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Networks and information in credit markets☆

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ABSTRACT

A large literature emphasizes financial networks, but understanding how these networks influence lending decisions over the business cycle remains challenging. We exploit the overlapping bank portfolio structure of US syndicated loans to construct a financial network. Using techniques from spatial econometrics, we document large spillovers in lending conditions during good times, driven by commonality in banks' loan portfolio exposures. A standard deviation increase in peers' lending rates is associated with an increase in a bank's lending rate of 17 basis points. However, these spillovers vanish in a large recession. We interpret these findings through a syndicate lending model where information spillovers driven by loan portfolio commonality dilute banks' incentives to produce private information on borrowers during good times.

1. Introduction

Financial networks play a key role in the operation of credit markets. It is then not surprising that a large theoretical literature has studied financial networks and how network interactions can affect the real economy via the transmission of credit risk (Allen and Gale, 2000; Freixas et al., 2000) or changes in information due to learning externalities (Babus and Kondor, 2018; Dang et al., 2020).[1] The empirical literature on financial networks has also grown substantially since the 2008–2009 global financial crisis, with a rich body of work focusing on bank interconnectedness in interbank markets and systemic risk (e.g., Iyer and Peydró (2011);

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[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) finds conditions under which diversification may have undesired effects (U-shaped) on the propagation of financial contagion by making systemic crises more likely. Blume et al. (2011) also suggest that denser interconnections can act as a destabilizing force, illustrating that the details of the network structure can be important in the propagation of shocks. In a similar spirit, Acemoglu et al. (2015b) point out that the precise propagation depends on both the network structure and the size of shocks hitting the economy.

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Georg (2013); Cai et al. (2018) and Georg et al. (2023); among others).[2] However, empirical research that investigates how financial networks shape the evolution of lending conditions and information production over the business cycle lags behind the theoretical frontier (for example, Babus and Kondor (2018) and Dang et al. (2020)). This gap is likely due to the challenges of constructing empirically plausible financial networks and linking them to loan-level outcomes over the business cycle.

This paper studies the existence of spillovers in financial networks that are associated with asset commonality and the implications of such spillovers for the evolution of firms' borrowing conditions in normal and crisis times. Using the syndicated loan market, where banks share common borrowers, we document empirically the existence of economically important spillovers in lending rates in normal times, and that this effect vanishes during downturns. With the help of a theoretical model, we show that our results are consistent with the presence of information linkages in a syndicated loan network associated with similarities in loan portfolio exposures and, more broadly, with theories that predict lower information production in financial markets with more asset commonality. Our empirical results are consistent with the view that credit spillovers can arise from the actions of peers, generating correlated credit risk pricing decisions in good times. In our setting, peers are banks with higher similarity in their sectoral exposures. Accordingly, we employ techniques from the spatial econometrics literature, where peers' actions are strategic complements and affect individual (own) decisions (Cliff and Ord, 1968, 1973; Lee, 2004).

In the empirical investigation, we first construct a financial network and then test for the existence of network effects or, equivalently, spillovers. To this end, we match data from three sources. Specifically, we use information from the Thomson-Reuter's Dealscan database on syndicated loans extended to US firms over a thirty year period, between 1987 and 2016. To enrich the information at the bank level, we hand-match the Dealscan loan-level data with banks' Call Reports. We do the same for firms, by matching our sample with Compustat. Our final sample consists of large US corporate loans from 825 US banks (lead arrangers and participants) to 7511 US firms (excluding utilities and financial companies).

We exploit banks' sectoral specialization to overcome the key challenge of mapping information in the syndicated loan market to a quantitative measure of the financial network (Paravisini et al., 2023). We follow two steps that are consistent with our theoretical framework. First, we use the bilateral distance between banks' sectoral specializations to construct a measure of banks' similarities. The sectoral exposure of a bank in each area of specialization is determined by its share of lending to different sectors, as in Cocco et al. (2009). Banks' sectoral similarities (via past transactions) partially aggregate the common information of all market participants, even when some banks are not counterparty in a transaction. Intuitively, a higher similarity between two banks indicates that they have more correlated information and credit exposures to a particular sector. Second, we aggregate the bank-pair similarities to the individual loan level decision to create a loan network.

An example helps to illustrate our approach. Consider an economy with four banks (say Citibank (C), JP Morgan (JPM), Wells Fargo (WF) and Bank of America (BoA)) and three loans, ℓ_1, ℓ_2 and ℓ_3. The four banks have different sectoral loan exposures as a proportion of their balance sheet. Moreover, loans ℓ_1 and ℓ_3 are both shared by C and JPM, while ℓ_2 is shared by WF and BoA. An intuitive network construction procedure should recognize that the loan pair (ℓ_1, 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). Nevertheless, 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 satisfies both requirements. In the first step, we compute pairwise distance measures between all possible bank pairs using their sectoral specializations (in this example, there are six possible pairs between C, JPM, WF and BoA). In the second step, we use the observed syndicated loan participation decision to aggregate the bank similarity measure to a loan similarity one. In our example, the loan similarity between (ℓ_1, ℓ_2) will be a weighted average of the four bank-pair sectoral similarities for the two loans, namely (C,WF), (C,BoA), (JPM,WF) and (JPM,BoA).

The two-step approach in constructing the loan network offers important advantages. Aggregation at the loan level replicates the syndicate structure and allows measurement error to be averaged out when aggregating from bank-level to loan-level data. Moreover, the aggregation step reduces the bias introduced by the endogeneity of a bank's participation decision (Hanushek et al., 1996). Specifically, aggregation reduces omitted variable bias because omitted variables have the clearest effects on estimates when the data are not aggregated to the level of the omitted factors.[3]

A natural empirical methodology to study spillovers is to estimate a spatial autoregressive (SAR) model with simultaneous network interactions. Indeed, a large body of recent work has analyzed network-based data with this modeling approach (see, e.g., Helmers and Patnam (2014), Hsieh and van Kippersluis (2018), Kuersteiner and Prucha (2020) and Comola and Prina (2021)). The syndicated loan market, with banks' overlapping portfolios, is well suited to test network theories using the SAR estimation method. In particular, in our loan network, lending decisions are determined by own actions but also by peers' decisions. A SAR model permits such behavior together with tractable estimation and inference.[4]

To control for different unobserved factors, we also exploit the multilevel structure of our data set to mitigate omitted-variable bias in a fashion similar to Jiménez et al. (2014) and Jiménez et al. (2017) and Paravisini et al. (2023). 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 for the inclusion of different types of granular fixed effects that help us isolate credit demand effects. We include sector × year and bank × sector fixed effects to account

2 For a broader overview of the literature, see Iori and Mantegna (2018), who provide a detailed summary of empirical and theoretical studies on financial networks.

3 For instance, this can happen when factors affecting a bank's participation decision are neglected.

4 This framework has been used widely in other areas, for instance mobility (Guerra and Mohnen, 2022), trade, regional and urban economics (Case, 1991; Pinkse et al., 2002; Conley and Dupor, 2003), conflict networks (König et al., 2017), and innovation networks (Bloom et al., 2013; König et al., 2019).

for unobserved time-varying potential shifts in borrower demand within the same sector and isolate the variation within the same bank-sector, thereby controlling for time-invariant portfolio-composition effects, respectively (Acharya et al., 2018; Giannetti and Saidi, 2019). We also saturate our analysis with other time-invariant demand factors at the firm level (firm fixed effects), common shocks (year fixed effects) and time-invariant supply factors at the bank level (bank fixed effects). Moreover, we further address endogeneity concerns using peer covariates, such as relationship lending over the past five years, as instruments for peer effects, following König et al. (2017).

We find evidence for network spillovers across loan pricing decisions in normal times. Specifically, a bank's rate decision is positively associated with its peers' loan pricing decisions, making these decisions strategic complements. On the other hand, the co-movement breaks down at the peak of the 2007-09 financial crisis, when the financial network becomes sparser.[5] We argue that the results may reflect informational channels, especially given how our financial network is constructed. We interpret the empirical findings through the lens of a theoretical model of the syndicated loan market where lending banks observe common signals about the quality of their borrowers and also engage in information acquisition about idiosyncratic shocks hitting borrowers. The model predicts that in good times banks' incentive to acquire information about idiosyncratic shocks is diluted, leading banks to rely more on public signals. Further, the dilution in information acquisition incentives is more pronounced when banks' portfolios of syndicated loans exhibit larger overlaps (that is, there is greater loan portfolio commonality).[6]

More broadly, our empirical results are consistent with theories of information production in financial networks over the business cycle. In Babus and Kondor (2018),[7] for instance, in good times a higher weight is assigned to the expectations of other participants, implying that producing (collecting) additional information about credit quality adds little value at the margin, and increasing the probability of positive peer effects.[8] Strategic complementarity can also arise from asset commonality between banks reducing information production (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012) or from 'comparables' pricing (Murfin and Pratt, 2019). Further, Sufi (2007) and Ivashina (2009) emphasize information asymmetries revealed through the observed share of the lead bank in the syndicate.

Our results are consistent with the idea that firms may face a distribution of borrowing conditions that varies significantly over the business cycle. To quantify the extent to which lending rates change due to the loan network evolution and spillover effects, we conduct a counterfactual simulation experiment. We find that in good times a networked economy with a time-evolving loan network structure has lending rates that are significantly different from a non-networked economy. Our largest estimated positive spillover suggests that in good times the networked economy has lending rates that are 13.46% higher, in basis points on average, than a non-networked economy. In contrast, the difference in lending rates between a networked and non-networked economy is negligible in bad times.

The roadmap of the paper is as follows. Section 2 motivates the empirical analysis through the lens of an illustrative model of the syndicated loan market. In Section 3, we describe the syndicated loan market structure, our data sources and the final sample. Section 4 describes how the loan network arises naturally from the syndicated loan market. Section 5 introduces the SAR model with the constructed network as the key input to test for network effects. Section 6 presents the empirical results. Section 7 conducts counterfactual experiments to examine the quantitative difference in lending rates between networked and non-networked economies. Section 8 concludes. Appendix A contains a battery of robustness tests while an Online Appendix, available on the authors' websites, contains supplementary material.

2. Theoretical framework

In this section we provide the theoretical motivation for our empirical analysis. We first discuss extant network and information diffusion theories in credit markets. Then, we develop a stylized model of a syndicated loan network that more precisely formalizes the forces that can drive our estimates.

2.1. Theoretical underpinnings

Network theories like (Acemoglu et al., 2015a) or (Babus and Kondor, 2018) provide support to the notion that credit spillovers might arise from the actions of other network members. One way individual pricing decisions might be affected by other participants' decisions is through the cost of collecting additional information about credit quality during good times. If the information is costly and adds relatively little value at the margin, the probability of positive peer effects increases.

For example, in Babus and Kondor (2018) higher order expectations about each lender's loan price mean that every loan price aggregates the private information of all banks that participate in the network. In bad times, the private value (soft information)

[5] We analyze whether the estimated spillover is different from the 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 (Khwaja and Mian, 2008). This provides a safeguard that variation in the co-movement of the lending rates is due to the loan network's structure rather than any heterogeneity in size, leverage, and fundamentals, among other variables.

[6] The spillovers we document are different from the liquidity spillovers identified by Ivashina and Scharfstein (2010). In their case, exposures to a central actor (Lehman Brothers) generate a liquidity shock that amplifies through the banking system. Therefore, this shock becomes more important during the crisis. In our case, on the other hand, the emphasis is on peer effects on pricing that depend on the whole network.

[7] Babus and Kondor (2018) work with markets where private information is important; the syndicated loan market is a sufficiently complex trading market where transactions under incomplete information arise.

[8] Craig and Ma (2022) provide similar evidence for the interbank market.

is less correlated with the wider price dispersion in the market and each bank increases the weight on its own signal (the private signal becomes more informative). Thus, a bank is less likely to trust and follow its peers' pricing decisions.[9]

Asset commonality between banks may also reduce information production, making rates strategic complements (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). A similar pattern might also arise through 'comparables pricing' (Murfin and Pratt, 2019) where financial institutions might be making pricing decisions by comparing similar-risk loans.

2.2. A model of loan syndication

To better rationalize the possible mechanisms at work, we develop a simple model of a syndicated loan network. Before presenting the model, we recall upfront the salient characteristics of syndicated loans (see, e.g., Sufi (2007), Delis, Kokas, and Ongena (2017) for further details on syndicated lending).

The syndicated loan market. Syndicated 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. In a syndicated loan the borrowing firm signs a loan agreement with the lead arranger which specifies the loan characteristics (such as collateral, loan amount, covenants, and a range for the interest rate). The lead arranger then invites other banks to participate in the loan.[10] The lenders with neither lead nor co-agent roles are classified as participant lenders. The participant lenders collaborate with the lead arranger in administrative responsibilities, as well as in screening and monitoring efforts.[11] These lenders can provide comments and suggestions when the syndication occurs prior to closing.

Participants actively acquire information during the syndication process through various channels. For example, they conduct independent research using SEC EDGAR filings to assess borrower risk (Chi et al.; 2020), rely on established relationships with lead arrangers, or rely on external analyses from analyst coverage to mitigate information asymmetries. In practice, digital platforms such as HUBX and Finastra facilitate real-time information sharing, improving transparency and coordination among the syndicate members. Moreover, cooperation agreements in distressed situations, such as Alkegen's debt refinancing led by Oak Hill Advisors, ensure unified strategies and informed participation by lenders. The price and the structure of a syndicated loan 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.

Model setup. We consider a general setting with $N \geq 2$ banks and lending syndicates, but also develop a simplified example with $N = 2$ banks and syndicates. Each syndicate extends a loan with size of one to a firm. The lenders can alternatively invest at a market gross interest rate normalized to one. We call $R(i)$ the total repayment on loan i, where $i = 1, 2, \dots, N$. Denote by $P(\psi(i)S, A)$ the probability that the borrower of loan i repays $R(i)$, where A is the publicly observable aggregate state of the economy, S denotes an imperfectly observable state common to all borrowers (e.g., the state of the local economy or sector; 'sectoral state' henceforth), and $\psi(i)$ captures an imperfectly observable idiosyncratic shock to the borrower. With the complementary probability $1 - P(\psi(i)S, A)$ the borrower defaults and repays zero. The sectoral shock S takes one of two values, high (S^H) or low (S^L) (with probability $\pi(S^H)$ and $\pi(S^L)$, respectively), and similarly for A (A^H or A^L). The idiosyncratic shock can take value ψ^H (with probability p) or ψ^L (with probability $(1 - p)$). Thus, the probability of repayment of a loan depends on the borrower's idiosyncratic quality, $\psi(i)$, on a sectoral state common to all the borrowers, S, and on the aggregate state of the economy, A.

Let α denote the share of a syndicated loan that the lead arranger retains and, correspondingly, $1 - \alpha$ be the loan share of the participant(s). Hence, in the event of success the repayment to the lead arranger is $\alpha R(i)$ and the repayment to the syndicate participant(s) is $(1 - \alpha)R(i)$. Further, Φ denotes the outside option the lenders in a syndicate receive if the borrower defaults. This can capture the salvage value of the borrower's collateral. Observe that we also allow for ex-ante side transfers between a borrower and the banks, for example implemented through the payment of the up-front arrangement fee of the syndicated loan.

Information structure. We aim at capturing in a parsimonious way the higher information associated with higher loan portfolio commonality, that is, when banks in syndicates have a more similar sectoral specialization they learn more precise sectoral information from interacting with each other in the arrangement and extension of loans.

To this end, we let the precision of the signal on the sectoral state be increasing in the share of syndicates ($\frac{\hat{N}}{N}$) in which each bank in the syndicated loan network participates (e.g., simply due to an unmodeled Bayesian update mechanism driven by the loan portfolio commonality). In particular, we posit that with probability $\lambda(\frac{\hat{N}}{N})$ the realization of the sectoral state S is revealed, while with probability $1 - \lambda(\frac{\hat{N}}{N})$ it remains unknown, where $\lambda'(.) > 0$ and $\lambda(1)$ ($\lambda(0)$) is normalized to one (zero) for simplicity. Further, we denote by $\overline{S}$ the expected realization of the sectoral state, if that state is not revealed through the sectoral signal.

A lead arranger can also observe an imperfect signal about the idiosyncratic quality of the borrower $\psi(i)$ by sustaining a monitoring/screening effort cost that is convex in the monitoring level, $\frac{c\mu^2}{2}$. By gathering a level of information μ, the lead arranger observes the idiosyncratic quality of the borrower with probability μ, while with the complementary probability he cannot observe it. If detected, the idiosyncratic quality is also revealed to the syndicate participants. We denote by $\overline{\psi}$ the expected idiosyncratic shock in the absence of monitoring/screening.

[9] Dang et al. (2020) also emphasize that: "*financial crises are precisely events in which this regime-switch happens: information-insensitive debt becomes information-sensitive*".

[10] If two or more lead arrangers are identified, then they are co-leads.

[11] Lead arrangers coordinate the documentation process and receive a fee from the borrower for arranging and managing the loan.

A 2-syndicate example. We first illustrate key mechanisms through a simplified example in which two banks participate in two lending syndicates ($N = 2$): by participating in both syndicates, each of the two banks can learn about the sectoral state common to the two borrowers. In this example, we fix the sectoral state at S for simplicity.

We study when a lead arranger has the incentive to monitor a borrower to find out the idiosyncratic quality of the borrower's project. When the realization of the aggregate state is high, A^H, a lead arranger knows that, even in the worst scenario in which he detects a low idiosyncratic quality of the borrower (ψ^L), he will anyway choose to finance the project. In this case, he will have no incentive to sustain an information acquisition cost, and the pricing of loans will only depend on the expected idiosyncratic quality and on the sectoral and aggregate states. If, instead, the aggregate state of the economy is low, A^L, then a lead arranger will have the incentive to acquire information about the borrower's quality, and the pricing of loans will also depend on the idiosyncratic shock, in the way detailed below.

Formally, let Y denote the maximum output of a financed project. Since

$$R \leq Y \tag{2.1}$$

the condition such that, under the good aggregate state A^H, a lead arranger has no incentive to acquire information is

$$P(\psi^L \times S, A^H)\alpha Y + \left[1 - P(\psi^L \times S, A^H)\right]\alpha\Phi - \alpha \geq 0. \tag{2.2}$$

By contrast, the condition such that, under the bad aggregate state A^L, a lead arranger has the incentive to acquire information is

$$P(\psi^L \times S, A^L)\alpha Y + \left[1 - P(\psi^L \times S, A^L)\right]\alpha\Phi - \alpha < 0. \tag{2.3}$$

Therefore, the benefit, in terms of avoided loss, from finding out the low quality of the borrower (net of the monitoring cost) is

$$\alpha\mu\left[1 - P(\psi^L \times S, A^L)Y - \left[1 - P(\psi^L \times S, A^L)\right]\Phi\right] - \frac{c\mu^2}{2} \tag{2.4}$$

and the optimal monitoring of the lead arranger satisfies

$$\mu^* = \frac{\alpha\left[1 - P(\psi^L \times S, A^L)Y - \left[1 - P(\psi^L \times S, A^L)\right]\Phi\right]}{c}. \tag{2.5}$$

In the high aggregate state, A^H, since lead arrangers have no incentive to acquire information on borrowers' idiosyncratic quality, the pricing of loans will be the same across syndicates, and given by

$$R = \frac{1 - \left[1 - P(\overline{\psi} \times S, A^H)\right]\Phi}{P(\overline{\psi} \times S, A^H)}. \tag{2.6}$$

Thus, there will be perfect pricing correlation across syndicates, as well as perfect correlation in banks' funding choice. Conversely, in the low aggregate state the distribution of possible outcomes will be as follows: low-quality unfunded borrower with probability $(1 - p)\mu$; funded borrower with probability $p\mu + 1 - \mu$. A borrower who gets funded will in turn be charged

$$R = \frac{1 - \left[1 - P(\overline{\psi} \times S, A^L)\right]\Phi}{P(\overline{\psi} \times S, A^L)} \tag{2.7}$$

with probability $(1 - \mu)$ and

$$R = \frac{1 - \left[1 - P(\psi^H \times S, A^L)\right]\Phi}{P(\psi^H \times S, A^L)} \tag{2.8}$$

with probability μp. Thus, there will be imperfect correlation across syndicates both in terms of loan pricing and in terms of funding choice.

We can then draw the following first implication.

Implication 1: In good aggregate states there is higher correlation in banks' syndicate loan pricing and funding choice than in bad aggregate states.

This implication captures the intuition that in normal times (good aggregate states) banks' incentive to acquire information on borrowers' idiosyncratic shocks is diluted, as banks do not need such precise information to make lending decisions. Thus, the pricing of loans will be less influenced by idiosyncratic shocks in good times than in bad times.

The N-syndicate case. Let us now return to the general N-syndicate case and re-evaluate a bank's incentive to acquire information in case of a high realization of the aggregate state. If the sectoral state is revealed to be good (S^H) through the sectoral signal, we have

$$P(\psi^L \times S^H, A^H)\alpha Y + \left[1 - P(\psi^L \times S^H, A^H)\right]\alpha\Phi - \alpha > 0. \tag{2.9}$$

If the sectoral state remains unknown, we have

$$P(\psi^L \times \overline{S}, A^H)\alpha Y + \left[1 - P(\psi^L \times \overline{S}, A^H)\right]\alpha\Phi - \alpha < 0. \tag{2.10}$$

And if the sectoral state is revealed to be bad (S^L),

$$P(\psi^L \times S^L, A^H)\alpha Y + \left[1 - P(\psi^L \times S^L, A^H)\right]\alpha\Phi - \alpha < 0. \tag{2.11}$$

Thus, if the sectoral state is not revealed, the benefit, in terms of avoided loss, from finding out a low idiosyncratic quality of the borrower (net of the monitoring cost) equals

$$\alpha\mu\left[1-P(\psi^L\times\overline{S},A^H)Y-\left[1-P(\psi^L\times\overline{S},A^H)\right]\Phi\right]-\frac{c\mu^2}{2} \tag{2.12}$$

and the optimal monitoring satisfies

$$\mu^*=\frac{\alpha\left[1-P(\psi^L\times\overline{S},A^H)Y-\left[1-P(\psi^L\times\overline{S},A^H)\right]\Phi\right]}{c}. \tag{2.13}$$

In turn, if the sectoral state is revealed to be bad, the net benefit from detecting a low quality of the borrower is

$$\alpha\mu\left[1-P(\psi^L\times S^L,A^H)Y-\left[1-P(\psi^L\times S^L,A^H)\right]\Phi\right]-\frac{c\mu^2}{2} \tag{2.14}$$

and the optimal monitoring satisfies

$$\mu^*=\frac{\alpha\left[1-P(\psi^L\times S^L,A^H)Y-\left[1-P(\psi^L\times S^L,A^H)\right]\Phi\right]}{c}. \tag{2.15}$$

The probability that in this generalized setting, in the high aggregate state, lead arrangers engage in costly information acquisition about the idiosyncratic borrower shock is $[1-\lambda(\frac{\hat{N}}{N})]+\lambda(\frac{\hat{N}}{N})\pi(S^L)$, while the probability of no information acquisition is $\lambda(\frac{\hat{N}}{N})\pi(S^H)$. The latter is increasing in the network density, $\frac{\hat{N}}{N}$, and, hence, in the precision of the public (sectoral) information available to lenders. This points to substitutability between public and private information.

More on the syndicate distribution. To further illustrate, suppose that the sectoral state is good (S^H). If $\frac{\hat{N}}{N}=1$, and, hence, the good sectoral state is observed by all banks, the loan price will be the same across all syndicates:

$$R=\frac{1-\left[1-P(\overline{\psi}\times S^H,A^H)\right]\Phi}{P(\overline{\psi}\times S^H,A^H)}. \tag{2.16}$$

If, instead, $\frac{\hat{N}}{N}=0$, then, conditional on a loan getting funded, the loan rate will be

$$R=\frac{1-\left[1-P(\overline{\psi}\times\overline{S},A^H)\right]\Phi}{P(\overline{\psi}\times\overline{S},A^H)} \tag{2.17}$$

with probability $(1-\mu)$ and

$$R=\frac{1-\left[1-P(\psi^H\times\overline{S},A^H)\right]\Phi}{P(\psi^H\times\overline{S},A^H)}. \tag{2.18}$$

with probability μp.

In the bad aggregate state, instead, regardless of the value of $\frac{\hat{N}}{N}$, lead arrangers will always acquire information about borrowers' idiosyncratic quality. Therefore, if $\frac{\hat{N}}{N}=1$, unlike in the good aggregate state, the loan rate will vary across syndicates and equal

$$R=\frac{1-\left[1-P(\overline{\psi}\times S^H,A^L)\right]\Phi}{P(\overline{\psi}\times S^H,A^L)}. \tag{2.19}$$

with probability $(1-\mu)$ and

$$R=\frac{1-\left[1-P(\psi^H\times S^H,A^L)\right]\Phi}{P(\psi^H\times S^H,A^L)}. \tag{2.20}$$

with probability μp. Moreover, if $\frac{\hat{N}}{N}=0$, the loan rate will equal

$$R=\frac{1-\left[1-P(\overline{\psi}\times\overline{S},A^L)\right]\Phi}{P(\overline{\psi}\times\overline{S},A^L)}. \tag{2.21}$$

with probability $(1-\mu)$ and

$$R=\frac{1-\left[1-P(\psi^H\times\overline{S},A^L)\right]\Phi}{P(\psi^H\times\overline{S},A^L)}. \tag{2.22}$$

with probability μp.

The generalized framework then leads to the following second implication.

Implication 2: When the syndicated loan network has higher density, that is, banks' loan portfolios have higher overlap ($\frac{\hat{N}}{N}$ is higher), then the gap in pricing and funding choice correlation between good and bad aggregate states is more pronounced.

By conveying more information about realizations of sectoral states, a higher overlap of banks' sectoral specializations in the loan network dilutes banks' effort in monitoring/screening borrowers' idiosyncratic shocks. This implies that in good times, if the network is more dense, one can observe relatively larger peer effects than in bad times.

3. Data

In the past two decades, syndicated lending has accounted for about half of total commercial and industrial (C&I) lending and is therefore often used to assess bank lending policies and the interactions between lenders and borrowers. We obtain data on syndicated loan deals from Dealscan. This database provides detailed information on the loan deal's characteristics (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. We categorize loans as credit line, term A, B, C, D, and E and exclude term loans B because banks hold none of these loans after the syndication. Term loans B are structured specifically for institutional investors and are almost entirely sold off in the secondary market. Also, we drop loans that are more likely to be amendments to existing loans, because these are misreported in Dealscan as new loans, but they do not necessarily involve new money.[12]

To complement the loan-level information from Dealscan, we match these data with banks' financial statements obtained from Call Reports. We hand-match Dealscan's lender ID with the commercial bank ID (RSSD9001). 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 bank 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 the year. Similarly, we obtain annual information for firms' financial statements from Compustat using the link provided by Chava and Roberts (2008).

The matching process yields a maximum of 52,810 loans originated by 823 banks involving 7511 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 the variables used in the empirical analysis and Table 2 displays summary statistics. The median borrowing firm in our sample has about 530 million in total assets. The all-in-spread drawn (AISD) is our main dependent variable 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 (with a median of 175 bps), while the standard deviation indicates sizeable variation (146 bps).

We show certain patterns of the data in the Online Appendix O.A. Panel (a) of Figure FO.1 shows the share of syndicated lending as a percentage of total C&I loans over time, while Panel (b) compares the distribution of syndicated loans as a proportion of C&I loans between small and large banks. The distinction between small and large banks is based on their average total assets, with banks above the median classified as large and those below the median classified as small. Additionally, Panel (c) visualizes the relationship between syndicated lending and total C&I lending. The scatter plot reveals a strong positive association, confirming that banks with larger C&I loan portfolios are also heavily involved in syndicates.

Consistent with previous studies, 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 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 the 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 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 total amount ($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 had a previous lending relationship with the lead arranger in the last five years; firm tangibility as 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 profitability (Adams and Ferreira, 2009).

4. Financial network construction

Our construction of the network is based on a two-step approach, which is consistent with the theoretical framework in Section 2. The first step involves constructing a similarity measure between banks based on past experience. The second step aggregates these bank-pair connections at the loan level to obtain a similarity measure between loans. The resulting loan network (denoted by W) is a key input in the econometric analysis.

[12] We apply two further 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 et al. (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 with 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 as a bank by Dealscan but actually are not, such as the General Motors Acceptance Corporation (GMAC) Commercial Finance. Second, we exclude loans granted to utilities or to financial companies.

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
Main explanatory variable:		
Bank's sectoral weights	$w^s_{b,t} = \frac{Loan_t^{b\to s}}{Total\ \ Loan_t^{b\to S}}$, 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
Banks' geographic weights	$w^g_{b,t} = \frac{Loan_t^{b\to g}}{Total\ \ Loan_t^{b\to G}}$, the amount (\$M) lent by bank b to state g at time t over the total amount (\$M) that bank b has lent during the same year.	Own calculations
Banks' geographic exposure	$w^{GB}_{b_1 b_2,t} = \sqrt{\frac{\sum_{g=1}^{G}\left(w^g_{b_1,t}-w^g_{b_2,t}\right)^2}{2}}$ is the Euclidean distance between banks b_1 and b_2 on a G-dimensional space at time t.	Own calculations
Geographic loan network	$w^{GL}_{ij,t} = \frac{1}{\mathcal{P}\{B_{ij,t}\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(w^{GB}_{b_1 b_2,t}\right)^{-1}, i \neq j$, where $\mathcal{P}\left\{B_{ij,t}\right\}$ is the number of bank 'pairs' formed in $B_{ij,t}$.	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
Total loans (\$M)	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

4.1. Banks' bilateral distance

We construct a measure of investment similarity at the bank level to capture possible common information sharing channels (Paravisini et al., 2023). 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.[13] 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 'sectoral specialization 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) that bank b has lent during the

[13] The Euclidean distance measure is employed by Cai et al. (2018) to measure bank interconnectedness in the syndicated loan market.

Table 2
Summary statistics.

Variables	Level	Obs.	Mean	Std. Dev.	Percentile distribution		
					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
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
Total loans ($M)	Firm	52,810	499.290	2077.151	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.

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

$$w^B_{b_1 b_2,t} = \sqrt{\frac{\sum_{s=1}^{S}\left(w^s_{b_1,t} - w^s_{b_2,t}\right)^2}{2}}, \tag{4.1}$$

with

$$w^s_{b,t} = \frac{Loan_t^{b\to s}}{Total\ Loan_t^{b\to S}}, \text{ for any bank } b.$$

[14]

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. Eq. (4.1) is a symmetric distance. Furthermore, note that, for all banks b, $\sum_{s=1}^{S} w^s_{b,t} = 1$.

4.2. Loan network

Before the origination of a new syndicated loan, bank sectoral similarity is not necessarily a sufficient statistic of a bank's participation. Nevertheless, the structure of the syndicate lends itself naturally to a two-step approach because we observe banks and loans (firms) at two different levels (see Fig. 1). The first level computes bank similarity by comparing bank sectoral exposures as a proportion of their total loan exposure (below dotted line in Fig. 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 Fig. 1).

We illustrate the procedure theoretically and provide a specific example in the Online Appendix O.B 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_t^B 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 Eq. (4.1). We then use the entries of W_t^B to construct a symmetric $L_t \times L_t$ matrix W_t^L whose (i,j)-th element $w^L_{ij,t}$, where the 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_t^L by

$$w^L_{ij,t} = \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(w^B_{b_1 b_2,t}\right)^{-1}, i \neq j, \tag{4.2}$$

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 Eq. (4.2). More similar banks have a bigger

[14] Cocco et al. (2009) use a similar weight to measure the intensity of lending activity in the interbank market.

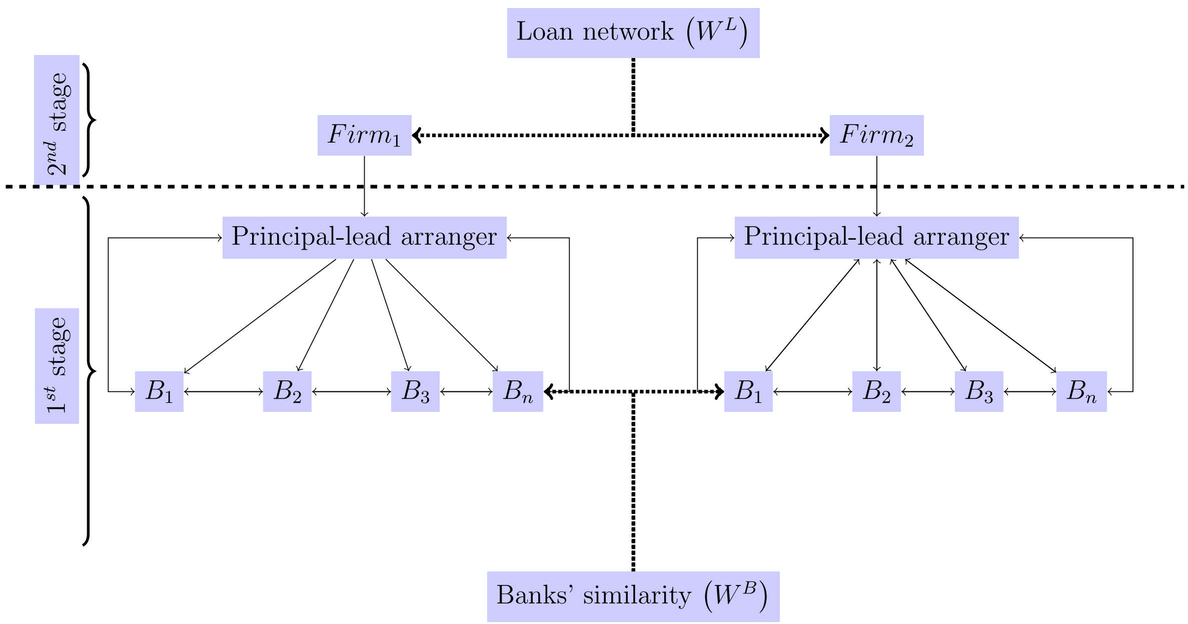

Fig. 1. Illustration of the syndicated loan market.
The figure illustrates the structure of the syndicated loan market and the two-step approach to calculate the loan network. The structure of the syndicate works as follows, the lead arranger is usually appointed by the firm. Furthermore, the lead bank 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 1st 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 2nd stage, we aggregate banks' similarities using information on bank participation in each syndicated loan.

effect on each other and therefore we need to convert sectoral distances to loan similarities by inverting bank sectoral distances ($w^B_{b_1b_2,t}$).[15] Loan interconnectedness is a positive number, with zero corresponding to lack of interconnectedness and larger values reflecting stronger interconnectedness. Non-zero entries occur if and only if there is an overlap in banks between two loans.

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

$$W^* = \begin{bmatrix} W_1^L & 0 & 0 & \dots & 0 \\ 0 & W_2^L & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & W_{30}^L \end{bmatrix}. \tag{4.3}$$

The block diagonal assumption in (4.3) captures the variation between loan networks but not between years.[16] Finally, with $\|W^*\|$ denoting the largest eigenvalue of W^*, we normalize the distances in W^* as

$$W = \frac{W^*}{\|W^*\|}. \tag{4.4}$$

Summary statistics for W are presented in Table 3. Note that some recent literature (e.g., Lam and Souza (2020)) has sought to estimate such spatial weight matrices by leveraging sparsity but our setting is less suited for such an approach due to a large number of links. We do not have access to multiple weight matrices that would enable Bayesian model averaging of the type considered by Debarsy and LeSage (2022), either.

In the Online Appendix O.B, we illustrate an example of the construction of the loan network. Appendix Table TO.1 shows the Euclidean distance between the loan portfolios of the top three loan arrangers in 2015, JPMorgan Chase (JPM), Bank of America (BoA), and Citigroup (C). JPM invests heavily in loans related to manufacturing (47.58%) and transportation & communication

[15] An aspect that arises in the computation of Eq. (4.2) is the possibility of $w^B_{\tilde{b}_1\tilde{b}_2,t} = 0$ for some 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. For instance, this would occur when we consider the same banks $\tilde{b}_1 = \tilde{b}_2$. We cannot use the inverse of $w^B_{\tilde{b}_1\tilde{b}_2,t}$ in this case, but instead assign 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, that is, the inverse of the smallest possible nonzero bank distance for year t, plus one.

[16] Acemoglu et al. (2012) use a similar assumption about idiosyncratic shocks at the firm or sectoral level that can propagate over input–output linkages within the economy.

Table 3
Summary statistics for the financial-loan network.

Year	Connections	Density	Mean	Standard deviation	Median
1987	135,384	0.820	0.0011	0.0036	0.0007
1988	592,796	0.778	0.0003	0.0019	0.0002
1989	470,986	0.772	0.0004	0.0017	0.0002
1990	438,868	0.737	0.0005	0.0020	0.0003
1991	449,703	0.737	0.0004	0.0019	0.0002
1992	785,305	0.825	0.0005	0.0018	0.0004
1993	1,222,989	0.837	0.0003	0.0010	0.0002
1994	1,875,841	0.848	0.0002	0.0011	0.0002
1995	1,960,685	0.880	0.0004	0.0009	0.0004
1996	3,269,952	0.912	0.0000	0.0005	0.0000
1997	4,276,647	0.889	0.0003	0.0008	0.0003
1998	3,350,512	0.930	0.0004	0.0004	0.0004
1999	3,133,673	0.941	0.0003	0.0004	0.0003
2000	2,481,579	0.820	0.0004	0.0005	0.0003
2001	2,286,081	0.803	0.0004	0.0004	0.0004
2002	2,019,354	0.761	0.0003	0.0009	0.0003
2003	1,964,372	0.790	0.0000	0.0007	0.0000
2004	1,714,494	0.695	0.0005	0.0004	0.0005
2005	1,830,760	0.702	0.0003	0.0007	0.0002
2006	1,602,091	0.723	0.0005	0.0005	0.0005
2007	1,456,653	0.679	0.0004	0.0008	0.0004
2008	538,521	0.783	0.0001	0.0014	0.0001
2009	248,942	0.781	0.0012	0.0019	0.0012
2010	691,150	0.834	0.0008	0.0009	0.0008
2011	1,480,782	0.878	0.0005	0.0003	0.0006
2012	1,069,311	0.862	0.0005	0.0010	0.0006
2013	1,039,918	0.864	0.0000	0.0010	0.0000
2014	839,052	0.877	0.0007	0.0006	0.0007
2015	684,351	0.926	0.0008	0.0005	0.0008
2016	95,288	0.923	0.0020	0.0019	0.0016

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.

(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. As a result, the distance between the sectoral specialization of JPM and BoA is smaller (0.0907), making them more similar, while BoA and C are less similar (0.1443). JPM and C have an intermediate Euclidean distance (0.1157).

Next, Table TO.2 shows how (the inverse of) these bank distance measures can be used to calculate the interconnectedness between loans. For loan ℓ_1 and loan ℓ_2 in the example, the interconnectedness ($w^L_{2,1}$) is equal to the sum of the inverses of the bilateral bank distances divided by the number of pairs. In this example, the pairs are [(JPM,JPM), (JPM,BoA), (C,JPM), (C,BoA)] yielding a value of $w^L_{2,1}$ equal to 9.6557.

In the Online Appendix O.C, we provide a detailed discussion and graphical illustrations of the dynamics of the network over time. This yields insights into the changes in loan interconnections before, during, and after the financial crisis, along with specific examples and figures highlighting the variation in the network density and structure.

5. Empirical specification and estimation

5.1. Empirical model

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

$$y = \lambda W y + X\beta + \epsilon. \tag{5.1}$$

A vector of actions y (loan spreads) 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. One key parameter of interest is λ which can be interpreted as a spillover, or peer effect, following the social interactions literature.[17] We also assume that $w^L_{ii,t} = 0$ for

[17] The scaling in Eq. (4.4) stems from the fact that without any normalization, λ in (5.1) 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 (2019) and choose (4.4).

all i, $w^L_{ij,t} = w^L_{ji,t}$ (symmetry) and a normalization of the network given in Eq. (4.4). In the Acemoglu et al. (2015b) 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 Eq. (5.1).

Eq. (5.1) features two 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 4. The second block involves a procedure to estimate and monitor the magnitude of network spillovers on economic variables like loan spreads. This is captured by λ.

In this model, the dependent variable corresponding to loan i depends 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. Eq. (5.1) translates to the following empirical model:

$$y_{i,t} = \alpha_f + \lambda \left(\sum_{j=1, j\neq i}^{L_t} w^L_{ij,t} y_{j,t} \right) + \beta_1 B_{i,t-1} + \beta_2 F_{i,t-1} + \beta_3 L_{i,t} + \epsilon_{i,t}. \tag{5.2}$$

In Eq. (5.2), the cost of lending, labeled $y_{i,t}$, for loan i at time t is regressed on the key independent variable $\sum_{j=1,j\neq i}^{L_t} w^L_{ij,t} y_{j,t}$ (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 between loan i and other loans at time t. α_f denotes a vector of fixed effects, while $\epsilon_{i,t}$ is a 'loan-level' shock, which captures stochastic disturbances to loan i.

In Eq. (5.2) we are interested in determining whether a correlation between the constructed loan network and individual loan rates exists. We control for 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 related to the bank, firm, or industry level that might bias the coefficient estimates on the loan network. Specifically, our dataset's structure allows us to include several detailed fixed effects (loan type, loan purpose, bank, firm, year, sector × year, bank × sector) because the individual loan facilities are non-repeated but the lenders originate multiple loans within a year. Among these fixed effects, the sector × year and bank × sector fixed effects are the most important because they capture unobserved time-varying shifts in borrower demand within the same sector and isolate the variation within the same bank-sector, thereby controlling for time-invariant portfolio-composition effects, respectively (Acharya et al., 2018; Giannetti and Saidi, 2019). In addition, the bank and firm fixed effects are also important because they control for time-invariant bank and firm characteristics that could lead to correlation between the financial network $\left(\sum_{j=1,j\neq i}^{L_t} w^L_{ij,t} y_{j,t}\right)$ and $\epsilon_{i,t}$ in Eq. (5.2). 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. 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 that involves two stages of aggregation. The first stage is illustrated in Eq. (4.1) where aggregation takes place over sectors, and the second stage is shown in Eq. (4.2) where aggregation takes place over bank pairs. These aggregation procedures mitigate the effect of unobserved heterogeneity at the sectoral and bank-pair level, alleviating endogeneity concerns arising from these sources. To be precise, suppose that inter-bank inverse distances are given by

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

where $\eta_{b_1,b_2,t}$ is the unobserved heterogeneity related to the portfolio overlap between banks b_1 and b_2 at time t. Our aggregation in Eq. (4.2) implies that

$$w^L_{ij,t} = \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(\tilde{w}^B_{b_1 b_2,t}\right)^{-1} + \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \eta_{b_1,b_2,t}, i \neq j. \tag{5.3}$$

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 endogeneity from this source.

We use the Gaussian quasi maximum likelihood (QMLE) (see e.g. Lee (2004)) to estimate the parameters λ and β in (5.2). 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

$$\log\left(2\pi\sigma^2\right) - 2n^{-1} \log|S(\lambda)| + \sigma^{-2} n^{-1} \|S(\lambda) y - X\beta\|^2. \tag{5.4}$$

We concentrate out β and σ^2. For given λ, (5.4) is minimized with respect to β and σ^2 by

$$\bar{\beta}(\lambda) = \left(X'X\right)^{-1} X' S(\lambda) y, \tag{5.5}$$

$$\bar{\sigma}^2(\lambda) = n^{-1} y' S'(\lambda) M S(\lambda) y, \tag{5.6}$$

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

$$\mathcal{Q}(\lambda) = \log \bar{\sigma}^2(\gamma) + n^{-1} \log\left|S^{-1}(\lambda) S^{-1\prime}(\lambda)\right|, \tag{5.7}$$

and Λ is a compact subset of $(-1,1)$. The QMLEs of β and σ^2 are defined as $\bar{\beta}(\hat{\lambda}) \equiv \hat{\beta}$ and $\bar{\sigma}^2(\hat{\lambda}) \equiv \hat{\sigma}^2$ respectively. We report standard errors assuming homoskedasticity as well as heteroskedasticity robust versions.[18]

5.2. More on the empirical strategy

A well-known impediment to identification in linear peer effect models is the 'reflection problem' (Manski, 1993). In such models peer effects in outcomes can arise through two sources in the reference group of a network member: the average outcome for the reference group and the average characteristics (covariates) of the reference group. In our setting the reference group is loan syndicates within the same year and the outcome variable is loan rates, thus the peer effects in rates are the rates (outcomes) of loans made by similar syndicates and the fundamental characteristics (covariates) of these loans. In certain situations where the network is extremely regular, perfect collinearity obtains and makes the identification of these two effects infeasible. However, Blume et al. (2015) show that this type of network regularity essentially only occurs in rather specific situations. An example would be networks with independent equal size groups within each of which all members have an equal effect on all others. Our network is certainly not of this stylized type (for example, we have different sized groups at the loan-year level), thereby inducing sufficient exclusion restrictions for identification (Lee, 2007).[19]

Moreover, we mitigate any lingering concerns regarding the potentially simultaneously endogenous actions of peers using SAR instrumental variable estimates with peer covariates as instruments (see Kelejian and Prucha (1998) for the theory of IV estimation in SAR models). We instrument peer rates using (for instance) a relationship lending variable for peers that is determined in the last five years. The idea is similar to Alesina et al. (2008) who instrument the output gap of each country with the output gap of its neighbors, and the approach of König et al. (2017). The key feature we exploit is that our instruments are likely to satisfy the exclusion and relevance restrictions because they affect only peers' activities. Our results are robust to this IV strategy.

6. Empirical results

In this section, we present the estimates for λ in Eq. (5.2). Of particular importance is determining whether there is evidence of spillover effects and whether these effects vary over time.

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 Eq. (5.2) is statistically significant at the 1% level. This implies that a one standard deviation change in the interconnectedness between loans (based on the specifications in column II and measured by $\sigma\left(\sum_{t=1}^{30}\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^{L} y_{j,t}\right) = 84.12$ bps) increases the *AISD* by approximately 16.65 basis points relative to their peers.[20] This effect is economically large: for the average loan in our sample (*AISD* equal to 187.11), this implies a dispersion in *AISD* by approximately 9%.[21] The general finding, without controlling for common shocks, is that the *financial-loan network* affects positively, and both statistically and economically, lending rates, providing evidence for the existence of spillovers from the loan network.

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 the

[18] Note that in general the QMLE is not consistency-robust to unknown heteroskedasticity. However, Liu and Yang (2015) point out that the QMLE can remain consistent despite unknown heteroskedasticity under conditions that seem appropriate in our setting.

[19] Our model in Eq. (5.2) 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 $E_{\mathrm{loc}}(\cdot)$ an expectation conditional on the process generating the observation locations, the 'reflection problem' of Manski (1993) makes identification infeasible when the model takes the form

$$y_{i,t} = \lambda E_{\mathrm{loc}}\left(y_{i,t}\right) + x_{i,t}'\gamma + \epsilon_{i,t}.$$

This issue typically does not arise in spatial econometrics because as, for instance, Lee (2007) and Pinkse and Slade (2010) point out, the actual intended regressor is $\sum_{j=1,j\neq i}^{L_t} w_{ij,t}^{L} y_{j,t}$, which is different from $E_{\mathrm{loc}}\left(y_{i,t}\right)$.

Furthermore, even if the reflection problem was taken to present a serious concern, Proposition 1 of Bramoullé et al. (2009) states that the linear independence of I, W and W^2 suffices for the identification of peer effects. It is clear from the network construction that our W satisfies this condition. In fact, the results of Blume et al. (2015) indicate that this identification assumption is not, in general, exceptionally costly. As explained in de Paula (2017), Theorem A2 of Blume et al. (2015) implies that the assumption essentially only fails for the case when the social network is made up of equally-sized components with equal non-zero entries, when W has been subject to normalization.

[20] Calculated from the product 0.198×84.12.

[21] Calculated from $((16.65/187.11) \times 100)$.

Table 4
Baseline results: Cost of lending (AISD)

	I	II	III	IV	V	VI
Financial-loan network	0.129***	0.198***	−0.018*	−0.004	−0.003	0.089***
	[16.471]	[21.953]	[1.929]	[0.486]	[0.352]	[8.856]
Secured	97.571***	91.712***	89.571***	59.378	59.497***	4.574*
	[76.533]	[72.014]	[72.101]	[39.720]	[39.031]	[1.867]
Refinancing	18.054***	15.387***	4.883***	3.942	3.807***	−12.230***
	[13.230]	[11.104]	[3.359]	[2.724]	[2.618]	[9.354]
Covenants	−4.154***	−5.792***	−2.748*	−1.711	−1.267	59.932***
	[2.746]	[3.796]	[1.767]	[1.093]	[0.799]	[38.569]
Guarantee	10.489***	10.174***	4.34*	1.988	2.482	3.804**
	[4.521]	[4.389]	[1.948]	[0.854]	[1.055]	[2.567]
Performance pricing	−24.816***	−20.107***	−15.600***	−12.191	−11.786***	−6.723***
	[19.400]	[15.705]	[12.514]	[9.681]	[9.268]	[2.734]
Tobin's q	−2.242***	−2.933***	−2.356***	−5.681	−5.496***	−24.969***
	[4.718]	[4.400]	[4.164]	[8.321]	[7.775]	[20.204]
ROA	−19.22***	−16.649***	−15.365***	−6.669	−6.249***	−3.187***
	[3.547]	[3.482]	[3.309]	[2.713]	[2.686]	[9.445]
Firm size	−7.417***	−6.834***	−7.372***	−3.603	−3.508***	114.308
	[31.778]	[27.703]	[30.738]	[10.428]	[10.054]	[1.289]
Tangibility	−38.506***	−27.502***	−34.241***	−20.112	−25.398	−0.001**
	[2.917]	[2.065]	[2.485]	[1.273]	[1.585]	[2.400]
Relationship lending	−7.957***	−4.546***	−5.490***	−2.708	−2.576**	−6.077***
	[7.115]	[4.060]	[4.981]	[2.562]	[2.405]	[8.210]
Total loans ($M)	−0.002***	−0.002***	−0.002***	−0.001	0.000**	−3.597***
	[3.408]	[3.274]	[3.224]	[2.265]	[2.410]	[3.295]
Interest expenses	313.901***	412.727***	799.342***	555.407	503.894***	−26.518*
	[5.247]	[7.230]	[12.738]	[8.639]	[7.740]	[1.655]
Loan-loss provision	437.178	284.733	104.608**	−36.357	−46.058	−0.581***
	[1.347]	[1.299]	[2.031]	[1.016]	[1.165]	[4.383]
Bank size	−0.523***	−0.749***	−1.397***	−0.817	−0.818***	−38.292***
	[3.209]	[5.325]	[11.245]	[6.587]	[6.443]	[5.713]
Observations	52,810	52,810	52,810	52,810	52,810	52,810
Loan-type FE	Y	Y	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y	Y	Y
Bank FE		Y	Y	Y	Y	Y
Year FE			Y	Y	Y	
Firm FE				Y	Y	Y
Sector × Year FE					Y	Y
Sector × Bank FE					Y	Y
Year FE (exc. Crisis FE)						Y

The table reports coefficients and t-statistics (in brackets) from the estimation of Eq. (5.2), 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, labeled $y_{i,t}$, 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. Regressions 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.

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* is nullified. Column III shows evidence of marginal statistical significance at 10%, but the economic significance is close to zero, while column IV shows neither statistical nor economic significance. The null finding on the effect of the *financial-loan network* holds even in the most restrictive specification, where the regression model is saturated with time-varying industry demand and bank-industry matching fixed effects (column V).

Building on the predictions of the theoretical model, the above results provide evidence for the existence of spillovers on lending rates via a loan network (beyond the effect of fundamentals) during expansionary periods. Interestingly, we find that the *Great Recession* is the driving force behind the spillover becoming statistically and economically insignificant (as seen in columns III and IV). To illustrate this, in column VI, we add the full set of fixed effects but exclude the crisis-year fixed effects (2007–2009). When this specification is used, we again estimate a positive and significant coefficient on the *financial-loan network*. This demonstrates that the magnitude of the co-movement in lending rates depends on whether the crisis-year fixed effects are included or not. The results in column VI make clear that the positive co-movement in lending rates can become economically insignificant during large recessions.

Table 5
Cost of lending (AISD): IV results and geographic network.

	I IV estimation	II	III Geographic network	IV
Financial-loan network	0.003 [0.283]	0.096*** [9.474]	−0.003 [0.390]	0.090*** [8.927]
Geographic-loan network			Y	Y
Loan-control variables	Y	Y	Y	Y
Firm-control variables	Y	Y	Y	Y
Bank-control variables	Y	Y	Y	Y
Observations	52,810	52,810	52,810	52,810
Loan-type FE	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Year FE	Y		Y	
Firm FE	Y	Y	Y	Y
Sector × Year FE	Y	Y	Y	Y
Sector × Bank FE	Y	Y	Y	Y
Year FE (exc. Crisis FE)		Y		Y

The table reports coefficients and t-statistics. Columns I and II introduce IV estimation. Columns III and IV incorporate a geographic loan network variable, constructed as described in Section 6.2 and controlling for geographic lending similarities in loan syndicates. Regressions 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.

6.2. Robustness tests

Instrumental variable estimates. In this section we estimate our most restrictive specifications from Table 4 (columns V and VI), which control for time-varying industry demand and bank-firm matching fixed effects, using an instrumental variables approach. This methodology is suggested for SAR models by Kelejian and Prucha (1998) and applied by König et al. (2017), for example. This procedure notes that the term Wy on the right side of Eq. (5.1) can cause endogeneity problems, and uses the linearly independent columns of WX as instruments for Wy. In other words, the potentially endogenous actions of neighbors in the network are instrumented by these neighbors' covariates. A similar approach has also been used in the trade literature; for example, Alesina et al. (2008) instrument the output gap of each country with the output gap of its neighbors. Thus, in their approach the instruments are the regional output gaps excluding the country itself. In our context, we use covariates such as relationship lending, performance pricing provisions and covenants from neighboring banks as instruments to capture variation in peer behavior. The results are displayed in columns I and II of Table 5 and show exactly the same patterns as observed in columns V and VI of Table 4.

Geographic similarity network. The above results point to network spillovers in loan pricing decisions during normal times. The financial-loan network measures loan interconnectedness through information acquisition and sectoral-loan similarities between bank pairs. However, one might be concerned that part of the information spillovers could arise from geographic overlap of the lending patterns of syndicate members. To address this concern, we construct a geographic bank network and incorporate it into our baseline regressions. The construction of the underlying geographic specialization index is detailed in Online Appendix Section O.D, where we show that this measure aligns closely with the geographic distribution of bank branches. Each firm is assigned to the state in which it is headquartered based on Compustat information.[22] Let $w^{GB}_{b_1,b_2,t}$ be the 'geographic specialization distance' between bank b_1 and bank b_2 at time t. Let $Loan^{b\to g}$ be the amount, in millions of dollars, lent by bank b to firms in state g at time t and $Total\ Loan^{b\to G}$ be the total amount that bank b has lent during the same year to firms in all the US states (G).

For each possible bank pair (b_1, b_2), we compute the normalized Euclidean distance as follows:

$$w^{GB}_{b_1 b_2,t} = \sqrt{\frac{\sum_{g=1}^{G}\left(w^{g}_{b_1,t} - w^{g}_{b_2,t}\right)^2}{2}}, \tag{6.1}$$

with

$$w^{g}_{b,t} = \frac{Loan_t^{b\to g}}{Total\ Loan_t^{b\to G}}, \text{ for any bank } b.$$

Denote, as before, by B_{ijt} the set of all the banks that share loan i and j at time t and define the elements of W^{GL}_t by

$$w^{GL}_{ij,t} = \frac{1}{\mathcal{P}\left\{B_{ij,t}\right\}} \sum_{(b_1,b_2)\in B_{ij,t}} \left(w^{GB}_{b_1 b_2,t}\right)^{-1}, i \neq j, \tag{6.2}$$

[22] Firms with more than one syndicated loan in our sample are consistently associated with the same state over time, allowing for a stable geographic mapping.

where $\mathcal{P}\left\{B_{ij,t}\right\}$ is the number of bank 'pairs' formed in $B_{ij,t}$.

This formula assigns a larger network 'edge' when two loan syndicates feature a greater overlap in their geographic lending, just like the $w_{ij,t}^{L}$ of Section 4 assigned a larger 'edge' for greater overlap in sectoral lending. Stacking the blocks W_t^{GL}, $t = 1, \dots, 30$, diagonally into a matrix W^{GL*} as in Eq. (4.3), we obtain the *geographic loan network* defined by

$$W^{GL} = \frac{W^{GL*}}{\left\|W^{GL*}\right\|}. \tag{6.3}$$

In columns III and IV of Table 5, we control for this geographic network in our regressions. The results show a consistent pattern: the null effect of the *financial loan network* during the crisis, as measured by $\hat{\lambda}_1$, remains unchanged (consistent with Table 4). Likewise, during good times we observe a positive $\hat{\lambda}_1$ with a magnitude similar to that reported in Table 4.

Sensitivity tests. Our results are robust to a variety of sensitivity tests, detailed in Appendix A. In Table A.1, we show that the findings carry through when using alternative measures for the cost of lending, such as the all-in-spread-undrawn (*AISU*), Spread over LIBOR (*Spread*), and letter-of-credit fees (*LOC fees*). The effect of the *financial-loan network* remains close to zero during the crisis period and significant during normal times. In Table A.2, we conduct 'placebo' tests by excluding randomly selected year fixed effects while retaining the crisis-year fixed effects. These tests confirm that the *Great Recession* is the primary driver behind the nullified spillover effect. Additionally, we compute t-statistics using spatial heteroskedasticity and autocorrelation consistent (SHAC) robust standard errors, following Kelejian and Prucha (2007), and confirm that our results are robust to this procedure.

7. Counterfactual evaluations: spillover effects

In this section we conduct a simulation study to quantify the difference between the effects of spillovers for our network structure. Imagine four economies, each with 52,810 loans (as in the data), in which an underlying stochastic process ζ determines the interest rates charged.[23] 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

$$y^1 = \lambda_1 W y^1 + \zeta = \lambda_1 W y^1 + y^0, \tag{7.1}$$
$$y^2 = \lambda_2 W y^2 + \zeta = \lambda_2 W y^2 + y^0, \tag{7.2}$$
$$y^3 = \lambda_3 W y^3 + \zeta = \lambda_3 W y^3 + y^0, \tag{7.3}$$

where each $\lambda \neq 0$. In keeping with our empirical results, we choose $\lambda_1 = 0.198$, $\lambda_2 = 0.089$ and $\lambda_3 = -0.003$ (the largest and smallest absolute values of λ as well as a middle-range value from our results in Table 4). Note that we can write (7.1)–(7.3) as

$$y^i = \left(I - \lambda_i W\right)^{-1} y^0 = \left(\sum_{\ell=0}^{\infty} \lambda_i^{\ell} W^{\ell}\right) y^0 = y^0 + \left(\sum_{\ell=1}^{\infty} \lambda_i^{\ell} W^{\ell}\right) y^0, i = 1, 2, 3. \tag{7.4}$$

The extra term on the farthest RHS of (7.4) 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

$$a_{\mathcal{E}_1}^{\mathcal{E}_0} = (52810)^{-1} \sum_{k=1}^{52810} \left(\frac{y_k^1 - y_k^0}{y_k^0}\right) - 1,$$
$$a_{\mathcal{E}_2}^{\mathcal{E}_0} = (52810)^{-1} \sum_{k=1}^{52810} \left(\frac{y_k^2 - y_k^0}{y_k^0}\right) - 1,$$
$$a_{\mathcal{E}_3}^{\mathcal{E}_0} = -(52810)^{-1} \sum_{k=1}^{52810} \left(\frac{y_k^3 - y_k^0}{y_k^0}\right) - 1,$$

with the k subscripts denoting kth 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 $\lambda_1 = 0.198$ and the interaction network. Analogous interpretations of $a_{\mathcal{E}_2}^{\mathcal{E}_0}$ and $a_{\mathcal{E}_3}^{\mathcal{E}_0}$ follow. We find that

$$a_{\mathcal{E}_1}^{\mathcal{E}_0} = 13.46\%,\ a_{\mathcal{E}_2}^{\mathcal{E}_0} = 5.54\%,\ a_{\mathcal{E}_3}^{\mathcal{E}_0} = -0.17\%.$$

Thus, a spillover of $\lambda_1 = 0.198$ leads to interest rates that are 13.46% higher, on average, in the networked economy $\mathcal{E}_1$ compared to the baseline economy $\mathcal{E}_0$. On the other hand, a smaller positive spillover of $\lambda_2 = 0.089$ implies that interest rates are 5.54% higher in economy $\mathcal{E}_2$ than in economy $\mathcal{E}_0$. These findings give us an idea of the gap between interest rates in a networked economy versus a

[23] 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 interest of simplicity.

non-networked economy in normal times. In contrast, in a large recession, when the spillover is $\lambda_3 = -0.003$, we find that on average interest rates are 0.17% lower in the networked economy $\mathcal{E}_3$ compared to the non-networked economy $\mathcal{E}_0$. From this experiment we can conclude that network spillovers driven by loan portfolio commonality play an important role in determining the pricing of loans in credit markets and their evolution in normal and crisis times.

8. 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. 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, making lending rates strategic complements during normal times. These spillovers are economically large, time-varying and can disappear during major negative shocks. By means of a model of the syndicated loan market, we have shown that informational learning externalities can rationalize our empirical findings.

Our analysis leaves open important questions. For example, our findings suggest an alternative transmission channel for aggregate conditions through the credit market based on the strength of informational linkages. However, to capture and quantify this channel it is important to expand the data to include smaller firms, which are traditionally more vulnerable to lending conditions. Such matters are left for future work.

CRediT authorship contribution statement

Abhimanyu Gupta: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sotirios Kokas:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alexander Michaelides:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Raoul Minetti:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

No Conflict of Interest.

Appendix A. Sensitivity tests

In this appendix, we present several robustness tests. In Table A.1 (columns I–VI) we report the results from alternative measures for the cost of lending. We observe similar results when using *AISU* (columns I and II). We find that in column I the effect of the *financial-loan network* for *AISU* is close to zero and slightly significant, 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 0.9 bps. This represents an increase in the average *AISU* in our sample by 5%. A similar interpretation holds for the *Spread* (columns III and IV) and the *letter-of-credit fees* (columns V and VI).[24]

In Table A.2 we present further robustness tests. In Table 4, we identified the *Great Recession* as the driver of the nullifying effect on the spillover. To test this further we estimate two specifications in which we randomly choose to exclude 1995–97 and 2001–03 fixed effects, respectively, while including fixed effects for the other years including the crisis. These specifications constitute a type of 'placebo' tests: we seek to verify that it is indeed the crisis that weakens the spillover. Columns I and II show that this is indeed the case, with statistically and economically insignficant spillover estimates.

Finally, the spatial correlation that we model may also affect the errors of the regression. With this in mind, in columns III and IV of Table A.2, we also estimate specifications where t-statistics are computed using spatial hetereskedasticity and correlation (SHAC) robust standard errors. Specifically, we use the instrumental variables SHAC estimate of Kelejian and Prucha (2007) with a bandwidth $(52810)^{1/4} = 15.16$ approximately, and the Bartlett kernel $k(x) = 1 - |x|$ for $x \leq 1$, and 0 for $x > 1$.[25] SHAC estimates of this type can be computationally onerous if the model has many regressors. Therefore we estimate our specifications without the large number of bank and firm fixed effects which would make the SHAC calculation infeasibly slow. As the results in columns IV and V show, we still observe the same spillover nullifying effect of the crisis using this type of robust standard error formula.

So far, our analysis has focused on the estimates of λ, but the coefficients in other control variables have the expected signs, with spreads being a function of borrower and loan risk. The estimated coefficients of the control variables are presented in Tables 4 and 5. While a full discussion of these coefficients is beyond the scope of this section, we highlight a few illustrative examples.

[24] For the alternative proxies of the cost lending, we rely on Berg et al. (2016).

[25] The IV estimation for the parameters is carried out exactly as in Section 6.2. Kelejian and Prucha (2007) provide a SHAC robust standard formula based on such estimates, and suggest a bandwidth of $n^{1/4}$, where n is sample size.

Table A.1
Sensitivity tests I.

	AISU	AISU	Spread	Spread	LOC fee	LOC fee
	I	II	III	IV	V	VI
Financial-loan network	0.026 [1.522]	0.111*** [6.294]	−0.000 [0.027]	0.095*** [8.852]	0.026 [0.956]	0.167*** [6.200]
Observations	52,810	52,810	52,810	52,810	52,810	52,810
Loan-control variables	Y	Y	Y	Y	Y	Y
Firm-control variables	Y	Y	Y	Y	Y	Y
Bank-control variables	Y	Y	Y	Y	Y	Y
Loan-type FE	Y	Y	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y	
Firm FE	Y	Y	Y	Y	Y	Y
Sector × Year FE	Y	Y	Y	Y	Y	Y
Sector × Bank FE	Y	Y	Y	Y	Y	Y
Year FE (exc. Crisis FE)		Y		Y		Y

The table reports coefficients and t-statistics (in brackets) from the estimation of Eq. (5.2), 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.

Table A.2
Sensitivity tests II.

	AISD	AISD	AISD	AISD
	'Placebo' estimates		SHAC IV estimates	
	II	II	III	IV
Financial-loan network	0.0049 [0.5089]	0.0012 [0.1236]	−0.0044 [0.1113]	0.0808*** [3.6744]
Observations	52,810	52,810	52,810	52,810
Loan-control variables	Y	Y	Y	Y
Firm-control variables	Y	Y	Y	Y
Bank-control variables	Y	Y	Y	Y
Loan-type FE	Y	Y	Y	Y
Loan-purpose FE	Y	Y	Y	Y
Bank FE	Y	Y		
Year FE			Y	
Firm FE	Y	Y		
Sector × Year FE	Y	Y		
Sector × Bank FE	Y	Y		
Year FE (exc. 1995–97)	Y			
Year FE (exc. 2001–03)		Y		
Year FE (exc. Crisis FE)				Y

The table reports coefficients and t-statistics (in brackets) from the estimation of Eq. (5.2), 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 also include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. Colmuns I-II are QML estimates with heteroskedasticity robust standard errors, while columns III and IV are IV estimates with SHAC robust standard errors. The *,**,*** marks denote the statistical significance at the 10, 5, and 1% level, respectively.

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)

[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).

and covenants tend to have lower spreads (Ioannidou and Ongena, 2010). 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 et al., 2017).

A similar analysis holds for the number of total 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.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2025.102840.

Data availability

The authors do not have permission to share data.

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