The Network Structure of Money Multiplier*

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Abstract

Deposits finance bank lending and function as means of payment for the rest of the economy. While loans are generally illiquid and often held until maturity, deposits circulate among banks as depositors transact with one another. Except for rare instances where payment inflows and outflows perfectly balance, payment introduces liquidity risks and constrains the "money multiplier"—the ratio of loans financed by deposits to banks' liquid assets that buffer potential deposit outflows. We develop a model of bank lending and payment system where this multiplier depends on the network topology of interbank payment flows that churn liquidity among banks. We estimate the model using Fedwire payment data and identify banks that have a large impact on the equilibrium multiplier due to their systemic importance in the payment network.

Keywords: Payment, network, deposits, credit supply, money multiplier, money velocity

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1 Introduction

At the core of a financial system are credit and money creation by banks. When extending loans, a bank grants borrowers newly issued deposits, engaging in a debt swap: The bank acquires borrowers' debts (loans) and issues debts (deposits) that borrowers hold as money.[1] This process expands the supply of inside money—the means of payment created within the private sector.

It may appear that banks possess the ability to create money ex nihilo thanks to the special status of their liabilities (deposits) as means of payment adopted by the rest of the economy. However, akin to other firms, banks' capacity to issue liabilities cannot be infinite in equilibrium as pointed out by Tobin (1963). What limits credit and money creation by banks? The answer also resides in the special status of deposits as money that circulates among depositors.

When the loan borrower turns the newly issued deposits into purchasing power, the bank faces three scenarios. First, the borrower withdraws cash, causing the bank to lose reserves. Second and more often, the borrower electronically pays depositors at other banks. The bank loses reserves and deposits to the payment recipients' banks. Lastly, should the recipients also be depositors at the lending bank, the bank simply alters the deposit ownership. However, the bank still faces liquidity loss if these recipients (the new depositors) pay others, triggering the first or second scenario.

Therefore, there is a liquidity constraint on credit and money creation: The ratio of loans funded by deposit issuance to the bank's liquid assets—the money multiplier—cannot be overstretched. Our notion of money multiplier differs from the traditional deposits-to-reserves ratio. What matters is not the total amount of deposits issued by a bank but the liquidity property of assets funded by deposits. Issuing deposits to acquire liquid assets is not liquidity transformation and therefore is not subject to the liquidity constraint, because payment outflows can be covered by selling the newly acquired liquid assets. In contrast, issuing deposits to fund loans requires the bank to have other (liquid) assets that buffer payment outflows because the loans are illiquid.

The money multiplier in equilibrium depends crucially on the liquidity churn among banks. In the second scenario of interbank electronic payment, the payment sender's bank loses reserves while the recipient's bank gains reserves and sees its liquidity constraint relaxed. In response, the recipient's bank may decide to fund new loans with deposits. Some of these newly issued deposits

[1] Money creation through bank lending was a popular theme in the classic literature (e.g., Wicksell, 1907; Schumpeter, 1954; Gurley and Shaw, 1960; Tobin, 1963). A growing literature revisits it (e.g., Gersbach, 1998; Cavalcanti and Wallace, 1999; Kiyotaki and Moore, 2002; Kahn and Roberds, 2007; Gu et al., 2013; Brunnermeier and Sannikov, 2016; Piazzesi and Schneider, 2016; Donaldson et al., 2018; Parlour et al., 2020; Bianchi and Bigio, 2022).

are then used in payment, sent to other banks and bringing along reserves. This process results in a ripple effect of reserve percolation. Such liquidity churn is large in magnitude. The average weekly volume in Fedwire—the primary payment settlement system in the U.S.—exceeds GDP.

In summary, banks are concerned about liquidity loss when financing lending with deposits but liquidity inflows from other banks relax the liquidity constraint. The problem is that when individual banks make decisions, they do not internalize the liquidity spillover to other banks as a result of their depositors paying depositors at other banks. This liquidity spillover effect leads to strategic complementarity: A bank will extend more loans funded by deposits when it receives payment inflows that result from the rest of the banking sector extending loans funded by deposits.

We develop a model that captures the payment externality in banks' lending decisions. Built upon insights from recent studies on payment and banking (Parlour et al., 2020; Bianchi and Bigio, 2022), our paper takes a step forward by modeling the network structure of payment flows and structurally estimating the network externality. A bank's decision to fund loans with deposits depends on the net interest margin, its liquid assets, and, importantly, its position in the payment network that determines its liquidity risk and liquidity spillover to other banks. Liquidity transformation capacity of the banking sector depends on topology of the entire network. When estimating the model, we map out the network using payment data from Fedwire. We find that strategic complementarity from payment externality amplifies the volatility of bank credit supply. By analyzing network topology, we identify systemically important banks that drive aggregate fluctuation.

Our paper revisits several historic concepts in monetary economics. Bank lending and liquidity percolation via payment are known to be the key ingredients of money multiplier, but little has been done in the modern literature to formalize the mechanism. Rather than relying on a binding reserve requirement, our model of money multiplier emphasizes bank liquidity management and payment-induced strategic complementarity in banks' decision to create credit and money.

Money velocity is a key ingredient in theories on money demand (e.g., Alvarez et al., 2009). We focus on money supply: An increase in velocity means more payments and greater liquidity risk for banks, reducing the money multiplier and slowing down money creation by banks.[2] Moreover, as reserves churn faster among banks, strategic complementarity strengthens, making the system more sensitive to shocks. Our paper differs from studies on payment and bank liquidity shocks (Bianchi and Bigio, 2022; Lagos and Navarro, 2023) in our network perspective on money velocity.

[2]This mechanism implies a negative correlation between money quantity and velocity. Our mechanism emphasizes banks, i.e., the money supply side, and complements the demand-side mechanism in Alvarez et al. (2009).

Recent studies on monetary assets focus on quantities and prices (or "liquidity premium"). In the tradition of liquidity preference (Keynes, 1936; Baumol, 1952; Tobin, 1956; Sidrauski, 1967), much progress has been made in reviving money demand functions (Alvarez and Lippi, 2009, 2014; Krishnamurthy and Vissing-Jørgensen, 2012; Lucas and Nicolini, 2015; Nagel, 2016). On the supply side, it has been shown that banks play an important role in supplying monetary assets, earning liquidity premium (Krishnamurthy and Vissing-Jørgensen, 2015; Brunnermeier and Sannikov, 2016; Drechsler et al., 2018; Wang, 2018; Begenau, 2020; Lenel et al., 2019; Piazzesi et al., 2019). Our paper goes beyond quantities and prices. By analyzing the circulation of inside money (deposits) among depositors and the resultant interbank network of payment flows, our approach highlights the defining feature of monetary assets—means of payment.[3]

In the recent decade, bank reserve holdings have increased through several channels (e.g., quantitative easing). Many hold the belief that banks are satiated with liquidity. To the contrary, evidence shows that reserve shortage still happens (Correa et al., 2020; Copeland et al., 2021; d'Avernas and Vandeweyer, 2021; Acharya et al., 2022; Afonso et al., 2022; Yang, 2022; Lopez-Salido and Vissing-Jørgensen, 2023). Our findings further this line of research by showing how payment-induced redistribution of liquidity across banks affects the supply of bank credit.

Next, we explain the model setup and summarize the main findings from our structural estimation. The model has N banks, each endowed with reserves. A bank chooses the amount of loans funded by deposits; afterwards, its depositors make payments, which result in a random fraction of deposits flowing to other banks, draining reserves. The bank incurs an increasing and convex (quadratic) cost of reserve loss. It is costly to lose liquid assets that serve as precautionary savings or be used for regulatory and other purposes. Moreover, it is costly to replenish liquidity through interbank borrowing or other sources of external funds.[4] The bank also receives reserve inflows as a result of the other banks financing loans with deposits and their depositors making payments.

Therefore, banks are interconnected through depositors' payment activities. A network of payment flows churns liquidity among banks. Under the increasing marginal cost of reserve loss, such liquidity churn makes banks' decisions to fund loans with deposits strategic complements.

[3] Moneyness of an asset refers to its use in payment for goods and services or the ease of conversion into means of payment (e.g., Grossman and Weiss, 1983; Rotemberg, 1984; Lucas, 1990; Chatterjee and Corbae, 1992; Alvarez and Atkeson, 1997; Eisfeldt, 2007; Chiu, 2014; Lagos et al., 2017; Kiyotaki and Moore, 2019).

[4] If interbank markets operate frictionlessly, a bank in surplus can lend to a bank in deficit, costlessly reversing payment shocks (Bhattacharya and Gale, 1987). Therefore, our work builds on the literature on interbank market frictions (e.g., Afonso and Lagos, 2015; Bigio and Sannikov, 2019). The freeze of interbank market can be interpreted as strong convexity in the cost of reserve loss, which reduces bank lending (Iyer et al., 2013; Ippolito et al., 2016).

When one bank extends loans funded by deposits, its depositors' payment to other banks' depositors brings reserves to other banks. With more reserves, the other banks' marginal cost of reserve loss declines, so they are more willing to fund new loans with deposits.

In our model, money velocity manifests itself in a random graph of interbank payment flows that are directed by depositors and out of control by banks. For a single bank, payment liquidity risk is a form of funding instability risk and constrains the elasticity of its balance sheet.[5] Beyond liquidity risk, payment also generates liquidity externality. When one bank expands its balance sheet, financing lending with deposits, it does not internalize the liquidity spillover that benefits its neighboring banks and relaxes their liquidity constraint. In equilibrium, bank i's lending depends on bank j's lending through a network-effect parameter, ϕ and the ij-th element of a network adjacency matrix that incorporates the first and second moments of pairwise payment flows between banks. The parameter ϕ is a key object of interest in our estimation. The larger its value is, the stronger strategic complementarity is in banks' decision to finance lending with deposits.

Our model is a quadratic game on a random graph (Galeotti et al., 2010; Jackson and Zenou, 2015). Its equilibrium conditions map to a spatial econometric model (Lee et al., 2010; de Paula, 2017), a common approach in the social interaction literature (e.g., Glaeser and Scheinkman, 2000; Ballester et al., 2006; Graham, 2008; Calvó-Armengol et al., 2009; Bramoullé et al., 2009; Blume et al., 2015) and recently adopted in financial economics (Cohen-Cole et al., 2014, 2015; Ozdagli and Weber, 2017; Herskovic, 2018; Lu and Luo, 2019; Herskovic et al., 2020; Denbee et al., 2021; Jiang and Richmond, 2021; Eisfeldt et al., 2022, 2023). We calculate the first and second moments of depositor-instructed payment flows for each bank pair using data from Fedwire. Our equilibrium structure bridges the vast information in the probability distribution of interbank payment flows to banks' decisions by embedding the information in a network adjacency matrix.

The equilibrium has a two-step structure.[6] First, we solve a bank's network-independent level of lending, that is the bank's optimal choice should it be isolated from other banks. Second, the network amplification mechanism works as an operator (a functional formed by ϕ and the

[5]The empirical literature has documented a large impact of funding risk on bank lending (Loutskina and Strahan, 2009; Ivashina and Scharfstein, 2010; Cornett et al., 2011; Dagher and Kazimov, 2015; Carletti et al., 2021). Bank runs have attracted the most attention (Gorton, 1988; Calomiris and Mason, 1997; Iyer and Puri, 2012; Martin et al., 2018; Brown et al., 2020; Artavanis et al., 2022). Payment risk differs from run risk as even insured deposits are used in payments. Liquidity regulations, such as reserve requirement or liquidity coverage ratio, amplify the cost of reserve loss and the impact of payment risk. A branch of literature on funding stability emphasizes legal and regulatory impact (Jayaratne and Strahan, 1996; Qian and Strahan, 2007; Di Maggio and Kermani, 2017; Cortés et al., 2020).

[6]This structure is in reminiscence of production network models (e.g., Acemoglu et al., 2012; Herskovic, 2018).

adjacency matrix) which we apply to network-independent lending to obtain the equilibrium value.

When estimating the model, our focus is on characterizing the network operator. We treat banks' network-independent lending as random variables that encapsulate banks' available reserves, shocks, and potentially other characteristics, and directly estimate their distributional properties (means and variances).[7] This approach allows us to stay agnostic about the amount of available reserves, which is empirically challenging to define. A bank may sell other assets for reserves, so available reserves depend on its reserve holdings and how liquid other assets are. The bank may also resort to external financing. Finally, the bank may hold reserves for different purposes, which implies the available reserves for covering payment outflows can be below the reserve holdings.

The estimate of ϕ is large in magnitude, which implies that the strategic complementarity is strong and the interbank payment network works as a shock amplification mechanism. Consider a positive shock that triggers all banks to extend loans funded by deposits. The neighboring banks, connected through depositors' payment flows, respond by further expanding balance sheets and thereby trigger another round of shock propagation. The network amplifies shocks by 17%.

To demonstrate the importance of network topology, we compare the mean and volatility of aggregate credit supply in equilibrium with those solved under a hypothetical network where banks are equally connected (payment flows are evenly distributed among bank pairs). Both networks amplify shocks. While the two networks generate similar levels of expected credit supply, they differ in volatility, with the volatility from the real network being 20% higher.

Following Diebold and Yılmaz (2014), we decompose the volatility of aggregate credit supply into individual banks' contributions and develop a metric of systemic risk.[8] A bank's contribution depends on the network amplification operator, which summarizes the routes of shock propagation via the payment linkages, and the volatility of its network-independent level of lending. Less than 10% of banks contribute to more than 90% of credit-supply volatility.

Next, we quantify the network externalities. In contrast to the market equilibrium, the planner's choice of bank lending internalizes the interbank liquidity spillover from depositors' payment activities. Therefore, by comparing the market equilibrium against the planner's solution, we are able to demonstrate the impact of payment network externalities on lending capacity of the banking system. Relative to the planner's solution, the market equilibrium generates an expected level of

[7]The shock to each bank can be interpreted as anything that contributes to the randomness of network-independent lending, such as shocks to net interest margin, regulatory cost, or available reserves.

[8]Our metric based on payment data contributes to the literature on systemic risk (Billio et al., 2012; Acharya et al., 2016; Adrian and Brunnermeier, 2016; Benoit et al., 2016; Bai et al., 2018; Duarte and Eisenbach, 2021).

bank lending that is 8.6% lower and a volatility that is 20% higher. Policy interventions that aim at correcting payment network externalities can potentially improve the aggregate credit condition.[9]

The planner's solution and market equilibrium also differ in the distribution of lending across banks. Under relationship lending, some borrowers cannot switch banks.[10] Inefficiency arises from bank-borrower mismatch. For example, a borrower who prefers stable credit may be matched with a bank whose lending is volatile. Banks' lending volatility and expected level both depend on their locations in the payment network. The bank-borrower mismatch is essentially between the bank's lending opportunities (i.e., the matched borrowers) and the payment characteristic of its deposits. In comparison with the planner's solution, the market equilibrium features stronger heterogeneity in expected lending and volatility across banks, creating more potential bank-borrower mismatch.

2 Model

2.1 The setup

There are N banks and three dates, $t = 0$, 1, and 2. Bank i, $i \in \{1, ..., N\}$, is endowed with reserves, m_i. We set up the model by describing bank i's problem. At $t = 0$, bank i chooses y_i, the amount of loans financed by deposits. The bank earns a net interest margin:

$$R_i y_i - r_i y_i + \varepsilon_i y_i, \tag{1}$$

where the loan rate, R_i, and deposit rate, r_i, can be bank i-specific, depending on the characteristics of bank i and its customers. The last term represents a shock to bank i's profits from financing new loans with deposits. ε_i is realized and known before bank i chooses y_i at $t = 0$.[11] After solving the equilibrium, we will show that how the shock enters can be flexible.

The goal of our analysis is two-fold. First, we characterize the link between liquidity base, m_i, and the equilibrium level of liquidity transformation, y_i, i.e., loans funded by deposits. Our

[9] Payment system reforms involve the design of netting mechanisms, interbank credit lines, and overdraft at the central bank (see, e.g., Calomiris and Kahn, 1996; Freixas and Parigi, 1998; Kahn and Roberds, 1998, 2015; Martin and McAndrews, 2008; Bech, Chapman, and Garratt, 2010; Bech, Martin, and McAndrews, 2012; Chapman, Gofman, and Jafri, 2019). These measures potentially reshape the payment-flow topology and affect bank lending.

[10] Relationship lending has been found to have a large impact on real activities (e.g., Berger and Udell, 1995; Berlin and Mester, 1999; Ongena and Smith, 2000; Dahiya et al., 2003; Degryse and Ongena, 2005; Bolton et al., 2016).

[11] The shock can be related to the demand for credit (collateral value and the profitability of borrowers' projects). It may also represent credit supply shock, for example, bank i's regulatory cost of expanding balance sheet.

second goal is to examine how ε_i is propagated and amplified in the banking system when depositors' payment flows generate interconnectedness between banks.

At $t = 1$, depositors at different banks make payments to one another. Let g_{ij} denote the fraction of bank i's deposits paid to depositors at bank j ($j \neq i$) by bank i's depositors. We define

$$z_i \equiv \sum_{j \neq i} g_{ij} y_i, \tag{2}$$

the total reserve and deposit outflow from bank i to other banks. Payment flows are risky: g_{ij} is random with mean μ_{ij} and variance σ_{ij}^2, and g_{ij} is out of bank i's control as the bank cannot interfere with depositors' payment decisions. Bank i transfers reserves, z_i, to the payment recipients' banks and deducts the corresponding amount of deposits, shrinking balance sheet, while the recipients' banks receive reserves and credit the recipients' deposit accounts with deposits, expanding balance sheets. On the liability side of balance sheet, a random fraction $\sum_{j \neq i} g_{ij}$ of deposits mature at $t = 1$ while the rest mature at $t = 2$.[12] The loans on asset side are illiquid and held until $t = 2$. At $t = 1$, bank i relies on reserves, m_i, to cover liquidity outflow. Therefore, its ability to finance lending with deposits and its choice of y_i at $t = 0$ depends on m_i. We broadly interpret m_i to include both reserves and other liquid assets that can be readily sold to cover payment outflows.

At $t = 1$, bank i experiences liquidity inflows that result from other banks' depositors making payments to bank i's depositors. From bank j, bank i receives payment inflows equal to $g_{ji} y_j$, where g_{ji} has mean μ_{ji} and variance σ_{ji}^2. The correlation between g_{ij} and g_{ji} is denoted by ρ_{ij}.[13]

Bank i's cost of covering payment outflow at $t = 1$ is specified as follows:

$$\tau_1 \left(z_i - \sum_{j \neq i} g_{ji} y_j - m_i \right) + \frac{\tau_2}{2} \left(z_i - \sum_{j \neq i} g_{ji} y_j - m_i \right)^2 + \frac{\kappa}{2} z_i^2 \,, \tag{3}$$

where $z_i - \sum_{j \neq i} g_{ji} y_j - m_i$ is the liquidity shortfall and $\tau_1 > 0$, $\tau_2 > 0$, and $\kappa > 0$. This quadratic form will lead to a set of linear equilibrium conditions that map to the well-known empirical framework of spatial models (Anselin, 1988; Lee et al., 2010; de Paula, 2017). This modeling approach follows the literature on social interaction (Glaeser and Scheinkman, 2000; Ballester et al., 2006;

[12] As in Bolton et al. (2020), deposits are essentially debts with random maturities.

[13] We would expect $\rho_{ij} < 0$ if economic activities are directional, involving mainly bank i's customers paying j's customers. The correlation ρ_{ij} can also be positive if bank i's customers' payments to j's customers stimulate economic activities between the two depositor clienteles and result in j's customers making payments to i's customers.

Graham, 2008; Calvó-Armengol et al., 2009; Bramoullé et al., 2009; Galeotti et al., 2010; Blume et al., 2015; Jackson and Zenou, 2015) and recent applications in financial economics (Cohen-Cole et al., 2014, 2015; Ozdagli and Weber, 2017; Herskovic, 2018; Lu and Luo, 2019; Herskovic et al., 2020; Denbee et al., 2021; Jiang and Richmond, 2021; Eisfeldt et al., 2022, 2023). We add $\frac{\kappa}{2}z_i^2$ because netting may not happen instantaneously, so gross outflow adds liquidity stress.[14] We only need to add a quadratic form of z_i because a linear coefficient of z_i will be absorbed by τ_1.

Incorporating both the net interest margin given by (1) and the liquidity cost from depositors' payment activities given by (3), we have the net profits for bank i:

$$R_i y_i - r_i y_i + \varepsilon_i y_i - \tau_1 \left(z_i - \sum_{j \neq i} g_{ji} y_j - m_i \right) - \frac{\tau_2}{2} \left(z_i - \sum_{j \neq i} g_{ji} y_j - m_i \right)^2 - \frac{\kappa}{2} z_i^2. \quad (4)$$

The first two terms of payment liquidity cost capture an increasing and convex cost of y_i. Note that y_i enters the payment liquidity cost via z_i (see (2)). The liquidity buffer, m_i, reduces the marginal cost of increasing y_i, suggesting a link exists between liquid assets, m_i, and bank i's optimal level of liquidity transformation (lending funded by deposits), y_i. In other words, when choosing y_i, bank i essentially faces a liquidity constraint: m_i is needed to buffer payment outflows.

Strategic complementarity emerges: An increase in y_j reduces bank i's marginal cost of y_i. This is the key force that we aim to capture in through the model and to quantify through our structural estimation. Intuitively, when bank j expands balance sheet by extending loans funded by deposits, it generates liquidity spillover to bank i through its depositors' payments to bank i's depositors. Such liquidity spillover relaxes the liquidity constraint on bank i's choice of y_i.

In sum, when extending loans funded by deposits, individual banks face potential liquidity loss due to depositors' payment outflows and have to rely on their liquid assets. However, when depositors at different banks transact with one another, one bank's payment outflow is another bank's inflow. Such liquidity churn within the system relaxes individual banks' liquidity constraint.

Such liquidity spillover effect is not internalized in individual banks' choice of y_i, and the strength of such externality depends on the network structure of payment flows. Moreover, the liquidity spillover induces strategic complementarity in banks' choice of y_i, which may amplify the response of the banking system to individual banks' shock to net interest margin, ε_i.

[14] A large literature studied the intraday payment stress (Poole, 1968; Afonso, Kovner, and Schoar, 2011; Ashcraft, McAndrews, and Skeie, 2011; Ihrig, 2019; Copeland, Duffie, and Yang, 2021; d'Avernas and Vandeweyer, 2021; Afonso, Duffie, Rigon, and Shin, 2022; Yang, 2022). Kahn and Roberds (2009) review the studies on payment system.

Our model is built upon the assumption that interbank market is imperfect. If banks that experience payment inflows lend to banks that experience outflows freely and at zero interest rate, banks are no longer concerned about the interbank payment flows, facing τ_1, τ_2, and κ all equal to zero in (3) and (4). To simplify the notations, we define the *net* payment outflow for bank i:

$$x_i = z_i - \sum_{j \neq i} g_{ji} y_j = \sum_{j \neq i} g_{ij} y_i - \sum_{j \neq i} g_{ji} y_j \,, \tag{5}$$

If $x_i - m_i > 0$, the first two terms in (3) captures an increasing and convex cost of interbank borrowing. The convexity, as microfounded in Bigio and Sannikov (2019) and Parlour, Rajan, and Walden (2020), reflects the impact of interbank market frictions (Afonso and Lagos, 2015).[15] When $x_i - m_i < 0$, this quadratic form presents an increasing and concave return on interbank lending, and the concavity is again due to the attribution from interbank market frictions.

It is uncommon to observe payment outflow greater than a bank's liquid assets. Thus, it is important to clarify the empirical counterpart of m_i. In our model, m_i represents liquid assets that bank i allocates towards buffering payment outflows; in other words, the bank may hold liquidity beyond m_i, but only a part of it is for covering payment outflows, while the rest are held for other reasons, such as liquidity needs from non-payment activities and investment opportunities that rely on internal funds. Payment-induced liquidity shortfall can potentially be covered by repurposing liquidity from other uses, and the associated cost is captured by the quadratic form (3).

We have focused on bank i's liquidity management captured by the liquidity cost (3). Next, we consider depositors' liquidity management. Depositors incur large expenses (z_i is large), they face difficulty in managing liquidity.[16] Bank i may generate profits from extending lines of credit:

$$\theta_1 \left(z_i - \sum_{j \neq i} g_{ji} y_j \right) + \frac{\theta_2}{2} \left(z_i - \sum_{j \neq i} g_{ji} y_j \right)^2 = \theta_1 x_i + \frac{\theta_2}{2} x_i^2 \,. \tag{6}$$

Appendix B lays out the microfoundation. The first term captures depositors' liquidity loss, with $\theta_1 > 0$. The second term capture the increasing marginal impact: As depositors lose more liquidity, they are willing to pay more for lines of credit, which implies $\theta_2 > 0$.[17] The deposit base, y_i, enters

[15] Banks may also borrow from the central bank but face the stigma effect (Copeland, Duffie, and Yang, 2021).

[16] For example, firms invest in inventory to boost sales but may not get paid in time by their customers, thus overstretching the cash conversion cycle. Households may incur large expenses before their payday.

[17] The increasing marginal value of liquidity arises in both static settings (see Appendix B) and dynamic settings

via z_i with the coefficient equal to the fraction of deposits spent (see the definition of z_i in (2)). The profits increase in y_i but the marginal profits decrease in y_j. When bank i's depositors receive payment inflow, $g_{ji}y_j$, from bank j's depositors, they have more liquidity and are less willing to pay for bank i's lines of credit. This generates strategic substitution in banks' choices of y_i and counteracts the force of strategic complementarity from the payment liquidity cost given by (3).

An alternative interpretation of (6) is regulatory cost (Baron, 2020). Deposit inflows force banks to raise leverage and tighten the regulatory constraint on leverage, for example, the supplementary leverage ratio (SLR) requirement. When the constraint binds, the bank may be forced to raise costly equity (Bolton et al., 2020). Deposit outflow, z_i, alleviates the regulatory pressure by deleveraging the bank. Under this interpretation, θ_1 is positive, but the sign of θ_2 is unclear so we allow both positive and negative. The goal of incorporating (6) is to acknowledge different forces that may counteract or compound the channel of bank liquidity management captured through (3).

It is assumed that the revenues and costs in (1), (3), and (6) are all time-zero values. At $t = 0$, bank i chooses y_i to maximize the following expected profits:

$$\max_{y_i} \mathbb{E}\left[(R_i - r_i + \varepsilon_i)y_i - \tau_1(x_i - m_i) - \frac{\tau_2}{2}(x_i - m_i)^2 - \frac{\kappa}{2}z_i^2 + \theta_1 x_i + \frac{\theta_2}{2}x_i^2\right].^{18} \tag{7}$$

Several observations are in order. The expectation is taken over the randomness in g_{ij}, not ε_i that is known at $t = 0$. Loan return, R_i, is not random and is already adjusted for systematic risk. This is without loss of generality as long as systematic shocks to loan return, driven by macroeconomic factors, are orthogonal to the randomness in interbank payment flows (i.e., in g_{ij}). Finally, our focus is on banks' normal-time operations, not crises. We assume that even when the realized payment flows cause the maximum loss (which is finite since g_{ij} is bounded in $[0, 1]$), the bank's profits remain positive. Thus, a bank is always solvent, and depositors do not have incentive to run.

Our model differs from the classic banking model in Diamond and Dybvig (1983). In our model, one bank's loss of deposits and reserves is another bank's gain. We model payment between depositors at different banks and emphasize the interconnectedness from payment flow and its network structure; in contrast, Diamond and Dybvig (1983) model depositors' cash withdrawal that does not lead to bank interconnectedness. Moreover, Diamond and Dybvig (1983) analyze bank run, while in our model, liquidity risk is solely from the role of deposits as means of payment.

(Riddick and Whited, 2009; Bolton, Chen, and Wang, 2011; Décamps, Mariotti, Rochet, and Villeneuve, 2011).

[18] The following parameter restriction ensures concavity in y_i: $\tau_2 + \kappa > \theta_2$.

Discussion: Money creation, liquidity transformation, and other assets and liabilities. When extending loans, a bank acquires borrowers' debts (loans) and issues debts (deposits) that borrowers can use as money. This practice has been adopted throughout the history of banking.[19] After obtaining the loan, the borrower may hold the newly issued deposits in her account at the lending bank or transfer the newly issued deposits to a depositor at the same bank. In both cases, the lending bank does not lose deposits. If the borrower transfers deposits to her account at another bank or pays a depositor at another bank, the lending bank loses deposits and must transfer reserves to the bank that receives the deposits, shrinking its balance sheet on both the asset and liability sides.

Liquidity transformation takes place the moment a bank extends loans at $t = 0$ because the bank may lose deposits at $t = 1$ before loans mature at $t = 2$. The bank can adjust capital structure after payment shocks (i.e., after g_{ij} and g_{ji} are realized). For example, the bank rebuilds its holdings of liquid assets by raising funds from bond or equity investors. The associated financing costs are captured through the cost of liquidity loss (3). A bank's capacity to create money (issue deposits) through lending is constrained by the amount of liquid assets it has to cover the potential deposit outflow, as the new loans are illiquid. In contrast, issuing deposits to purchase liquid assets is not constrained, as those newly acquired assets can be readily sold to cover deposit outflows.

To sum up, we model bank loans funded by deposit issuance, y_i, in line with the practice in banking and characterize the link between m_i, the liquidity base, and y_i. We do not model banks acquiring liquid assets with deposits as it is not liquidity transformation and is not constrained by m_i. On the asset side of balance sheet, we focus on loans. On the liability side, we do not explicitly model other bonds or equity, but allow these instruments to be used as costly sources of liquidity.

2.2 Equilibrium

We solve bank i's optimal choice of y_i, given other banks' choices, y_j ($j \neq i$). To simplify the notations, we introduce the mean of gross payment outflows as a fraction of y_i:

$$\overline{\mu}_{-i} \equiv \mathbb{E}\left[\sum_{j\neq i} g_{ij}\right], \tag{8}$$

[19] There is a classic literature and a growing modern literature on this topic (e.g., Gurley and Shaw, 1960; Tobin, 1963; Gersbach, 1998; Cavalcanti and Wallace, 1999; Kiyotaki and Moore, 2000, 2002; Kahn and Roberds, 2007; Gu et al., 2013; McLeay et al., 2014; Hart and Zingales, 2014; Quadrini, 2017; Brunnermeier and Sannikov, 2016; Piazzesi and Schneider, 2016; Donaldson et al., 2018; Wang, 2019; Parlour et al., 2020; Bianchi and Bigio, 2022).

and the variance of gross payment outflows as a fraction of y_i:

$$\overline{\sigma}^2_{-i} = \mathrm{Var}\left(\sum_{j\neq i} g_{ij}\right) . \tag{9}$$

We derive the following first-order condition for y_i:

$$\begin{aligned} R_i - r_i + \varepsilon_i =& (\tau_1 - \theta_1)\overline{\mu}_{-i} + y_i\left(\kappa + \tau_2 - \theta_2\right)\left(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}\right) - \tau_2\overline{\mu}_{-i} m_i \\ & - (\tau_2 - \theta_2)\sum_{j\neq i}\left(\overline{\mu}_{-i}\mu_{ji} + \rho_{ij}\sigma_{ij}\sigma_{ji}\right) y_j . \end{aligned} \tag{10}$$

The net interest margin is equal to the marginal cost associated with depositors' payment activities. The first two terms on the right side depend on the first and second moments of payment outflows, and the third term reflects the fact that having more liquid assets, m_i, reduces the marginal cost of liquidity loss. In the last term, $\overline{\mu}_{-i}\mu_{ji}y_j$ shows that if bank i experiences more outflow ($\overline{\mu}_{-i}$), the inflow from bank j (μ_{ji}) becomes more valuable. We call this term *liquidity externality* following Parlour et al. (2020). The other component is the covariance between g_{ij} and g_{ji}, $\rho_{ij}\sigma_{ij}\sigma_{ji}$. This *hedging externality* represents a form of risk sharing on the network (Eisfeldt et al., 2022).[20] A negative correlation, $\rho_{ij} < 0$, dampens the peer effect, while a positive correlation amplifies it.

Rearranging the first-order condition (10), we solve the optimal y_i:

$$y_i^* = \phi\sum_{j\neq i} w_{ij} y_j^* + a_i, \tag{11}$$

where the network attenuation factor, ϕ, is given by

$$\phi = \frac{\tau_2 - \theta_2}{\kappa + \tau_2 - \theta_2} , \tag{12}$$

the ij-th element of the network adjacency matrix, denoted by $\mathbf{W}$, is given by

$$w_{ij} = \frac{\overline{\mu}_{-i}\mu_{ji} + \rho_{ij}\sigma_{ij}\sigma_{ji}}{\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}} . \tag{13}$$

and a_i is the optimal y_i without peer effect, i.e., the solution under $g_{ji} = 0$, $j \neq i$. When $g_{ji} = 0$

[20] In our derivation, g_{ij} is assumed to be uncorrelated with g_{ki} ($k \neq j$), consistent with our data.

(constant), $\mu_{ji} = 0$, $\sigma_{ji} = 0$, $\rho_{ij} = 0$, and as a result, $w_{ij} = 0$ (thus, $y_i = a_i$). Under $g_{ji} = 0$, bank i experiences payment outflows but does not receive inflows from other banks.

The peer effect depends on ϕw_{ij}, the attenuation factor, ϕ, and the ij-th element of the adjacency matrix. If $\phi w_{ij} > 0$ (< 0), the model features strategic complementarity (substitution). As will be shown later, in our sample, there are only 0.39% of non-zero w_{ij} that are negative. Therefore, whether the pair $\{i, j\}$ exhibits strategic complementarity or substitution depends on the sign of ϕ. As previously discussed, an increase in y_j has two opposing implications on bank i's choice of y_i. First, bank i receives liquidity inflows as its depositors receive payment from bank j's depositors; with a larger liquidity buffer, the marginal cost of liquidity loss declines, so bank i increases y_i. Second, the payment inflows to bank i's depositors also bring these depositors liquidity, so they rely less on bank i for liquidity provision (and thus there are fewer opportunities for bank i to profit from depositors' liquidity needs). Moreover, deposit inflow can push the bank against regulatory constraints on leverage. Therefore, when y_j increases, bank i can be less interested in raising deposits against loans. If $\tau_2 > \theta_2$ ($\phi > 0$), the first force dominates, and strategic complementarity emerges: y_i is increasing in y_j. The expected payment flow from j to i, μ_{ji}, is valuable especially when bank i's expected outflow, $\overline{\mu}_{-i}$, is large. If $\tau_2 < \theta_2$ ($\phi < 0$), the second force dominates, and strategic substitution emerges: Bank i is averse to payment inflows from j.

Proposition 1 *Suppose $|\phi \lambda^{\max}(\mathbf{W})| < 1$, where the function $\lambda^{max}(\cdot)$ returns the largest eigenvalue. Then, there is a unique interior solution for the Nash equilibrium outcome given by*

$$y_i^* = \{\mathbf{M}(\phi, \mathbf{W})\}_{i.}\, \mathbf{a}, \tag{14}$$

where $\mathbf{I}$ is the $N \times N$ identity matrix, $\{\}_{i.}$ returns the i-th row of its argument, and

$$\mathbf{M}(\phi, \mathbf{W}) \equiv \mathbf{I} + \phi \mathbf{W} + \phi^2 \mathbf{W}^2 + \phi^3 \mathbf{W}^3 + \ \ldots = \sum_{k=0}^{\infty} \phi^k \mathbf{W}^k = (\mathbf{I} - \phi \mathbf{W})^{-1}. \tag{15}$$

The i-th element of $N \times 1$ column vector, $\{\mathbf{a}\}_i = a_i$, records bank i's optimal choice of y_i under $g_{ji} = 0$. a_i satisfies $\frac{da_i}{dm_i} > 0$, $\frac{d^2 a_i}{dm_i d\overline{\mu}_{-i}} > 0$, $\frac{da_i}{d\tau_1} < 0$, $\frac{d^2 a_i}{d\tau_1 d\overline{\mu}_{-i}} < 0$, $\frac{da_i}{d\overline{\sigma}_{-i}^2} < 0$, and $\frac{da_i}{d\varepsilon_i} > 0$.

Proposition 1 summarizes the equilibrium solution. In vector form, we can rewrite (14):

$$\mathbf{y}^* = \mathbf{M}(\phi, \mathbf{W})\, \mathbf{a} = (\mathbf{I} - \phi \mathbf{W})^{-1} \mathbf{a}\,. \tag{16}$$

The condition $|\phi\lambda^{\max}(\mathbf{W})| < 1$ states that network externalities must be small enough to prevent the feedback triggered by such externalities from escalating without bounds.[21] Proposition 1 characterizes the link between m_i, the liquidity base, and y_i, the equilibrium level of liquidity transformation and shows how the shocks to individual banks, ε_i, are propagated in the system.

The equilibrium multiplier that links m_i to y_i has a two-step structure: First, the liquidity base, m_i, enters into a_i; then the network operator, $\mathbf{M}(\phi, \mathbf{W})$, is applied to a_i, accounting for the interconnectedness between banks. The properties of a_i are intuitive. The liquidity base, m_i, contributes to "network-independent" lending financed by deposits, $\frac{da_i}{dm_i} > 0$, because it buffers bank i's liquidity loss from payment outflows. When bank i expects more payment outflows, having liquid assets becomes more important, $\frac{d^2 a_i}{dm_i d\overline{\mu}_{-i}} > 0$. In bank i's liquidity cost given by (3), τ_1 represents a baseline cost of borrowing reserves, which has a negative impact on bank lending, $\frac{da_i}{d\tau_1} < 0$, in line with the evidence (Jiménez et al., 2012, 2014). When bank i expects more liquidity loss, the negative impact of τ_1 is amplified, $\frac{d^2 a_i}{d\tau_1 d\overline{\mu}_{-i}} < 0$. Finally, when bank i faces more payment liquidity risk, a_i becomes smaller, $\frac{da_i}{d\overline{\sigma}^2_{-i}} < 0$, in line with the findings in Li and Li (2021).

Proposition 1 also shows that bank i's shock, ε_i, enters into the equilibrium in two steps. First, it affects a_i, i.e., $\frac{da_i}{d\varepsilon_i} > 0$, and then the network operator, $\mathbf{M}(\phi, \mathbf{W})$, is applied to a_i, and the shock impact is transmitted to the other banks. In our model setup, ε_i hits bank i's net interest margin before bank i chooses y_i at $t = 0$. In fact, we can be very flexible about how the shock is specified. Any source of randomness in a_i will be propagated through the system via the network operator, $\mathbf{M}(\phi, \mathbf{W})$. For example, we may assume that a shock to a_i originates from a shock to bank i's liquidity buffer, m_i, rather than its net interest margin. When mapping the model to data, we shall treat a_i as a random variable that has an expected level and a random component:

$$a_i = \bar{\alpha}_i + \nu_i, \tag{17}$$

where ν_i has a zero mean and variance δ_i^2. We estimate the mean and volatility of a_i directly (in full sample and rolling windows) without unpacking the structure of a_i. Doing so has several advantages. Beyond a flexible interpretation of ε_i, we can stay agnostic about the empirical counterpart of m_i, as m_i enters y_i only through a_i. It is challenging to specify m_i empirically, as it depends on bank i's reserves, holdings of liquidity securities, liquidity that can be obtained by selling or pledg-

[21] The sequence in (15) converges under $|\phi\lambda^{\max}(\mathbf{W})| < 1$ (Debreu and Herstein, 1953). The equilbrium definition is akin to that of Calvó-Armengol, Patacchini, and Zenou (2009) who study peer effects in education.

ing other assets, and liquidity from external sources (e.g., central bank liquidity facilities). It is also unclear how banks allocate liquidity between covering payment outflows and other activities.

When estimating and quantifying the model, our focus will be on the network operator $\mathbf{M}(\phi, \mathbf{W})$. Define $\bar{\alpha} = [\bar{\alpha}_1, ..., \bar{\alpha}_N]$ and $\nu = [\nu_1, ..., \nu_N]$. We rewrite (16) as

$$\mathbf{y}^* = \underbrace{\mathbf{M}(\phi, \mathbf{W})\,\bar{\alpha}}_{\text{level propagation}} + \underbrace{\mathbf{M}(\phi, \mathbf{W})\,\nu}_{\text{risk propagation}}. \tag{18}$$

The matrix $\mathbf{M}(\phi, \mathbf{W})$ has an important economic interpretation: It aggregates all direct and indirect links among banks using an attenuation factor, ϕ, that penalizes, as in Katz (1953), the contribution of links between distant nodes at the rate ϕ^k, where k is the length of the path between nodes. In the infinite sum in equation (15), the identity matrix captures the (implicit) link of each bank with itself, the second term in the sum captures all the direct links between banks, the third term in the sum captures all the indirect links corresponding to paths of length two, and so on. The elements of $\mathbf{M}(\phi, \mathbf{W})$, given by $m_{ij}(\phi, \mathbf{W}) \equiv \sum_{k=0}^{+\infty} \phi^k \left\{\mathbf{W}^k\right\}_{ij}$, aggregates all paths from j to i.

The matrix $\mathbf{M}(\phi, \mathbf{W})$ contains information about the network centrality of banks. Multiplying the rows (columns) of $\mathbf{M}(\phi, \mathbf{W})$ by a unit vector of conformable dimensions, we recover the indegree (outdegree) Katz–Bonacich centrality measure. The indegree centrality measure provides the weighted count of the number of ties directed to each node (i.e., inward paths), while the outdegree centrality measure provides the weighted count of ties that each node directs to the other nodes (i.e., outward paths). The i-th row of $\mathbf{M}(\phi, \mathbf{W})$ captures how bank i loads on the network as whole, while the i-th column of $\mathbf{M}(\phi, \mathbf{W})$ captures how the network as a whole loads on i.

The matrix $\mathbf{M}(\phi, \mathbf{W})$ itself is not enough to determine the systemic importance of a bank. Regardless of $\mathbf{M}(\phi, \mathbf{W})$, i.e., how the shocks are propagated, banks with large shocks (large δ_i^2) have a large influence on other banks and the aggregate $Y = \sum_i y_i$. The network not only propagates shocks but also amplifies the impact of $\bar{\alpha}$, the expected level. In Section 3.4, we show how to utilize the equilibrium structure to empirically identify systemically important banks.

2.3 The planner's solution

We consider a planner that equally weights the objective of each bank and chooses $\{y_i\}_{i=1}^N$,

$$\max_{\{y_i\}_{i=1}^N} \mathbb{E}\left[\sum_{i=1}^N (R_i - r_i + \varepsilon_i)y_i - \tau_1(x_i - m_i) - \frac{\tau_2}{2}(x_i - m_i)^2 - \frac{\kappa}{2}z_i^2 + \theta_1 x_i + \frac{\theta_2}{2}x_i^2\right]. \quad (19)$$

We do not aim for welfare implications as the planner's objective only incorporates banks' profits instead of the total welfare of banks, borrowers, and depositors. The focus is on characterizing network externalities through the wedge between the planner's solution and market outcome.

The planner's first order condition for bank i's lending amount, y_i, yields:

$$\begin{aligned} R_i - r_i + \varepsilon_i =& y_i\left(\kappa + \tau_2 - \theta_2\right)\left(\overline{\sigma}_{-i}^2 + \overline{\mu}_{-i}^2\right) - \tau_2\overline{\mu}_{-i}m_i - (\tau_2 - \theta_2)\sum_{j\neq i}\left(\overline{\mu}_{-i}\mu_{ji} + \rho_{ij}\sigma_{ij}\sigma_{ji}\right)y_j \\ &+ y_i(\tau_2 - \theta_2)\overline{\sigma}_{-i}^2 - (\tau_2 - \theta_2)\sum_{j\neq i}(\overline{\mu}_{-j}\mu_{ij} + \rho_{ij}\sigma_{ij}\sigma_{ji})y_j \\ &+ (\tau_2 - \theta_2)\sum_{j\neq i}\left(\sum_{k\neq j}\mu_{kj}y_k\right)\mu_{ij} - \sum_{j\neq i}\tau_2 m_j\mu_{ij} \end{aligned} \quad (20)$$

The planner's marginal cost of bank i's lending is on the right side of (20). Its first three terms also appear on the right side of first-order condition (10) in the market equilibrium, but the rest differ and reflect the planner internalizing spillover effects. First, bank i's costs or benefits associated with the expected outflow, $(\tau_1 - \theta_1)\overline{\mu}_{-i}$ in (10), disappear because, from the planner's perspective, bank i's expected outflow is the other banks' expected inflow and thus i's losses are offset by j's gains. Second, the new term, $y_i(\tau_2 - \theta_2)\overline{\sigma}_{-i}^2$, reflects the fact that when bank i lends more, it adds payment-flow risk not only to itself (via the first term on the right side of (20)) but also to its neighboring banks. Third, the fifth term, $-(\tau_2 - \theta_2)\sum_{j\neq i}(\overline{\mu}_{-j}\mu_{ij} + \rho_{ij}\sigma_{ij}\sigma_{ji})y_j$, captures the liquidity externality and hedging externality of bank i's lending on bank j ($j \neq i$). In particular, the liquidity externality of bank i's marginal lending (through the marginal outflow, μ_{ij}) has a stronger impact on bank j when j expected a large outflow $\overline{\mu}_{-j}$. The sixth term, $(\tau_2 - \theta_2)\sum_{j\neq i}(\sum_{k\neq j}\mu_{kj}y_k)\mu_{ij}$, shows that if bank j already receives inflows due to bank k's lending ($k \neq j$), the marginal impact of liquidity from bank i (i.e., μ_{ij}) is smaller. Finally, the last term shows that if bank j already has large reserve holdings, the marginal impact of liquidity from bank i is smaller.

Rearranging the planner's first-order condition (20), we solve the optimal y_i:

$$y_i = \widetilde{\phi}_i \sum_{j \neq i} \widetilde{w}_{ij} y_j - \widetilde{\phi}_i \sum_{j \neq i} \mu_{ij} \left(\sum_{k \neq j} \mu_{kj} y_k \right) + \widetilde{a}_i \tag{21}$$

where the network attenuation factor for bank i, $\widetilde{\phi}_i$, is given by,

$$\widetilde{\phi}_i = \frac{(\tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})}{(\kappa + \tau_2 - \theta_2)\left(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}\right) + (\tau_2 - \theta_2)\,\overline{\sigma}^2_{-i}} = \left(\frac{1}{\phi} + \frac{\overline{\sigma}^2_{-i}}{\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}} \right)^{-1}, \tag{22}$$

the ij-th element of the network adjacency matrix, denoted by $\widetilde{\mathbf{W}}$, is given by

$$\widetilde{w}_{ij} = \frac{\overline{\mu}_{-i}\mu_{ji} + 2\rho_{ij}\sigma_{ij}\sigma_{ji} + \overline{\mu}_{-j}\mu_{ij}}{\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}}. \tag{23}$$

and the expression of $\widetilde{a}_i$, the planner's choice of network-independent bank lending financed by deposits, is provided in the appendix. Throughout this paper, "$\widetilde{\cdot}$" differentiates the variable in the planner's solution from its counterpart in the market equilibrium. The planner's network attenuation factor differs from ϕ in (12) and is i-specific due to the additional term, $(\tau_2 - \theta_2)\,\overline{\sigma}^2_{-i}$, in the denominator that reflects the payment risk spillover of bank i's choice of y_i. Moreover, the ij-th element of the adjacency matrix in (23) differs from its decentralized counterpart in (13) by incorporating the hedging and liquidity externalities of bank i's choice of y_i.

Let $\widetilde{\Phi}$ denote the diagonal matrix with the i-th diagonal element equal to $\widetilde{\phi}_i$ and $\mathbf{U}$ denote the matrix with the ij-th element equal to μ_{ij}. We rewrite the planner's solution (21) in vector form:

$$\mathbf{y}^* = \widetilde{\Phi}\widetilde{\mathbf{W}}\mathbf{y} - \widetilde{\Phi}\mathbf{U}\mathbf{U}^\top\mathbf{y} + \widetilde{\alpha} \tag{24}$$

where $\widetilde{\mathbf{a}} = [\widetilde{a}_1, ..., \widetilde{a}_N]$, and we have the closed-form solution

$$\mathbf{y}^* = \left(\mathbf{I} - \widetilde{\Phi}\widetilde{\mathbf{W}} + \widetilde{\Phi}\mathbf{U}\mathbf{U}^\top \right)^{-1} \widetilde{\alpha}. \tag{25}$$

Proposition 2 *Suppose* $\left| \lambda^{\max}\left(\widetilde{\Phi}\widetilde{\mathbf{W}} + \widetilde{\Phi}\mathbf{U}\mathbf{U}^\top \right) \right| < 1$, *where the function* $\lambda^{max}(\cdot)$ *returns the largest eigenvalue. Then, the planner's optimal solution is uniquely defined and given by (25).*

Discussion: Payment network vs. other networks. The modern payment system settles depositors' transactions by requiring the payment senders' banks to transfer reserves and deposits to the recipients' banks (Piazzesi and Schneider, 2016). In our model, the interconnectedness between banks emerges from transactions among depositors. The literature on interbank network focuses instead on banks' transactions rather than depositors' transactions.[22] In particular, the interbank network of reserve borrowing and lending has attracted most attention.[23]

The network of depositors' transactions and that of interbank credit differ but can be related. The interbank credit network can help mitigate the impact of payment flows, allowing the payment recipients' banks to lend to the senders' banks that experience liquidity loss (Bhattacharya and Gale, 1987). However, as previously discussed, the interbank reserve market has frictions, captured via the quadratic cost of liquidity loss. By analyzing the network of depositors' interbank payment flows, we uncover a new source of externality and systemic risk. Moreover, our network analysis is not subject to the common challenges in the literature, such as a lack of bilateral linkage data, endogenous linkages, and randomness in linkages. In our setting, depositor-initiated payments are observed from Fedwire, and this network is not endogenous to banks' choices (unlike, for example, the network of interbank credit) but results from depositors' payments. Finally, we directly model a random graph and quantify the joint probability distribution of depositors' payment flows across banks (i.e., g_{ij}). The randomness in payment flows is a key feature of our model and is important empirically in explaining banks' incentive to finance lending with deposits (Li and Li, 2021).

[22] The literature considers three types of network: (1) interbank financial contracts, mainly reserve loans (e.g., Allen and Gale, 2000; Furfine, 2000; Boss et al., 2004; Upper and Worms, 2004; Wells, 2004; Brusco and Castiglionesi, 2007; Degryse and Nguyen, 2007; Cocco et al., 2009; Bech and Atalay, 2010; Iyer and Peydró, 2011; Castiglionesi and Wagner, 2013; Kuo et al., 2013; Zawadowski, 2013; Farboodi, 2014; Gabrieli and Georg, 2014; Acemoglu et al., 2015; Elliott et al., 2015; Babus, 2016; Bräuning and Fecht, 2016; Erol and Ordoñez, 2017; Gofman, 2017; Blasques et al., 2018; Castiglionesi and Eboli, 2018; Craig and Ma, 2021; Corbae and Gofman, 2019; Anderson et al., 2020; Jasova et al., 2021), (2) linkages via common assets (e.g., Cifuentes et al., 2005; Leitner, 2005; Acharya and Yorulmazer, 2007; Ibragimov et al., 2011; Allen et al., 2012; Greenwood et al., 2015; Caccioli et al., 2015; Cabrales et al., 2017; Albuquerque et al., 2019; Heipertz et al., 2019; Kopytov, 2019), (3) connections from OTC bilateral trading (e.g., Duffie et al., 2009; Hugonnier et al., 2014; Afonso and Lagos, 2015; Bech and Monnet, 2016; Farboodi et al., 2017; Chang and Zhang, 2019; Eisfeldt et al., 2022; Li and Schürhoff, 2019; Üslü, 2019; Hendershott et al., 2020).

[23] The interbank network literature is reviewed by Allen and Babus (2009), Glasserman and Young (2016), and Jackson and Pernoud (2021). One reason behind the exclusive focus on interbank reserve borrowing rather than the more primitive network of depositor payment flows is a legacy institutional setup, deferred net settlement (DNS) that was phased out in the U.S. in 1980s (Bech and Hobijn, 2007). In DNS, banks facing payment outflows automatically obtain a loan from counterparties that experience inflows; in contrast, under the current protocol of real-time gross settlement, payments are no longer settled via interbank credit but by same-day transfer of reserves. In DNS, interbank borrowing happens simultaneously with depositors' payments, so, in a way, the network of interbank reserve borrowing is correlated with that of interbank depositor payment. Under RTGS, the two networks are no longer coupled.

3 Empirical Methodology

3.1 Data

We obtain confidential transaction-level data from the Fedwire Funds Service ("Fedwire") that spans from 2010 to 2020. Fedwire is a system for real-time gross settlement (RTGS) used to electronically settle U.S. dollar payments among member institutions (including more than two thousand banks). The system processes trillions of dollars daily. The Federal Reserve maintains accounts for both payment sender banks and receiver banks and settles transactions by transferring reserves between banks without netting. In 2020, the average weekly transaction value exceeded the U.S. annual GDP. Fedwire accounts for roughly two-thirds of payment volume in the U.S. The rest of the transactions are mainly settled through the Clearing House Interbank Payments System (CHIPS) of more than forty member banks, which, unlike Fedwire, allows netting (and potentially members' exposure to counterparty risks) and thus does not fit our setting where payments are settled on gross terms and the concern for banks is reserve loss rather than counterparty risks.[24] In Appendix A, we provide more details on the structure of U.S. payment system. Bech and Hobijn (2007) provide an overview on the adoption of RTGS around the world.

For each transaction, Fedwire records the time and date of the transaction, identities of sender bank and receiver bank, payment amount, and type (instructed by customers or by banks themselves). We focus on transactions instructed by customers (depositors), which are out of the banks' control as in our theoretical model. In particular, we exclude bank-scheduled transfers and banks' purchases and sales of federal funds. Customer-initiated transactions make up about 85% of transactions (in terms of the number of transactions). We obtain data on bank balance sheets and income statements from U.S. Call Report. We merge the Fedwire data with the Call Report data using Federal Reserve's internal identity system. Our merged sample covers 83% of banks in Call Report (in terms of total assets). We provide the summary statistics in Table D.1 in the appendix.

[24] Kahn and Roberds (2009) review the payment literature. Related studies analyze intraday reserve constraints, coordination failure in payment timing (Poole, 1968; Hamilton, 1996; McAndrews and Potter, 2002; Bech and Garratt, 2003; Ashcraft and Duffie, 2007; Bech, 2008; Afonso, Kovner, and Schoar, 2011; Afonso and Shin, 2011; Ashcraft, McAndrews, and Skeie, 2011; Bech, Martin, and McAndrews, 2012; Ihrig, 2019; Afonso, Duffie, Rigon, and Shin, 2022; Yang, 2022), and stress in short-term funding markets (Ashcraft and Bleakley, 2006; Ashcraft, McAndrews, and Skeie, 2011; Acharya and Merrouche, 2013; Chapman, Gofman, and Jafri, 2019; Correa, Du, and Liao, 2020; d'Avernas and Vandeweyer, 2021; Copeland, Duffie, and Yang, 2021). Our focus is on how payment liquidity risk propagates into banks' decisions on lending and balance-sheet composition at lower (quarterly) frequencies.

3.2 The empirical specification

We estimate the model with quarterly data. For quarter t, the amount of new loans extended by a bank, y_i, is calculated as the difference between loans in quarter t and loans in quarter $t-1$ (Call Report). As shown in (11), bank i's choice of y_i depends on other banks' y_j through w_{ij}, a function of statistics of g_{ij} and g_{ji} defined in (13). We calculate these statistics using daily observations of g_{ij} and g_{ji} in quarter $t-1$ so that w_{ij} is known (predetermined) when bank i chooses y_i for quarter t. Our results are robust when the statistics are calculated with lagged four quarters of data. To calculate daily observations of g_{ij}, we follow the definition in our model, dividing daily net payment flow from bank i to j in quarter $t-1$ (Fedwire) by bank i's deposits in quarter $t-1$ (Call Report). In Figure 1, we report the frequency distribution of g_{ij}. Note that our sample only contains Fedwire payments instructed by customers (depositors) as our model focuses on interbank reserve transfer due to depositors' payment activities rather than banks transacting with one another.

To maintain the standard assumption of stationarity of data generating processes (Hayashi, 2000), we use banks' quarterly loan growth rates instead of loan amounts. We divide (11) by the loan amount at quarter $t-1$ to obtain the loan growth rate of bank i in quarter t, denoted by $n_{i,t}$

$$n_{i,t} \equiv \frac{y_{i,t}}{y_{i,t-1}} = \phi \sum_{j \neq i} w_{ij} \frac{y_{j,t}}{y_{i,t-1}} + \frac{a_{i,t}}{y_{i,t-1}} \,. \tag{26}$$

To simplify the notation, we use $a'_{i,t}$ to denote $a_{i,t}/y_{i,t-1}$. For the decomposition in (17), we have

$$a'_{i,t} = \bar{\alpha}'_i + \nu'_{i,t} \,, \tag{27}$$

where, $\bar{\alpha}'_i = \bar{\alpha}_i / y_{i,t-1}$, and the shock, $\nu'_{i,t}$, has a zero mean and a conditional variance $\delta_i'^2$ ($\delta'_i = \delta_i / y_{i,t-1}$). Next, we substitute bank j's loan growth rate, $n_{j,t} = \frac{y_{j,t}}{y_{j,t-1}}$ in (26) to obtain:

$$n_{i,t} = \phi \sum_{j \neq i} w'_{ij} n_{j,t} + \bar{\alpha}'_i + \nu'_{i,t} \,, \tag{28}$$

where the loan amount-adjusted adjacency matrix, denoted by $\mathbf{W}'$, has the ij-th element given by

$$w'_{ij} \equiv w_{ij} \frac{y_{j,t-1}}{y_{i,t-1}} \,. \tag{29}$$

A key target of our estimation is the parameter ϕ. An estimate of ϕ that is statistically signifi-

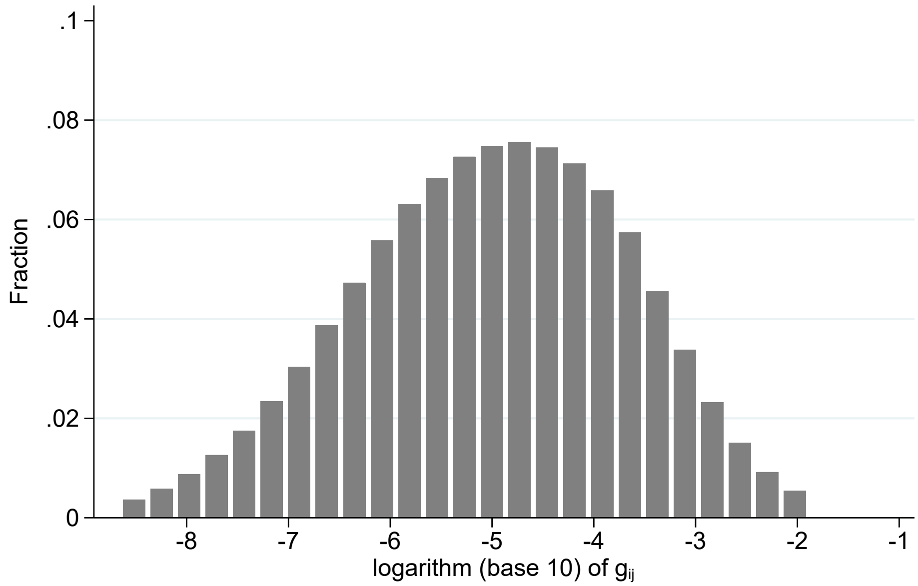

Figure 1: **Distribution of g_{ij}.** This figure reports the frequency distribution of g_{ij}. The x-axis shows the logarithm (base 10) of g_{ij} (for example, -2 corresponds to -0.01) and the y-axis shows the fraction of observations in a bin.

cant from zero suggests that the network as a whole has a significant impact on bank lending. And, together with the network adjacency matrix, $\mathbf{W}'$, the parameter ϕ determines whether bank lending decisions are strategic complements or substitutes. Instead of directly estimating the equilibrium condition (28) using observations of loan growth rates and w_{ij} from last quarter, we recognize that empirically, a bank's lending decision depends on bank characteristics and macroeconomic variables outside of our theoretical model. Therefore, our empirical model of loan growth rate will contain two components, $q_{i,t}$ that is outside of our model (driven by bank characteristics and macro variables), and $n_{i,t}$, which is the component that reflects the mechanism in our model.

In data, we only observe $l_{i,t} = q_{i,t} + n_{i,t}$, not $q_{i,t}$ and $n_{i,t}$ separately. However, by observing bank characteristics (denoted by $x^m_{i,t}$) and macroeconomic variables (denoted by x^p_t) that drive $q_{i,t}$, we are able to estimate the network attenuation factor, ϕ, effectively using the regression residuals of $l_{i,t}$. In our estimation, the bank characteristics include the logarithm of total assets, the ratio of liquid securities (reserves and available-for-trade securities) to total assets, the ratio of equity capital to total assets, the ratio of deposits to total assets, the ratio of loans to total assets, the return on assets, and the macroeconomic variables (from FRED) include the change in effective federal funds rate (EFFR), real GDP growth, inflation, stock market return, and housing price growth.[25] All control variables are lagged by one quarter for predeterminacy. We also include the constant as a control variable. We provide the summary statistics in Table D.1 in the appendix.

In sum, our empirical model of the observed loan growth rate is

$$l_{i,t} = \sum_{m=1}^{M} \beta_m^{bank} x_{i,t}^m + \sum_{p=1}^{P} \beta_p^{macro} x_t^p + n_{i,t}, \tag{30}$$

where, according to (28), we have

$$n_{i,t} = \phi \sum_{j \neq i} w'_{ij} n_{j,t} + \bar{\alpha}'_i + \nu'_{i,t} \quad \nu'_{i,t} \sim \mathcal{N}\left(0, \delta_i'^2\right). \tag{31}$$

Equation (30) and (31) together constitute a spatial error model (SEM) (e.g., Anselin, 1988; Elhorst, 2010). Such models allow the joint estimation of β coefficients in the observational equation (30), and $\bar{\alpha}'_i$, $\delta_i'^2$, and ϕ in the error (or residual) equation (31). Therefore, even though the econometrician does not observe $n_{i,t}$ directly, the parameters of the network game can still be recovered. In Appendix C.1, we explain the optimization algorithm for the maximum likelihood estimation.

We can rewrite the system of (30) and (31) in vector form:

$$\boldsymbol{\ell}_t = X_t \beta + \mathbf{n}_t, \tag{32}$$

$$\mathbf{n}_t = \phi \mathbf{W}' \mathbf{n}_t + \bar{\alpha}' + \nu'_t. \tag{33}$$

Following Proposition 1, we require that $|\phi \lambda^{\max}(\mathbf{W}')| < 1$, where the function $\lambda^{max}(\cdot)$ returns the largest eigenvalue. Under this restriction, we have

$$\mathbf{n}_t = (\mathbf{I} - \phi \mathbf{W}')^{-1} (\bar{\alpha}' + \nu'_t). \tag{34}$$

The control variables, X_t, absorb part of the variation in loan growth rates and only leave the residual variation for estimating the network effect, ϕ. This is a conservative approach. Any comovement in $\boldsymbol{\ell}_t$ across banks that is driven by common variation in bank characteristics or common

[25] The stock market return is the quarterly change of the Wilshire 5000 Total Market Index (a market-capitalization-weighted index of the market value of all American-stocks actively traded in the United States). The housing price growth is the quarterly change of the S&P/Case-Shiller U.S. National Home Price Index.

loadings on macroeconomic factors (X_t) cannot be attributed to peer effects. Given the strong heterogeneity in bank sizes, w'_{ij} in (29) can be prohibitively large if i is much smaller than j, which then implies that for small banks, the component related to network effects, $n_{i,t}$, will mechanically account for a large share of loan growth relative to $q_{i,t}$. Since our model does not address the relative importance of $n_{i,t}$ and $q_{i,t}$, $\mathbf{W}'$ is normalized to be right-stochastic (row sums equal to one); thus the relative importance of $n_{i,t}$ and $q_{i,t}$ is not mechanically driven by size. The normalization also prevents the estimate of ϕ from being disproportionately influenced by small banks.

We estimate the parameters ϕ, $\bar{\alpha}'$, δ', and β by maximizing the following joint likelihood

$$-\frac{T}{2}\ln\left((2\pi)^N|\Delta'|\right) - \frac{1}{2}\sum_{t=1}^{T}\left[(\mathbf{I}-\phi\mathbf{W}')\left(\boldsymbol{\ell}_t - X_t\beta\right) - \bar{\alpha}'\right]^\top \Delta'^{-1}\left[(\mathbf{I}-\phi\mathbf{W}')\left(\boldsymbol{\ell}_t - X_t\beta\right) - \bar{\alpha}'\right],$$

where N is the number of banks, T is the number of quarters, Δ' is the covariance matrix with the i-th diagonal element equal to δ'^2_i, and $|\Delta'|$ is the determinant. An identification condition is that the off-diagonal elements of Δ' are zero, that is the structural shocks, ν'_t, are uncorrelated across banks. In the next subsection, we discuss its implication for identifying ϕ. Empirically, it is reasonable to assume that, after controlling for a sufficiently large set of bank characteristics and macroeconomic variables (X_t), comovement in the residual loan growth rates, $n_{i,t}$, has been significantly reduced, and after teasing out the network propagation mechanism, the structural shocks, ν'_t, should be uncorrelated across banks. In other words, comovement in loan growth rate, $l_{i,t}$, across banks has two sources, from X_t and from the network propagation mechanism, i.e., $(\mathbf{I}-\phi\mathbf{W}')^{-1}$ in (34), that transmits individual banks' uncorrelated shocks to their peers.

When the shocks ν'_t are normally distributed, we have a maximum likelihood estimator (MLE). If the shocks are not normally distributed, the estimator is quasi-MLE. When the score of normal log-likelihood has the martingale difference property and the first two conditional moments are correctly specified, the quasi-MLE is consistent and has a limiting normal distribution (Bollerslev and Wooldridge, 1992). For inference, we apply the classic delta method.[26]

3.3 Parameter identification

To clarify the intuition about how the key network parameter, ϕ, is identified from the data, it is useful to consider a simplified version of the model in equations (30) and (31). Let $L_t \in \mathbb{R}^N$

[26] We follow Bollerslev and Wooldridge (1992) to calculate the asymptotic standard errors robust to non-normality.

denote the vector containing loan growth rates of individual banks at quarter t, and, to simplify exposition, let us disregard the fixed effects, $\bar{\alpha}_i'$, in equation (31) and assume that the network matrix has constant weights $\mathbf{W}'$. The model given by (32) and (33) can be rewritten in vector form:

$$\boldsymbol{\ell}_t = X_t\beta + \mathbf{n}_t, \quad \mathbf{n}_t \sim \mathcal{N}\left(\mathbf{0}_N, \Omega\right), \tag{35}$$

where $\mathbf{0}_N$ denotes an N-dimensional vector of zeros, $\Omega = \mathbf{M}\Delta'\mathbf{M}^\top$ with $M = (\mathbf{I} - \phi\mathbf{W}')^{-1}$, Δ' is a diagonal matrix with elements given by $\left\{\delta_i'^2\right\}_{i=1}^N$. In deriving the covariance Ω, we used equation (31), i.e., that in equilibrium we can rewrite $\mathbf{n}_t$ (having, for now, removed $\bar{\alpha}_i$) as $\mathbf{n}_t = (\mathbf{I} - \phi\mathbf{W}')^{-1}\nu_t'$, where ν_t' has a distribution with zero mean and a diagonal covariance matrix Δ'.

We can consistently estimate β via linear projection, and use the residuals to construct a consistent estimator of covariance matrix Ω.[27] The key question is whether we can recover the structural parameters ϕ and $\left\{\delta_i'^2\right\}_{i=1}^N$. Being symmetric, the estimated $\widehat{\Omega}$ gives $N(N+1)/2$ equations, while we have to recover $N+1$ parameters in $\mathbf{M}\Delta'\mathbf{M}^\top$. Therefore, as long as Ω is full-rank, the system is over-identified. The identification is akin to that of structural vector autoregressions (Sims and Zha, 1999) where shock propagation is recovered from residual covariance.

To further sharpen the intuition, let us consider a system of three banks and the simplest network, a chain: Bank 1 is connected with Bank 2, and 2 with 3, so

$$\mathbf{W}' = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \text{ and } \mathbf{M}\Delta'\mathbf{M}^\top = \begin{bmatrix} \delta_1'^2 + \phi^2\delta_2'^2 + \phi^4\delta_3'^2 & \phi\delta_2'^2 + \phi^3\delta_3'^2 & \phi^2\delta_3'^2 \\ \phi\delta_2'^2 + \phi^3\delta_3'^2 & \delta_2'^2 + \phi^2\delta_3'^2 & \phi\delta_3'^2 \\ \phi^2\delta_3'^2 & \phi\delta_3'^2 & \delta_3'^2 \end{bmatrix}.$$

The volatility of n_1 is $\delta_1'^2 + \phi^2\delta_2'^2 + \phi^4\delta_3'^2$. The first term is the volatility of Bank 1's shock, ν_1'. The second term is the volatility of Bank 2's shock transmitted to Bank 1, i.e., ϕn_2, and the third term reflects Bank 3's shock transmitted in two steps (via Bank 2) to Bank 1, i.e., $\phi^2 n_3$. By the same logic, the volatility of n_2 is $\delta_2'^2 + \phi^2\delta_3'^2$, capturing Bank 2's exposure to its own shock and Bank 3's shock, while Bank 3 only loads on its own shock, so the volatility of n_3 is $\delta_3'^2$. The covariance between n_1 and n_2 is $\phi\delta_2'^2 + \phi^3\delta_3'^2$, reflecting Bank 1's and 2's exposure to 2's and 3's shocks. The covariance between n_2 and n_3 is $\phi\delta_3'^2$ as it only arises from the one-step transmission of Bank 3's shock to 2, i.e., ϕn_3. Covariances emerge from network linkages, and their estimates identify the network effect, ϕ. Given $\delta_3'^2 = \{\widehat{\Omega}\}_{3,3}$, we can solve for ϕ using either the covariance between

[27] The model in (35) has the same structure and properties as the Seemingly Unrelated Regressions (Zellner, 1962).

n_1 and n_3, i.e., $\{\widehat{\Omega}\}_{1,3} = \phi^2\delta_3'^2$, or the covariance between n_2 and n_3, i.e., $\{\widehat{\Omega}\}_{2,3} = \phi\delta_3'^2$, so the system is clearly over-identified. Moreover, given the estimates of $\delta_3'^2$ and ϕ, either the volatility of n_2, i.e., $\{\widehat{\Omega}\}_{2,2} = \delta_2'^2 + \phi^2\delta_3'^2$, or the covariance between n_1 and n_2, i.e., $\{\widehat{\Omega}\}_{1,2} = \phi\delta_2'^2 + \phi^3\delta_3'^2$, gives a solution for $\delta_2'^2$. In the last step, given ϕ, $\delta_2'^2$, and $\delta_3'^2$, $\{\widehat{\Omega}\}_{1,1}$ pins down $\delta_1'^2$.

The structural shocks, ν_i', are uncorrelated across banks. Thus, after controlling for bank characteristics and macro variables, the residuals' (n_i's) correlations are from the network linkages. Therefore, the network effect, ϕ, is identified by such correlations. Accordingly, we saturate the empirical model with a rich set of control variables (X_t) so that the residual correlations are driven by the network linkages instead of missing variables that induce comovement between banks.

3.4 Systemic risk

As shown in (33), an increase in $\bar{\alpha}_i'$ or a positive shock to bank i, $\nu_{i,t}' > 0$, is transmitted to other banks via $\phi\mathbf{W}'$ and, after rounds of propagation, all routes of transmission are summarized by

$$\mathbf{M}(\phi, \mathbf{W}') \equiv \mathbf{I} + \phi\mathbf{W}' + \phi^2\mathbf{W}'^2 + \phi^3\mathbf{W}'^3 + \ldots = \sum_{k=0}^{\infty}\phi^k\mathbf{W}'^k = (\mathbf{I} - \phi\mathbf{W}')^{-1}, \qquad (36)$$

as shown in (34). Consider an increase of $\bar{\alpha}_i'$ by ϵ for all banks or a shock $\nu_{i,t}' = \epsilon$ to all banks. Under $\mathbf{W}'$ being right-stochastic (i.e., $\mathbf{W}'\mathbf{1} = \mathbf{1}$), we have the equilibrium impact given by

$$\mathbf{M}(\phi, \mathbf{W}')\,\mathbf{1}\epsilon = \Big(\mathbf{I} + \phi\mathbf{W}'\mathbf{1} + \phi^2\mathbf{W}'^2\mathbf{1} + \phi^3\mathbf{W}'^3\mathbf{1} + \ldots\Big)\,\epsilon = \frac{1}{1-\phi}\mathbf{1}\epsilon\,. \qquad (37)$$

Therefore, for the same variation in $\bar{\alpha}_i'$ across banks or the same shock, $\nu_{i,t}'$, to all banks, the network multiplier, $1/(1-\phi)$, is a sufficient statistic for the equilibrium impact. If $\phi > 0$, the network amplifies the impact, i.e., $\frac{1}{1-\phi} > 1$; under $\phi < 0$, the network dampens the impact.

Definition 1 (Network Multiplier) *The network multiplier is defined as* $\frac{1}{1-\phi}$.

Given the estimates of ϕ, $\bar{\alpha}_i'$, and $\delta_i'^2$, we use our structural model to identify systemically important banks. A bank is systemically important if it has a disproportionately large impact on the aggregate credit supply. Let N_t denote the network-dependent component of aggregate lending:

$$N_t = \sum_{i=1}^{N} y_{i,t-1}n_{i,t} = \mathbf{y}_{t-1}^{\top}\mathbf{n}_t\,. \qquad (38)$$

Substituting the solution of loan growth rates, $\mathbf{n}_t$, given by (34), we obtain

$$N_t = \mathbf{y}_{t-1}^{\top} \left(\mathbf{I} - \phi \mathbf{W}'\right)^{-1} \left(\bar{\alpha}' + \nu_t'\right) = \mathbf{y}_{t-1}^{\top} \mathbf{M}\left(\phi, \mathbf{W}'\right) \left(\bar{\alpha}' + \nu_t'\right). \tag{39}$$

Before the shocks, ν_t', are realized for quarter t, we calculate the conditional mean of N_t,

$$\mathbb{E}_{t-1}[N_t] = \mathbf{y}_{t-1}^{\top} \mathbf{M}\left(\phi, \mathbf{W}'\right) \bar{\alpha}', \tag{40}$$

and the conditional variance of N_t,

$$\mathrm{Var}_{t-t}\left(N_t\right) = \mathbf{y}_{t-1}^{\top} \mathbf{M}\left(\phi, \mathbf{W}'\right) \Delta' \mathbf{M}\left(\phi, \mathbf{W}'\right)^{\top} \mathbf{y}_{t-1}, \tag{41}$$

where Δ' is the covariance matrix of ν_t', a diagonal matrix whose i-th diagonal element is $\delta_i'^2$.

Definition 2 (Network Impulse Response Function and Volatility Key Bank) *The impulse response of aggregate credit supply to a one standard-deviation shock to a bank i is given by*

$$NIRF_{i,t-1}\left(\phi, \delta_i', \mathbf{W}'\right) \equiv \frac{\partial N_t}{\partial \nu_{i,t}'} \delta_i' = \mathbf{y}_{t-1}^{\top} \left\{\mathbf{M}\left(\phi, \mathbf{W}'\right)\right\}_{.i} \delta_i' \tag{42}$$

where the operator $\{\}_{.i}$ returns the i-th column of its argument. Volatility key bank is defined as

$$i_{t-1}^{*} = \underset{i \in \{1, \ldots, N\}}{\arg\max} \; NIRF_{i,t-1}\left(\phi, \delta_i', \mathbf{W}'\right). \tag{43}$$

A bank's NIRF records the impact of its shock on the aggregate credit supply. It depends on the network attenuation factor, ϕ, the network topology given by $\mathbf{W}'$, and the size of the bank's shock, δ_i'. Our estimation method allows us to identify both ϕ and δ_i'. Next, we show that NIRFs measure banks' contributions to the conditional volatility of aggregate credit supply.

Proposition 3 (Credit-Supply Volatility Decomposition) *Let "vec" denote the vectorization operator. NIRFs decompose the conditional volatility of aggregate credit supply:*

$$\mathrm{Var}_{t-t}\left(N_t\right) = vec\left(\left\{NIRF_{i,t-1}\left(\phi, \delta_i', \mathbf{W}'\right)\right\}_{i=1}^{N}\right)^{\top} vec\left(\left\{NIRF_{i,t-1}\left(\phi, \delta_i', \mathbf{W}'\right)\right\}_{i=1}^{N}\right). \tag{44}$$

3.5 Comparing the planner's solution and market equilibrium

We compare the conditional expectation and conditional volatility of aggregate credit supply from the market equilibrium with those from the planner's solution. First, we show how to utilize the parameter estimates to compute the planner's solution. Following Section 3.2, we define

$$\widetilde{w}'_{ij} = \widetilde{w}_{ij} \frac{y_{j,t-1}}{y_{i,t-1}}\,, \tag{45}$$

where $\widetilde{w}_{ij}$ is defined in (23), and

$$\mu'_{ij} = \mu_{ij} \frac{y_{j,t-1}}{y_{i,t-1}}\,. \tag{46}$$

Throughout this paper, we use "$\sim$" to denote variables in the planner's solution. Dividing the planner's solution (21) by $y_{i,t-1}$ and substituting $y_{j,t}$ with $y_{j,t-1}\widetilde{n}_{j,t}$, we obtain

$$\widetilde{n}_{i,t} = \widetilde{\phi}_i \sum_{j \neq i} \widetilde{w}'_{ij} \widetilde{n}_{j,t} - \widetilde{\phi}_i \sum_{j \neq i} \mu_{ij} \left(\sum_{k \neq j} \mu'_{kj} \widetilde{n}_{k,t} \right) + \widetilde{a}'_{i,t} \tag{47}$$

where $\widetilde{\phi}_i$ is defined in (22) and $\widetilde{a}'_{i,t} = \widetilde{a}_{i,t}/y_{i,t-1}$. Let $\widetilde{\mathbf{W}}'$ and $\mathbf{U}'$ denote the matrices whose the ij-th elements are equal to $\widetilde{w}'_{ij}$ and μ'_{ij}, respectively. Let $\widetilde{\mathbf{a}}'_t$ denote the vector for $\widetilde{a}'_{i,t}$. And, let $\widetilde{\Phi}$ denote the diagonal matrix with the i-th diagonal element equal to $\widetilde{\phi}_i$. In vector form, we have:

$$\widetilde{\mathbf{n}}_t = \widetilde{\Phi} \left(\widetilde{\mathbf{W}}' - \mathbf{U}\mathbf{U}'^{\top} \right) \widetilde{\mathbf{n}}_t + \widetilde{\mathbf{a}}'_t\,. \tag{48}$$

The planner's choice of individual banks' lending can be solved as follows:

$$\widetilde{\mathbf{n}}_t = \widetilde{\mathbf{M}} \left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}' \right) \widetilde{\mathbf{a}}'_t\,. \tag{49}$$

where we define

$$\widetilde{\mathbf{M}} \left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}' \right) \equiv \left(\mathbf{I} - \widetilde{\Phi}\widetilde{\mathbf{W}}' + \widetilde{\Phi}\mathbf{U}\mathbf{U}'^{\top} \right)^{-1}\,. \tag{50}$$

Following the definition (23), we compute $\widetilde{w}_{ij}$ using the statistics of g_{ij} and g_{ji} discussed in Section 3.2 and compute $\widetilde{w}'_{ij}$ in (45) and μ'_{ij} in (46). Comparing the planner's solution (48) and the market equilibrium (33), we can see that $\widetilde{\mathbf{W}}' - \mathbf{U}\mathbf{U}'^{\top}$ plays a similar role in the planner's solution, capturing the peer effects, as $\mathbf{W}'$ in the market equilibrium. Therefore, we normalize $\widetilde{\mathbf{W}}' - \mathbf{U}\mathbf{U}'^{\top}$ to be right-stochastic as we do for $\mathbf{W}'$ in Section 3.2. We calculate $\widetilde{\phi}_i$, defined in (22), using the estimate of ϕ and the statistics of g_{ij} and g_{ji}. To compute the mean and standard deviation of $\widetilde{a}'_{i,t}$, we solve the connection between $\widetilde{a}'_{i,t}$ and $a'_{i,t}$, given by (27) from the market equilibrium:

$$\widetilde{a}'_{i,t} = \frac{b_{i,t}}{y_{i,t-1}} + \frac{\widetilde{\phi}_i}{\phi} a'_{i,t}\,. \tag{51}$$

The details are provided in equation (C.27) the appendix, and $b_{i,t}$ is defined in (C.28). We define $b'_{i,t} = b_{i,t}/y_{i,t-1}$ and rewrite the planner's solution (49) in vector form:

$$\widetilde{\mathbf{n}}_t = \widetilde{\mathbf{M}}\left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}'\right)\mathbf{b}'_{t-1} + \widetilde{\mathbf{M}}\left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}'\right)\frac{1}{\phi}\widetilde{\Phi}\,\mathbf{a}'_t\,. \tag{52}$$

The aggregate credit supply by banks chosen by the planner is

$$\widetilde{N}_t = \sum_{i=1}^{N} y_{i,t-1}\widetilde{n}_{i,t} = \mathbf{y}_{t-1}^\top \widetilde{\mathbf{n}}_t\,. \tag{53}$$

With the estimates of ϕ, $\bar{\alpha}'_i$ (the mean of $a'_{i,t}$) and δ'_i (the volatility of $a'_{i,t}$), our goal is to compute the conditional mean and volatility of planner's choice of bank lending. Because the first term in $\widetilde{\mathbf{n}}_t$, $\widetilde{\mathbf{M}}(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}')\mathbf{b}'_{t-1}$, is not random, we solve the conditional volatility of $\widetilde{N}_t$:

$$\mathrm{Var}_{t-1}\left[\widetilde{N}_t\right] = \frac{1}{\phi^2}\mathbf{y}_{t-1}^\top \widetilde{\mathbf{M}}\left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}'\right)\widetilde{\Phi}\,\Delta'\widetilde{\Phi}^\top \widetilde{\mathbf{M}}\left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}'\right)^\top \mathbf{y}_{t-1}, \tag{54}$$

where, as previously defined, Δ' is a diagonal matrix with the i-th diagonal element equal to $\delta_i'^2$. The calculation of the conditional mean of $\widetilde{N}_t$,

$$\mathbb{E}_{t-1}\left[\widetilde{N}_t\right] = \mathbf{y}_{t-1}^\top \widetilde{\mathbf{M}}\left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}'\right)\mathbf{b}'_{t-1} + \mathbf{y}_{t-1}^\top \widetilde{\mathbf{M}}\left(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}'\right)\frac{1}{\phi}\widetilde{\Phi}\,\bar{\alpha}'\,, \tag{55}$$

requires $\mathbf{b}'_{t-1}$ (and $b_{i,t}$ given by (C.28) in the appendix) that depends on τ_1, τ_2, θ_1, and θ_2 that cannot be identified in our estimation (as we only estimate the composite parameter, $\phi = \frac{\tau_2-\theta_2}{\kappa+\tau_2-\theta_2}$ defined in (12)). Therefore, when comparing the conditional mean of N_t of the market equilibrium and that of $\widetilde{N}_t$, we focus on the second component of $\mathbb{E}_{t-1}[\widetilde{N}_t]$ that can be computed with our parameter estimates. This second component, $\mathbf{y}_{t-1}^\top \widetilde{\mathbf{M}}(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}')\frac{1}{\phi}\widetilde{\Phi}\,\bar{\alpha}'$, is more comparable to the market equilibrium, $\mathbb{E}_{t-1}[N_t] = \mathbf{y}_{t-1}^\top \mathbf{M}\left(\phi, \mathbf{W}'\right)\bar{\alpha}'$ in (40). The differences are in the network propagation ($\widetilde{\mathbf{M}}(\widetilde{\Phi}, \widetilde{\mathbf{W}}', \mathbf{U}, \mathbf{U}')$ vs. $\mathbf{M}\left(\phi, \mathbf{W}'\right)$) and the deviations of $\widetilde{\phi}_i$ from ϕ (captured by $\frac{1}{\phi}\widetilde{\Phi}$).

Number of Banks:	500	500 (Not winsorized)	300	400	600	700
$\hat{\phi}$	0.1452 (3.44)	0.1377 (3.43)	0.1499 (3.16)	0.1562 (3.42)	0.1396 (3.17)	0.1373 (3.06)
$1/\left(1-\hat{\phi}\right)$	1.1698	1.1597	1.1764	1.1852	1.1623	1.1591
R^2	0.1139	0.1138	0.1205	0.1150	0.1183	0.1167

Table 1: **Network multiplier**. The table reports the estimate of ϕ in the system of equations (30) and (31). The t-statistics are calculated with quasi-MLE robust standard errors and are reported in parentheses under the estimated coefficients. The network multiplier, $1/(1-\hat{\phi})$, is reported in the second line, and the R^2 in the third line is the fraction of variation explained by the control variables (i.e., the bank characteristics and macroeconomic variables).

4 Estimation Results

4.1 The network multiplier

Table 1 reports the estimate of ϕ, and the implied network multiplier given by (37). Our estimation is done on different samples of banks ranked by the size of their deposits. The main specification includes the top 500 banks (first column). In the second column, the results are similar without winsorizing g_{ij} at 0.5% for the calculation of payment statistics in w_{ij} (such as μ_{ij}, σ_{ij}, and ρ_{ij}). In the last four columns, we report the results based on the top 300, 400, 600, and 700 banks.[28]

As discussed in Section 3.2, under $\phi > 0$ (or $1/(1-\phi) > 1$), the network amplifies a common variation in all banks' $\bar{\alpha}'_i$ (expected level of network-independent lending) or a common shock to banks' network-independent lending, say, $\bar{\nu}'_{i,t} = \epsilon$, by $1/(1-\phi) - 1$. An estimate of ϕ equal to 0.1452 in the sample of top 500 banks implies a multiplier equal to 1.17 and an amplification effect of 17%. As discussed in Section 2, the sign of $\phi w'_{ij}$ determines whether banks' decisions are strategic complements or substitutes. In our sample, only 0.39% of non-zero w'_{ij} are negative.[29] Therefore, $\phi > 0$ indicates strategic complementarity, which is the source of network amplification effect. Finally, note that the estimate of ϕ is stable across samples, indicating that the network effects can be reliably estimated once the largest hundreds of banks are included in the sample.

We have hundreds of banks in each sample, so there are hundreds of $\bar{\alpha}'_i$ and δ'_i. Since the samples differ in the number of banks, we present the estimates of $\bar{\alpha}'_i$ and δ'_i through their distri-

[28]The network adjacency matrix, $\mathbf{W}'$, is independently constructed for banks in each subsample.

[29]Among all the potential pairs, there are 6.47% that have non-zero w'_{ij}, so the payment-flow network is sparse.

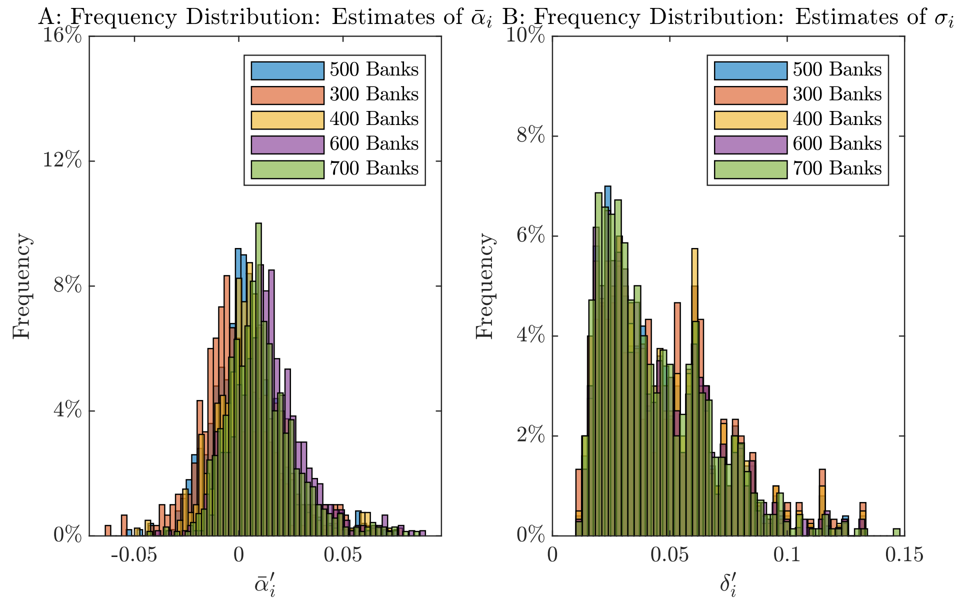

Figure 2: **The estimates of $\bar{\alpha}'_i$ and δ'_i.** This figure reports the frequency distribution of the estimates of $\bar{\alpha}'_i$ (Panel A) and δ'_i (Panel B) across different samples of banks ranked by the size of their deposits.

bution for each sample. Figure 2 shows that across samples, the distributions of these parameters are fairly consistent, which suggests that once we have included the largest hundreds of banks, the distribution of network-independent level of expected loan growth rate and volatility (i.e., $\bar{\alpha}'_i$ and δ'_i) can be reliably estimated. In the appendix, we report the estimates of control variable coefficients in Table D.2 and show that these estimates are stable across samples in Figure D.1. In the following, our analysis will be based on the sample of top 500 banks.

4.2 The importance of network topology

The estimate of $\phi > 0$ in Table 1 indicates that the network is an amplification mechanism. In Section 3.4, we have shown that when $\bar{\alpha}'_i$ changes by the same amount for all banks, or when all banks are hit by shocks of the same size ($\nu'_{i,t}$), the network multiplier, $1/(1-\phi) > 1$, is a sufficient statistic for the network amplification effect. Our estimation reveals that $\bar{\alpha}'_i$ differs across banks, and the size of shock, measured by δ'_i, the standard deviation or volatility of $\nu'_{i,t}$, also differs across banks. In the following, we further demonstrate the network amplification mechanism by incorporating the heterogeneity in $\bar{\alpha}'_i$ and δ'_i. Under such heterogeneity, the network multiplier,

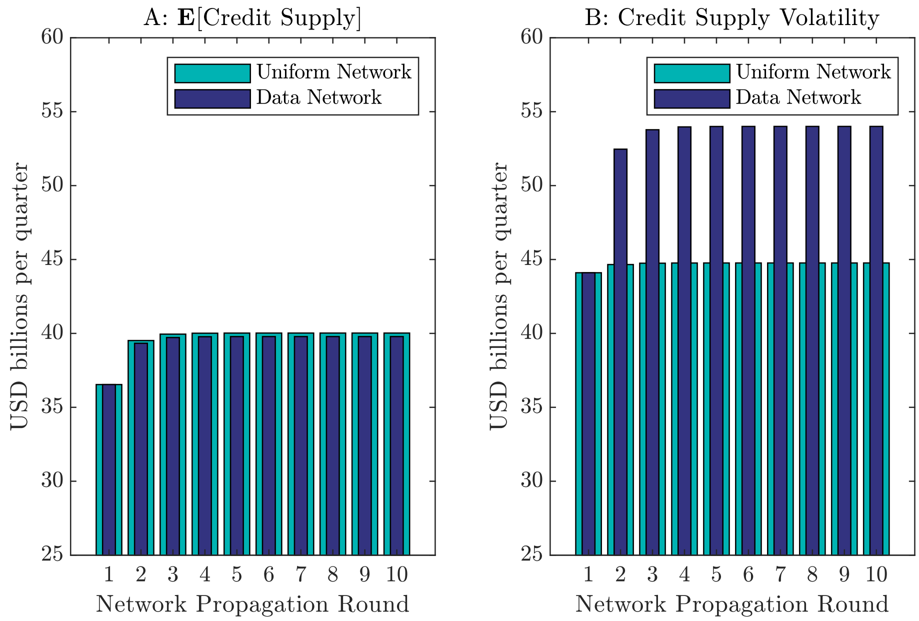

Figure 3: **Network propagation and aggregate credit supply**. This figure reports the mean (Panel A) and volatility (Panel B) of aggregate credit supply conditional on the outstanding loan amounts of the previous period (i.e., $\{y_{i,t-1}\}_{i=1}^N$) equal to the sample average. In both panels, the statistics are decomposed into each round of network propagation. We report results from our data network and the uniform network with equally connected banks.

$1/(1-\phi)$, is no longer a sufficient statistic for the amplification mechanism, and the topology of network linkages, encoded in the network adjacency matrix, $\mathbf{W}'$, plays an important role.

As discussed in Section 2.1, the main mechanism in our model can be summarized in two steps. When extending loans funded by deposits, banks face potential liquidity loss due to depositors' payment outflows and have to rely on their liquid assets. Therefore, the network-independent level of lending, a_i, depends on the liquidity base, m_i, in Proposition 1. The liquidity constraint is then relaxed by liquidity churn within the system: When depositors at different banks transact with one another, one bank's payment outflow is another's inflow. Such liquidity churn is captured by the network amplification operator in Proposition 1, which, as a reminder, is reproduced here

$$\mathbf{M}(\phi, \mathbf{W}) \equiv \mathbf{I} + \phi\mathbf{W} + \phi^2\mathbf{W}^2 + \phi^3\mathbf{W}^3 + \ldots = \sum_{k=0}^{\infty} \phi^k \mathbf{W}^k = (\mathbf{I} - \phi\mathbf{W})^{-1}. \tag{56}$$

As discussed in Section 2.2, we directly estimate the distributional properties of $a'_{i,t} = a_{i,t}/y_{i,t-1}$

(mean, $\bar{\alpha}'_i$, and standard deviation, δ'_i) rather than unpacking its internal structure, for example, how $a_{i,t}$ depends on bank i's liquid assets in quarter t. Therefore, our empirical exercise focuses on characterizing this network amplification operator, i.e., the second step of the model mechanism.

As shown in (34), the network amplification mechanism increases the equilibrium level of bank lending relative to the level without network effects (i.e., $(\mathbf{I} - \phi\mathbf{W})^{-1}\bar{\alpha}'$ vs. $\bar{\alpha}'$) but it also amplifies the sensitivity of aggregate bank lending to shocks through strategic complementarity in banks' decisions (i.e., $(\mathbf{I} - \phi\mathbf{W})^{-1}\nu'_t$ vs. ν'_t). Next, we characterize how the network amplification mechanism affects both the expected level of bank lending and volatility.

For implications of network amplification on loan amount, we multiply the model-implied loan growth rate, $n_{i,t}$, by the average loan amounts in our sample. We compute the expected level and volatility of $y_{i,t}$, i.e., $\mathbb{E}_{t-1}[y_{i,t}] = y_{i,t-1}\mathbb{E}_{t-1}[n_{i,t}]$ and $\sqrt{\mathbf{Var}_{t-1}[y_{i,t}]} = y_{i,t-1}\sqrt{\mathbf{Var}_{t-1}[n_{i,t}]}$, conditional on $y_{i,t-1}$ being equal to the sample average. The steps have been laid out in (38) to (41) in Section 3.4. When computing the equilibrium, we use the estimates of ϕ, $\bar{\alpha}'_i$, and δ'_i and, for the adjacency matrix, we take the average of $\mathbf{W}'$ across the 44 quarters in our sample.

In Figure 3, we decompose the mean (Panel A) and volatility (Panel B) of aggregate bank lending into rounds of network propagation as shown in (56). In both panels, the first column shows the value without network effects and each subsequent column corresponds to the cumulative effect after each round of network propagation. For both mean and volatility, the second and third columns correspond respectively to direct network linkages and first-degree of indirect linkages. Both direct and first-degree indirect linkages have significant influence on the equilibrium level of aggregate lending. Linkages that are more than two steps away are less important. This feature can be attributed to both $\mathbf{W}'$ and ϕ. The smaller ϕ is, the weaker the effects of distant linkages are. As shown in (56), ϕ is effectively the discount factor for network linkages.

In Figure 3, we demonstrate the importance of network topology. In the counterfactual network ("uniform network"), banks are equally connected or edges are evenly distributed among bank pairs ($w'_{ij} = 1/(N-1)$). The network amplification mechanism depends on ϕ and $\mathbf{W}'$. By comparing the data network and this counterfactual network, we focus on the role of $\mathbf{W}'$ as the amplification effects of both networks incorporate $\phi > 0$. In Panel A, relative to the uniform network, the data network generates a slightly lower expected level of aggregate credit supply, and in each round of network propagation, the cumulative effects of data network are dominated by those of the uniform network. In Panel B, relative to the uniform network, the data network generates a much higher volatility. In both panels, the first columns under the two networks have

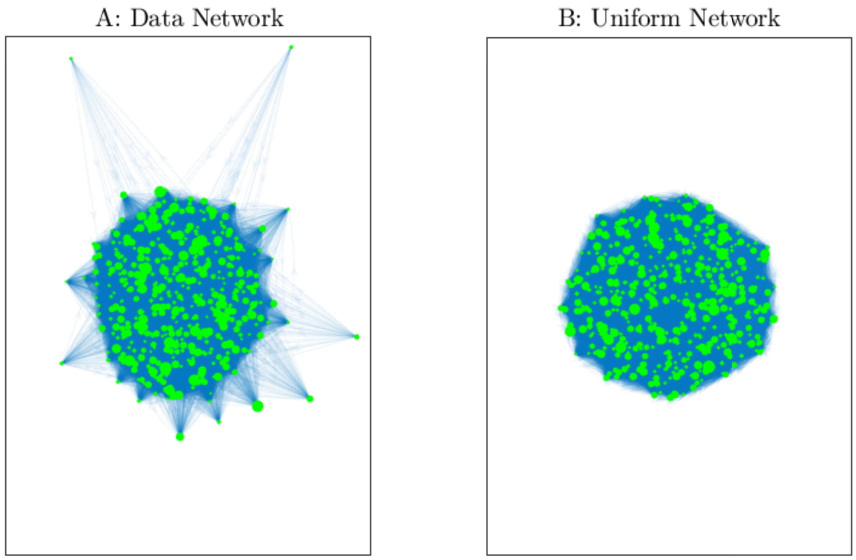

Figure 4: **Network topology.** This figure compares the data network given by the average adjacency matrix W' and the uniform network. The size of node i is proportional to δ_i' (the volatility of structural shock to loan growth).

the same value because they represent the values without network effects. The divergence starts in the first round of network propagation that is captured by the second column.

To put the numbers in perspective, the value of all banks' loan assets is \$6.4 trillion, averaged over the 44 quarters in our sample of 500 banks. The annualized volatility generated by the data network is $54 \times 4/6400 = 3.4\%$, where we multiply 4 on the quarterly standard deviation of \$54 billion per quarter in Panel B of Figure 3. The uniform network generates an annualized volatility of 2.8% (implied by \$45 billion in Panel B). The key takeaway is that, relative to the uniform network, the real network generates a similar level of expected bank lending but a higher volatility.

In Figure 4, we compare the data network, given by the average adjacency matrix W', and uniform network. The size of node i is proportional to δ_i' (volatility of bank-level shock). The most connected nodes are placed at the center while the least connected are at the periphery (Fruchterman and Reingold, 1991).[30] The distribution of edges of the data network is much more uneven than that of the uniform network, suggesting stronger heterogeneity in banks' network positions.

The topology of network is important for the aggregation of idiosyncratic shocks (Acemoglu et al., 2012). We show in Figure 5 that the data network generates a higher volatility than the uni-

[30] In Fruchterman and Reingold (1991), linked nodes are close and nodes should be distributed widely for visibility.

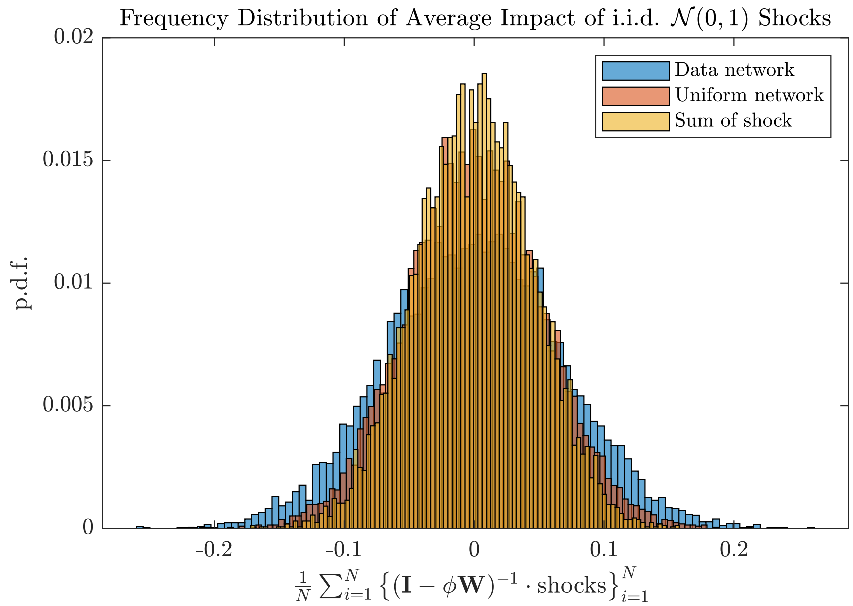

Figure 5: **Network and fat tails.** We simulate 10,000 times a vector of 500 i.i.d. standard normal shocks and, for each simulation, we calculate the average of the shocks and the averages of shocks (denoted by ν) amplified by two networks, i.e., the averages of vector $(\mathbf{I}-\phi\mathbf{G})^{-1}\nu$ where the two networks are $\mathbf{G}=\mathbf{W}'$ (the data network) and the uniform network. The figure reports the frequency distribution of the three averages over 10,000 simulations.

form network. We simulate 10,000 times a vector of 500 i.i.d. standard normal shocks, ν'. For each simulation, we calculate the simple average (which has a standard deviation of $\sqrt{\frac{1}{500}}=0.045$) and the average of shocks amplified by two networks, i.e., the averages of vector $(\mathbf{I}-\phi\mathbf{G})^{-1}\nu'$ where the two networks are $\mathbf{G}=\mathbf{W}'$ (the data network) and the uniform network. The simple average represents one hypothetical scenario without any network propagation of shocks, and intuitively, the aggregation exhibits the smallest volatility (dispersion of outcome of the 10,000 experiments). The case with shocks propagated by a uniform network features network amplification, and the aggregation generates a higher volatility than that from the simple average. Finally, the data network generates the highest volatility, suggesting that, relative to the uniform network, the data network has a topology of linkages that is more prone to amplify the fluctuation of aggregate bank lending.

4.3 Identifying systemically important banks

We define volatility key bank in (42) as the bank with the highest network impulse response function (NIRF). In (44), we show that the volatility of aggregate credit supply can be decomposed into

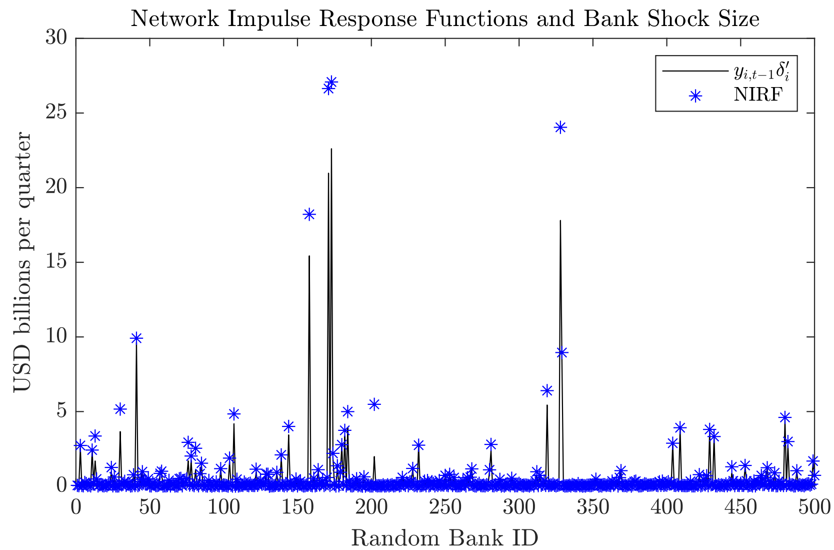

Figure 6: **Bank shock size and NIRF.** In this figure, we plot the size of bank-specific shock, δ_i', and network impulse response function (NIRF) for the top five hundred banks (ranked by deposit size) in our sample.

individual banks' NIRFs. Therefore, ranking banks by their NIRFs is equivalent to ranking banks by their contributions to credit-supply fluctuation. Next, we demonstrate how banks' positions in the network, given by the adjacency matrix $\mathbf{W}'$, and the sizes of their structural shocks, $\{\delta_i'^2\}_{i=1}^N$, determine their NIRFs. Banks differ significantly in both aspects (and thus in their NIRFs).

In Figure 6, we plot the loan amount implied by the size of bank-specific shock to growth rate (i.e., $y_{i,t-1}\delta_i'$), and network impulse response function (NIRF) for the top 500 banks. For both quantities, we set the loan amounts from the previous period, $y_{i,t-1}$, to the sample average. When $y_{i,t-1}\delta_i'$ and NIRF are close for a bank, the payment network does not generate powerful externality for this bank; in other words, what the bank contributes is close to the size of its own shock. In contrast, when NIRF and $y_{i,t-1}\delta_i'$ differ for a bank, the bank's position in payment network significantly affects its contribution to the volatility of aggregate credit supply. In Figure 6, we see the wedge between NIRF and $y_{i,t-1}\delta_i'$ is particularly large for a handful of banks. This finding suggests that the payment network amplifies the shocks to a relatively small number of banks and therefore generates heterogeneity in banks' contribution to the volatility of aggregate credit supply that is beyond the heterogeneity from banks' difference in the size of their shocks δ_i'.

Bank size is not an adequate proxy for its systemic importance. In Panel A of Figure 7, we take the ratio of a bank's network impulse response function (NIRF) to its average loan amount in

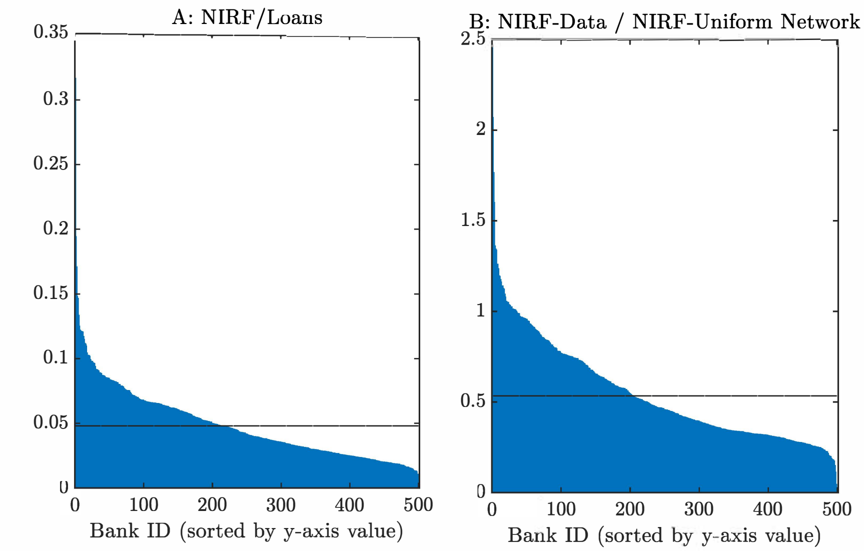

Figure 7: **Network topology and bank NIRF.** In Panel A, we take the ratio of a bank's NIRF to its average loan amount in our sample. The flat line represents the average NIRF divided by the cross-section average of banks' average loan amount in our sample. In Panel B, we take the ratio of a bank's NIRF to the counterfactual NIRF implied by a uniform network, where all banks are equally connected. The flat line represents the average NIRF dividend by the average NIRF implied by the uniform network. When calculating both NIRFs, we use the same estimates of parameters of the network game. In both panels, we rank banks by their NIRFs and plot the ratio for each bank.

our sample (proxy for size). We rank banks by their NIRF and plot the ratio for each bank. Note that a bank's NIRF is comparable in magnitude to its loan value. As shown in the definition (42), NIRF is given by the product between a bank's lending in the previous period and its equilibrium growth loan growth rate (with the shock size equal to the standard deviation of structural shock, δ_i'). If bank size were an adequate proxy for a bank's systemic importance, we would expect a relatively flat line. In contrast, the figure shows strong heterogeneity. Scaled by the size of loan book, banks differ significantly in their contributions to the credit-supply volatility; in other words, larger banks are not necessarily more important in generating systemic risk in credit supply. To demonstrate the heterogeneity, we plot in Panel A a flat line that represents the average NIRF divided by the cross-section average of banks' loan amount averaged over the 44 quarters in our sample.

To further investigate the impact of network topology on banks' contributions to credit-supply volatility, we take the ratio of a bank's NIRF to the counterfactual NIRF implied by the uniform network. If the ratio is close to one, the topology of payment network does not affect the bank's contribution to credit-supply volatility relative to the uniform network. If the ratio is

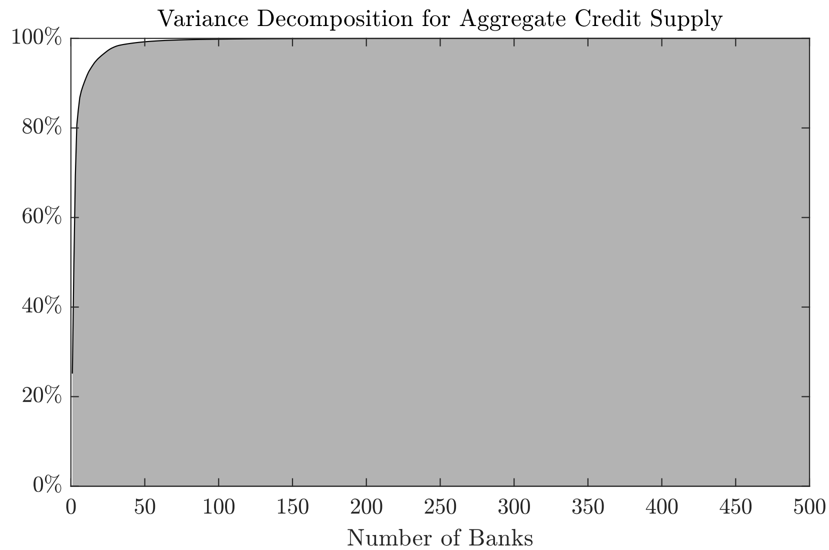

Figure 8: **Variance Decomposition for Aggregate Credit Supply.** We rank banks by their NIRFs and, starting from the bank with highest NIRF, we accumulate contribution to the volatility of aggregate credit supply (conditional on the lending distribution of previous period, i.e., $\{y_{i,t-1}\}_{i=1}^{N}$, equal to the sample average). The cumulative volatility is divided by the total conditional volatility of aggregate credit supply given by (41).

greater (smaller) than one, the payment network has an amplification (dampening) effect. In Panel B of Figure 7, we rank banks by their NIRFs and plot the ratio for each bank. Except for less than fifty banks having a ratio greater than one, the network actually has a buffering effect relative to a uniform network, when it comes to the shock propagation. However, for banks with the ratio greater than one, the amplification effect is quite significant. To demonstrate the heterogeneity, we plot a flat line that represents the average NIRF divided by the average NIRF implied by the uniform network. As discussed in Section 4.1, $\phi > 0$ generates a shock amplification mechanism. Our analysis in Figure 6 and 7 shows that the amplification works through a small subset of banks.

As shown in (44), the volatility of aggregate credit supply can be decomposed into individual banks' NIRFs. In Figure 8, we rank banks by their NIRFs and, starting from the bank with the highest NIRF, we accumulate banks' contribution to the conditional volatility of aggregate credit supply (conditional on the lending distribution of previous period, i.e., $\{y_{i,t-1}\}_{i=1}^{N}$, being equal to the sample average). The cumulative volatility is divided by the total volatility of aggregate credit supply given by (41). The curve ends at 100% because after fully accounting for all banks' contributions (i.e., NIRFs), we arrive at the total volatility (see Proposition 3). A key finding is that

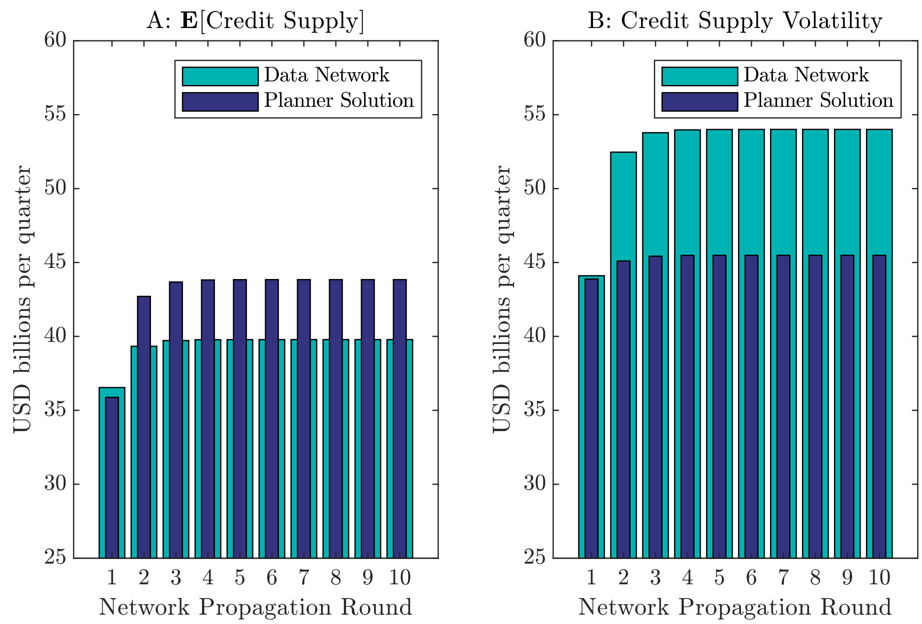

Figure 9: **Network propagation: The planner's solution vs. market equilibrium**. This figure reports the mean (Panel A) and volatility (Panel B) of aggregate credit supply conditional on the outstanding loan amounts of the previous period (i.e., $\{y_{i,t-1}\}_{i=1}^{N}$). The loan amounts of the previous period are set to the full-sample average. In both Panel A and B, the statistics are decomposed into each round of network propagation.

a group of slightly more than fifty banks out of the 500 account for almost 100% of credit-supply volatility. This is consistent with our previous finding that the network amplification mechanism works through a small subset of banks. From a policy perspective, it is important to monitor these systemically important banks as any shocks to these banks are amplified disproportionately by the payment network to strongly affect the aggregate supply of bank credit.

4.4 Quantifying the network externalities

Network propagation. We apply the framework in Section 3.5 to compare the market equilibrium and the planner's solution. The planner maximizes the total profits of all banks, internalizing the network externality generated by depositors' payment flows. In Panel A of Figure 9, we decompose the expected aggregate credit supply (conditional on lagged loan amounts, i.e., $\{y_{i,t-1}\}_{i=1}^{N}$, equal to the sample average) into rounds of network propagation. The first column in both cases is generated by the loan growth rate absent of network effects (i.e., $\bar{\alpha}_i'$ for the market equilibrium and $\widetilde{\phi}_i \alpha'_i / \phi$ in the planner's solution). The second column adds to the first column impact of direct network linkages, and the third column adds to the second column impact of first-degree indirect linkages. Once the network effects are activated (starting from the second column), the planner's solution features a higher expected level of credit supply. The wedge is stable across rounds of network propagation, suggesting that the main difference between the planner's solution and market equilibrium is due to direct network linkages. In Panel B of Figure 9, we decompose the volatility of aggregate credit supply (conditional on $\{y_{i,t-1}\}_{i=1}^{N}$) into rounds of network propagation. By internalizing the spillover effects of individual banks' lending decisions, the planner becomes less responsive to shocks than the market equilibrium, generating a volatility that is around 10% lower.

Overall, the results in Figure 9 show that, by internalizing the liquidity spillover effects of payment network, the planner generates a higher expected level and lower volatility of aggregate bank lending than the market equilibrium; in other words, payment network externality induces a lower expected level of credit supply and higher volatility without a planner's intervention.

The misallocation of lending opportunities. Next, we compare the planner's solution and market equilibrium through the distribution of lending across banks. Banks differ in lending opportunities, because, due to relationship lending, borrowers cannot freely change lenders.[31] A source of inefficiency is that a borrower, who needs a high level of expected credit supply, is matched with a bank whose expected lending is low. Another form of mismatch is that a borrower who prefers stable credit is matched with a bank whose lending is volatile. As we have shown, banks' expected level and volatility of lending all depend on their positions in the payment-flow network. Therefore, such mismatch is essentially between banks' lending opportunities and the payment characteristics of their depositor base. When borrowers cannot easily switch between banks, banks would not fully compensate the mismatched borrowers with lower loan rates, so the cost of bank-borrower mismatch is at least partly passed to the borrowers and affects the real economy.

In Panel A of Figure 10, we plot the histogram of volatilities of banks' lending (scaled by banks' average lending amount in our sample) from the market equilibrium, given by (34), and from the planner's solution, given by (49). The distribution from the market equilibrium is tilted to the right and more dispersed relative to the planner's distribution, suggesting a more volatile credit supply and stronger heterogeneity in volatility across banks. In Panel B of Figure 10, we calculate

[31] Ongena and Smith (2001) document firms with different degrees of mobility in relationship lending. Loan terms are often better at the onset of a lending relationship and toughen as time goes (Ioannidou and Ongena, 2010).

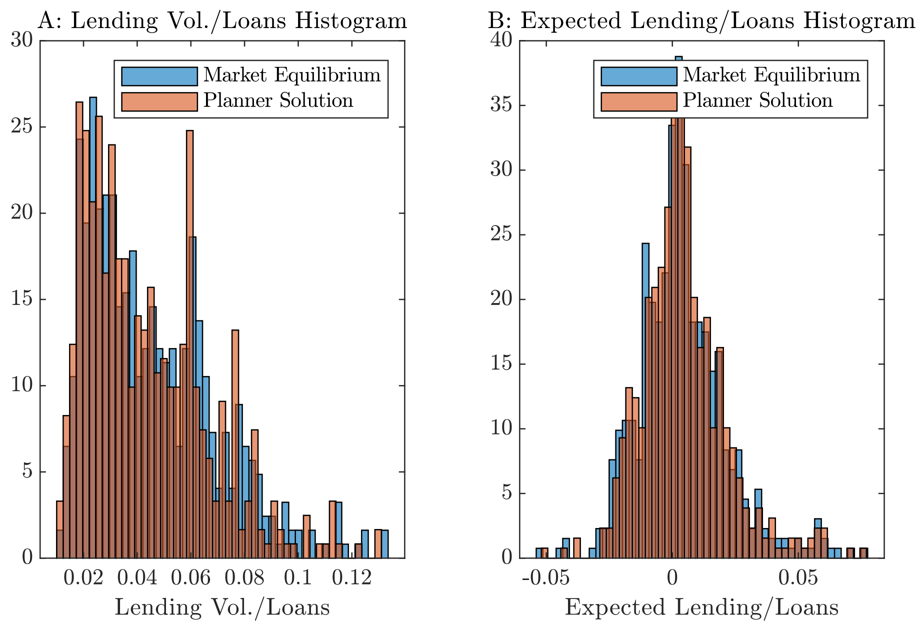

Figure 10: **The cross-sectional distribution of credit volatility and expected level: The planner's solution vs. market equilibrium.** We calculate the level of a bank's credit supply by applying the model-implied loan growth rate, given by (34) for the market equilibrium and (49) for the planner's solution, to the average level of loan amount of that bank in our sample. The uncertainty in the level of a bank's credit supply arises from the model-implied loan growth rate whose mean and variance can be calculated from the estimated parameters. In Panel A, we plot the histogram of the volatility of individual banks' credit supply. In Panel B, we plot the expected level of individual banks' lending. The histogram is for the sample of top 500 banks (ranked by deposit size).

banks' expected levels of lending in the market equilibrium, given by (34), and from the planner's solution (49), and plot the histogram for both cases. Note that, as discussed in Section 3.2, the constant among control variables (X_t) absorbs the average lending, so the estimates of $\bar{\alpha}_i'$ can be negative. The distribution of expected lending in the market equilibrium exhibits wider dispersion than that of the planner's solution. In sum, relative to the planner's solution that corrects payment network externality, the market equilibrium generates a more dispersed cross-sectional distribution of expected lending and volatility, which leaves room for potential mismatch between borrowers and banks and makes any frictions limiting borrowers' mobility more costly.

Rolling-sample estimation. In Figure 11, we present the rolling-window estimation results. Each window contains 22 quarters (half of the full sample). Panel A shows the estimate of network multiplier and confidence interval of two standard errors. The horizon axis marks the last quarter of

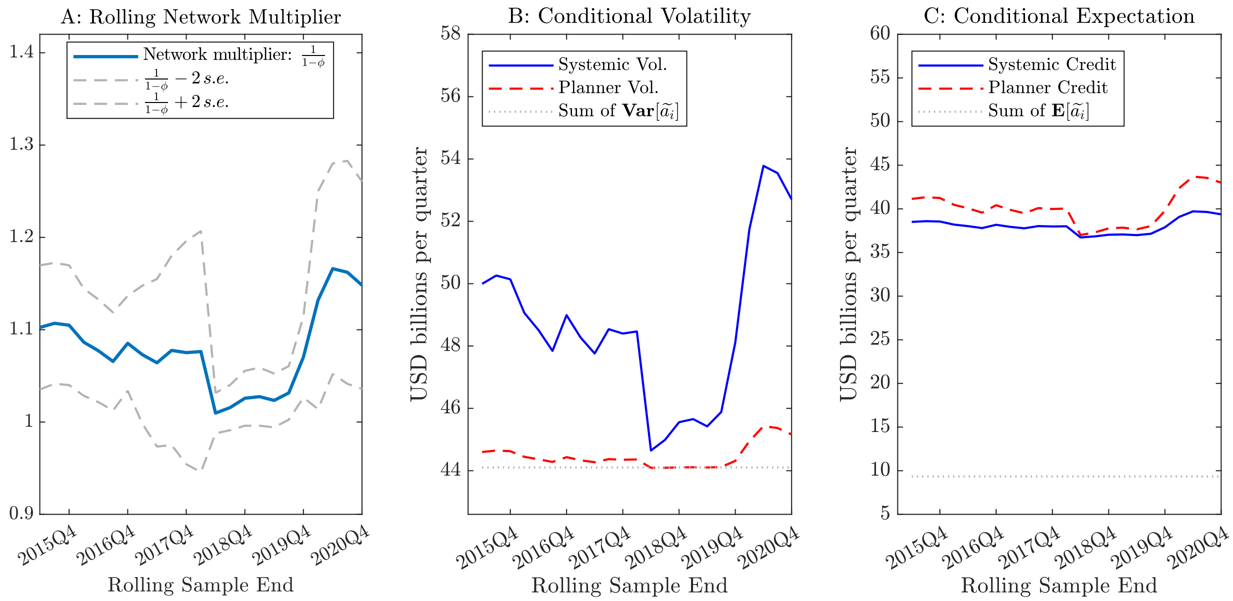

Figure 11: **Rolling estimation: The planner's solution vs. market equilibrium.** Each rolling window has 22 quarters. We report the estimate of network multiplier in Panel A together with the confidence band of two standard errors. In Panel B and C, we compare respectively the volatility and expectation of aggregate credit supply implied by the loan growth rates in the market equilibrium and planner's solution (conditional on previous lending amounts, $\{y_{i,t-1}\}_{i=1}^{N}$ where $y_{i,t-1}$ is set to the full-sample average). In Panel B, we also plot the sum of banks' network-independent volatilities conditional on previous loan amounts (i.e., $\{y_{i,t-1}\delta_i'\}_{i=1}^{N}$). In Panel C, we also plot the sum of banks' network-independent expected lending conditional on previous loan amounts (i.e., $\{y_{i,t-1}\bar{\alpha}_i'\}_{i=1}^{N}$).

a rolling sample. The multiplier demonstrates significant variation over time. For example, at the onset of Covid-19 pandemic, banks experienced larger shocks and greater heterogeneity in shock exposure, so, intuitively, our estimate of ϕ contains more noise (a wider confidence interval).

Next, we compare the volatility and expectation of aggregate credit supply implied by the loan growth rates in the market equilibrium and planner's solution (conditional on previous lending amounts, $\{y_{i,t-1}\}_{i=1}^{N}$ where $y_{i,t-1}$ is set to the full-sample average). The wedge evolves over time following the network multiplier.[32] When ϕ is higher, the network externality is stronger, which then implies a greater difference between the planner's solution and market equilibrium.

In Panel B of Figure 11, during the period of low ϕ (rolling windows ending in 2018 and 2019), the volatility of planner's credit supply is close to the sum of volatilities of individual banks'

[32]Time variation in network externality is mainly attributed to variation in ϕ rather than variation in the adjacency matrix, $\mathbf{W}'$ due to the stability of $\mathbf{W}'$ over time. In Figure E.1 in the appendix, we report the absolute values of largest eigenvalues of $\mathbf{W}'$. As discussed in Section 3.2, $\mathbf{W}'$ for quarter t is calculated from payment data in quarter $t-1$.

structural shocks. In contrast, the market equilibrium still generates a higher volatility despite a low network multiplier, $1/(1-\phi)$. The difference between market equilibrium and planner's solution is that the former does not internalize network externality. Under a low ϕ, the strength of network externality is largely attributed to network topology, encoded in the adjacency matrix, $\mathbf{W}'$. The volatility wedge can be as high as \$8 billion per quarter, implying an annualized volatility of $8 \times 4/6400 = 0.5\%$ (aggregate lending by the 500 banks averaged \$6.4 billion in our sample).

In Panel C of Figure 11, we plot the expected aggregate lending per quarter. Both the market equilibrium and planner's solution feature a higher level of credit supply than what is implied by the simple sum of banks' lending absent of network effects, in line with the intuition from Section 2 that liquidity churn within the banking system relaxes the liquidity constraint. When financing new loans with deposits, individual banks are concerned about liquidity loss due to their depositors' payment outflows, but such concern is alleviated by their depositors receiving payment from other banks' depositors. Across different time periods, the wedge between the market equilibrium and planner's solution is larger when the estimate of ϕ is larger in Panel A.

In Figure 11, both the volatility (Panel B) and expected level (Panel C) of planner's supply of bank credit exhibit less fluctuation over time than those of market equilibrium, suggesting that payment network externality amplifies uncertainty in aggregate credit conditions.

5 Conclusion

When financing loans with deposits, a bank must hold enough liquid assets to cover potential deposit outflow, as loans are illiquid and cannot be readily sold for cash. The money multiplier—the ratio of loans funded by deposits to a bank's liquid assets—cannot be overstretched. Except for the extreme events of bank run, deposit outflows occur because depositors make payments to one another, causing liquidity to churn among banks. The payment senders' banks lose deposits and reserves (the settlement assets in payment system), while the recipients' banks gain deposits and reserves. Therefore, banks' liquidity conditions are intrinsically interconnected, and the equilibrium money multiplier depends on the random graph of depositors' interbank payment flows.

The payment function of deposits gives rise to strategic complementarity in banks' lending decisions, amplifying shocks to individual banks and contributing to the fluctuation in aggregate credit supply. Our network analysis reveals a subset of systemically important banks that drive the aggregate fluctuation due to their special positions in the payment-flow network. We also quantify the network externality by comparing the planner's solution and market equilibrium. Policy interventions targeted at correcting the network externality can improve aggregate credit conditions and alleviate the misallocation of lending opportunities across banks.

Our paper offers a new perspective on money multiplier and velocity. The traditional concept of money multiplier is often explained in an artificial setting that is disconnected from the practice of modern banking (McLeay et al., 2014). We formalize the money multiplier through the natural link between the monetary base and the creation of credit and deposits: When financing lending with deposits, banks must have enough reserves to cover subsequent payment outflows. Moreover, we provide a network perspective on money velocity. The network structure of how deposits circulate across banks determines banks' liquidity risk and to what extent liquidity recycling within the banking system relaxes this liquidity constraint on banks' credit and money creation. Overall, we highlight the dual role of deposits as sources of funds for banks and means of payment for the rest of the economy, building a bridge between payment system and macro finance.

In the foreseeable future, payment system will undergo fundamental technological changes. In the area of digital payment, entrants with new technologies provide payment netting services, effectively rewiring payment flows and changing the network topology of interbank liquidity churn. Central banks around the world have been actively researching on new payment systems and their own digital payment platforms that will challenge the central role of deposits in payment systems and change how payment systems redistribute liquidity across banks. So far, the discussion on payment systems has largely focused on operational efficiency and technological vulnerabilities. Our paper draws attention to bank credit supply and provides a novel framework for quantifying the impact of changes in payment-flow networks on aggregate credit conditions.

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A Appendix: Background Information on Payment Systems

The Fedwire Funds Service is the primary payment system in U.S. for large-value domestic and international USD payments. It is a real-time gross settlement system that enables participants to initiate funds transfer that are immediate, final, and irrevocable once processed. The service is operated by the Federal Reserve Banks. Financial institutions that hold an account with a Federal Reserve Bank are eligible to participate in the service and electronically transfer funds between each other. Such institutions include Federal Reserve member banks, nonmember depository institutions, and certain other institutions, such as U.S. branches and agencies of foreign banks.

Participants originate funds transfers by instructing a Federal Reserve Bank to debit funds from their own accounts and credit funds to the account of another participant. To make transfers, the following information is submitted to the Federal Reserve: the receiving bank's routing number, account number, name, and dollar amount being transferred. Each transaction is processed individually and settled upon receipt. Wire transfers sent via Fedwire are completed the same business day, with many being completed instantly. Participants may originate funds transfers online, by initiating a secure electronic message, or offline, via telephone procedures.

Participants of Fedwire Funds Service can use the platform to send or receive payments for their own accounts or on behalf of corporate or individual clients (i.e., the depositors). In the paper, we focus on Fedwire fund transfers made on behalf of banks' corporate or individual clients, which make up about 80% of total transactions in terms of transaction number.

The Fedwire Funds Service business day begins at 9:00 p.m. Eastern Standard Time (EST) on the preceding calendar day and ends at 7:00 p.m. EST, Monday through Friday, excluding designated holidays. For example, the Fedwire Funds Service opens for Monday at 9:00 p.m. on the preceding Sunday. The deadline for initiating transfers on behalf of a third party (i.e., a bank's depositor) is 6:00 p.m. EST on each business day and 7:00 p.m. EST for banks' own transactions. Under certain circumstances, Fedwire Funds Service operating hours may be extended.

To facilitate the smooth operation of the Fedwire Funds Service, the Federal Reserve Banks offer intraday credit, in the form of daylight overdrafts, to financially healthy Fedwire participants with regular access to the discount window. Many Fedwire Funds Service participants use daylight credit to facilitate payments throughout the operating day. Nevertheless, the Federal Reserve Policy on Payment System Risk prescribes daylight credit limits, which can constrain some Fedwire Funds Service participants' payment operations. Each participant is aware of these constraints and is responsible for managing its account throughout the day.

The usage of Fedwire Funds Service grows over our sample period from 2010 to 2020, with the total number of transfers and transaction dollar value increasing by 47% and 38%, respectively. In 2020, approximately 5,000 participants initiate funds transfers over the Fedwire Funds Service, which processed an average daily volume of 727,313 payments, with an average daily value of approximately \$3.3 trillion.[33] The distribution of these payments is highly skewed, with a median value of \$24,500 and an average value of approximately \$4.6 million. In particular, only about 7% of Fedwire fund transfers are for more than \$1 million.

The other important interbank payment system in U.S. is the Clearing House Interbank Payments System (CHIPS), which is a private clearing house for large-value transactions between banks. In 2020, CHIPS processed an average daily volume of 462,798 payments, with an average daily value of approximately \$1.7 trillion, about half of the daily value processed by Fedwire.[34] There are three key differences between CHIPS and Fedwire Funds Service. First, CHIPS is privately owned by The Clearing House Payments Company LLC, while Fedwire is operated by the Federal Reserve. Second, CHIPS has less than 50 member participants as of 2020, compared with thousands of banking institutions sending and receiving funds via Fedwire. Third, CHIPS is not a real-time gross settlement (RTGS) system like Fedwire, but a netting engine that uses bilateral and multi-lateral netting to consolidates pending payments into single transactions. The netting mechanism significantly reduces the impact of payment flows on banks' decision making (and therefore our sample focuses on the RTGS, Fedwire) but exposes banks to potential counterparty risks.

[33]Data source: www.frbservices.org. Federal Reserve also operates two smaller payment systems, National Settlement Service (NSS) with an average daily settlement value of \$93 billions in 2020 (source: www.frbservices.org), and ACH with an average daily settlement value of \$122.8 billion in 2020 (source: www.federalreserve.gov).

[34]Data source: https://www.theclearinghouse.org

B Appendix: Bank Depositor Liquidity Management

In this section, we microfound the component, $\theta_1 x_i + \frac{\theta_2}{2} x_i^2$, of bank i's objective function by modeling the liquidity management problem of bank i's depositors.

In aggregate, bank i's depositors lose liquidity x_i, which is equal to the payment outflow to other banks' depositors. To cover the liquidity shortfall, bank i's depositors may borrow from bank i, for example, in the form of lines of credit.[35] Consider a unit mass of depositors and the evenly distributed loss of liquidity (i.e., each depositor's loss of liquidity is equal to x_i). A representative depositor chooses c, the amount of liquidity obtained from bank i (for example, the size of lines of credit). Bank i charges a proportional price P_c. The depositor's problem is given by

$$\max_c \xi_1 \left[c - x_i - \frac{1}{2\xi_2}(c - x_i)^2 \right] - cP_c \,, \tag{B.1}$$

where the parameter ξ_1 (> 0) captures the overall demand for liquidity and the parameter ξ_2 (> 0) captures the decreasing return to liquidity. A key economic force is that a higher x_i increases the marginal benefit of c. In other words, when bank i's depositors lose liquidity through payment outflows to other banks' depositors, they rely more on bank i for liquidity provision.

From the depositor's first order condition for c,

$$\xi_1 - \frac{\xi_1}{\xi_2}(c - x_i) = P_c \,, \tag{B.2}$$

we solve the optimal c:

$$c = \xi_2 \left(1 - \frac{P_c}{\xi_1} \right) + x_i \,. \tag{B.3}$$

The depositor's liquidity demand is stronger following a greater payment outflow, x_i and when the marginal value of liquidity declines slower (i.e., under a greater value of ξ_2). A higher value of ξ_1 or a lower price P_c also increase c. Under the homogeneity of bank i's depositors, equation (B.3) is also the aggregate liquidity demand for the unit mass of bank i's depositors.

Bank i sets the price P_c to maximize its profits from liquidity provision:

$$\max_{P_c} \left[\xi_2 \left(1 - \frac{P_c}{\xi_1} \right) + x_i \right] P_c \,. \tag{B.4}$$

[35]Empirically, cash and lines of credit are substitutes (Lins, Servaes, and Tufano, 2010).

Here we assume relationship banking so bank i's depositors cannot obtain liquidity elsewhere. This translates into bank i's market power and monopolistic profits. From the first-order condition for P_c,

$$-\frac{\xi_2}{\xi_1}P_c + \xi_2\left(1 - \frac{P_c}{\xi_1}\right) + x_i = 0\,, \tag{B.5}$$

we solve the optimal P_c:

$$P_c = \frac{\xi_1}{2}\left(1 + \frac{x_i}{\xi_2}\right)\,. \tag{B.6}$$

Substituting the optimal P_c into bank i's profits, we obtain the maximized profits:

$$\frac{\xi_1\xi_2}{4}\left(1 + \frac{x_i}{\xi_2}\right)^2 = \frac{\xi_1\xi_2}{4} + \frac{\xi_1}{2}x_i + \frac{\xi_1}{4\xi_2}x_i^2\,, \tag{B.7}$$

which corresponds to the component, $\theta_1 x_i + \frac{\theta_2}{2}x_i^2$, of bank i's objective function in the main text with

$$\theta_1 = \frac{\xi_1}{2}\,,\text{ and, }\ \theta_2 = \frac{\xi_1}{2\xi_2}\,. \tag{B.8}$$

The constant $\frac{\xi_1\xi_2}{4}$ is omitted in bank i's objective function in the main text.

C Appendix: Derivation Details

C.1 Maximum likelihood formulation

We rewrite the variables and coefficients of the model in equations (30) and (31) in matrix form following Lee and Yu (2010):

$$
\begin{aligned}
B &\equiv [\beta_1^{bank}, .., \beta_m^{bank}, ..., \beta_M^{bank}, \beta_1^{macro}, ..., \beta_p^{macro}, ..., \beta_P^{macro}]^\top, \\
L &\equiv [l_{1,1}, ..., l_{N,1}, ..., l_{i,t}, ..., l_{1,T}, ..., l_{N,T}]^\top, \\
\mathbf{n} &\equiv [n_{1,1}, ..., n_{N,1}, ..., n_{i,t}, ..., n_{1,T}, ..., n_{N,T}]^\top \\
\nu' &\equiv [\nu'_{1,1}, ..., \nu'_{N,1}, ..., \nu'_{i,t}, ..., \nu'_{1,T}, ..., \nu'_{N,T}]^\top \\
\underline{\alpha} &\equiv \mathbf{1}_T \otimes \bar{\alpha}' = \mathbf{1}_T \otimes [\bar{\alpha}'_1, ..., \bar{\alpha}'_N]^\top,
\end{aligned}
$$

and

$$
\mathbf{W}' \equiv diag\left(\mathbf{W}_t\right)_{t=1}^T = \begin{bmatrix} \mathbf{W}'_1 & \mathbf{0} & ... & \mathbf{0} \\ \mathbf{0} & \mathbf{W}'_2 & ... & ... \\ ... & ... & ... & \mathbf{0} \\ \mathbf{0} & ... & \mathbf{0} & \mathbf{W}'_T \end{bmatrix}, \quad \mathbf{X} \equiv \left[\mathbf{X}^{bank}, \mathbf{X}^{macro}\right],
$$

where we define

$$
\mathbf{X}^{macro} = \begin{bmatrix} x_1^1 & ... & x_1^p & ... & x_1^P \\ ... & ... & ... & ... & ... \\ x_t^1 & ... & x_t^p & ... & x_t^P \\ ... & ... & ... & ... & ... \\ x_T^1 & ... & x_T^p & ... & x_T^P \end{bmatrix} \otimes \mathbf{1}_N, \quad \mathbf{X}^{bank} = \begin{bmatrix} x_{1,1}^1 & ... & x_{1,1}^m & ... & x_{1,1}^M \\ ... & ... & ... & ... & ... \\ x_{N,1}^1 & ... & x_{N,1}^m & ... & x_{N,1}^M \\ ... & ... & ... & ... & ... \\ x_{N,T}^1 & ... & x_{N,T}^m & ... & x_{N,T}^M \end{bmatrix},
$$

we can then rewrite the empirical model as

$$
L = \mathbf{X}B + \mathbf{n}, \quad \mathbf{n} = \phi \mathbf{W}'\mathbf{n} + \underline{\alpha} + \nu', \quad \nu'_{i,t} \sim \mathcal{N}\left(0, \delta_i'^2\right). \tag{C.1}
$$

This, in turn, implies that

$$
\nu'\left(B, \underline{\alpha}, \phi\right) = \left(I_{N\times T} - \phi\mathbf{W}'\right)\left(L - \mathbf{X}B\right) - \underline{\alpha}. \tag{C.2}
$$

Using the Gaussian distribution to model the exogenous error terms ν' yields the log likelihood

$$
\ln \mathcal{L}\left(B, \phi, \underline{\alpha}, \left\{\delta_i'^2\right\}_{i=1}^N\right) \equiv -\frac{TN}{2}\ln\left(2\pi\right) - \frac{T}{2}\sum_{i=1}^N \ln \delta_i'^2 - \sum_{i=1}^N \frac{1}{2\delta_i'^2}\sum_{t=1}^T \nu'_{i,t}\left(B, \underline{\alpha}, \phi\right)^2, \tag{C.3}
$$

We maximize the likelihood to estimate the parameters, $B, \phi, \underline{\alpha}, \left\{\delta_i'^2\right\}_{i=1}^N$. In the numeric solution of likelihood maximization, we first estimate B using ordinary least squares (OLS), and use the first-order condition for $\delta_i'^2$, i.e.,

$$\widehat{\delta_i'^2} = \frac{1}{T}\sum_{t=1}^{T} \nu_{i,t}'\left(B, \underline{\alpha}, \phi\right)^2 ,$$

to substitute out $\delta_i'^2$ in the log likelihood function, forming a concentrated likelihood that only depends on ϕ. By maximizing the concentrated likelihood, we obtain $\hat{\phi}$. Next, using the aforementioned first-order conditions for $\delta_i'^2$, we obtain estimates of $\delta_i'^2$. We then re-estimate B as in feasible generalized least squares (FGLS), using $\hat{\phi}$ and $\delta_i'^2$ to form the heteroskedastic covariance matrix in the observational equation of L. Next, $\hat{B}$ is used to form a new concentrated likelihood, which is used to update the estimate of ϕ. We iterate this process until convergence. In the above formulation, the identification of ϕ is ensured by the conditions in Bramoullé, Djebbari, and Fortin (2009). In Section 3.3, we explain the intuition.

C.2 Solving the bank's optimization

First, it is straightforward to derive the moments in the bank's objective function:

$$\begin{aligned}
\mathbb{E}\left[(x_i - m_i)^2\right] &= \mathrm{Var}(x_i) + \mathbb{E}\left[x_i - m_i\right]^2 \\
&= \mathrm{Var}\left(\sum_{j\neq i} g_{ij}y_i - \sum_{j\neq i} g_{ji}y_j\right) + \mathbb{E}\left[\sum_{j\neq i} g_{ij}y_i - \sum_{j\neq i} g_{ji}y_j - m_i\right]^2 \\
&= \sum_{j\neq i}\left(y_i^2\sigma_{ij}^2 + y_j^2\sigma_{ji}^2 - 2y_iy_j\sigma_{ij}\sigma_{ji}\rho_{ij}\right) + \left(\sum_{j\neq i}\mu_{ij}y_i - \sum_{j\neq i}\mu_{ji}y_j - m_i\right)^2 ,
\end{aligned} \tag{C.4}$$

$$\begin{aligned}
\mathbb{E}\left[x_i^2\right] &= \mathrm{Var}(x_i) + \mathbb{E}\left[x_i\right]^2 = \mathrm{Var}(x_i) + \mathbb{E}\left[\sum_{j\neq i} g_{ij}y_i - \sum_{j\neq i} g_{ji}y_j\right]^2 \\
&= \sum_{j\neq i}\left(y_i^2\sigma_{ij}^2 + y_j^2\sigma_{ji}^2 - 2y_iy_j\sigma_{ij}\sigma_{ji}\rho_{ij}\right) + \left(\sum_{j\neq i}\mu_{ij}y_i - \sum_{j\neq i}\mu_{ji}y_j\right)^2 ,
\end{aligned} \tag{C.5}$$

$$\mathbb{E}\left[z_i^2\right] = \mathrm{Var}(z_i) + \mathbb{E}\left[z_i\right]^2 = \mathrm{Var}(z_i) + \mathbb{E}\left[\sum_{j\neq i} g_{ij}y_i\right]^2 = y_i^2(\overline{\sigma}_{-i}^2 + \overline{\mu}_{-i}^2) , \tag{C.6}$$

To simplify the notations, we define

$$\overline{\mu}_{-i} \equiv \sum_{j \neq i} \mu_{ij} \tag{C.7}$$

$$\overline{\sigma}^2_{-i} = \sum_{j \neq i} \sigma^2_{ij}. \tag{C.8}$$

To solve the first-order condition for y_i, note that

$$\frac{\partial \mathbb{E}\left[x_i - m_i\right]}{\partial y_i} = \sum_{j \neq i} \mu_{ij} = \overline{\mu}_{-i}\,, \tag{C.9}$$

$$\frac{\partial \mathbb{E}\left[x_i\right]}{\partial y_i} = \sum_{j \neq i} \mu_{ij} = \overline{\mu}_{-i}\,, \tag{C.10}$$

$$\frac{\partial \mathbb{E}\left[(x_i - m_i)^2\right]}{\partial y_i} = 2\sum_{j \neq i} \left(y_i \sigma^2_{ij} - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + 2\left(y_i\overline{\mu}_{-i} - \sum_{j \neq i} \mu_{ji}y_j - m_i\right)\overline{\mu}_{-i} \tag{C.11}$$

$$\frac{\partial \mathbb{E}\left[x_i^2\right]}{\partial y_i} = 2\sum_{j \neq i} \left(y_i \sigma^2_{ij} - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + 2\left(y_i\overline{\mu}_{-i} - \sum_{j \neq i} \mu_{ji}y_j\right)\overline{\mu}_{-i} \tag{C.12}$$

$$\frac{\partial \mathbb{E}\left[z_i^2\right]}{\partial y_i} = 2y_i(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}) \tag{C.13}$$

Under parameter restriction, $\tau_2 + \kappa > \theta_2$, that ensures the concavity of objective function in y_i, we solve y_i from the first-order condition:

$$\begin{aligned} 0 =& \varepsilon_i + R - r_i - \tau_1\overline{\mu}_{-i} + \theta_1\overline{\mu}_{-i} - y_i\kappa(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}) \\ &- \tau_2\left[\sum_{j \neq i} \left(y_i \sigma^2_{ij} - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + \left(y_i\overline{\mu}_{-i} - \sum_{j \neq i} \mu_{ji}y_j - m_i\right)\overline{\mu}_{-i}\right] \\ &+ \theta_2\left[\sum_{j \neq i} \left(y_i \sigma^2_{ij} - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + \left(y_i\overline{\mu}_{-i} - \sum_{j \neq i} \mu_{ji}y_j\right)\overline{\mu}_{-i}\right] \end{aligned}$$

which can be further simplified to

$$\begin{aligned} 0 =& \varepsilon_i + R - r_i - (\tau_1 - \theta_1)\overline{\mu}_{-i} + \tau_2\overline{\mu}_{-i}m - y_i\left(\kappa + \tau_2 - \theta_2\right)\left(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i}\right) \\ &+ (\tau_2 - \theta_2)\sum_{j \neq i} \left(\rho_{ij}\sigma_{ij}\sigma_{ji} + \overline{\mu}_{-i}\mu_{ji}\right)y_j. \end{aligned} \tag{C.14}$$

From this condition, we solve the optimal y_i in the main text, and we obtain

$$a_i \equiv \frac{R_i - r_i + \varepsilon_i - (\tau_1 - \theta_1)\overline{\mu}_{-i} + \tau_2 \overline{\mu}_{-i} m_i}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} \,. \tag{C.15}$$

and the following derivatives of a_i,

$$\frac{d^2 a_i}{d\varepsilon_i} = \frac{1}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} > 0 \tag{C.16}$$

$$\frac{da_i}{dm_i} = \frac{\tau_2 \overline{\mu}_{-i}}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} > 0. \tag{C.17}$$

$$\frac{da_i}{d\tau_1} = -\frac{\overline{\mu}_{-i}}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} < 0\,. \tag{C.18}$$

$$\frac{d^2 a_i}{dm_i d\overline{\mu}_{-i}} = \frac{\tau_2}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} > 0. \tag{C.19}$$

$$\frac{d^2 a_i}{d\tau_1 d\overline{\mu}_{-i}} = -\frac{1}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} < 0\,. \tag{C.20}$$

$$\frac{da_i}{d\overline{\sigma}^2_{-i}} = -\frac{R_i - r_i + \varepsilon_i - (\tau_1 - \theta_1)\overline{\mu}_{-i} + \tau_2 \overline{\mu}_{-i} m_i}{(\kappa + \tau_2 - \theta_2)(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})^2} = -\frac{a_i}{(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} < 0 \tag{C.21}$$

C.3 Solving the planner's optimization

To solve the planner's solution, we calculate the following derivatives:

$$\begin{aligned}\frac{\partial \mathbb{E}\left[(x_j - m_j)^2\right]}{\partial y_i} &= \frac{\partial \left\{ \sum_{k \neq j} \left(y_j^2 \sigma_{jk}^2 + y_k^2 \sigma_{kj}^2 - 2 y_j y_k \sigma_{jk} \sigma_{kj} \rho_{jk} \right) + \left(\sum_{k \neq j} \mu_{jk} y_j - \sum_{k \neq j} \mu_{kj} y_k - m_j \right)^2 \right\}}{\partial y_i} \\ &= 2\left(y_i \sigma_{ij}^2 - \rho_{ij} \sigma_{ij} \sigma_{ji} y_j \right) - 2 \left(y_j \overline{\mu}_{-j} - \sum_{k \neq j} \mu_{kj} y_k - m_j \right) \mu_{ij}\end{aligned} \tag{C.22}$$

$$\frac{\partial \mathbb{E}\left[x_j^2\right]}{\partial y_i} = \frac{\partial \left\{ \sum_{k\neq j} \left(y_j^2\sigma_{jk}^2 + y_k^2\sigma_{kj}^2 - 2y_j y_k \sigma_{jk}\sigma_{kj}\rho_{jk}\right) + \left(\sum_{k\neq j}\mu_{jk}y_j - \sum_{k\neq j}\mu_{kj}y_k\right)^2 \right\}}{\partial y_i}$$

$$= 2\left(y_i\sigma_{ij}^2 - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) - 2\left(y_j\overline{\mu}_{-j} - \sum_{k\neq j}\mu_{kj}y_k\right)\mu_{ij} \tag{C.23}$$

$$\frac{\partial \mathbb{E}\left[z_j^2\right]}{\partial y_i} = 0 \tag{C.24}$$

The first-order condition for y_i:

$$\begin{aligned}
0 =& \varepsilon_i + R - r_i - \tau_1\overline{\mu}_{-i} + \theta_1\overline{\mu}_{-i} - y_i\kappa(\overline{\sigma}_{-i}^2 + \overline{\mu}_{-i}^2) \qquad\qquad (C.25)\\
&- \tau_2\left[\sum_{j\neq i}\left(y_i\sigma_{ij}^2 - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + \left(y_i\overline{\mu}_{-i} - \sum_{j\neq i}\mu_{ji}y_j - m_i\right)\overline{\mu}_{-i}\right]\\
&+ \theta_2\left[\sum_{j\neq i}\left(y_i\sigma_{ij}^2 - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + \left(y_i\overline{\mu}_{-i} - \sum_{j\neq i}\mu_{ji}y_j\right)\overline{\mu}_{-i}\right] + \sum_{j\neq i}(\tau_1 - \theta_1)\mu_{ij}\\
&- (\tau_2 - \theta_2)\left(y_i\sigma_{ij}^2 - \rho_{ij}\sigma_{ij}\sigma_{ji}y_j\right) + (\tau_2 - \theta_2)\left(y_j\overline{\mu}_{-j} - \sum_{k\neq j}\mu_{kj}y_k\right)\mu_{ij} - \tau_2 m_j\mu_{ij}\\
=& \varepsilon_i + R - r_i + \tau_2\overline{\mu}_{-i}m - y_i\left(\kappa + 2\tau_2 - 2\theta_2\right)\overline{\sigma}_{-i}^2 - y_i\left(\kappa + \tau_2 - \theta_2\right)\overline{\mu}_{-i}^2 - \sum_{j\neq i}\tau_2 m_j\mu_{ij}\\
&+ (\tau_2 - \theta_2)\sum_{j\neq i}\left(2\rho_{ij}\sigma_{ij}\sigma_{ji} + \overline{\mu}_{-i}\mu_{ji} + \overline{\mu}_{-j}\mu_{ij}\right)y_j - (\tau_2 - \theta_2)\sum_{j\neq i}\mu_{ij}\left(\sum_{k\neq j}\mu_{kj}y_k\right)
\end{aligned}$$

From this condition, we solve the planner's optimal y_i in the main text. And, the planner's choice of network-independent bank lending financed by deposits is given by

$$\widetilde{a}_i \equiv \frac{\varepsilon_i + R_i - r_i + \tau_2\overline{\mu}_{-i}m_i - \sum_{j\neq i}\tau_2 m_j\mu_{ij}}{\left(\kappa + \tau_2 - \theta_2\right)\left(\overline{\sigma}_{-i}^2 + \overline{\mu}_{-i}^2\right) + \left(\tau_2 - \theta_2\right)\overline{\sigma}_{-i}^2}. \tag{C.26}$$

Different from the decentralized counterpart in (C.15), the numerator of $\widetilde{a}_i$ no longer has the expected outflow (which, from the planner's perspective, is offset by other banks' inflow) but it has an additional term $\sum_{j\neq i}\tau_2 m_j\mu_{ij}$ because the liquidity externality of bank i's lending is less valuable when bank j ($j \neq i$) already hold more liquid assets.

Next, we solve the connection between $\widetilde{a}_i$ in the planner's solution and a_i in (C.15) of the market equilibrium:

$$\widetilde{a}_i = b_{i,t} + \frac{\widetilde{\phi}_i}{\phi} a_{i,t}\,, \tag{C.27}$$

where,

$$b_i \equiv \frac{\widetilde{\phi}_i}{(\overline{\sigma}^2_{-i} + \overline{\mu}^2_{-i})} \left[\left(\frac{\tau_1 - \theta_1}{\tau_2 - \theta_2} \right) \overline{\mu}_{-i} - \left(\frac{\tau_2}{\tau_2 - \theta_2} \right) \sum_{j \neq i} \mu_{ij} m_j \right] . \tag{C.28}$$

D Appendix: Additional Tables and Figures

Variable	N	Mean	S.D.	P25	P50	P75
Quarterly loan growth rate	22000	0.0230	0.0550	-0.0016	0.0143	0.0341
Bank Characteristics:						
log(Asset) (unit: log(USD '000))	22000	15.13	1.41	14.15	14.69	15.72
Liquid Assets/Total Assets	22000	0.18	0.12	0.10	0.16	0.24
Capital/Total Assets	22000	0.11	0.03	0.09	0.10	0.12
Deposits/Total Assets	22000	0.68	0.12	0.63	0.70	0.75
Return on asset	22000	0.0026	0.0025	0.0018	0.0025	0.0033
Loans/Total Assets	22000	0.67	0.15	0.60	0.70	0.77
Macroeconomic Variables:						
Effective Fed Funds Rate change (%)	22000	-0.0007	0.2361	-0.0101	0.0119	0.0521
GDP growth (%)	22000	0.51	3.09	-2.59	1.43	2.29
Inflation (%)	22000	0.43	0.66	0.11	0.46	0.82
Stock market return (%)	22000	3.68	8.06	0.51	4.52	7.97
Housing price growth (%)	22000	1.13	1.87	0.14	1.15	2.29
Cross-Section Payment Statistics:						
Average net daily payment flow/Deposits (%)	500	0.01	0.91	-0.14	0.01	0.17
s.d. of net daily payment flow/Deposits (%)	500	0.97	0.83	0.48	0.74	1.14
Average gross daily outflow/Deposits (%)	500	1.82	4.31	0.35	0.74	1.47
s.d. of gross daily outflow/Deposits (%)	500	1.11	1.34	0.41	0.70	1.18

Table D.1: **Summary Statistics**. This table reports the number of observations, mean, standard deviation, and percentiles of variables in our sample. Our sample contains 500 banks and 44 quarters from 2010 to 2020. We calculate μ_{ij} (σ_{ij}) as the within-quarter average (standard deviation) of daily payment outflows from bank i to bank j divided by bank i's deposits at the beginning of the quarter. Therefore, $\sum_{j \neq i} \mu_{ij}$ is the average daily payment outflow as a fraction of deposits for bank i within a quarter and $\sum_{j \neq i} \sigma_{ij}^2$ measures the payment-flow risk for bank i.

Number of Banks:	500	500 (Not winsorized)	300	400	600	700
Constant	0.0897 (0.90)	0.0863 (0.86)	0.1449 (1.33)	0.0973 (0.96)	0.0765 (0.76)	0.0609 (0.60)
<u>Bank Characteristics</u>:						
log(Asset)	−0.0039 (−0.80)	−0.0038 (−0.76)	−0.0067 (−1.37)	−0.0046 (−0.92)	−0.0042 (−0.81)	−0.0032 (−0.62)
Liquid Assets/Assets	0.0144* (1.77)	0.0142* (1.74)	−0.0011 (−0.12)	0.0098 (1.03)	0.0200*** (2.58)	0.0252*** (3.52)
Capital/Assets	0.0931*** (3.28)	0.0941*** (3.28)	0.1086*** (4.63)	0.0971*** (3.58)	0.0607 (1.51)	0.0531 (1.32)
Deposits/Assets	−0.0108** (−2.27)	−0.0104** (−2.22)	−0.0080 (−1.47)	−0.0079 (−1.51)	−0.0111*** (−2.65)	−0.0097** (−2.34)
Return on asset	1.2726*** (4.19)	1.2789*** (4.17)	1.3469*** (3.54)	1.3646*** (4.00)	1.2911*** (4.55)	1.3236*** (4.67)
Loans/Assets	−0.0296*** (−2.96)	−0.0294*** (−2.90)	−0.0380*** (−4.14)	−0.0331*** (−3.47)	−0.0241** (−2.32)	−0.0172 (−1.64)
<u>Macro. Variables</u>:						
EFFR change (%)	−0.0111 (−1.30)	−0.0111 (−1.31)	−0.0102 (−1.41)	−0.0108 (−1.27)	−0.0125 (−1.37)	−0.0123 (−1.31)
GDP growth (%)	−0.0007 (−1.00)	−0.0007 (−0.98)	−0.0005 (−0.85)	−0.0007 (−0.97)	−0.0009 (−1.16)	−0.0009 (−1.15)
Inflation (%)	0.0032 (1.11)	0.0032 (1.13)	0.0032 (1.13)	0.0029 (1.03)	0.0036 (1.23)	0.0036 (1.23)
Stock return (%)	−0.0009** (−2.28)	−0.0009** (−2.30)	−0.0008** (−2.50)	−0.0009** (−2.26)	−0.0009** (−2.22)	−0.0009** (−2.17)
Housing price growth (%)	0.0022** (2.52)	0.0022** (2.50)	0.0018** (2.19)	0.0020** (2.25)	0.0024** (2.56)	0.0025*** (2.64)
(* p<0.10 ** p<0.05 *** p<0.01)						

Table D.2: **Control Variable Coefficients**. This table reports the estimates of control variable coefficients across samples of different sizes that contain banks ranked by the size of their deposits. The t-stats are in the parentheses. The abbreviation, EFFR, is for effective fund funds rate.

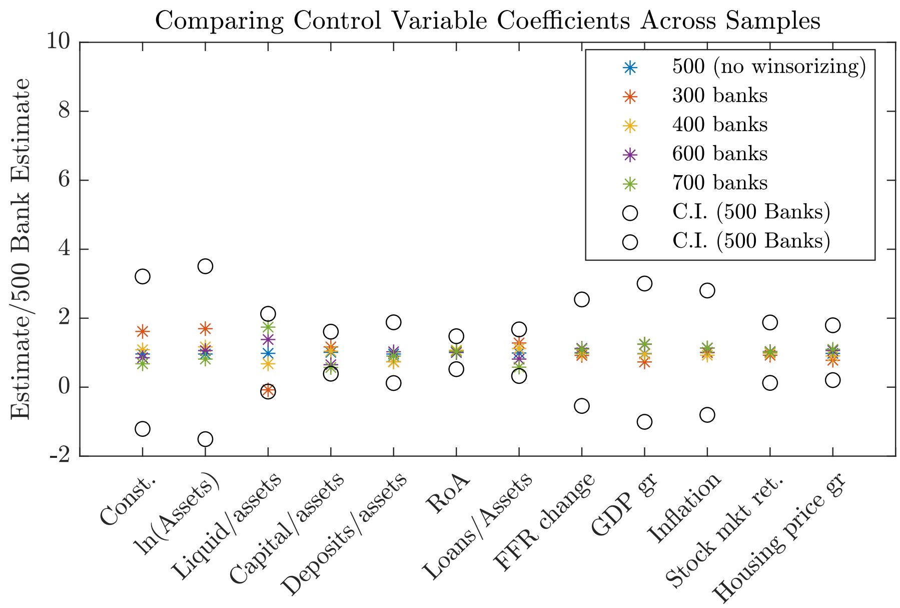

Figure D.1: **Control variable coefficients across samples**. This figure reports the ratio of an estimate from an alternative sample to the estimate from our main sample of the top 500 banks by deposit size. A ratio around one indicates that the two estimates are close. We plot the 95% confidence interval of each estimate from our main sample scaled by the estimate so the mid-point is equal to one.

E Network Eigenvalues

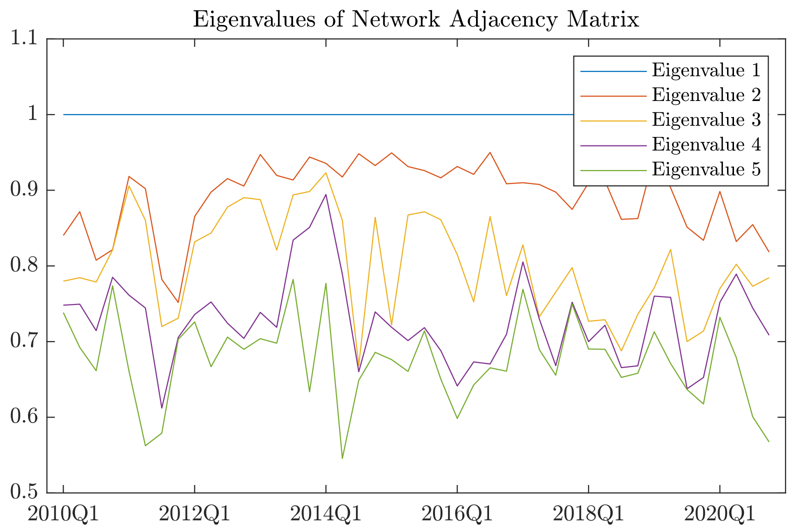

Figure E.1: **Eigenvalues of network adjacency matrix.** In this figure, we plot the absolute values of the five largest eigenvalues of $\mathbf{W}'$. $\mathbf{W}'$ for quarter t is calculated from payment data from quarter $t-1$ (see Section 3.2).

The eigenvalues of network adjacency matrix are important in determining the strength of network propagation. Let $\mathbf{\Lambda}$ denote the diagonal matrix whose diagonal elements are the eigenvalues of $\mathbf{W}'$ ranked by absolute values. In our sample, the square matrix, $\mathbf{W}'$, has linearly independent eigenvectors, so we apply the eigendecomposition:

$$\mathbf{W}' = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^{-1}. \tag{D.1}$$

where $\mathbf{V}$ is the square $N \times N$ matrix whose i-th column is the i-th largest eigenvector. Substituting the decomposition of $\mathbf{W}'$ into (36), we obtain

$$\mathbf{M}\left(\phi, \mathbf{W}'\right) = \mathbf{I} + \mathbf{V}\phi\mathbf{\Lambda}\mathbf{V}^{-1} + \mathbf{V}\phi^2\mathbf{\Lambda}^2\mathbf{V}^{-1} + \ldots = \mathbf{V}\left(\sum_{k=0}^{\infty}\phi^k\mathbf{\Lambda}^k\right)\mathbf{V}^{-1}. \tag{D.2}$$

where $\sum_{k=0}^{\infty}\phi^k\mathbf{\Lambda}^k$ is a diagonal matrix and its i-th diagonal element is

$$\left\{\sum_{k=0}^{\infty}\phi^k\mathbf{\Lambda}^k\right\}_{ii} = \left\{\left(\mathbf{I} - \phi\mathbf{\Lambda}\right)^{-1}\right\}_{ii} = \frac{1}{1 - \phi\mathbf{\Lambda}_{ii}}, \tag{D.3}$$

where $\mathbf{\Lambda}_{ii}$ is the i-th largest eigenvalue of $\mathbf{W}'$. The strength of network as a shock amplification mechanism depends on the eigenvalues of the network, which capture the network topology, and ϕ. The stability of eigenvalues over time suggests that the time variation of network effects is mainly driven by the variation in the network attenuation factor, ϕ.

To see the mechanism more clearly, we multiply both sides of (D.4) by $\mathbf{V}^{-1}$ and obtain

$$\mathbf{V}^{-1}\epsilon_t = \mathbf{V}^{-1}\mathbf{M}\left(\phi, \mathbf{W}'\right)\nu_t' = \left(\sum_{k=0}^{\infty}\phi^k\mathbf{\Lambda}^k\right)\mathbf{V}^{-1}\nu_t' \tag{D.4}$$

Up to a monotonic linear transformation given by $\mathbf{V}^{-1}$, the ultimate impact of shock on all banks depends on how strongly the network propagates shocks through the eigenvalues, $\{\mathbf{\Lambda}_{ii}\}_{i=1}^N$, and the network attenuation factor ϕ. We may decompose the shock propagation into two steps. First, the system-wide strength of propagation is governed by ϕ and $\{\mathbf{\Lambda}_{ii}\}_{i=1}^N$. Second, after the propagation, the distribution of amplified shocks over banks depends on $\mathbf{V}$.