread over LIBOR plus the facility fee (bps). The average of AISD in our sample is 187 bps, while the standard deviation indicates sizeable variation (146 bps). The mean of our second main dependent variable (Deal amount) is around 625 ($M), confirming the large transaction size.

We now briefly discuss the control variables used in our analysis. Consistent with previous studies (e.g., Sufi (2007); Ivashina and Scharfstein (2010)), we include several loan-level, bank-level, and firm-level control variables to rule out other possible explanations for our results. At the loan level, we use a dummy that equals one if the loan is linked with financial covenants to control for unobservable borrower risk factors (Carey and Nini, 2007); a dummy that equals one if the loan is a revolver (credit line), and a series of dummy variables describing a number of loan-quality characteristics. Specifically, we include a dummy variable equal to one if the loan is secured to control for problems of information asymmetry; a dummy variable equal to one when the loan has a guarantor to control for risk in case of adverse developments for the borrower; a dummy variable equal to one if performance pricing is included in the loan contract to control for borrower's business prospects (Ross, 2010); and a dummy equal to one if a loan refinances a previous loan.

Concerning the bank-level control variables, we use non-performing loans as a measure

as a bank by Dealscan but actually are not, such as the General Motors Acceptance Corporation (GMAC) Commercial Finance. We went through all the syndicated loans manually, one-by-one. Second, we exclude loans granted to utilities or to financial companies.

of ex-post bank credit risk; the ratio of interest expenses to total assets (interest expenses) to control for interest coverage and bank efficiency in managing core liabilities; and the natural logarithm of real total assets (bank size). At the firm level, we control for firm size, measured by the natural logarithm of total assets; the amounts ($M) of syndicated loans that a firm has received during the last five years as a proxy for useful information to participant banks; a dummy variable that equals one if the firm has a previous lending relationship with the lead arranger in the last five years; firm tangibility measured by the ratio of tangible assets over total assets to control for asset turnover; the natural logarithm of market-to-book (Tobin's q) as a proxy for the cost of equity; and the ratio of net income over total assets (ROA) to control for profits (Adams and Ferreira, 2009).

3 Construction of the financial network W

Our construction of the network is based on a two-step approach following the structure of the syndicate. The first step involves constructing a distance measure between banks based on their sectoral exposures, while the second aggregates these interbank connections at the syndicated loan level to obtain a distance measure between loans. The resulting loan network (W) is a key input in the econometric analysis.

3.1 Bank's bilateral distance

We construct a measure of investment similarity at the bank level to capture possible common information sharing channels. We therefore do not interpret proximity as closeness in terms of physical distance, but instead as similarity or dissimilarity regarding investment exposure, i.e. asset exposure, of banks. Specifically, to measure the proximity between individual banks within a year we compute a distance measure between banks. Each bank's similarity with other banks is given by the Euclidean distance from other banks within a year based on their sectoral loan portfolio weights.[8] The smaller (higher) the distance, the more similar (dissimilar) are the banks that are being compared. Let $w^B_{b_1,b_2,t}$ be the distance between bank b_1 and bank b_2 at time t, where superscript B emphasizes that this is a bank distance. Let $Loan^{b\to s}$ be the amount (in millions of dollars) lent by bank b to sector s at time t and $Total\ Loan^{b\to S}$ be the total amount (in millions of dollars)

[8] The Euclidean distance measure is employed by Giannetti and Yafeh (2012) to measure cultural differences between lead arrangers and borrowers in loan syndicates and also in Cai, Saunders and Steffen (2016) to measure the bank interconnectedness in the syndicated loan market.

that bank b has lent during the same year to the total number of sectors (S). For each bank pair (b_1, b_2), we compute the normalized Euclidean distance as follows:

$$w^B_{b_1 b_2,t} = \sqrt{\frac{\sum_{s=1}^{S}\left(w^s_{b_1,t} - w^s_{b_2,t}\right)^2}{2}}, \tag{1}$$

with

$$w^s_{b,t} = \frac{Loan^{b\to s}_t}{Total\ Loan^{b\to S}_t}, \text{ for any bank } b.$$[9]

Thus $w^B_{b_1 b_2,t}$ is the distance between banks b_1 and b_2 on Euclidean S-dimensional space at time t and lies in $[0, 1]$. It is also evident that $w^B_{b_1 b_2,t} = w^B_{b_2 b_1,t}$, i.e. equation (1) is a symmetric distance. Furthermore, note that, for all banks b, $\sum_{s=1}^{S} w^s_{b,t} = 1$. From equation (1), it is clear that bank similarity ($w^B_{b_1 b_2,t}$) measures how similar the sectoral exposures of banks b_1 and b_2 are.

Table (A1) provides an example of how the composition of industry investments per bank, $w^s_{b,t}$, is constructed (for the two-digit SIC industry)[10] and also the computation of the Euclidean distance based on SIC industry division among the top three arrangers in 2015 (JPMorgan Chase (JPM), Bank of America (BoA), and Citigroup (C), in this example). We observe that the allocation of funding between these banks differs. More precisely, JPM invests heavily in loans related to manufacturing (47.58%) and transportation & communication (27.89%). BoA invests more than half of its total funding in manufacturing (51.5%) and allocates similar weights between transportation & communication (17.58%) and retail trade (15.58%). In contrast, C invests 35.86% in manufacturing, 29.31% in transportation & communication and 19.70% in retail trade. The weights per industry reveal banks' preferences to invest and therefore their sectoral specialization. As a result, the distance between JPM and BoA is smaller compared to the other bilateral distances (0.2167). Thus, JPM and BoA are more similar to each other, in terms of sectoral exposure. On the other hand, BoA and C are less similar because they have a higher distance (0.3816).

[9] Cocco, Gomes and Martins (2009) use a similar weight to measure the intensity of lending activity in the interbank market.

[10] We have constructed similar measures for the one, three and four-digit SIC industry.

3.2 Loan network

Bank exposures to each industry, or similarities ($w^B_{b_1 b_2,t}$), are not necessarily an appropriate measure of bank preferences to do business with other banks because, for example, banks are engaged in other markets like interbank or secondary markets. However, in the context of the syndicated loan market, banks can be 'aggregated' into the loans they participate in. In other words, each bank may be treated as being comprised of a number of loans, or equivalently, participation decisions. This loan level participation decision is a more appropriate measure of a bank's connection to other banks, because loan making is the basic granular decision of a bank. In addition, the structure of the syndicate lends itself naturally to our two-step approach because we observe banks and loans (firms) at two different levels (see Figure 1). The first level computes bank similarity by comparing bank sectoral exposures as a proportion of their total loan exposure (below dotted line in Figure 1). The second level uses this information to construct loan similarity based on both participation in a syndicated loan and the constructed bank similarity measure. We can therefore use the inter-bank distances to construct inter-loan distances that explicitly account for syndicated loan portfolio overlaps. This second-stage aggregation at the loan level yields distances that form the loan network (above dotted line in Figure 1).

We first illustrate the procedure theoretically and then provide a specific example to flesh out the intuition. Suppose that we observe B_t banks and L_t loans at time t, $t = 1, \ldots, 30$. Let W^B_t be a symmetric $B_t \times B_t$ matrix whose (b_1, b_2)-th element is $w^B_{b_1 b_2,t}$ as defined in equation (1). We then use the entries of W^B_t to construct a symmetric $L_t \times L_t$ matrix W^L_t whose (i, j)-th element $w^L_{ij,t}$, where superscript L emphasizes that this is an inter-loan distance, is a measure of interconnectedness of *loan* i and *loan* j at time t. Denote by B_{ijt} the set of all the banks that share loan i and j at time t. Define the elements of W^L_t by

$$w^L_{ij,t} = \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(w^B_{b_1 b_2,t}\right)^{-1}, i \neq j, \tag{2}$$

where $\mathcal{P}\left\{B_{ij,t}\right\}$ is the number of bank 'pairs' formed in $B_{ij,t}$. Note that our analysis will assign a greater interconnection measure to loans that are 'closer' to each other, hence the use of inverse distances in the sum in equation (2). More similar banks have a bigger effect on each other and therefore we need to convert the sectoral distances to loan similarities by inverting and standardizing bank sectoral distances ($w^B_{b_1 b_2,t}$).[11] Loan interconnectedness

[11] An aspect that arises in the computation of equation (2) is the possibility of $w^B_{\tilde{b}_1 \tilde{b}_2,t} = 0$ for some

ranges between zero and one, with zero corresponding to lack of interconnectedness and larger values reflecting stronger interconnectedness.

We will use the same example as in the previous subsection to clarify the loan network construction. The procedure is illustrated in Panel A of Table A2, where Loan ℓ_1 is shared by banks JPM, C, Loan ℓ_2 by banks JPM, BoA and Loan ℓ_3 by banks JPM, C. In Panel B, we observe bank similarities by using the inverted and standardized inter-bank distances. A higher value reflects greater similarity between banks. We observe that JPM and the BoA are more similar (0.6592), in terms of their investment preferences, in contrast with JPM and C (0.4818) or BoA and C (0.3749). In panel C, we show how we have constructed the interconnectedness between loans. For example, for loan ℓ_1 and loan ℓ_2 the interconnectedness ($w^L_{2,1}$) is equal to the inverse of the bilateral bank exposures divided by the number of pairs. In this example, the pairs are [(JPM,JPM), (JPM,BoA), (C,JPM), (C,BoA)] yielding 0.6290. As expected, loan ℓ_1 and ℓ_3 have the biggest interconnection ($w^L_{3,1}$) because they are shared by the same bank pair. However, the loan interconnectedness is close, but not equal to one, because these banks differ in sectoral exposures.

To obtain W, we use each $w^L_{ij,t}$ computed above in the block-diagonal matrix

$$W^* = \begin{bmatrix} W^L_1 & 0 & 0 & \dots & 0 \\ 0 & W^L_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & W^L_{30} \end{bmatrix}. \tag{3}$$

The block diagonal assumption in (3) captures the variation between loan networks but not between years.[12] Finally, with $\|W^*\|$ denoting the largest eigenvalue of W^*, we normalize the distances in W^* as

$$W = \frac{W^*}{\|W^*\|}. \tag{4}$$

pair $\tilde{b}_1$ and $\tilde{b}_2$. This entails an exact overlap of portfolios between banks $\tilde{b}_1$ and $\tilde{b}_2$ and therefore implies that these banks are very 'close', in fact arbitrarily so. We cannot use the inverse of $w^B_{\tilde{b}_1\tilde{b}_2,t}$ in this case, but assign instead the value $\max_{b_1,b_2;w^B_{b_1b_2,t}\neq 0} \left(w^B_{b_1b_2,t}\right)^{-1} + 1$. In other words, we assign the largest possible interconnection measure i.e. the inverse of the smallest possible nonzero bank distance for year t, plus one.

[12] Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) use a similar assumption about idiosyncratic shocks at the firm or sectoral level that can propagate over input-output linkages within the economy.

4 Characterizing the loan network evolution

Matrix W forms a network of loans made up of a set of 30 square matrices W_t^L, $t = 1, \ldots, 30$, providing a loan network evolution between 1987 and 2016. In Table 3 we provide summary statistics for each of the networks W_t^L. The second column, titled "Connections", lists the number of bilateral loan relationships per year. This is computed as the number of nonzero off-diagonal entries in each W_t^L.[13] Greater numbers of "Connections" reveal two features: more loans in the network and more interaction between these loans. Since connections are an absolute measure, we also construct a measure relative to network size. The third column displays a measure called "Density" defined as #(nonzero off-diagonal elements of W_t^L)/#(off-diagonal elements of W_t^L), i.e. the proportion of nonzero off-diagonal elements of W_t^L.

Connections are quite similar in number from 2006 to 2007, but the density in 2007 is less than in 2006, reflecting the onset of the crisis during the latter half of the year. In 2008 the number of connections falls dramatically, and then even more so in 2009. This is caused by the collapse of the syndicated loan market in the aftermath of the crisis. However, density shows signs of recovery from 2007, indicating that while the number of connections is small, the proportion of connections has increased. The remaining columns of the table provide mean, standard deviations and quantiles for the nonzero elements of the W_t^L matrices.

Figures 2-8 provide a graphical illustration of both the dynamic evolution of the network, as well as the loan network construction procedure. Our discussion in the previous section describes how we construct the loan network via bank participation in multiple loans in the syndicated loan market. In Figure 2 we show the structure of the syndicated loan network in 1987 at two levels. The purple nodes correspond to banks and the orange nodes correspond to individual loans. A line from a purple node to an orange node indicates that the bank represented by the former is a member of the loan syndicate of the latter, while larger purple nodes indicate banks that are involved in a greater number of loan syndicates. This figure forms the basis for the construction of the W_t^L matrices defined above.

Figure 3 is a particular example showing the part of W_1^L for 10 loans in 1987. We again reserve orange nodes to correspond to individual loans, while the thickness of the

[13] In networks terminology, a nonzero off-diagonal entry corresponds to an "edge" between the corresponding "nodes" and the magnitude of this entry is the "edge weight".

line joining the nodes reflects the magnitude of the corresponding element of W_1^L. The thicker the line, the greater the element and thus the larger the interconnection. We can see that loans 1 and 6 have the greatest interconnection, in other words the banks that are members of the syndicates for these loans have the greatest average pairwise similarity (by our aforementioned similarity measure (1)) of all the loans in the figure. On the other hand, note that loans 3 and 4 and loans 4 and 5 have no interconnecting lines. This means that they do not influence each other (or, in network terms, there is no edge between nodes 3 and 4 and nodes 4 and 5) and thus have corresponding W_1^L elements equal to zero because these loans have no banks in common in their syndicates. Furthermore, loans 3, 4, 5 and 7 have few connections, while loans 1, 2, 6, 8 and 10 have more. In peer effects terminology, the latter group of loans is 'more social' relative to the former group.

Focussing again on Figure 2, we can also use network figures to examine the evolution of the syndicated loan market. In our data there are 575 syndicated loans in 1987, and 155 banks are involved in loan syndicates. By 2006, with the financial crisis looming, loans in the syndicated loan market rose to 2106 and banks to 176. This constitutes an increase of 366% in the number of loans and 13.5% in the number of "players" (banks). This is clearly visible in Figure 4, which replicates the way we generate Figure 2, but now for 2006. We can see a much denser diagram with many more loans and players.

Next, we show the corresponding diagram for 2009 in Figure 5, in the aftermath of the crisis. By this time the syndicated loan market was down to 799 loans with 137 banks involved in syndication, and this is evident in Figure 5. The network appears much more sparse as compared to the one in 2006 and there are less than half as many orange nodes, corresponding to loans, and fewer purple nodes (banks). Finally, in Figure 6 we plot the network for 2010, when the syndicated loans market showed some signs of recovery. It was now up to 1288 loans involving 163 banks. Figure 6 illustrates clearly this aspect. The network is denser than the one for 2009 in Figure 5 but not as much as the one for 2006 in Figure 4.

Our empirical analysis will be based on loan similarity, and we can also depict the evolution of this measure over time. We focus on 2007 (during the crisis) and 2011 (after the crisis). Not only do we know that there were only 799 loans in 2007 as opposed to 1837 in 2011, we can also use the loan networks (W_t^L) corresponding to these years to illustrate the density of the interconnections. Because connections form via the banks in the syndicates, fewer connections imply a breakdown in both bank participation in the market as well as the connections between the banks themselves. The "Density" column in

Table 3 ranges from 67.89% (in 2007), the smallest number in the whole period, to 94.12% (in 1999). In 2011 the value is 87.8%. Thus, if we plot the network links we would expect the 2007 ones to show a sparser set of edges than the 2011 ones. Due to the sheer number of loans and connections it is neither feasible nor informative to plot the entire network for these years, and we therefore focus on a plot for a subset of 150 loans for each year. These representations are shown in Figures 7 for 2007 and 8 for 2011, where once again orange nodes are individual loans and node size corresponds to how "social" the loans are. Comparing the two figures shows that in 2011 (Figure 8) the loan network has a much denser set of connections than 2007 (Figure 7), implying a greater degree of interaction as the market regains its vigour after the crisis.

5 Empirical specification and estimation

To analyze how the structure of the constructed loan network affects lending rates and quantities we use the following spatial autoregressive (SAR) model:

$$y = \lambda(Wy) + X\beta + \epsilon. \tag{5}$$

A vector of actions y (loan spreads or lending quantities) depends not only on own characteristics ($X\beta$), but also on the actions of other connected individuals via the financial-loan network W, which determines the intensity of connections.[14] One key parameter of interest is λ which can be interpreted as a spillover, or peer effect, following the social interactions literature. As explained below, equation (5) can be viewed as a particular case of the linear interaction function used in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015).[15]

Our financial network is similar to the setup in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015). Like them we assume that $w^L_{ii,t} = 0$ for all i, $w^L_{ij,t} = w^L_{ji,t}$ (symmetry) and a normalization of the network given in equation (4).[16] In their terminology, W is an interaction network, while the interaction function is parameterized to be a linear function with unknown parameters λ and β, as in equation (5).

[14] Appendix B contains a discussion, with key references, of the SAR model.

[15] The scaling in equation (4) stems from the fact that without any normalization, λ in (5) is not identified. In the absence of normalization we could simply replace W by cW for any $c \in (0, \infty)$ and then $\lambda^\dagger = \lambda/c$ would give the same data generating process. Given its necessity, the question arises as to which normalization is most appropriate. We follow here the recommendation in Gupta (2017) and choose (4).

[16] Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) use row-normalization.

Equation (5) features three main building blocks. The first block involves the construction of a financial network (W) using bilateral exposure from the syndicated loan market, as we have done in Section (3). The second block involves a procedure to estimate and monitor the magnitude of network spillovers (externalities) on economic variables like loan spreads and quantities. This is captured by λ. The third block is the loan-level shock ϵ, which captures stochastic disturbances emerging from financial uncertainty or network complexity that banks face when they make loan participation decisions.

In this model, the dependent variables corresponding to loan i depend not only on bank-firm-loan characteristics and aggregate fundamentals, but also on those loans that banks participate in with an overlapping pattern via an interaction network. Writing equation (5) translates to an empirical model of the following form:

$$y_{i,t} = \alpha_f + \lambda \left(\sum_{j=1, j\neq i}^{L_t} w_{ij,t}^L y_{j,t} \right) + \beta_1 B_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 L_{i,t} + \epsilon_{i,t} \tag{6}$$

In equation (6), the cost of lending or the lending quantity, labelled $y_{i,t}$, for loan i at time t is regressed on the key independent variable $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}$ (we will call this regressor the *financial-loan network*), which measures the financial network dependence between loan i and other loans at time t, a vector of weighted banks' characteristics B at $t-1$, a vector of firm characteristics F at $t-1$ and a vector of loan characteristics L at t. λ measures the spillover or the co-movement in the lending rates or quantities between loan i and other loans at time t. α_f denotes a vector of fixed effects, while $\epsilon_{i,t}$ is an 'loan-level' shock, which captures stochastic disturbances to loan i.[17]

In equation (6) we are interested in determining whether a correlation between the constructed loan network and individual loan rates and quantities exists. We control for

[17] Our model in equation (6) is of the form

$$y_{i,t} = \lambda \left(\sum_{j=1, j\neq i}^{L_t} w_{ij,t}^L y_{j,t} \right) + x_{i,t}' \gamma + \epsilon_{i,t}.$$

Denoting by $E_{\text{loc}}(\cdot)$ an expectation conditional on the process generating the observation locations, the 'reflection problem' of Manski (1993) occurs when in fact the model is of the form

$$y_{i,t} = \lambda E_{\text{loc}}(y_{i,t}) + x_{i,t}' \gamma + \epsilon_{i,t},$$

and the term $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}$ is treated like a nonparametric estimate of $E_{\text{loc}}(y_{i,t})$. This issue typically does not arise in spatial econometrics because, as pointed out for instance by Lee (2007) and Pinkse and Slade (2010), the actual intended regressor is $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}$ and not $E_{\text{loc}}(y_{i,t})$.

reverse causality by lagging all the right-hand side variables except for loan characteristics. To control for omitted variable bias, our analysis accounts for potential unobserved variables, especially the bank- and firm-level ones that might bias the coefficient estimates on the loan network. Specifically, our dataset's structure allows us to include a number of fixed effects (bank, firm, year, loan type, loan purpose) because the individual loan facilities are non-repeated but the lenders originate multiple loans within a year. Among these fixed effects, the bank and firm fixed effects are particularly important because we control for time-invariant bank-and-firm characteristics that could lead to correlation between the financial network $\left(\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}\right)$ and $\epsilon_{i,t}$ in equation (6).[18] To capture the systemic risk component, we use year fixed effects. The inclusion of year fixed effects accounts for annual common shocks across all banks and firms (e.g., the effect of the subprime crisis). We also use loan type and loan purpose fixed effects to insulate our model from differences in syndicate structure due to loan type or purpose (for more extensive definitions, see Table 1).

Moreover, unobserved heterogeneity is mitigated by our two-step loan network construction procedure involving two stages of aggregation. The first stage is illustrated in equation (1), where aggregation takes place over sectors. The second stage is shown in equation (2), where aggregation is over bank pairs. These aggregation procedures will mitigate the effect of unobserved heterogeneity at sectoral and bank-pair level, alleviating endogeneity concerns arising from these sources. To be precise, suppose that inter-bank inverse distances are given by

$$\left(w_{b_1 b_2,t}^B\right)^{-1} = \left(\tilde{w}_{b_1 b_2,t}^B\right)^{-1} + \eta_{b_1,b_2,t},$$

where $\eta_{b_1,b_2,t}$ is unobserved heterogeneity relating to the portfolio overlap between banks b_1 and b_2 at time t. Our aggregation in equation (2) implies that

$$w_{ij,t}^L = \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(\tilde{w}_{b_1 b_2,t}^B\right)^{-1} + \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \eta_{b_1,b_2,t}, i \neq j. \tag{7}$$

Assuming that unobserved heterogeneity $\eta_{b_1,b_2,t}$ is a random variable with zero mean, the sample average $\left(\mathcal{P}\left\{B_{ij,t}\right\}\right)^{-1} \sum_{(b_1,b_2)\in B_{ij,t}} \eta_{b_1,b_2,t}$ will approach zero, thus eliminating

[18] In Table 7, we show that our findings are robust to the analysis being conducted for bank $\times$ year fixed effects.

endogeneity from this source.[19]

We use the Gaussian quasi maximum likelihood (QMLE) (see e.g. (Lee, 2004)) to estimate the parameters λ and β in (6). This estimator uses a likelihood based on Gaussian ϵ, although Gaussianity is nowhere assumed. The intuition is that we can identify λ and β via the first two moments of y, so that an approach based on Gaussianity, even if misspecified, will work. Writing $S(\lambda) = I_n - \lambda W$ and taking $E(\epsilon\epsilon') = \sigma^2 I_n$ (I_n denotes the $n \times n$ identity matrix), the negative likelihood function is

$$\log\left(2\pi\sigma^2\right) - 2n^{-1}\log\left|S\left(\lambda\right)\right| + \sigma^{-2}n^{-1}\left\|S\left(\lambda\right)y - X\beta\right\|^2. \tag{8}$$

We concentrate out β and σ^2. For given λ, (8) is minimized with respect to β and σ^2 by

$$\bar{\beta}\left(\lambda\right) = \left(X'X\right)^{-1}X'S\left(\lambda\right)y, \tag{9}$$

$$\bar{\sigma}^2\left(\lambda\right) = n^{-1}y'S'\left(\lambda\right)MS\left(\lambda\right)y, \tag{10}$$

with $M = I_n - X\left(X'X\right)^{-1}X'$. The QMLE of λ is $\hat{\lambda} = \arg\min_{\lambda\in\Lambda}\mathcal{Q}\left(\lambda\right)$, where $\mathcal{Q}\left(\lambda\right)$ is the concentrated likelihood function,

$$\mathcal{Q}\left(\lambda\right) = \log\bar{\sigma}^2\left(\gamma\right) + n^{-1}\log\left|S^{-1}\left(\lambda\right)S^{-1\prime}\left(\lambda\right)\right|, \tag{11}$$

and Λ is a compact subset of $(-1, 1)$. The QMLEs of β and σ^2 are defined as $\bar{\beta}\left(\hat{\lambda}\right) \equiv \hat{\beta}$ and $\bar{\sigma}^2\left(\hat{\lambda}\right) \equiv \hat{\sigma}^2$ respectively. We report standard errors assuming homoskedasticity as well as heteroskedasticity robust versions.[20]

[19] A similar analysis can be carried out for unobserved heterogeneity at sectoral level in equation (1).

[20] Note that in general the QMLE is not consistency-robust to unknown heteroskedasticity, as noted by Lin and Lee (2010). However, Liu and Yang (2015) point out that the QMLE can remain consistent despite unknown heteroskedasticity under conditions that seem appropriate in our setting. Furthermore, the inconsistency is related to the sparsity, or the number of zero elements, of W or, in our block-diagonal case, the sparsity of $W_t^L, t = 1, \ldots, 30$. In particular, the less sparse each W_t^L is the less acute the asymptotic bias. Our W_t^L matrices are not sparse and thus the use of heteroskedasticity-consistent standard errors in our setting is further justified. Standard errors computed using the 'sandwich' covariance matrix give similar results, again because lack of sparsity mitigates the effect of the misspecification part of the covariance matrix.

6 Empirical results

Having characterized the evolution of the loan network over time, we can now discuss the estimates for λ in equation (6). Of particular importance is whether there exists any evidence for spillover effects, whether such effects vary over time and whether such effects also exist in the residual, signifying time-varying trends in network uncertainty.

6.1 Baseline results on lending rates

Table 4 reports our baseline results for the AISD using bank-loan-firm level variation. The first two columns in Table 4 report results from network specifications that do not include year fixed effects to control for common shocks. Thus, in these specifications the effect of the structure of the loan network is identified from the cross-sectional differences between loans in Column I (loan-purpose and loan-type fixed effects (FE)) and between banks that participate in each loan in Column II (Bank FE). We add bank FE to control for bank-specific supply shocks. In this case the heterogeneity comes from comparing the cost of lending across banks, implying that λ is identified from the variation stemming between banks. The coefficient estimate $\hat{\lambda}$ of the *financial-loan network* (recall that this is the regressor $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^{L} y_{j,t}$ in equation (6)) is statistically significant at the 1% level, indicating that one standard deviation change in the interconnectedness between loans (based on the specifications in column II and measured by $\sigma\left(\sum_{t=1}^{30}\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^{L} y_{j,t}\right) = 84.12bps$) increases the *AISD* by approximately 7.32 basis points (calculated from the product 0.087×84.12). Economically this effect is large: for the average loan in our sample (having an *AISD* equal to 187.11), this implies an increase in *AISD* by approximately 4% (calculated from $(7.32/187.11) \times 100$). Similarly, this represents around 5% of its standard deviation.

The general finding, without controlling for common shocks, is that the *financial-loan network* positively, and both statistically and economically, affects lending rates, providing evidence for the existence of spillovers from the loan network to lending rates. Moreover, the difference between the estimates with bank FE (Column II) and without (Column I) is almost zero in magnitude (0.002). This suggests that unobserved bank-specific credit supply shocks are not correlated with the changes in the $\hat{\lambda}$ (Jiménez, Ongena, Peydró and Saurina (2017)), mitigating endogeneity concerns.

Columns III and IV show the network effect after controlling for common shocks by adding year FE to the regressions reported in Columns I and II, respectively. Relative to Columns I and II, $\hat{\lambda}$ is determined from the banks in which we observe a change in loan participation decision due to common shocks. In Column IV we also add firm FE to exclude other firm time-invariant reasons as potential omitted-variables, as long as these variables do not change in the same period with the financial-loan network. In the presence of common shocks the results in Columns III and IV show that the effect of the *financial-loan network* changes sign and becomes negative and statistically significant at the 1% level. Based on the results from the regression including all fixed effects (Column IV), a one standard deviation (84.12 bps) increase in the *financial-loan network* yields a decrease in loan spreads by approximately 3.95 basis points (calculated from the product 0.047×84.12). Economically this is a large effect, equal to a 2.1% decrease for the average loan in our sample.

Since the empirical evidence suggests that the inclusion of common shocks might reverse the sign or the magnitude of the financial loan network spillover, the next step is to investigate further the transition of shocks between loans. In Table 6, we report results from estimating equation (6) with the full set of control variables as in Table 4, sequentially adding year fixed effects to control separately for the common shocks per year. The dependent variable in panel A is *AISD*. The coefficient on the *financial-loan network* is positive and statistically significant at 1% level until 2007. However, from 2005-2007 the magnitude of $\hat{\lambda}$ decreases. This decline culminates in a *financial-loan network* spillover that is statistically insignificant and close to zero in 2008, at the peak of the crisis. However, after 2008 the coefficient turns negative and statistically significant at 1% level (except in 2009, when the significance level is 5%). The evolution of $\hat{\lambda}$ as we sequentially add year fixed effects to the specification can also be illustrated graphically (Figure 9). The blue dashed lines trace out a 95% confidence interval based on standard errors assuming homoskedasticity and the green dashed lines trace out heteroskedasticity robust 95% confidence intervals. The blue and green stars denote the respective confidence interval bounds, while the black circles mark the point estimates, which we also trace out with a solid black line. The figure illustrates quite clearly the decline of the spillover as the crisis approaches, and the subsequent negative value that it takes.

Our results in Columns I and II provide the first important empirical finding of the paper, namely evidence for the existence of spillovers on lending rates via a loan network. These findings are consistent with the interpretation that the syndicated loan market allows for asset commonality between different banks and reduces banks' information production. Acharya and Yorulmazer (2007) and Farhi and Tirole (2012) argue that banks choose to correlate their risk exposure by investing in the same assets (herding). A positive correlation between lending rates suggests that banks participating in the syndicate might treat rates as strategic complements, with benefit of charging a higher spread increasing with the spread neighbours charge.[21] Other examples of such complementary interactions include network interactions in micro-economic shocks (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015), municipalities' state capacity choices (Acemoglu, Garcia-Jimeno and Robinson, 2015) and peer effects and education decisions in social networks (Calvó-Armengol, Patacchini and Zenou, 2009; Blume, Brock, Durlauf and Jayaraman, 2015).

Our results in Columns III, IV and V, but also in the graphical illustrations, show that the spillover estimates can vary over time and this change in spillover sign happens during large turmoil periods. A theoretical finding of Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) is that networks can act as shock propagators when the number of shocks is large, or when a large, single shock occurs.[22] Given that the financial crisis of 2007-09 is a large single financial shock, the observed change in spillover sign is empirically consistent with Acemoglu, Ozdaglar and Tahbaz-Salehi (2015). To confirm this, in Column V we add the full set of fixed effects but exclude the crisis FE. We observe a switch in the sign of the co-movement with, and without, the crisis FE. The baseline results clarify that increasing the size (by adding year FE) of the shocks yields a shift from positive to negative co-movement in the lending rates, thus reversing the role of the network in curtailing or causing financial spillovers. These empirical findings are similar to the reversal pattern in federal fund market rates during the crisis (Afonso, Kovner and Schoar, 2011).

Our results are also consistent with findings in the peer-effects literature, and thus can also be imbued with a behavioural flavour. This literature observes that negative peer effects (in our setting this means $\hat{\lambda} < 0$) result when individuals seek status by differentiating themselves from their peers (Ridgeway, 1978; Akerlof, 1997; Ahern, Duchin and Shumway, 2014). During times of financial distress, such as a major financial crisis, there is a trust deficit in the economy, and signals of quality become important. One channel through which such a signal can be sent is the "differentiation" channel, in which banks attempt to assert their quality by behaving differently from their peers. Another strand of the peer-effects literature emphasizes also the presence of negative co-movements when confirmation bias leads to polarized attitudes (Lord, Ross and Lepper, 1979). This

[21] Recall that "neighbour" is defined via W.

[22] Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) find a change in sign in the comparative statics with respect to the network structure when common shocks are large.

study stresses that individuals with very strong opinions on social issues interpret evidence not on its own merit but rather on whether it conforms with their initial belief. This generates further polarization, i.e. negative co-movement, taking place as all individuals "draw undue support" for their initial positions from mixed information. We conjecture that credit markets during a grave financial crisis, when information is unreliable and emotions run high, are ripe environments for such mistrust and polarization, reflected in negative spillovers in interest rates.

[Please insert Table 4 about here]

[Please insert Table 6 about here]

6.2 Baseline results on loan amounts

In Columns I-V of Table 5, we replicate the analysis as in Table 4, but this time the dependent variable is the *Deal amount*. The general finding is that $\hat{\lambda}$ is economically large and statistically significant at 1% (and 5% in Column III) when we do not control for common shocks (year FE). The estimate of the *financial-loan network* indicates that a one standard deviation ($\sigma\left(\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^{L} y_{j,t}\right) = 479.18(\$M)$) increase in the interconnectedness between loans (based on the specifications in column II) increases the *Deal amount* by approximately 129.37 \$M (calculated from the product 0.270×479.18). Economically this is a large effect; for the average loan in our sample (having an *Deal amount* equal to 479.18), this implies an increase in *Deal amount* by approximately 27% (calculated from $(129.37/479.18) \times 100$). Including year FE (Column V) reduces the economic magnitude and the financial loan network becomes statistically insignificant. The results remain qualitatively similar to the ones in Table 4 showing that changes in the magnitude of spillovers can also take place for other variables like loan quantities.

As in the previous subsection, we can examine the time-series evolution of the estimated spillover $\hat{\lambda}$ in *Deal amount* as we add, sequentially, year fixed effects. Table 6, Panel B reports the results when the dependent variable is *Deal amount*. We again observe that the magnitude of $\hat{\lambda}$ decreases as we approach the financial crisis, and while statistical significance at 5% is present, this ultimately finally dies out as the 2013 fixed effect is added. In tandem with results observed in columns IV and V of Table 5, where the inclusion or exclusion of the 2007-09 fixed effects drives the significance or insignificance of the spillover, we confirm the crucial role of the crisis. The graphical illustration is provided in Figure 10 where, as before, the blue dashed lines trace out a 95% confidence interval based on standard errors assuming homoskedasticity and the green dashed lines trace out heteroskedasticity robust 95% confidence intervals.

[Please insert Table 5 about here]

Our results on loan quantities are also consistent with the theoretical results in Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) where a large shock can lead to a network propagating rather than absorbing shocks through the change in the spillover magnitude. Moreover, the positive co-movement in both lending rates and quantities during good periods is consistent with Acharya and Yorulmazer (2007) and Farhi and Tirole (2012), who argue that banks choose to invest in the same assets (herding) and increase their exposure to the same risk. Thus, banks increase their participation in the syndicated loan market (reflected in higher deal amounts) in order to correlate their portfolios with a common set of borrowers.

6.3 Robustness tests

We now present some robustness tests for our empirical results. In the specification of Table 7, we report results from three alternative measures for the cost of lending (Columns I-VI) and one other measure of lending amount (Columns VII-VIII). We observe equivalent results in the *AISU* for the full set of fixed effects (Column I) and when excluding the crisis FE (Column II). We find that in Column I the effect of the *financial-loan network* for *AISU* is negative but statistically insignificant, while when we exclude the crisis FE (Column II) we observe a positive and statistically significant effect at 1% level. Based on the specification in column II, the $\hat{\lambda}$ indicates that one standard deviation (7.93 bpt) change in loan interconnectedness increases the *AISU* by approximately 0.7 bps. This represents an increase in the average *AISU* in our sample by 4.2%. A similar interpretation holds for the *Spread* and the *letter-of-credit fees*.[23] Regarding the lending quantities (*Deal amount*), we observe equivalent results for the amount of the letter-of-credit. More precisely, when we control for common shocks (column VI), a one standard deviation (18.87 $M) change in loan interconnectedness increases the *LOC* by approximately 2.58 $M. This represents an increase in the average *LOC* in our sample of 14%.

The set of fixed effects that we have previously used control for time-invariant unobserved variables that may simultaneously affect the *financial-loan network* and the lending

[23] For the alternative proxies of the cost lending, we rely on Berg, Saunders and Steffen (2016).

rates or quantities. In Column IX and X, we replicate the baseline results of Column IV of Tables 4 and 5 but now with additional bank × year FE.[24] The inclusion of the bank × year FE allows to saturate the model from an alternative within bank-year (supply-side) explanation of our findings.[25] More precisely, we account for changes in bank behaviour that affect the terms of lending or the lending quantities. Furthermore, it is important to note that we are primarily interested in the effect of the *financial-loan network* on loan rates and quantities, once these banks have made their participation decision.

Our analysis has focussed on the estimates of λ, but the coefficients on other control variables have the expected signs, with spreads being a function of borrower and loan risk. For instance, loan deals that refinance a previous loan and incorporate internal guarantees tend to be more risky and therefore have higher spreads, while secured facilities tend to be more risky, and hence have higher spreads.[26] Loans with performance-related pricing provisions (this is an indicator takes the value one if the spread is adjustable based on pre-defined performance metrics) and covenants tend to have lower spreads (Ioannidou and Ongena, 2010; Lim, Minton and Weisbach, 2014). Concerning the firm-level variables, larger firms, with higher Tobin's q (market-to-book ratios), and higher volumes of tangible assets pay lower spreads. Also, firms that had at least one previous relationship with the lead arranger in the past five years receive a lower spread because there is a smaller deviation from the "soft information" (Delis, Kokas and Ongena, 2017). A similar analysis holds for the amount ($M) of loans that a firm has received over the last five years. These results are intuitive given the share and reputation of larger firms and the adverse effects of firm risk on obtaining cheaper loans. Firms perceived as less risky have loan deals with lower spreads, and a firm's profitability in the form of ROA is associated with lower spreads. The bank-level control characteristics exhibit similar features. Banks with higher exposure to interest expenses and provisions will tend to charge higher spreads, in contrast with larger banks.

[Please insert Table 7 about here]

[24]The structure of our dataset is a multi-level dataset with the different levels stemming from the fact that multiple loan deals are given by the same bank within a year.

[25]Our dataset lacks sufficiently many firms that receive more than one loan within one year, ruling out the inclusion of firm×year FE. Furthermore, this effect almost completely identifies equation (6) and may not add much to the empirical strategy, given that the bank-loan-firm level controls and the bank and firm FE already incorporate the information defining the bank-firm relationship.

[26]Security by itself lowers the risk of a loan. However, secured loans tend to be issued by younger, riskier firms with lower cash flows, so the positive relation with spreads likely reflects this additional risk. See Berger and Udell (1990).

7 Testing for complexity and uncertainty

In the aftermath of Lehman Brother's bankruptcy there was a substantial dry-up of liquidity in the syndicated loan market. One interpretation is that participants face a game of strategic substitutes (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015) to avoid being connected to one another because market participants are aware that overlapping portfolios could deteriorate their positions and make them over-exposed to their counter-parties. More precisely, the participation in the syndicated loan market decreases, the higher the initial intensity of participation of the connected banks. That is, the pay-off for each bank depends not only on loan's and borrower's characteristics, but also on those of their connected partners. In the admittedly extreme but still suggestive case of the Lehman Brothers failure, banks that were participating in syndicated loans with them during 2008 suffered more in the period after their collapse (Ivashina and Scharfstein, 2010). This was mainly due to the fact that these banks had to complement the Lehman Brothers share in existing credit-lines and, thus, to reduce the financing of new projects. One interpretation of these facts is that uncertainty rises has real effects through a financial network after a negative shock. Another interpretation is that a central factor behind this uncertainty lies in the complexity of the linkages among modern banks (Caballero and Simsek, 2013).

In our model, the structure of the error term that captures all unobserved spatial heterogeneity between loans, can be interpreted as a measure of network complexity (Caballero and Simsek, 2013) and/or counterparty uncertainty (Ivashina and Scharfstein, 2010). Moreover, our framework allows us to therefore explicitly test for the presence of network spillovers in the error term. We describe the technical details below but the basic idea is to use a spatial analog of the Durbin-Watson serial correlation testing procedure familiar from time series analysis.

More specifically, we analyse the cross-sectional correlation via W in the disturbances ϵ of equation (6). In particular we are seeking to test the null hypothesis

$$H_0^{\epsilon} : \rho = 0 \tag{12}$$

in the specification

$$\epsilon = \rho W \epsilon + \eta, \tag{13}$$

where η is a disturbance. (13) captures the spatial complexity and/or uncertainty and a failure to reject (12) can be interpreted as evidence consistent with the existence of complexity and/or uncertainty in the network.

Moran's $\mathscr{I}$ statistic, due to Moran (1950) is a way to test the null hypothesis H_0^ϵ against the alternative of cross sectional correlation, i.e. $\rho \neq 0$. The statistic is given by

$$\mathscr{I} = \frac{\hat{\epsilon}' W \hat{\epsilon}}{n^{-1}\hat{\sigma}^2 \sqrt{2trace\left(W^2\right)}}, \tag{14}$$

where $\hat{\epsilon} = y - \hat{\lambda} W y - X\hat{\beta}$, i.e. the QMLE residuals. Kelejian and Prucha (2001) showed that $\mathscr{I}$ is asymptotically standard normal under reasonable regularity conditions. A large absolute value of $\mathscr{I}$ leads to rejection of H_0^ϵ and thus evidence of the presence of a network effect, via W, in the errors ϵ. On the other, small absolute values give evidence of the absence of a network effect, via W, in ϵ.

Tables 4 and 5 also display the $\mathscr{I}$ test-statistic for various specifications and for both choices of dependent variable. For both dependent variables, the statistic is large when year fixed effects are not included. Including year fixed effects makes the statistic negative, but still significant when bank or bank and loan purpose fixed effects are included, indicating the presence of negative spillovers, i.e. $\rho < 0$ in (13). However, when we control for firm fixed effects together with year fixed effects, the $\mathscr{I}$ statistic becomes less than 1.96 in absolute value, leading to a failure to reject (12) at the 5% significance level. In other words, the loan network collapses when all these effects are controlled for. When the dummies for 2007, 2008 and 2009 are excluded from the specification, the $\mathscr{I}$ statistics become large again and imply that (12) is rejected. Thus this loan network collapse is clearly driven by the crisis. It is noteworthy that the same pattern is evident for both lending rates and deal amount as the the response variables.

8 Networked versus non-networked economies: a counterfactual evaluation

In this section we conduct a simulation study to quantify the difference between an economy in which interest rates or lending amounts are determined independently of the interaction network W, and economies in which the interaction network plays a role in the determination of interest rates. Specifically, imagine that there are four economies, each with 52,810 loans (as in the data), in which an underlying stochastic process ζ determines the interest rates charged.[27]. In economy $\mathcal{E}_0$, $\lambda = 0$ and interest rates y^0 are determined as $y^0 = \zeta$: this is an economy with no network effects (and therefore no spillovers). On the other hand, in economies $\mathcal{E}_1$, $\mathcal{E}_2$ and $\mathcal{E}_3$ the network W determines interest rates in the following way

$$y^1 = \lambda_1 W y^1 + \zeta = \lambda_1 W y^1 + y^0, \tag{15}$$

$$y^2 = \lambda_2 W y^2 + \zeta = \lambda_2 W y^2 + y^0, \tag{16}$$

$$y^3 = \lambda_3 W y^3 + \zeta = \lambda_3 W y^3 + y^0, \tag{17}$$

where each $\lambda \neq 0$. In keeping with our empirical results, we choose $\lambda_1 = 0.087$, $\lambda_2 = 0.062$ and $\lambda_3 = -0.05$ (the largest and smallest positive values of λ as well as the negative value with largest magnitude from our results in Table 4). Note that we can write (15)-(17) as

$$y^i = (I - \lambda_i W)^{-1} y^0 = \left(\sum_{\ell=0}^{\infty} \lambda_i^\ell W^\ell \right) y^0 = y^0 + \left(\sum_{\ell=1}^{\infty} \lambda_i^\ell W^\ell \right) y^0, i = 1, 2, 3. \tag{18}$$

The extra term on the farthest RHS of (18) shows transparently what distinguishes economies $\mathcal{E}_1$, $\mathcal{E}_2$ and $\mathcal{E}_3$ from economy $\mathcal{E}_0$. Our simulation procedure is to generate the 52,810 dimensional vector ζ as the average of 500 replications from a uniform distribution with mean 187.5, to match the mean of AISD in the summary statistics of Table 2. After doing this we compute

$$a_{\mathcal{E}_1}^{\mathcal{E}_0} = (52810)^{-1} \sum_{k=1}^{52810} \left(\frac{y_k^2 - y_k^0}{y_k^0} \right) - 1,$$

$$a_{\mathcal{E}_2}^{\mathcal{E}_0} = (52810)^{-1} \sum_{k=1}^{52810} \left(\frac{y_k^3 - y_k^0}{y_k^0} \right) - 1,$$

$$a_{\mathcal{E}_3}^{\mathcal{E}_0} = -(52810)^{-1} \sum_{k=1}^{52810} \left(\frac{y_k^4 - y_k^0}{y_k^0} \right) - 1,$$

with the k subscripts denoting k-th element of the vector. Notice that $a_{\mathcal{E}_1}^{\mathcal{E}_0}$ is a measure of the average difference in the interest rates between economies $\mathcal{E}_0$ and $\mathcal{E}_1$, as a percentage of the interest rates in economy $\mathcal{E}_0$. In other words, it is a measure of the average percentage change in interest rates due to the presence of a spillover $\lambda_1 = 0.087$ and the interaction

[27] Of course interest rates may be determined by many fundamentals, but as our aim is to quantify the effect of the interaction network we abstract away from this in the interests of simplicity.

network. Analogous interpretations of $a^{\mathcal{E}_0}_{\mathcal{E}_2}$ and $a^{\mathcal{E}_0}_{\mathcal{E}_3}$ follow. We find that

$$a^{\mathcal{E}_0}_{\mathcal{E}_1} = 5.54\%,\ a^{\mathcal{E}_0}_{\mathcal{E}_2} = 3.86\%,\ a^{\mathcal{E}_0}_{\mathcal{E}_3} = -2.81\%.$$

Thus, a spillover of $\lambda_1 = 0.087$ leads to interest rates that are 5.54% higher, on average, in the networked economy $\mathcal{E}_1$ as compared to the baseline economy $\mathcal{E}_0$. On the other hand, a smaller positive spillover of $\lambda_2 = 0.062$ implies that interest rates are 3.86% higher in economy $\mathcal{E}_2$ compared to economy $\mathcal{E}_0$. When the spillover is negative, i.e. $\lambda_3 = -0.05$, we find that, on average, interest rates are 2.81% lower in economy $\mathcal{E}_3$ as compared to economy $\mathcal{E}_0$. From this experiment we can conclude that network spillovers play an important role in determining the pricing of loans in credit markets.

We can, however, go a step further. In section 4, we studied the evolution of the loan networks W^L_t over time and concluded that certain changes take place during the financial crisis of 2007-09. The preceding simulation took this evolution into account. But can we conduct a counterfactual simulation that allows us to determine what might have happened had the loan network remained constant over time? Even more specifically, can we determine how interest rates in economy $\mathcal{E}_0$ compare with those in a networked economy for which the the network structure remained constant over 30 years?

The answer is yes, and we proceed as follows. First, imagine nine new networked economies in which the loan network remains constant over all 30 years. These economies are defined by the same three values $\lambda_1 = 0.087$, $\lambda_2 = 0.062$ and $\lambda_3 = -0.05$ that we used previously, but also by three choices of fixed network, corresponding to those for 2006 (identified by superscript BC), 2008 (superscript C) and 2011 (superscript AC), respectively. The years are chosen to correspond to just before the financial crisis (hence BC), the peak of the financial crisis (C) and after the financial crisis (AC). We denote these economies as $\mathcal{E}^{BC}_1$, $\mathcal{E}^{BC}_2$, $\mathcal{E}^{BC}_3$, $\mathcal{E}^{C}_1$, $\mathcal{E}^{C}_2$, $\mathcal{E}^{C}_3$, $\mathcal{E}^{AC}_1$, $\mathcal{E}^{AC}_2$ and $\mathcal{E}^{AC}_3$, with the subscripts signifying the values of λ as before. Thus, for example, economy $\mathcal{E}^{C}_3$ has $\lambda_3 = -0.05$ and $W = diag\left[W^L_{22}, \ldots, W^L_{22}\right]$ while economy $\mathcal{E}^{AC}_1$ has $\lambda_1 = 0.087$ and $W = diag\left[W^L_{25}, \ldots, W^L_{25}\right]$. We generate ζ as in the preceding paragraph, and the interest rates in these new economies analogously to equation (18). Carrying out a similar computation to the paragraph above we find

$$\begin{array}{lll} a^{\mathcal{E}_0}_{\mathcal{E}_1,BC} = 7.35, & a^{\mathcal{E}_0}_{\mathcal{E}_2,BC} = 5.12, & a^{\mathcal{E}_0}_{\mathcal{E}_3,BC} = -3.7, \\ a^{\mathcal{E}_0}_{\mathcal{E}_1,C} = 1.18, & a^{\mathcal{E}_0}_{\mathcal{E}_2,C} = 0.83, & a^{\mathcal{E}_0}_{\mathcal{E}_3,C} = -0.64, \\ a^{\mathcal{E}_0}_{\mathcal{E}_1,AC} = 8.38, & a^{\mathcal{E}_0}_{\mathcal{E}_2,AC} = 5.84, & a^{\mathcal{E}_0}_{\mathcal{E}_3,AC} = -4.21. \end{array}$$

In the results displayed above, we define the $a_{\cdot,\cdot}^{\mathcal{E}_0}$ as before, except we now have more cases with the nine difference types of economies to be compared to $\mathcal{E}_0$. If the loan network had been the one for 2006 in every year, then the corresponding economies ($\mathcal{E}_1^{BC}$, $\mathcal{E}_2^{BC}$, $\mathcal{E}_3^{BC}$) would have interest rates that are 7.35% higher, 5.12% higher and 3.7% lower, on average, than those prevalent in $\mathcal{E}_0$. On the other hand, as we observed in section 4, the network for 2008 is much 'weaker', with the crisis at its peak. With this network governing interactions over all 30 years the same range of λ values yield interest rates that are only 1.18% higher, 0.83% higher and 0.64% lower, on average, than in $\mathcal{E}_0$. The network recovers vitality in 2011, however, as the effects of the crisis are left behind. Indeed, if such a network had been in operation over all 30 years, the corresponding interest rates, on average, are 8.38% higher, 5.84% higher and 4.21% lower than in economy $\mathcal{E}_0$.

We therefore conclude that economies with financial networks have lending rates that are substantially higher (lower) depending on whether the spillover through the network is positive (negative), as opposed to economies with no such networks. Furthermore, for the same spillover magnitude, the network structure can evolve sufficiently to quantitatively change the conclusions from relying on a static network. Network structure can undergo particularly stark changes and can be especially visible after large shocks like the 2008 crisis.

A similar analysis holds for lending amounts. The procedure follows exactly as above, except we now generate the 52,810 dimensional vector ζ as the average of 500 replications from a uniform distribution with mean 625 to match the mean of Deal Amount in Table 2. We now choose $\lambda_1 = 0.278$, $\lambda_2 = 0.083$ and $\lambda_3 = 0.006$, according to Table 5, obtaining the following results:

$$
\begin{array}{lll}
a_{\mathcal{E}_1}^{\mathcal{E}_0} = 20.59, & a_{\mathcal{E}_2}^{\mathcal{E}_0} = 5.27, & a_{\mathcal{E}_3}^{\mathcal{E}_0} = 0.36, \\
a_{\mathcal{E}_1,BC}^{\mathcal{E}_0} = 27.59, & a_{\mathcal{E}_2,BC}^{\mathcal{E}_0} = 6.99, & a_{\mathcal{E}_3,BC}^{\mathcal{E}_0} = 0.47, \\
a_{\mathcal{E}_1,C}^{\mathcal{E}_0} = 4.02, & a_{\mathcal{E}_2,C}^{\mathcal{E}_0} = 1.12, & a_{\mathcal{E}_3,C}^{\mathcal{E}_0} = 0.08, \\
a_{\mathcal{E}_1,AC}^{\mathcal{E}_0} = 31.49, & a_{\mathcal{E}_2,AC}^{\mathcal{E}_0} = 7.97, & a_{\mathcal{E}_3,AC}^{\mathcal{E}_0} = 0.54.
\end{array}
$$

As for lending rates, the first row above corresponds to a time-varying network, while the next three correspond to static networks for 2006, 2008 and 2011 respectively. Thus, a spillover of $\lambda_1 = 0.278$ leads to lending amounts that are 20.59% higher, on average, in the time-varying networked economy $\mathcal{E}_1$ as compared to the baseline economy $\mathcal{E}_0$, while a smaller positive spillover of $\lambda_2 = 0.083$ implies that amounts are 5.27% higher in economy $\mathcal{E}_2$ compared to economy $\mathcal{E}_0$. When the spillover is close to zero, i.e. $\lambda_3 = 0.006$, we find that, on average, amounts are only 0.36% higher in economy $\mathcal{E}_3$ as compared to economy $\mathcal{E}_0$.

If the loan network had been static, taking the form of the network for 2006 in every year, then the corresponding economies ($\mathcal{E}_1^{BC}$, $\mathcal{E}_2^{BC}$, $\mathcal{E}_3^{BC}$) would have lending amounts that are 27.59%, 6.99% and 0.47% higher, on average, than those prevalent in $\mathcal{E}_0$. As above, with the static 2008 network, lending amounts are only 4.02%, 1.12% and 0.08% higher, on average, than in $\mathcal{E}_0$. With the recovered network of 2011, the corresponding amounts, on average, are 31.49%, 7.97% and 0.54% higher than in economy $\mathcal{E}_0$, signifying the regained strength of the financial network.

9 Conclusion

We use the syndicated loan market to construct a dynamic loan network that measures proximity in terms of sectoral investment exposure between individual banks, and characterize its evolution over time. The key insight is that banks interact not only through direct interbank connections, but also through indirect connections due to, for example, investment in common syndicated loans. The way that we have developed the loan network is a direct measure of interconnectedness: less interconnected loans have less similar banks and less common exposure.

Using a spatial autoregressive model that allows direct network interactions, we find strong spillovers from the financial network to lending rates and quantities. These spillovers are economically large, time varying and can switch sign after major economic shocks. The switch from positive to negative co-movements in lending rates during and after the financial crisis of 2007-09 signifies that the loan network is acting as a shock propagator rather than an absorber in periods of greater turmoil. The baseline findings are therefore consistent with Acemoglu, Ozdaglar and Tahbaz-Salehi (2015), who observe a switch in sign in comparative statics with respect to the network structure when common shocks are large.

Our approach also allows us to explicitly test for the presence of cross-sectional network spillovers in the error term. Such a test provides evidence for network complexity and uncertainty rising after a large negative shock, consistent with recent theoretical network models (Caballero and Simsek, 2013). Given this empirical support, one interesting area for future research is to better understand models with differential bank participation in financial networks and subsequently construct structural models that can also allow for non-linear externalities.

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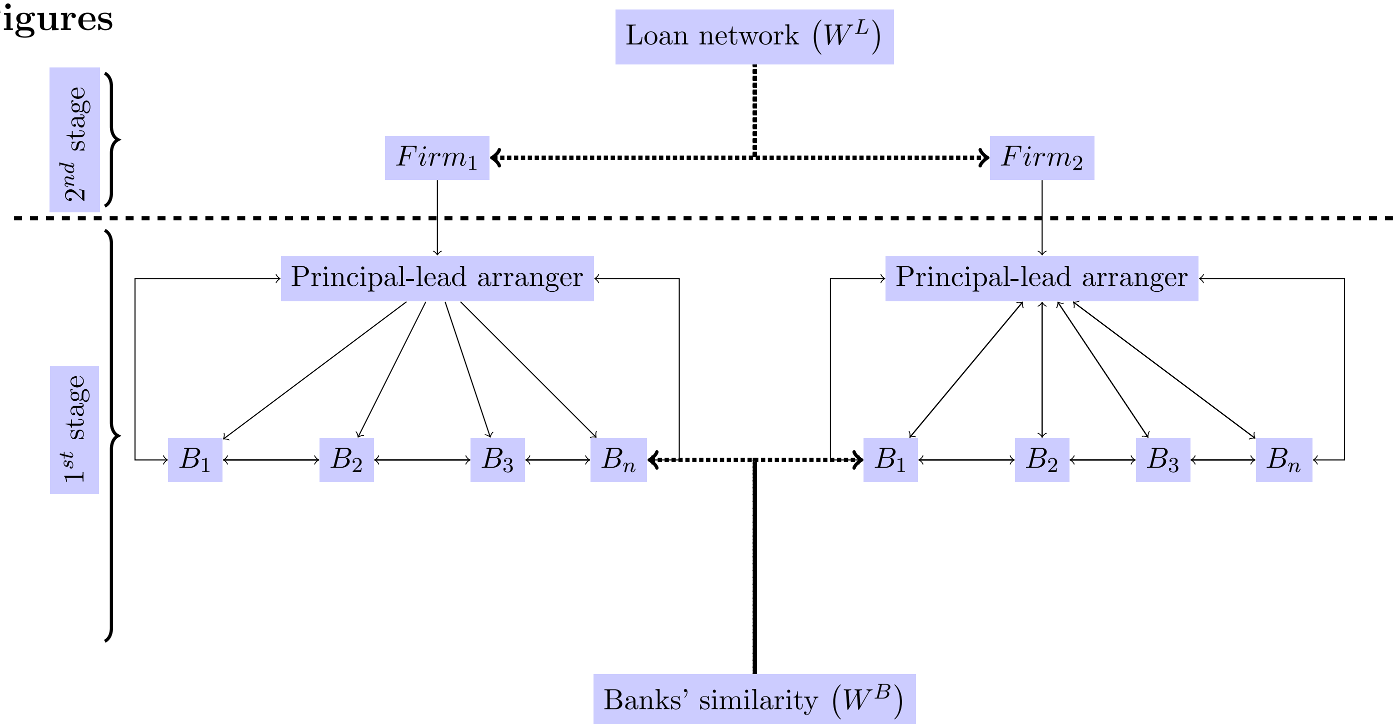
Figures

Figure 1: Illustration of the syndicated loan market



The figure illustrates the structure of the syndicated loan market and the two-step approach to calculate the loan network. The structure of the syndicate works as follows, the lead arranger is usually appointed by the firm. Furthermore, the lead bank negotiates and drafts all the loan documents, but participants can provide comments and suggestions when the syndication occurs prior to closing. Each bank is a direct lender to the firm, with every member's claim evidenced by a separate note, although there is only a single loan agreement contract. In the 1^{st} stage we construct bilateral investment exposure for each bank that participates in the syndicated loan market at time t by comparing sectoral investment similarity. The banks' similarity is weighted (in millions of dollars) through the percentage involvement of each bank B at time t in loan l that is granted to sector s. In the 2^{nd} stage, we aggregate banks' similarities using information on bank participation in each syndicated loan.

Figure 2: Bank and loan network for 1987. Purple nodes indicate banks while orange nodes are loans. A line from a purple node to an orange node means that the bank represented by the purple node is a member of the loan syndicate for the loan represented by the orange node. The larger a purple node, the more loan syndicates the bank is a member of.

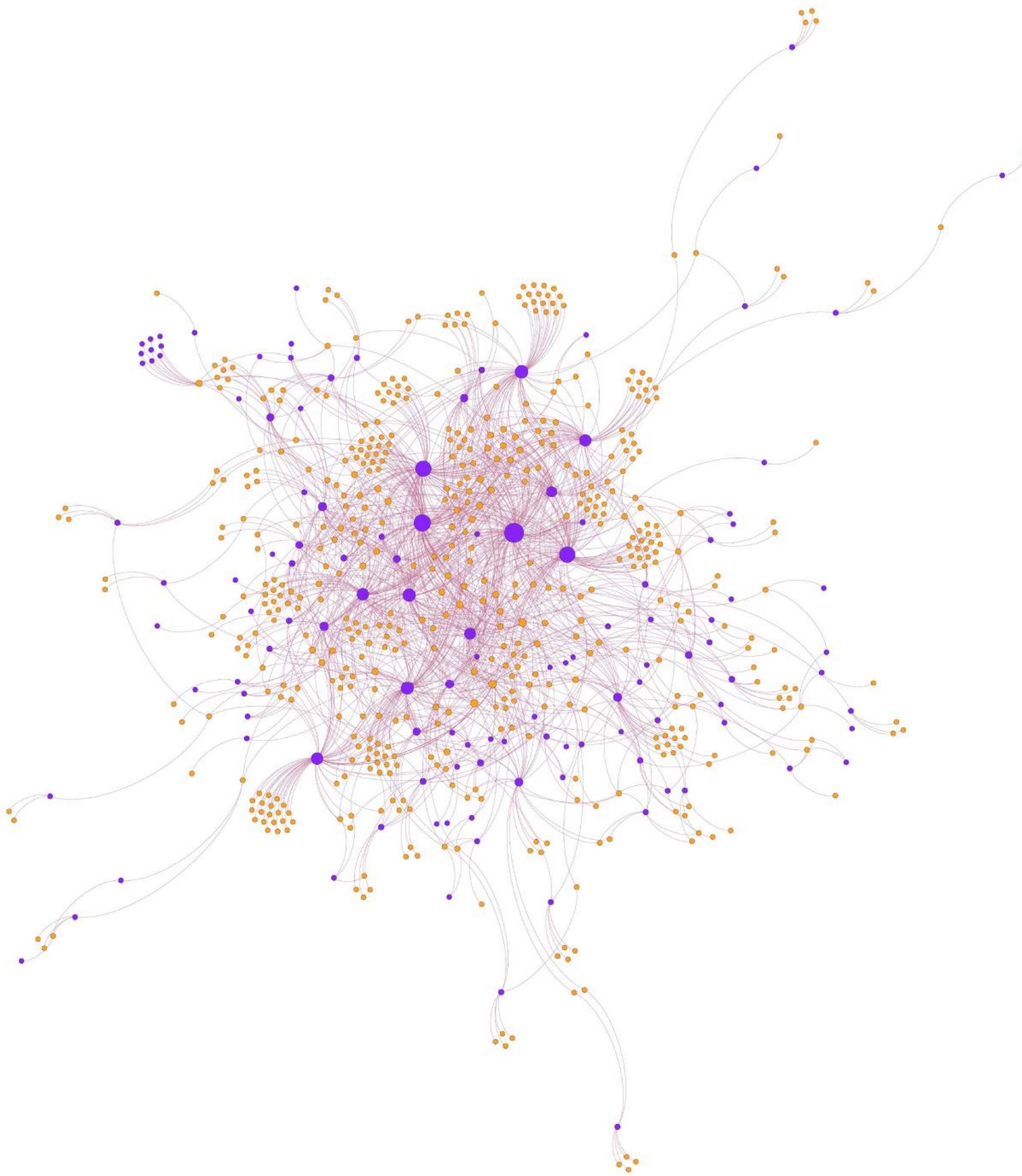


Figure 3: Illustration of loan network for 10 loans in 1987. Thicker lines indicate stronger interconnection, larger orange nodes indicate greater number of connections.

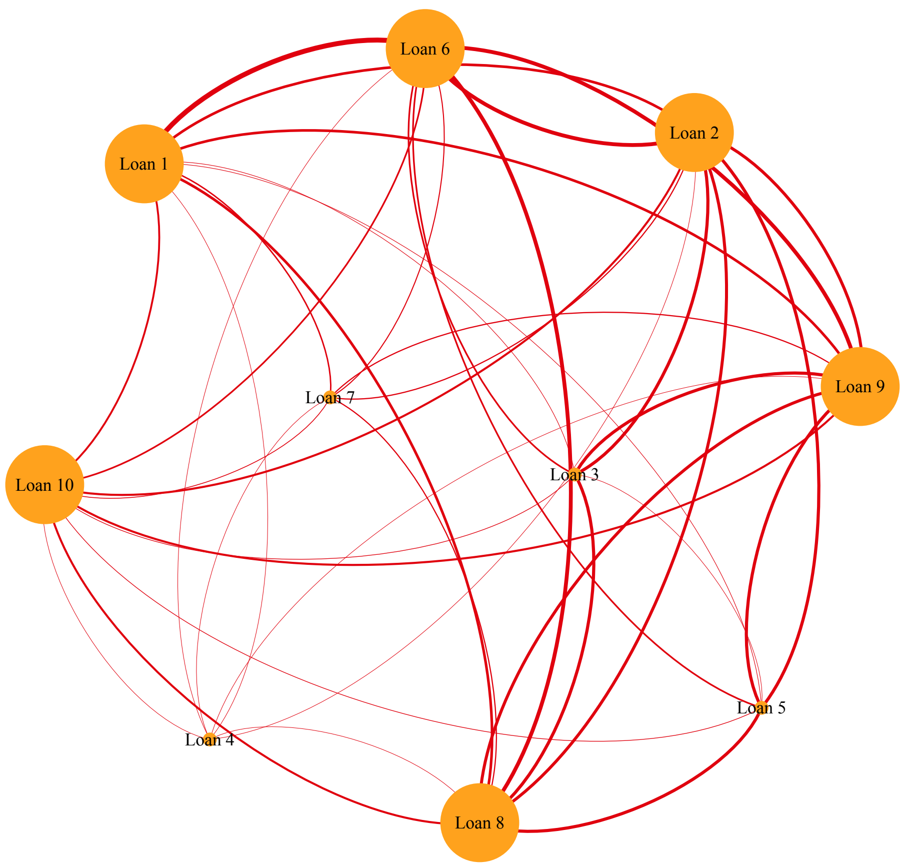


Figure 4: Bank and loan network for 2006. Purple nodes indicate banks while orange nodes are loans.

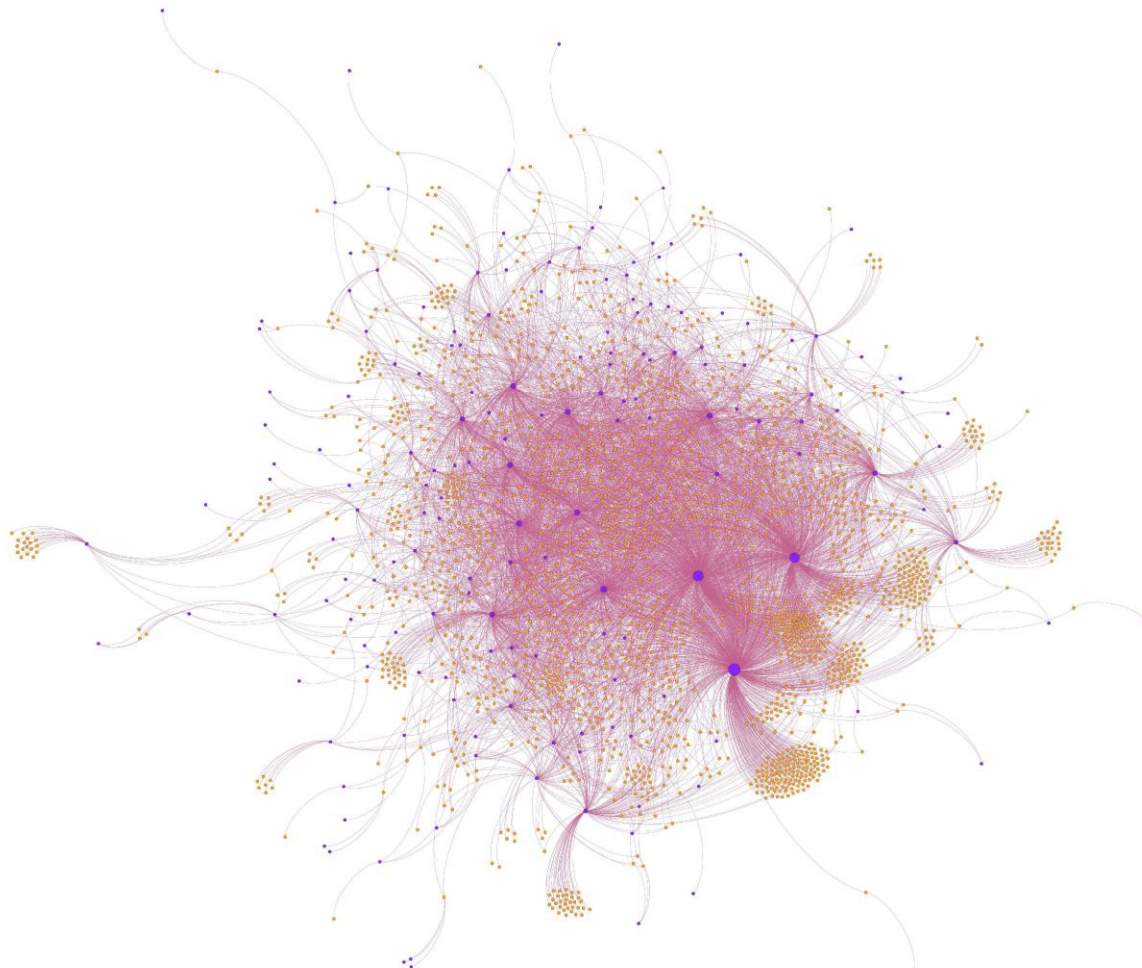


Figure 5: Bank and loan network for 2009. Purple nodes indicate banks while orange nodes are loans. A line from a purple node to an orange node means that the bank represented by the purple node is a member of the loan syndicate for the loan represented by the orange node. The larger a purple node, the more loan syndicates the bank is a member of.

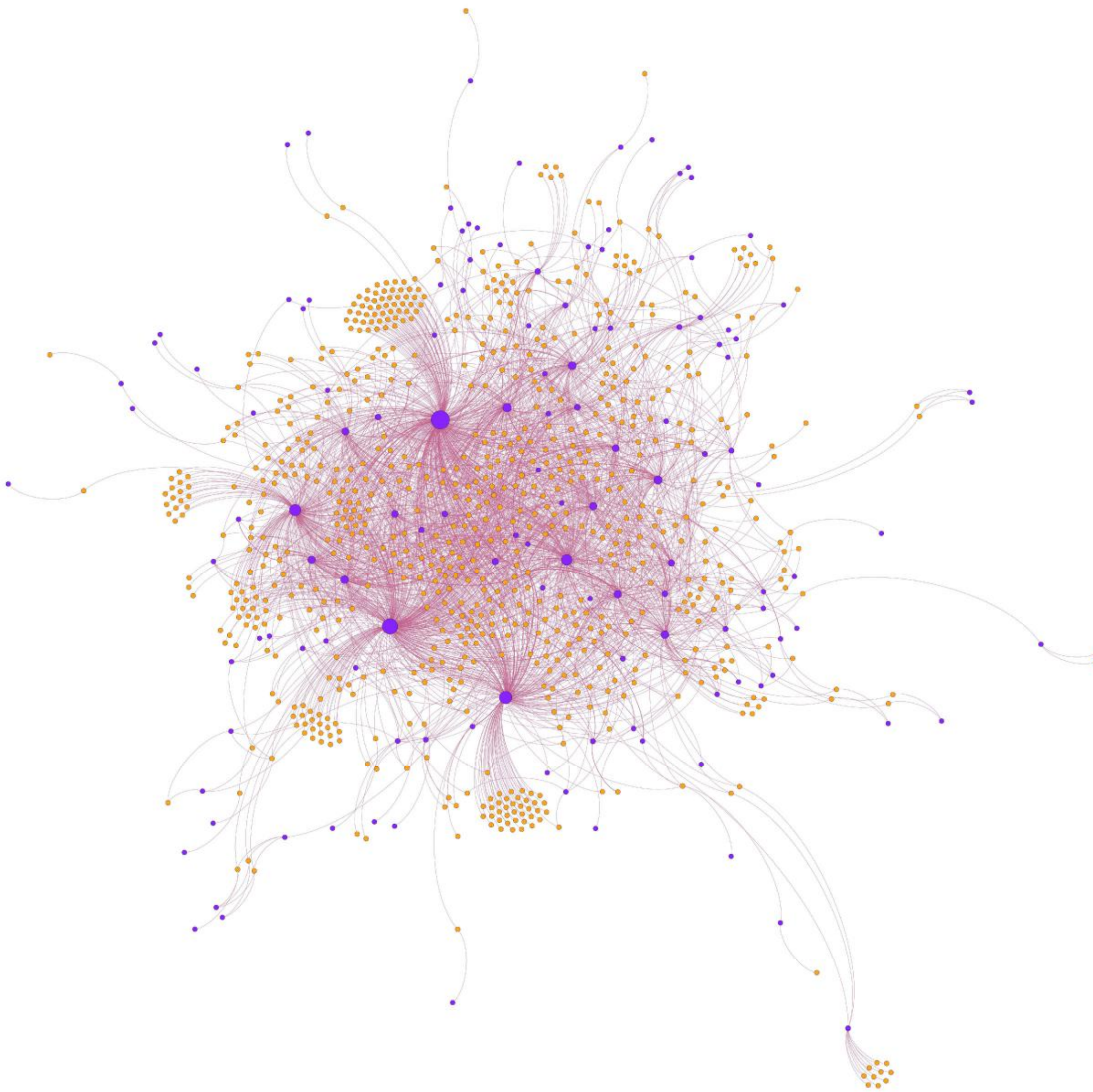


Figure 6: Bank and loan network for 2010. Purple nodes indicate banks while orange nodes are loans. A line from a purple node to an orange node means that the bank represented by the purple node is a member of the loan syndicate for the loan represented by the orange node. The larger a purple node, the more loan syndicates the bank is a member of.

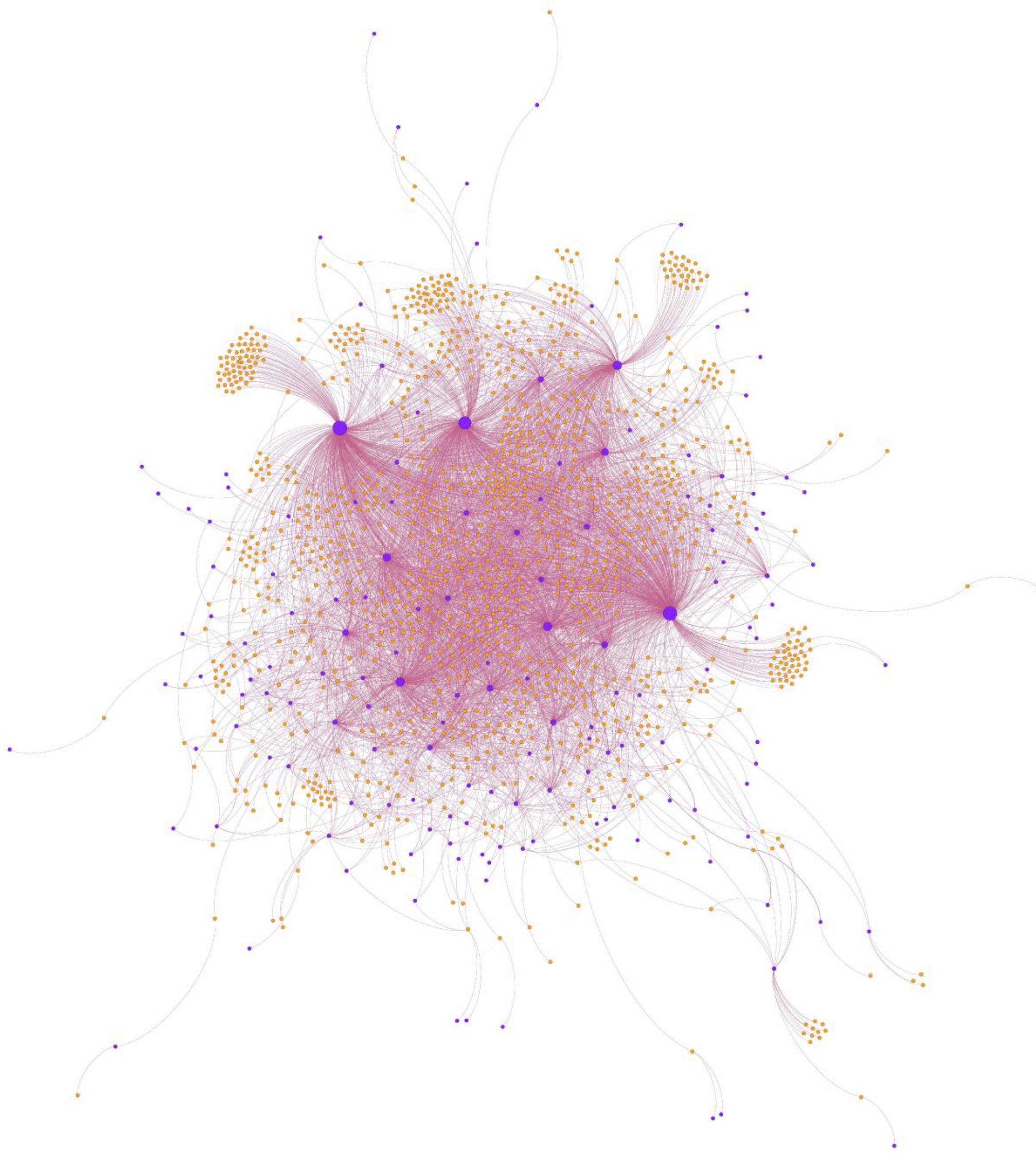


Figure 7: Loan network for 2007, 150 loans. Larger orange nodes indicate loans with a greater number of connections.

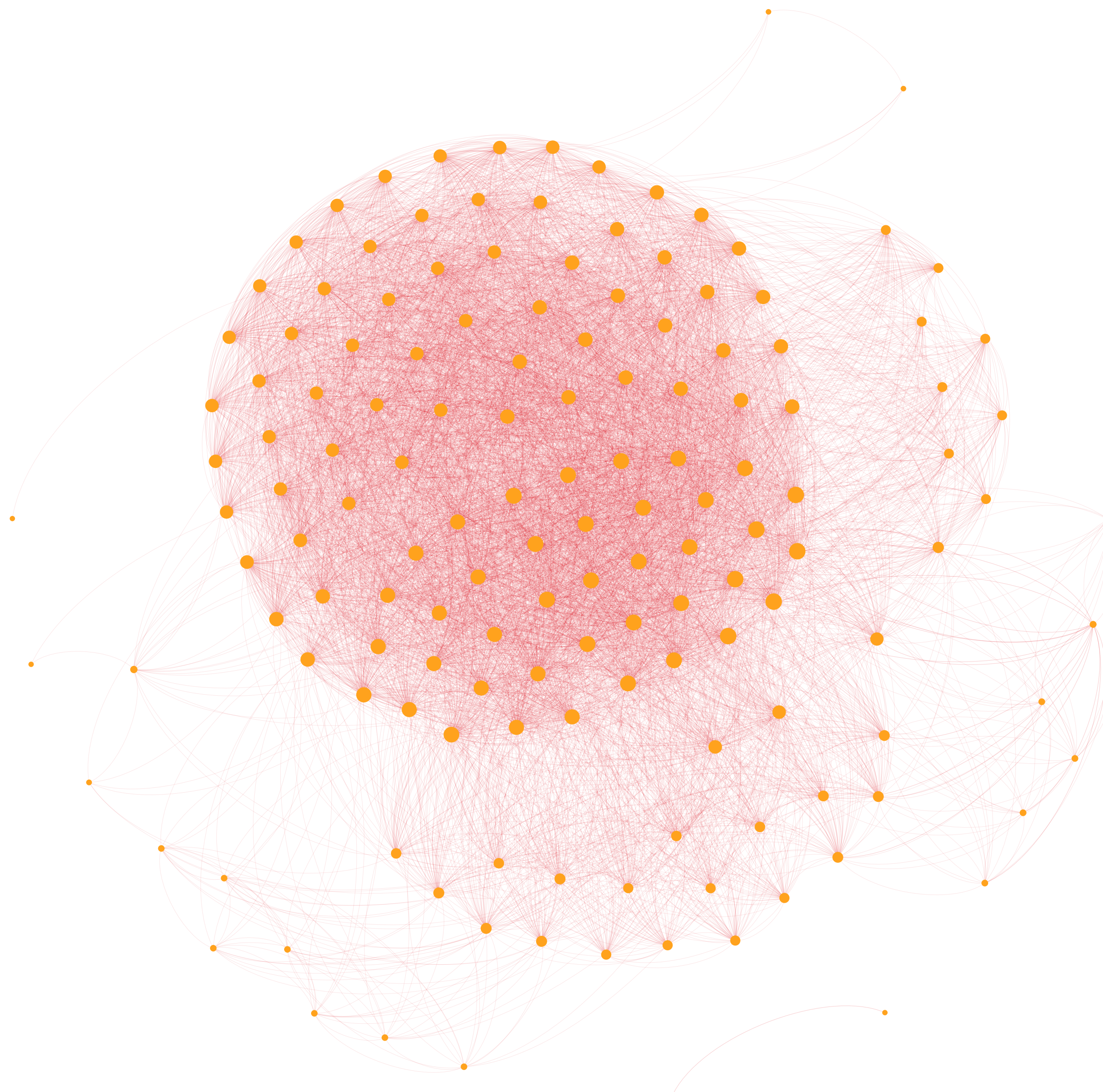
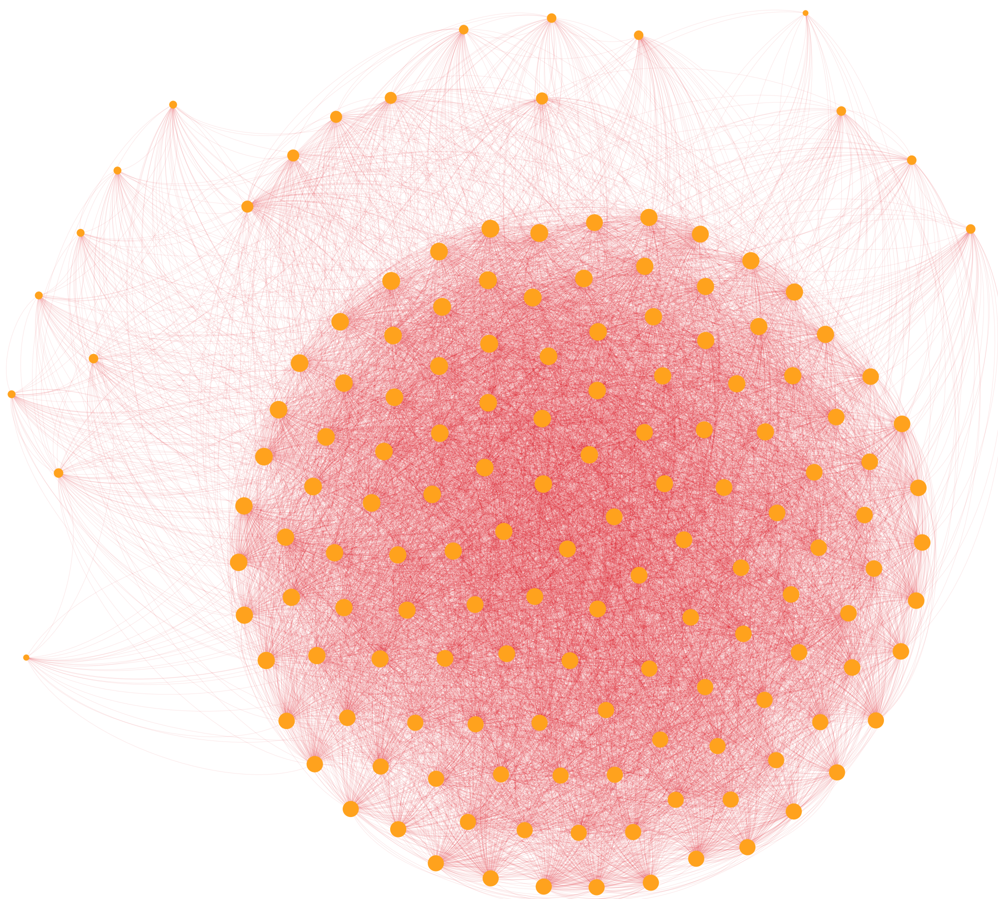


Figure 8: Loan network for 2011, 150 loans. Larger orange nodes indicate loans with a greater number of connections.



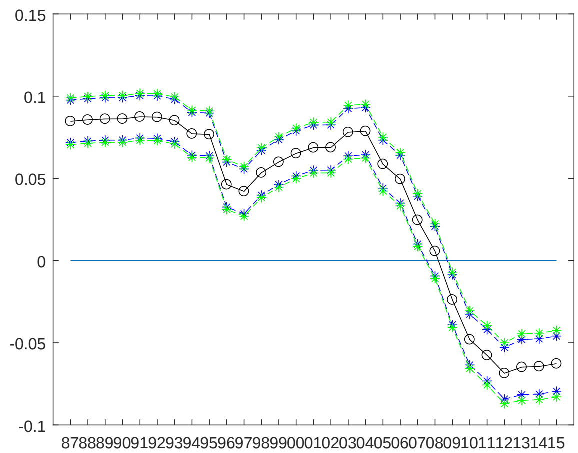


Figure 9: $\hat{\lambda}$ (black circles) with lending rates (AISD) as dependent variable as we add year fixed effects sequentially. We also trace out the 95% confidence interval assuming homoskedasticity (blue stars) and the heteroskedasticity robust 95% confidence interval (green stars).

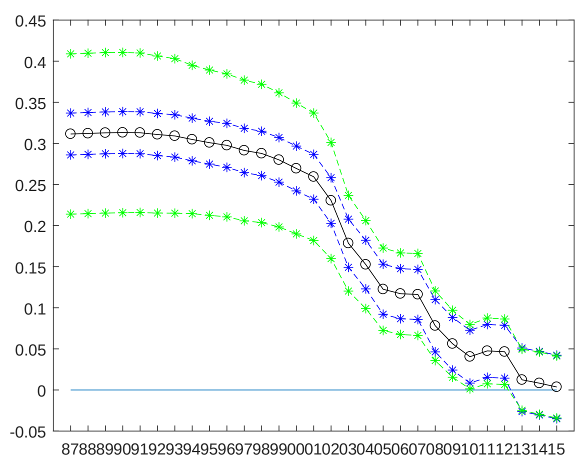


Figure 10: $\hat{\lambda}$ (black circles) with deal amount as dependent variable as we add year fixed effects sequentially. We also trace out the 95% confidence interval assuming homoskedasticity (blue stars) and the heteroskedasticity robust 95% confidence interval (green stars).

Tables

Table 1: Variable definitions and sources

Name	Description	Source
Dependent variables:		
AISD	All-in-spread-drawn, defined as the sum of the spread over LIBOR plus the facility fee (bps).	Dealscan
AISU	All-in-spread-undrawn, defined as the sum of the facility fee and the commitment fee (bps).	Dealscan
Spread	Spread over LIBOR (non-LIBOR-based loans are excluded from the sample) paid on drawn amounts on credit lines (bps).	Dealscan
LOC fee	Fee paid on drawn amounts on the letter-of-credit sublimit (bps).	Dealscan
Deal amount (\$M)	The loan amount in \$M held by each lender.	Dealscan
LOC (\$M)	Letter of credit in \$M.	Dealscan
Main explanatory variable:		
Bank's weights	$w^s_{b,t} = \frac{Loan^{b \to s}_t}{Total\ Loan^{b \to S}_t}$, the amount (\$M) lent by bank b to sector s at time t over the total amount (\$M) that bank b has lent during the same year.	Own calculations
Banks' sectoral exposure	$w^B_{b_1 b_2,t} = \sqrt{\frac{\sum_{s=1}^{S}\left(w^s_{b_1,t} - w^s_{b_2,t}\right)^2}{2}}$ is the Euclidean distance between banks b_1 and b_2 on an S-dimensional space at time t.	Own calculations
Financial-loan network	$w^L_{ij,t} = \frac{1}{\mathcal{P}\{B_{ij,t}\}} \sum_{(b_1,b_2) \in B_{ij,t}} \left(w^B_{b_1 b_2,t}\right)^{-1}, i \neq j$, where $\mathcal{P}\left\{B_{ij,t}\right\}$ is the number of bank 'pairs' formed in $B_{ij,t}$. Note that our analysis will assign a greater interconnection measure to loans that are 'closer' to each other.	Dealscan
Loan-level explanatory variables:		
Secured	Dummy variable equal to one if the loan is secured and zero otherwise.	Dealscan
Refinancing	Dummy variable equal to one if the loan is refinancing a previous loan.	Dealscan
Covenants	Dummy variable equal to one if the loan has covenants and zero otherwise.	Dealscan

Guarantee	A facility backing the assumption of accountability for payment of a debt or performance of a person or entity obligation if the liable party fails to comply with expectations.	Dealscan
Performance pricing	Dummy variable equal to one if the loan has performance pricing provisions and zero otherwise.	Dealscan
Loan default	A dummy variable equal to one if the S&P loan credit rating change to "D" within the life of loan and zero otherwise.	Dealscan
Loan purpose	Set of dummy variables describing the loan's primary purpose.	Dealscan
Revolver	Dummy equal to one if the loan type is a revolver loan (credit line) such as Revolver/Line, 364-Day Facility or Limited Line.	Dealscan
Term	Dummy equal to one if the loan type is a term loan such as term loan A, B, C, D or E.	Dealscan
Bridge loan	Dummy equal to one if the loan type is a bridge loan.	Dealscan
Firm-level explanatory variables:		
Tobin's q	The natural logarithm of market-to-book value.	Compustat
ROA	Return on Assets	Compustat
Firm size	The natural logarithm of total assets.	Compustat
Relationship lending	Dummy variable equal to one if the lender lent to the same borrower in the past five years and zero otherwise.	Dealscan
Tangibility	The ratio of tangible assets to total assets.	Compustat
Number of loans	The total amount ($M) of syndicated loans that a firm has received in the past five years.	Dealscan
Firm opacity	Dummy for firms' investment grades by S&P.	Dealscan
Bank-level explanatory variables:		
Interest expenses	The ratio of interest expenses to total assets weighted by the shares of each bank in the syndicated loan.	Call Reports
Loan-loss provisions	The ratio of loan-loss provisions to total loans.	Call Reports
Bank size	The natural logarithm of total assets weighted by the shares of each bank in the syndicated loan	Call Reports

Table 2: Summary statistics

					Percentile Distribution		
Variables	Level	Obs.	Mean	Std. Dev.	25th	Median	75th
AISD	Loan	52,810	187.116	145.999	72.500	175.000	275.000
AISU	Loan	52,810	16.599	22.698	0.000	6.500	27.500
Spread	Loan	52,810	168.767	161.367	50.000	150.000	250.000
Letter-of-credit (LOC) fee	Loan	52,810	42.546	89.239	0.000	0.000	0.000
Deal amount ($M)	Loan	52,810	624.795	1,722.658	55.000	200.000	600.000
Letter-of-credit ($M)	Loan	52,810	18.517	104.529	0.000	0.000	0.000
Secured	Loan	52,810	0.519	0.500	0.000	1.000	1.000
Refinancing	Loan	52,810	0.519	0.500	0.000	1.000	1.000
Covenants	Loan	52,810	0.477	0.499	0.000	0.000	1.000
Guarantee	Loan	52,810	0.061	0.240	0.000	0.000	0.000
Performance pricing	Loan	52,810	0.336	0.472	0.000	0.000	1.000
Tobin's q	Firm	52,810	1.375	1.671	0.000	1.307	1.886
ROA	Firm	52,810	0.009	0.440	0.000	0.022	0.057
Firm size	Firm	52,810	5.714	3.080	4.181	6.269	7.889
Relationship lending	Firm	52,810	0.444	0.497	0.000	0.000	1.000
Tangibility	Firm	52,810	0.008	0.043	0.000	0.000	0.000
Number of loans	Firm	52,810	499.290	2,077.151	35.000	150.000	450.000
Interest expenses	Bank	52,810	0.008	0.016	0.000	0.000	0.011
Loan-loss provisions	Bank	52,810	0.002	0.010	0.000	0.000	0.002
Bank size	Bank	52,810	4.505	6.627	0.000	0.000	9.072

Summary statistics for the variables used in the empirical analysis. The variables are defined in Table 1.

Table 3: Summary Statistics for the financial-loan network

					Percentile Distribution		
Variables	Connections	Density	Mean	Std. Dev.	25th	Median	75th
1987	135,384	0.820	0.109	0.360	0.049	0.066	0.088
1988	592,796	0.778	0.034	0.192	0.017	0.024	0.030
1989	470,986	0.772	0.037	0.172	0.015	0.022	0.029
1990	438,868	0.737	0.048	0.204	0.020	0.032	0.044
1991	449,703	0.737	0.040	0.194	0.016	0.024	0.031
1992	785,305	0.825	0.046	0.178	0.022	0.036	0.048
1993	1,222,989	0.837	0.027	0.104	0.015	0.022	0.028
1994	1,875,841	0.848	0.024	0.108	0.016	0.021	0.026
1995	1,960,685	0.880	0.045	0.087	0.029	0.040	0.049
1996	3,269,952	0.912	0.001	0.052	0.000	0.001	0.001
1997	4,276,647	0.889	0.028	0.077	0.019	0.026	0.032
1998	3,350,512	0.930	0.038	0.041	0.029	0.037	0.043
1999	3,133,673	0.941	0.034	0.042	0.026	0.031	0.037
2000	2,481,579	0.820	0.041	0.048	0.027	0.034	0.044
2001	2,286,081	0.803	0.041	0.042	0.028	0.039	0.049
2002	2,019,354	0.761	0.034	0.090	0.021	0.030	0.038
2003	1,964,372	0.790	0.004	0.070	0.002	0.003	0.004
2004	1,714,494	0.695	0.049	0.042	0.030	0.046	0.061
2005	1,830,760	0.702	0.025	0.073	0.009	0.018	0.027
2006	1,602,091	0.723	0.051	0.048	0.025	0.052	0.067
2007	1,456,653	0.679	0.042	0.075	0.019	0.041	0.053
2008	538,521	0.783	0.014	0.144	0.007	0.010	0.012
2009	248,942	0.781	0.124	0.186	0.067	0.116	0.146
2010	691,150	0.834	0.078	0.092	0.054	0.080	0.097
2011	1,480,782	0.878	0.055	0.028	0.042	0.056	0.068
2012	1,069,311	0.862	0.054	0.103	0.041	0.056	0.065
2013	1,039,918	0.864	0.001	0.099	0.000	0.000	0.000
2014	839,052	0.877	0.070	0.060	0.038	0.065	0.087
2015	684,351	0.926	0.078	0.052	0.062	0.077	0.090
2016	95,288	0.923	0.197	0.187	0.111	0.159	0.215

Summary statistics for the construction of the financial network $w^L_{ij,t} = \frac{1}{\mathcal{P}\{B_{ij,t}\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(w^B_{b_1 b_2,t}\right)^{-1}, i \neq j,$. The variables are defined in Table 1. Density of w^L_t is defined as the proportion of nonzero off-diagonal elements.

Table 4: Baseline results: Cost of lending (AISD)

	I	II	III	IV	V
Financial-loan network	0.085***	0.087***	-0.050***	-0.047***	0.062***
	[12.038]	[11.645]	[-4.859]	[-4.732]	[6.141]
Secured	97.459***	92.834***	90.145***	59.261***	3.911
	[76.308]	[72.201]	[71.923]	[41.084]	[1.616]
Refinancing	20.724***	18.684***	4.156***	4.086***	-13.003***
	[15.240]	[13.967]	[3.436]	[2.971]	[-10.040]
Covenants	-5.237***	-6.331***	-3.083*	-1.612	60.445***
	[-3.442]	[-3.979]	[-1.785]	[-1.556]	[39.702]
Guarantee	12.733***	11.695***	3.712*	2.002	4.023***
	[5.475]	[5.272]	[1.927]	[0.792]	[2.725]
Performance pricing	-25.356***	-20.395***	-14.387***	-11.930***	-7.342***
	[-19.745]	[-16.231]	[-12.295]	[-10.041]	[-2.845]
Tobin's q	-2.488***	-3.184***	-2.443***	-5.695***	-24.600***
	[-4.750]	[-4.439]	[-4.142]	[-8.069]	[-19.970]
ROA	-19.005***	-16.609***	-15.326***	-6.601***	-3.273***
	[-3.603]	[-3.562]	[-3.295]	[-2.654]	[-9.933]
Firm size	-7.185***	-6.694***	-7.309***	-3.570***	126.207
	[-30.720]	[-26.685]	[-30.481]	[-10.829]	[1.326]
Tangibility	-41.171***	-26.960***	-32.588***	-19.531*	-0.001**
	[-3.121]	[-1.965]	[-2.440]	[-1.800]	[-2.132]
Relationship lending	-5.515***	-3.196***	-5.725***	-2.843***	-6.349***
	[-4.929]	[-2.913]	[-5.053]	[-2.895]	[-8.771]
Number of loans	-0.001***	-0.002***	-0.002***	-0.001**	-3.437***
	[-3.430]	[-3.261]	[-3.237]	[-2.222]	[-3.186]
Interest expenses	353.813***	423.930***	781.506***	545.188***	-22.285
	[5.839]	[7.386]	[12.496]	[8.894]	[-1.410]
Loan-loss provisions	441.970	317.794	103.640**	-36.922	-0.661***
	[1.355]	[1.332]	[1.982]	[-0.470]	[-5.040]
Bank size	-0.748***	-0.882***	-1.430***	-0.784***	-39.497***
	[-4.602]	[-5.810]	[-10.880]	[-6.039]	[-6.096]
Observations	52,810	52,810	52,810	52,810	52,810
Moran's $\mathscr{I}$	163.76	147.43	-2.53	-1.46	78.21
$-$Log likelihood	6.217	6.187	6.149	5.951	5.970
Loan-type FE	Y	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y	Y
Bank FE	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	N
Firm FE	N	N	N	Y	Y
Year FE (exc. crisis FE)	N	N	N	N	Y

The table reports coefficients and t-statistics (in brackets) from the estimation of equation (6), which is given by $y_{i,t} = \alpha_f + \lambda \left(\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t} \right) + \beta_1 B_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 L_{i,t} + \epsilon_{i,t}$. The cost of lending, labelled $y_{i,t}$, for loan i at time t is regressed on the key independent variable $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}$, which measures the financial network between loan i and loan j at time t, a vector of weighted banks' characteristics B at $t-1$, a vector of firm characteristics F at $t-1$ and a vector of loan characteristics L at t. All variables are defined in Table 1. Each observation in the regressions corresponds to a different loan facility. All regressions are estimated with QMLE for SAR models and also include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are heteroskedasticity robust. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 5: Baseline results: Deal amount ($M)

	I	II	III	IV	V
Financial-loan network	0.278***	0.270***	0.039**	0.006	0.083***
	[6.057]	[5.952]	[1.985]	[0.358]	[3.228]
Secured	-27.174	-18.269	-25.185	-10.663**	-13.683
	[-0.773]	[-0.524]	[-0.709]	[-2.179]	[-0.615]
Refinancing	190.400***	171.728***	123.227***	20.064***	16.536
	[9.258]	[9.204]	[7.303]	[5.164]	[0.811]
Covenants	-55.125*	-32.242	-3.892	46.962***	42.598**
	[-1.819]	[-1.138]	[-0.125]	[4.165]	[2.082]
Guarantee	52.847*	22.293	3.688	94.188	90.886***
	[1.829]	[0.832]	[0.147]	[0.441]	[5.102]
Performance pricing	-9.407	-6.143	21.102	-13.084	-14.270
	[-0.581]	[-0.355]	[1.136]	[-0.966]	[-2.158]
Tobin's q	-19.158**	-16.259**	-14.364*	-71.586***	-74.594***
	[-2.283]	[-2.145]	[-1.947]	[-3.863]	[-4.889]
ROA	-13.226*	-11.376	-14.763	18.127*	6.525
	[-1.791]	[-1.449]	[-1.630]	[1.810]	[0.821]
Firm size	62.590***	57.088***	61.689***	-587.385**	-930.104*
	[3.426]	[3.311]	[3.394]	[-1.988]	[-1.667]
Tangibility	-189.661	-125.174	-221.267**	0.355*	0.355
	[-1.303]	[-1.002]	[-2.225]	[1.896]	[1.736]
Relationship lending	117.710***	108.746***	61.223***	-32.188	-33.339***
	[3.511]	[3.539]	[2.573]	[-0.665]	[-4.064]
Number of loans	0.451***	0.443***	0.437***	11.412*	17.494
	[2.491]	[2.445]	[2.404]	[1.734]	[1.152]
Interest expenses	-1604.52	-1786.343**	-1171.585*	-197.607	-169.736
	[-2.237]	[-2.301]	[-1.847]	[-0.759]	[-1.624]
Loan-loss provisions	-225.475	-280.504	-579.147	1.7287	1.5412
	[-1.254]	[-1.303]	[-1.404]	[1.487]	[0.919]
Bank size	-0.669	0.853	-0.485	-1044.088	-328.386***
	[-0.419]	[0.478]	[-0.2692]	[-1.022]	[-2.555]
Observations	52,810	52,810	52,810	52,810	52,810
Moran's $\mathscr{I}$	16.02	14.76	-4.13	-1.56	4.46
$-$Log likelihood	8.625	8.615	8.606	8.481	8.482
Loan-type FE	Y	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y	Y
Bank FE	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	N
Firm FE	N	N	N	Y	Y
Year FE (exc. crisis FE)	N	N	N	N	Y

The table reports coefficients and t-statistics (in brackets) from the estimation of equation (6), which is given by $y_{i,t} = \alpha_f + \lambda \left(\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t} \right) + \beta_1 B_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 L_{i,t} + \epsilon_{i,t}$. The Deal amount ($M), labelled $y_{i,t}$, for loan i at time t is regressed on the key independent variable $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}$, which measures the financial network between loan i and loan j at time t, a vector of weighted banks' characteristics B at $t-1$, a vector of firm characteristics F at $t-1$ and a vector of loan characteristics L at t. All variables are defined in Table 1. Each observation in the regressions corresponds to a different loan facility. All regressions are estimated with QMLE for SAR models and also include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are heteroskedasticity robust. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

Table 6: Sequential inclusion of year fixed effects

	Panel A		Panel A	
	AISD		Deal amount	
Years	Financial-loan network ($\hat{\lambda}$)	t-statistic	Financial-loan network ($\hat{\lambda}$)	t-statistic
1987	0.085***	12.871	0.311***	23.981
1988	0.086***	13.012	0.312***	24.027
1989	0.086***	13.090	0.313***	24.091
1990	0.086***	13.096	0.313***	24.101
1991	0.087***	13.279	0.313***	24.039
1992	0.087***	13.247	0.311***	23.790
1993	0.085***	12.903	0.309***	23.518
1994	0.077***	11.601	0.305***	22.992
1995	0.077***	11.565	0.301***	22.644
1996	0.046***	6.614	0.297***	21.795
1997	0.042***	6.039	0.291***	21.193
1998	0.053***	7.677	0.288***	20.888
1999	0.056***	8.576	0.279***	20.217
2000	0.065***	9.301	0.269***	19.387
2001	0.069***	9.787	0.259***	18.615
2002	0.069***	9.796	0.230***	16.261
2003	0.078***	10.646	0.178***	11.939
2004	0.079***	10.739	0.152***	10.110
2005	0.059***	7.869	0.122***	7.893
2006	0.049***	6.665	0.117***	7.544
2007	0.025***	3.310	0.116***	7.482
2008	0.006	0.740	0.078***	4.820
2009	-0.024**	-3.071	0.056**	3.444
2010	-0.048***	-6.109	0.040**	2.470
2011	-0.058***	-7.235	0.047***	2.896
2012	-0.069***	-8.552	0.046***	2.834
2013	-0.065***	-7.567	0.012	0.628
2014	-0.064***	-7.522	0.008	0.420
2015	-0.063***	-7.324	0.003	0.183

Estimated coefficients of the financial network (λ) and t-statistics from the estimation of equation (6), i.e. $y_{i,t} = \alpha_f + \lambda \left(\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^{L} y_{j,t} \right) + \beta_1 B_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 L_{i,t} + \epsilon_{i,t}$, when we sequentially add year fixed effects. The dependent variables in Panel A and B are the lending rate (AISD) and the Deal amount, respectively. The *,**,*** marks denote statistical significance at the 10, 5, and 1% level, respectively.

Table 7: Sensitivity tests

	AISU	AISU	Spread	Spread	LOC fee	LOC fee	LOC	LOC	AISD	Deal amount ($M)
	I	II	III	IV	V	VI	VII	VIII	IX	X
Financial-loan network	-0.011	0.0880***	-0.0604***	0.0617***	-0.017	0.1805***	0.137***	0.176***	-0.052***	0.030
	[-0.697]	[5.383]	[-5.117]	[-5.375]	[-0.590]	[-6.339]	[3.869]	[4.781]	[-4.275]	[1.223]
Observations	52,810	52,810	52,810	52,810	52,810	52,810	52,810	52,810	52,810	52,810
Loan-control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm-control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank-control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan-type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	N	N
Year FE	Y	N	Y	N	Y	N	Y	N	N	N
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE (exc. crisis FE)	N	Y	N	Y	N	Y	N	Y	N	N
Bank*Year FE	N	N	N	N	N	N	N	N	Y	Y

The table reports coefficients and t-statistics (in brackets) from the estimation of equation (6), which is given by $y_{i,t} = \alpha_f + \lambda\left(\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}\right) + \beta_1 B_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 L_{i,t} + \epsilon_{i,t}$. The dependent variable, which is reported in the second line of the table, for loan i at time t is regressed on the key independent variable $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^L y_{j,t}$, which measures the financial network between loan i and loan j at time t, a vector of weighted banks' characteristics B at $t-1$, a vector of firm characteristics F at $t-1$ and a vector of loan characteristics L at t. All specifications include the control variables reported in Table 4. All variables are defined in Table 1. Each observation in the regressions corresponds to a different loan facility. All regressions are estimated with QMLE for SAR models and also include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Standard errors are heteroskedasticity robust. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

A Financial network

Table A1: Illustration of banks' sectoral exposure and Euclidean distance

SIC codes (2 digit division)	JPM	BoA	C	$\sqrt{(JPM-BoA)^2}$	$\sqrt{(JPM-C)^2}$	$\sqrt{(BoA-C)^2}$
Mining (10-14)	2.09%	1.81%	4.41%	0.0027	0.0232	0.0259
Construction (15-17)	1.25%	1.00%	1.63%	0.0024	0.0038	0.0062
Manufacturing (20-39)	47.58%	51.50%	35.86%	0.0392	0.1172	0.1564
Transp. & Commun. (40-49)	27.89%	17.58%	29.31%	0.1030	0.0142	0.1173
Wholesale Trade (50-51)	2.96%	3.21%	0.00%	0.0025	0.0295	0.0321
Retail Trade (52-59)	9.00%	15.58%	19.70%	0.0657	0.1070	0.0412
Services (70-89)	9.23%	9.32%	9.09%	0.0008	0.0014	0.0023
Total	100.00%	100.00%	100.00%	0.2167	0.2965	0.3816

In the first three columns, we show banks' weights (exposures) for JP Morgan (JPM), Bank of America Merrill Lynch (BoA) and Citi (C), the top 3 U.S. lead arrangers in 2015. In the last three, we show the computation of banks' sectoral similarity by using the Euclidean distance given by equation (1), i.e. $w^B_{b_1 b_2,t} = \sqrt{\frac{\sum_{s=1}^{S}\left(w^s_{b_1,t} - w^s_{b_2,t}\right)^2}{2}}$. The smaller (higher) the value, the more similar (dissimilar) the two banks considered.

Table A2: Illustration of loan interconnectedness

Panel A: Banks' participation per loan

	Loan ℓ_1	Loan ℓ_2	Loan ℓ_3
Banks:	JPM	JPM	JPM
	C	BoA	C

Panel B: Matrix for banks' similarities $\left(w^B_{b_1 b_2,t}\right)^{-1}$

	JPM	BoA	C
JPM	1		
BoA	0.6592	1	
C	0.4818	0.3749	1

Panel C: Matrix for loan interconnectedness $\left(w^L_{i,j}\right)$

	Loan ℓ_1	Loan ℓ_2	Loan ℓ_3
Loan ℓ_1	$w^L_{1,1}$ =0		
Loan ℓ_2	$w^L_{2,1}$ =0.6290	$w^L_{2,2}$ =0	
Loan ℓ_3	$w^L_{3,1}$ =0.8272	$w^L_{3,2}$ =0.6290	$w^L_{3,3}$ =0

The table illustrates the procedure that we use to measure loan interconnectedness. In Panel A, we hypothesize banks' participation decision with equal shares for JP Morgan (JPM), Bank of America Merrill Lynch (BoA) and Citi (C), the top 3 U.S. lead arrangers in 2015. Therefore, loan ℓ_1 is shared between JP Morgan (JPM) and Citi (C), and analogously for loan ℓ_2 and ℓ_3. In Panel B, we show bank similarities by using the inverted and standardized interbank distances. The higher the value, the more similar the two banks considered. In Panel C, we show the loan interconnectedness computed using equation (2), i.e. $w^L_{ij,t} = \frac{1}{\mathcal{P}\{B_{ij,t}\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(w^B_{b_1 b_2,t}\right)^{-1}, i \neq j$, where $\mathcal{P}\{B_{ij,t}\}$ is the number of bank 'pairs' formed in $B_{ij,t}$ (the set of banks that share loans i and j). For example, loan interconnectedness between loan ℓ_1 and loan ℓ_2 ($w_{2,1}$) is equal to bank pairs [(JPM,JPM),(JPM,BoA),(C,JPM)(C,BoA)] yielding 0.6290. Loan interconnectedness ranges between 0-1, with the higher value reflecting higher loan interconnectedness.

B Spatial Autoregressive (SAR) model

A natural method to estimate spillovers uses the spatial autoregressive (SAR) model due to (Cliff and Ord, 1973). While initially confined to geographers and regional scientists, the SAR model has also attracted the attention of economists. This is primarily due to its ability to capture cross-sectional dependence parsimoniously, with only knowledge of some economic distance required between units. The locations of the observations are not restricted to be geographic, nor is the process generating them required to be known, so 'spatial' does not refer necessarily to geographic space. Instead the SAR model requires some user-chosen distance measures contained in a spatial weights matrix, denoted W, with (i, j)-th element w_{ij}. w_{ij} is an (inverse) economic distance between the observations indexed i and j, which may be a continuous measure or a binary one, and $w_{ii} = 0$ for every i. An example of binary W would be a network 'adjacency matrix'.

A clearer picture of the equation (5) may be obtained by writing it in scalar notation:

$$y_i = \lambda \sum_{j \neq i} w_{ij} y_j + x_i' \beta + \epsilon_i, \tag{19}$$

where x_i is the i-th column of X'. As is apparent from equation (19), the SAR model permits direct interaction between the y_i through the elements of the spatial weights matrix W and the strength of this interaction is measured by λ.

The model (5) can viewed as a generalization of time series autoregressive models, which we would obtain by taking lower-triangular W. In keeping with this analogy, Wy is termed a *spatial lag* of y. However, spatial or network data do not typically permit the natural ordering of time series data, so W is usually not a triangular matrix. In keeping with the time series analogy, one may see that (5) is a 'dynamic' model, in the sense that each observation y_i is determined simultaneously by other observations y_j, $j \neq i$. However, when the W is not triangular this simultaneous determination is both 'backward' and 'forward' looking. The end result of this general dynamic feature is that the spatial lag is endogenous in general, and this aspect has meant that the literature on estimation of SAR models has evolved as a separate field.

(Kelejian and Prucha, 1998) were the first to provide rigorous theory for the estimation of the parameters of (5), in particular focussing on IV estimation. In a seminal paper, (Lee, 2004) established asymptic theory for a Gaussian quasi maximum likelihood estimator (QMLE) and this is the estimator we choose in this paper. Gaussian QMLE has the well-known property of being efficient when ϵ is normal, but also having an easy to compute covariance matrix when this is not the case. Other estimators include the GMM estimator of (Kelejian and Prucha, 1999), the OLS estimator of (Lee, 2002) (in special cases where the endogeneity of Wy vanishes asymptotically) and the 'higher-order' estimators of (Gupta and Robinson, 2015, 2017).

C Further understanding spillover magnitude

The spatial autoregressive model that we use for our empirical analysis has another feature that further illustrates the magnitude of the spillover λ. Due to the simultaneous interactions that the model allows, we can write down the covariance matrix of the dependent variable, *AISD* or *Deal amount*, explicitly as a function of λ and W. Because a spillover is interpreted as a co-movement, it is natural to anticipate that the elements of this covariance matrix will increase in magnitude with estimated spillover magnitude. In this subsection we confirm this using the spillover estimates that we have obtained, and also understand further the implications of changes both in spillover magnitude and sign.

Note that (5) has a reduced form

$$y = S(\lambda)^{-1} (X\beta + \epsilon), \tag{20}$$

so the covariance matrix of y conditional on X is

$$cov(y) = \sigma^2 \left(S(\lambda)^{-1}\right)^2 = \sigma^2 \left((I_n - \lambda W)^{-1}\right)^2 = \sigma^2 \sum_{j,k=0}^{\infty} \lambda^{j+k} W^{j+k}, \tag{21}$$

where n is our total sample size (52,810) and the infinite-series representation of the inverse is guaranteed by taking $|\lambda| < 1$. Thus $\lambda > 0$ implies that all elements of $cov(y)$ are positive, while $\lambda < 0$ implies that *most* elements of $cov(y)$ are negative. Thus the difference between positive λ and negative λ is that the former implies positive co-movements between lending rates or deal amounts always, according to what we choose y to be, whereas the latter implies that most co-movements are negative while some are positive. Of course when $\lambda = 0$, $cov(y)$ is diagonal and we are in the state of no cross-sectional dependence in lending rates or deal amounts.

The discussion above suggests a natural way to interpret the magnitude of λ via $cov(y)$. In Table C1 we analyze $cov(y)$. Note that because W is block-diagonal, $cov(y)$ is also a block-diagonal matrix with (ignoring the σ^2 factor) typical diagonal block

$$C_t(\lambda) = \left(\left(I_{L_t} - \lambda W_t^L \right)^{-1} \right)^2 = \sum_{\ell,k=0}^{\infty} \lambda^{\ell+k} \left(W_t^L \right)^{\ell+k}, t = 1, \ldots, 30, \tag{22}$$

where L_t denotes the number of loans in year t. In our results we obtain a number of estimates of λ, with different magnitudes and signs. Denoting a generic estimate by $\tilde{\lambda}$, we seek to explore the properties of the matrices $C_t\left(\tilde{\lambda}\right)$, $t = 1, \ldots, 30$ as $\tilde{\lambda}$ varies. We choose a range of values from Table 6, namely $\tilde{\lambda} = 0.087, 0.049, 0.006, -0.024, -0.069$. For positive $\tilde{\lambda}$ we report

$$a_{1t} = \frac{\text{average}\left(C_t(0.087)\right)}{\text{average}\left(C_t(0.049)\right)} \quad , \quad a_{2t} = \frac{\text{average}\left(C_t(0.087)\right)}{\text{average}\left(C_t(0.006)\right)}, t = 1, \ldots, 30, \tag{23}$$

$$m_{1t} = \frac{\text{median}\left(C_t(0.087)\right)}{\text{median}\left(C_t(0.049)\right)} \quad , \quad m_{2t} = \frac{\text{median}\left(C_t(0.087)\right)}{\text{median}\left(C_t(0.006)\right)}, t = 1, \ldots, 30, , \tag{24}$$

where the average and median is of all the matrix elements. Thus a_{1t} and a_{2t} (respectively m_{1t}, m_{2t}) are ratios of average (respectively median) covariances for year t, for a large positive value of $\tilde{\lambda}$ relative to a smaller one. An average or median may not be appropriate when the elements of $C_t\left(\tilde{\lambda}\right)$ are not of the same sign. Thus, for the two negative values of $\tilde{\lambda}$ we report as a scalar measure $\text{norm}_{1t} = \left\|C_t\left(-0.024\right)\right\|$ and $\text{norm}_{2t} = \left\|C_t\left(-0.069\right)\right\|$. Recall that $\left\|C_t\left(\tilde{\lambda}\right)\right\|$ is the largest eigenvalue of $C_t\left(\tilde{\lambda}\right)$. Finally, for the two negative $\tilde{\lambda}$ values we also report the proportion of elements of $C_t\left(\tilde{\lambda}\right)$ that are negative, these corresponding to negative covariances. We denote these prop_{1t} and prop_{2t} for $\tilde{\lambda} = -0.024, -0.069$, respectively.

On average, the covariances are between 1.001 and 1.08 times larger for $\tilde{\lambda} = 0.087$ as opposed to $\tilde{\lambda} = 0.049$, and between 1.002 and 1.176 times larger for $\tilde{\lambda} = 0.087$ as opposed to $\tilde{\lambda} = 0.006$. The differences in medians are larger still, ranging from factors of 1.76 to 1.92 for m_{1t} and between 15 and 20 for m_{2t}. It is clear that economically significant co-movements are generated even by fairly small values of $\tilde{\lambda}$. The variation in the $a_{1t}, a_{2t}, m_{1t}, m_{2t}$ between years is due to the differences in the W_t^L.

Moving on to the negative values of $\tilde{\lambda}$, we note that $\|C_t(-0.024)\| < \|C_t(-0.069)\|$ always, indicating stronger co-movements for a larger absolute value of $\tilde{\lambda}$. These co-movements may be positive or negative, and from the last two columns of Table C1 we observe that the proportion of negative covariances is quite similar for both negative values of $\tilde{\lambda}$. This similarity persists across years, so is not very sensitive to differences in W_t^L. Thus, on the basis of the last four columns of Table C1, we deduce that negative values of $\tilde{\lambda}$ that are larger in magnitude do not necessarily generate a greater proportion of negative covariance, but do generate covariances that are typically larger in absolute magnitude.

Table C1: Year-by-year measures of covariance intensities implied by estimates of λ. Definitions of measures are explained in Appendix C.

Year	a_1	a_2	m_1	m_2	norm_1	norm_2	prop_1	prop_2
1987	1.0436	1.0934	1.8757	17.5912	1.0451	1.1381	0.8173	0.8128
1988	1.0276	1.0589	1.8361	16.7284	1.0486	1.1497	0.7772	0.7731
1989	1.0281	1.0589	1.8441	17.1182	1.0464	1.1424	0.7651	0.751
1990	1.0335	1.0711	1.8962	17.951	1.0484	1.1491	0.7324	0.7258
1991	1.0276	1.0586	1.8546	17.2735	1.0487	1.15	0.7342	0.7273
1992	1.046	1.0979	1.8773	17.6703	1.0472	1.145	0.8218	0.8167
1993	1.0308	1.0666	1.8296	16.5235	1.0491	1.1512	0.8368	0.836
1994	1.0347	1.075	1.8274	16.5227	1.0495	1.1525	0.8495	0.8488
1995	1.0713	1.1551	1.9009	17.8203	1.0271	1.081	0.8804	0.8773
1996	1.0013	1.0029	1.768	15.3803	1.0436	1.1333	0.9117	0.9116
1997	1.0646	1.1406	1.8739	17.3882	1.0448	1.1371	0.8887	0.887
1998	1.08	1.1756	1.8838	17.5353	1.0167	1.0493	0.9296	0.9291
1999	1.0705	1.1533	1.8781	17.5152	1.0245	1.0729	0.9408	0.9382
2000	1.0709	1.1543	1.8921	17.7952	1.0281	1.0839	0.8203	0.8183
2001	1.0685	1.1486	1.8935	17.7931	1.0151	1.0443	0.8053	0.8049
2002	1.0516	1.1109	1.8731	17.3561	1.0456	1.1398	0.7614	0.7607
2003	1.0049	1.0106	1.7755	15.499	1.0476	1.1462	0.7911	0.7911
2004	1.0657	1.1421	1.9159	18.3365	1.0149	1.0438	0.6981	0.6979
2005	1.036	1.0756	1.8628	19.6593	1.0431	1.1316	0.6914	0.6779
2006	1.0672	1.1456	1.9192	18.3069	1.0172	1.0506	0.7228	0.7227
2007	1.0509	1.1093	1.8927	18.4579	1.0397	1.1208	0.6809	0.6767
2008	1.0106	1.0225	1.8072	16.2745	1.0446	1.1364	0.7842	0.7821
2009	1.0664	1.1439	1.9042	18.0159	1.0358	1.1082	0.7841	0.7837
2010	1.0718	1.1564	1.8877	17.67	1.0327	1.0985	0.8362	0.836
2011	1.0759	1.1659	1.8854	17.5961	1.0073	1.0212	0.8776	0.8776
2012	1.062	1.1349	1.8669	17.2789	1.0453	1.1388	0.8608	0.8607
2013	1.001	1.002	1.7667	15.3567	1.0495	1.1527	0.8636	0.8634
2014	1.0727	1.1585	1.896	17.8514	1.0135	1.0395	0.8762	0.8761
2015	1.0753	1.1644	1.879	17.4728	1.0139	1.0408	0.9257	0.9257
2016	1.071	1.1545	1.9052	18.0226	1.0164	1.0481	0.9207	0.9197