Banking in Production Networks: Evidence and Theory from Supply Chain Finance*

Wukuang Cun SUFE
Dongmei Guo CUFE
Junjie Xia CUFE & PKU
Changhua Yu PKU

August 29, 2024

Abstract

This paper investigates how coordination between lenders influences the loan supply to firms within industrial chains. Utilizing Chinese firm-level data, we demonstrate that the financing activities of firms within the same industrial chain are more highly correlated when these firms are connected to the same bank, compared to when they are connected to different banks. Firms that share a common bank with their business partners along the industrial chain tend to borrow more frequently and exhibit higher leverage. Additionally, using granular loan-level data for supply chain finance from a major commercial bank in China, we provide evidence on how banks coordinate loan supply to their customers within industrial chains through internal management processes. To explain our findings, we propose a model of industrial chains with relationship banking that aligns with the empirical evidence. We show that when lenders are branches of the same bank and coordinate their lending decisions, they extend more credit to firms, leading to a more stable loan supply. Our paper offers new insights to the discourse on how credit supply can facilitate industrial supply chains.

Keywords: supply chain finance; coordination; credit supply; production networks;

JEL Classification: E23, E32, E44, G20, G21, L14

*Wukuang Cun, Shanghai University of Finance and Economics, China, email: wukuang.cun@outlook.com; Dongmei Guo, Central University of Finance and Economics, China, email: guodongmeicufe@163.com; Junjie Xia, Central University of Finance and Economics & Peking University, China, email: junjiexia@nsd.pku.edu.cn; Changhua Yu, Peking University, China, email: changhuayu@nsd.pku.edu.cn. All errors are ours.

1 Introduction

To support the economic recovery following the COVID-19 outbreak, the Chinese government launched a series of financial stimulus plans in 2020 to tackle the systemic shortage of liquidity in the real sectors. The People's Bank of China (PBOC) not only lowered the policy interest rate to unprecedented lows but also significantly reduced the required reserve ratio, thereby stimulating the overall supply of bank credit. These measures were aimed at ensuring that businesses, especially those hit hardest by the pandemic, could access the necessary funds to maintain operations and sustain employment levels.

However, the recent credit expansion in 2020 differs in many ways from the one following the 2008 Global Financial Crisis. Notably, the recent credit expansion is largely directed towards industrial chains facing liquidity problems. Regulatory authorities have placed particular emphasis on 'coordination' in providing financial support to both upstream and downstream firms within these industrial chains. This approach is intended to prevent bottlenecks in production and supply processes, ensuring that liquidity issues in one part of the chain do not disrupt the entire network. Moreover, the regulatory framework has been adjusted to enhance the effectiveness of these measures. Authorities have implemented policies to facilitate better information sharing and coordination among banks, encouraging them to work together in supporting the financial needs of interconnected firms. This coordinated effort aims to stabilize industrial chains, promote smoother operations, and ultimately, foster a more resilient economic recovery.

In March 2020, the China Banking and Insurance Regulatory Commission (CBIRC) released the '*Notice on Strengthening Financial Supports for Coordinated Resumption of Production across Industrial Chains*', which provides a guide for financial institutions offering financial supports. The *Notice* urges banks to strengthen credit supports for all the firms in industrial chains, including not only the core firms (i.e., the large leading companies in industrial chains) but also their upstream and downstream firms. As of the end of 2020, the outstanding balance of loans extended by banks in support of industrial chains totaled RMB 41.6 trillion (around 20% of M2). These loans are lent to 1.03 million firms, including both the core firms and their upstream and downstream firms in industrial chains.[1]

This paper investigates both empirically and theoretically the rationale behind the importance of coordinating loan supply to firms along an industrial chain and explore the implications for the effectiveness of credit stimulus. By delving into the mechanics of how coordinated lending can enhance the financial health and operational efficiency of intercon-

[1]For more details on the outcomes of the 2020 credit stimulus in China, see the '*Practices and Experiences of China's Banking and Insurance Industries in Combating COVID-19*' released by the CBIRC in December 2021.

nected firms, we aim to shed light on the broader economic benefits of such strategies.

In the first part of this paper, we establish a set of empirical patterns using data on publicly traded firms and detailed loan-level data from a major commercial bank in China. Publicly traded firms are required to disclose their major business partners (i.e., suppliers and customers) and significant financing activities (e.g., bank loans) annually. Utilizing this information, we identified approximately 2,000 supplier-customer pairs and around 80,000 loans these firms borrowed. We document four key stylized facts about bank lending to firms. First, aach firm is connected to a small number of banks and does not switch banks frequently. Approximately 35% of the firms share common banks with their business partners (firms borrow from the same banks). Second, the financing activities of firms in a supply chain are more correlated when they are connected to the same bank compared to when they are connected to different banks. Third, A firm borrows more frequently and has higher leverage when it shares more common banks with its business partners. Fourth, After a negative collateral shock, a firm's borrowing activities decrease less when it shares more common banks with its business partners.

Based on granular loan-level data for supply chain finance from a major bank in China, we further investigate whether bank lending to firms depends on their status within a supply chain. The data enables us to identify the loans associated with different supply chains. For each supply chain, we can pinpoint the core firm and the upstream and downstream firms. We find that loans lent through the supply chain platform (tagged with the supply chain number) are correlated with each other, while regular loans (without a supply chain number) are not correlated. When a bank expands credit to a core firm in an industrial supply chain, its customers and suppliers subsequently receive more credit compared to firms that are not part of a supply chain.

These stylized facts suggest that lending coordination among banks to firms along a supply chain plays a critical role in bank lending and firms' performance within the supply chain. Firms extensively utilize intermediate inputs from their upstream suppliers and sell outputs to various downstream customers. Due to the strong complementarity of intermediate inputs in production in the short run and the significant role of downstream customers in determining a firm's sales, the credit conditions of a firm's suppliers and customers significantly affect its profits. In other words, credit conditions along a supply chain are complementary, with all firms in the chain benefiting from improved credit conditions, which in turn generate higher output for all firms involved.

When there is a bottleneck in credit conditions within a supply chain, such as some firms experiencing adverse shocks, these adverse shocks are propagated to other firms along the supply chain. This, in turn, amplifies the adverse impact on all firms. One way to avoid

such cascading effects is to expand credit to all firms in the supply chain simultaneously through lending coordination among banks. Without such coordination, the bottleneck of credit constraints faced by some firms in the supply chain will limit the effectiveness of credit expansion to other firms within the same supply chain.

We formalize this argument in a stylized model of a supply chain. The model features firms in two industries within a vertical supply chain that employ labor to produce goods but face working capital constraints when borrowing from banks. Each firm is also endowed with a level of cash. To capture the structure of the banking sector, we assume that each bank serves only firms in one industry, possibly due to relationship banking. In the benchmark model, we assume that these two banks do not coordinate their lending decisions. Each bank is endowed with one unit of funds, which can either be lent to the connected firm or invested in an alternative project.

At one extreme, when the gross returns on alternative projects are high enough, banks will not lend to firms in either industry. At the other extreme, when the gross returns on alternative projects are sufficiently low, banks will always lend to firms. In the intermediate range, one bank's lending decision critically depends on the other bank's decision due to the strategic complementarity of bank lending to different industries. As a result, multiple equilibria exist: either both banks lend to firms in these two sectors, or neither bank lends to firms. Without bank loans, firms would contract employment and production, resulting in lower aggregate output and welfare. We further find that in response to a negative liquidity shock, the likelihood of multiple equilibria increases and the aggregate lending to firms declines.

Would banks provide more credit to firms if they could coordinate with each other? Ideally, banks could avoid coordination failure by merging with each other, effectively becoming two subsidiaries of a single bank, as observed in our empirical analysis. We find that under coordination, the lending decisions of banks are perfectly aligned, and the required cutoff return for alternative projects is much lower than in the non-coordinated scenario. Our model's predictions align well with the stylized facts observed in the data.

Related Literature. Our paper is closely related to three branches of literature.The first branch of literature is the linkage between banking structure and bank lending to firms in supply chains. Houston et al. (2016) studies how a firm's bankruptcy affects the bank financing costs of its key suppliers. Schwert (2018) find that bank-dependent firms borrow from well-capitalized banks, while firms with access to the bond market borrow from banks with less capital. Saidi and Streitz (2021) examines a link between bank concentration and markups in nonfinancial sectors due to the greater incidence of competing firms sharing common lenders that induce less aggressive product market behavior among their borrowers.

Martins et al. (2023) explore how lending to a firm is affected by same-bank lending to the firm's customers and suppliers and find that the supply of loans to a firm increases when the firm's customers have loans from the same bank. The most related paper is Giannetti and Saidi (2019), who find that high-market-share lenders are more likely to internalize negative spillovers of industry downturns and show that they provide liquidity to industries in distress when fire sales are likely to ensue, while our paper focuses instead on bank lending coordination among banks, and show that this coordination plays an important role in affecting firms credits in supply chains, thereby offer new insights on the discourse on how credit provision can enhance industrial supply chains.

The second branch of related literature is supply chain credit and payments. Jacobson and Schedvin (2015) quantify the importance of trade credit chains for the propagation of corporate bankruptcy based on an exhaustive data set on claims held by trade creditors (suppliers) on failed trade debtors (customers). Costello (2019) demonstrate the important role of laws that support suppliers' rights to reclaim and liquidate collateral. Kouvelis et al. (2019) investigate hedging cash-flow risks in a supply chain where firms invest internal funds to improve production efficiencies. Chod et al. (2019) explores how competition among suppliers affects their willingness to provide trade credit financing. Gofman and Wu (2022) document that more upstream firms borrow more from suppliers, lend more to customers, and hold more net trade credit based on a comprehensive data on supply chain and trade credit. Grigoris et al. (2023) focuse on trade credit, asset prices, and production-network linkages. Ersahin et al. (2024) study that trade credit flows increase when a firm in a production network becomes a less reliable supplier due to an operating shock. Some recent studies focus on macroeconomic implications of trade credits. Bigio (2023) explores an endogenous network of payments chains in a business cycle model, in which payment delays affect firms production and total factor productivity. Bocola and Bornstein (2023) studies the macroeconomic implications of trade credit links, and focuses on how trade credits give rise to a credit multiplier: suppliers can enforce repayment of these IOUs, and they can discount these bills with banks to obtain liquidity. Using detailed loan-level data for supply chain finance, our paper provides fresh empirical evidence to the trade credit literature by exploring how coordination among banks determine credits to firms in supply chains.

The third branch of related literature investigates production networks in macroeconomics. In the previous work on production networks and macroeconomics, researchers find that sectoral linkages help propagate shocks across sectors (Gabaix, 2011; Acemoglu et al., 2012; Acemoglu et al., 2015 and others). Liu (2019) finds that market imperfections create distortions that are amplified by backward demand connections, leading to upstream sectors

absorbing these imperfections and experiencing the most significant distortions in size, and there is an incentive for a well-meaning government to subsidize upstream sectors. Bigio and La'O (2020) explore the role of sectoral financial distortions in determining total output, and find that the U.S. input-output structure amplified financial distortions by roughly a factor of two during the crisis. Hertzel et al. (2008) examine the wealth effects of distress and bankruptcy filing for suppliers and customers of filing firms, and find that Significant wealth effects are observed before and during bankruptcy filings, with implications that extend beyond industry rivals throughout the supply chain. Barrot and Sauvagnat (2016) find that during the occurrence of natural disasters, affected suppliers impose substantial output losses on their customers, especially when they produce specific inputs. By using data of interfirm sales, Costello (2020) show that suppliers exposed to a large and exogenous decline in bank financing pass this liquidity shock to their downstream customers. Recent literature focuses on demand side shocks in multi-sector New Keynesian economies (see for instance, Galí, 2015; Nakamura and Steinsson, 2010; Carvalho and Nechio, 2011; Pasten et al., 2017; Pasten et al., 2020; Ghassibe, 2021a).[2] Several recent papers explore optimal monetary policy in economies with production networks (La'O and Tahbaz-Salehi, 2022; Rubbo, 2023; Afrouzi and Bhattarai, 2023). Our paper complements this literature by focusing on how banking structure affects bank lending to firms in supply chains, and consequently output produced by different sectors.

In summary, our study underscores the critical role of banking coordination within industrial chains. Through our combined empirical and theoretical analysis, we highlight the potential of coordinated loan supply to amplify the positive impacts of financial stimulus programs and bolster the resilience of industrial sectors during economic stress. Policymakers might consider promoting relationship banking within industrial chains to enhance financial stability and efficiency. Encouraging banks to develop specialized internal management processes for supply chain finance could facilitate more synchronized lending decisions, ultimately supporting the growth and resilience of interconnected firms. This approach could be particularly beneficial in emerging markets, where industrial chains are often more vulnerable to financial disruptions.

The structure of the paper is as follows. Section 2 provides empirical stylized facts based on publicly listed firms and loan-level data for supply chain finance. Section 3 develops a model with supply chain and banking structure to show how coordination of banks determines credits to firms in supply chains. The last section concludes.

[2]See more recent studies Altinoglu (2021), Ghassibe (2021b), Giovanni and Hale (2022), Luo and Villar (2023), Devereux et al. (2023), and Xu and Yu (2025).

2 Empirical evidence

We provide two sets of empirical results using Chinese data. First, we provide the firm-level evidence using the data on publicly traded firms. Second, we use detailed loan-level data for supply chain finance from a major bank in China to provide an example on how bank coordinates the loan supply to its customers in industrial chains through internal management process.

2.1 Firm-level evidence

We first investigate the financing activities of the publicly traded firms using the data obtained from the China Stock and Accounting Research (CSMAR). This data set includes information on firms' balance sheets, and their major financing activities and business partners.

Our empirical strategy is as follows. We first identify the supplier-customer relationship between firms. We then identify the banks from which the firms have borrowed loans. When a firm and its business partners are connected to the same bank, it should be relatively easier for the common bank to coordinate the loan supply to these firms. In contrast, when a firm and its business partners are connected to different banks, the coordination between the different lending banks should be more difficult. To investigate if coordination has played any role in the loan supply to supply chains, we compare the financing activities of firms that share common banks with their business partners versus those without shared common bank. Our main findings are:

- **Fact 1 (Firm-bank connections).** Each firm is connected to a small number of banks and does not switch banks frequently. Around 35% of the firms have shared common banks with their business partners.

- **Fact 2 (Correlation).** The financing activities of firms in a supply chain are more correlated with each other when they are connected to the same bank than when they are connected to different banks.

- **Fact 3 (Intensity).** A firm borrows more frequently and has higher leverage when it shares more common banks with its business partners.

- **Fact 4 (Fragility).** After a negative collateral shock, a firm's borrowing activities decrease less when it shares more common banks with its business partners.

2.1.1 Supplier-customer pairs and the connected banks

We start by identifying the supplier-customer relationship between firms, and the banks connected to these firms.

Supplier-customer pairs. In each year, the publicly traded firms report their top five suppliers and customers in their annual reports. If firm j is reported as a major supplier or customer by firm i during the sample period (2013-2023), then firm j is considered as a 'business partner' of the reporting firm i. The type of connection between i and j is $s_{ij} = 1$ if firm j is a major customer, and $s_{ij} = 2$ if firm j is a major supplier. Thus, a supplier-customer (SC) pair is characterized by vector (i, j, s), as illustrated in Figure 1.

Using the data over 2013-2023, we have identified around 2000 supplier-customer pairs, with around 900 of them being type 1 ($s_{ij} = 1$) and the rest of them being type 2 ($s_{ij} = 2$). For most of these supplier-customer pairs, the reporting firms are from manufacturing sectors, and for around 57% of these pairs, the reporting firms are state-owned (see Table 7 in Appendix A).

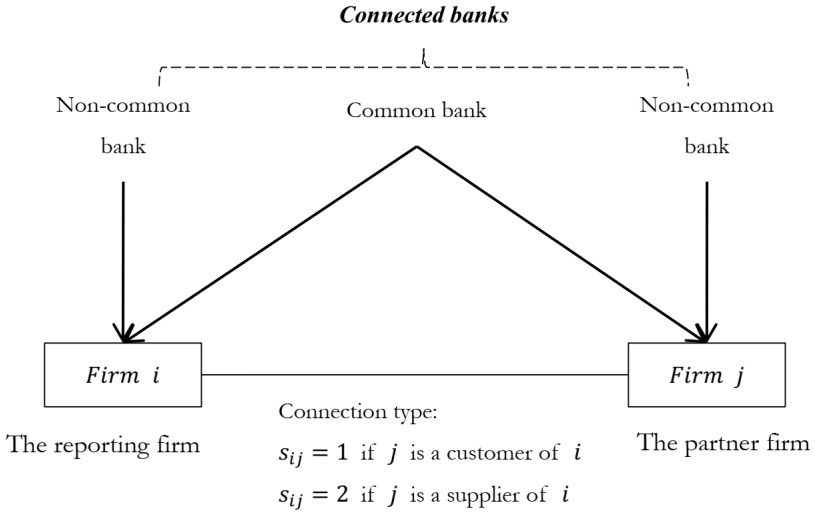


Figure 1: A supplier-customer pair and the connected banks

Connected banks. In each year, firms are required to disclose their significant financing activities within the year. When a firm borrows a loan that is large enough to affect its financial status, the information on this loan should be disclosed to the public. However, we can observe only the lending limit specified in the loan contracts (i.e., the maximum amount the firm can borrow), while the actual amounts borrowed are unobservable.

The loan data are available over the period 2013-2023. During the sample period, the total number of loans are around 80 thousand. For around 80% of the loans, we can identify the lending banks using the reported bank names.

The purpose of 63% of the loans is for business operations, as can be seen in Table 8 in Appendix A.

We use the information on loans to identify the lending banks. As shown in Table 1, the share of the loans from the top ten lenders in the total loans is around 50%. The top ten lenders are the largest national banks, including the four state-owned banks and six joint-stock banks.

Table 1: The major lenders in the loan market

		No. of loans	Share	Weighted Share
1	Bank of China	4783	7.2%	9.3%
2	China Merchants Bank	4050	6.1%	11.5%
3	Industrial and Commercial Bank of China	3962	6.0%	5.5%
4	Bank of Communications	3549	5.4%	4.0%
5	China Construction Bank	3457	5.2%	5.5%
6	Industrial Bank (China)	3279	5.0%	3.8%
7	Agricultural Bank of China	3062	4.6%	4.1%
8	China CITIC Bank	3037	4.6%	3.0%
9	China Everbright Bank	2833	4.3%	2.0%
10	Shanghai Pudong Development Bank	2820	4.3%	2.6%
11	China Minsheng Bank	2759	4.2%	2.8%
12	Ping An Bank	1785	2.7%	2.1%
13	Huaxia Bank	1749	2.6%	1.1%
14	Bank of Beijing	1410	2.1%	1.0%
15	China Guangfa Bank	1395	2.1%	1.4%
	Others	22104	33.5%	40.0%

Notes: The market share of a bank is computed as the ratio of the number of loans extended by that bank to the total number of loans. The weighted share is computed using the maximum loan amount specified in the loan contracts as the weight.

We first identify the connected banks for each firm s, with $s \in \{i, j\}$, in the supplier-customer pairs. If firm s borrowed at least one loan from bank z during the sample period (2013-2023), then firm s is considered to be a 'customer' of bank z, and in turn bank z is a 'connected bank' of firm s.

We denote by N_s^B the number of banks connected with firm s. As shown in Panel I of Table 2, there are 549 firms (43.4% of all firms) with less than 6 connected banks ($N_s^B \leq 5$), i.e., these firms borrowed from less than 6 different banks during 2013-2023. Remember that there are 15 major banks firms can potentially borrow from (Table 1). Thus, our result indicates that firms tend to maintain relationships with only a small number of banks and do not switch banks very frequently, which is consistent with the relationship banking theory.

For each supplier-customer pair we compare the connected banks of firm i with those of j. If there is a bank z^* connected with both i and j, then bank z^* is referred to as a 'common bank' of the two firms (see Figure 1). Let CB_{ij} be an indicator of whether firms i and j share a common bank, and $CB_{ij} = 1$ if the two firms have at least one common bank and $CB_{ij} = 0$

Table 2: The connection between firms and banks

	I. Number of a firm's connected banks (N_s^B)			
	with $N_s^B \in [1,5]$	with $N_s^B \in [6,10]$	with $N_s^B \in [11,15]$	with $N_s^B > 15$
Number of firms	549	233	160	321
Share in all firms	43.4%	18.5%	12.7%	25.4%
Cumulative frac.	43.4%	61.9%	74.6%	100.0%
	II. Whether the two firms of a SC pair shares a common bank (CB_{ij})			
	with common bank ($CB_{ij=1}$)		without common bank ($CB_{ij=0}$)	
Number of SC pairs	773		1386	
Share in all SC pairs	35.8%		64.2%	

otherwise.

$$CB_{ij} = \begin{cases} 1 & \textit{if } i \textit{ and } j \textit{ are connected to at least one common bank} \\ 0 & \textit{otherwise,} \end{cases} \tag{1}$$

We find that for around 35% of the supplier-customer pairs, both firms i and j are connected to at least one common bank ($CB_{ij} = 1$), as shown in Panel II of Table 2.

Notice that a firm may have more than one business partners (i.e., suppliers and customers). Let $\mathcal{I}_i^C$ be the set containing all the business partners of firm i. Thus, each $j \in \mathcal{I}_i^C$ is a business partner of i. Let N_i^C be the number of partner firms in set $\mathcal{I}_i^C$. Let CB_i denote the fraction of firm i's business partners that share a common bank with i. Thus, CB_i is defined as

$$CB_i = \frac{1}{N_i^C} \sum_{j \in \mathcal{I}_i^C} CB_{ij}. \tag{2}$$

2.1.2 Financing activities of firms

Correlation of financing activities. We first investigate if the financing activities of firms of a supplier-customer pair (Figure 1) are more correlated when they are connected to a common bank. To this end, we denote by D_{it} and D_{jt} the indicators for financing activities of firms i and j in a supplier-customer pair (Figure 1), where $D_{st} = 1$, with $s \in \{i, j\}$, if firm s borrowed at least one loan in year t, and $D_{st} = 0$ otherwise.

$$D_{st} = \begin{cases} 1 & \textit{if firm } s \textit{ borrows at least one loan in period } t \\ 0 & \textit{otherwise,} \end{cases} \tag{3}$$

where $s \in \{i, j\}$. Thus, the expected values of D_{it} and D_{jt} represent respectively the frequency of financing activities of firms i and j, and the correlation between D_{it} and D_{jt} measures the extent to which the financing activities of two paired firms are correlated.

Panel(a) of Figure 2 shows the financing activities of the supplier-customer pairs. The whole bars represent the numbers of supplier-customer pairs with financing activities in each

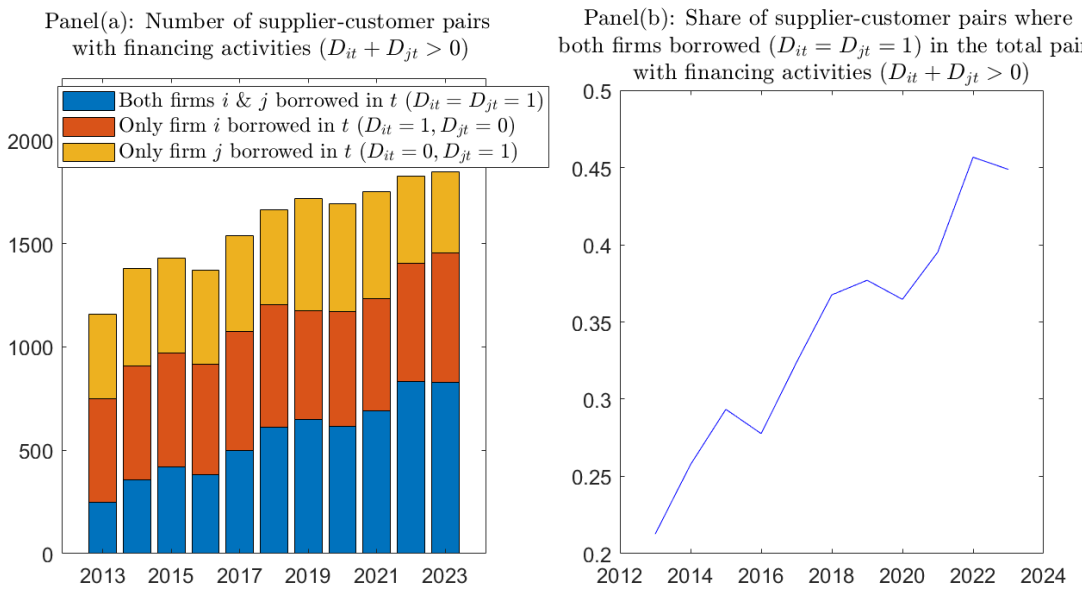


Figure 2: Financing activities of supplier-customer pairs

Notes: In Panel (a) the whole bar represents the number of supplier-customer pairs where at least one firm borrowed in year t ($D_{it} + D_{jt} > 0$). The blue segment represents the number of pairs where both firms borrowed ($D_{it} = D_{jt} = 1$), the red segment represents the number of pairs where only firm i borrowed ($D_{it} = 1$ and $D_{jt} = 0$), and the yellow segment represents the number of pairs where only firm j borrowed ($D_{it} = 0$ and $D_{jt} = 1$). Panel (b) shows the ratio of the number of supplier-customer pairs where both firms borrowed ($D_{it} = D_{jt} = 1$) to the number of pairs where at least one firm borrowed ($D_{it} + D_{jt} > 0$).

year (i.e., $D_{it} + D_{jt} > 0$). For example, in 2023 there are around 1800 supplier-customer pairs where either or both firms i and j borrowed. The blue segment of each stack bar represents the number of supplier-customer pairs where both firms i and j borrowed within the year. The red segment represents the number of pairs where only firm i borrowed within the year, and the yellow segment represents the number of pairs where only firm j borrowed.

Also, as shown in Panel (b) of the figure, the share of supplier-customer pairs where both firms borrowed simultaneously (i.e., $D_{it} = D_{jt} = 1$) in the total number of pairs with financing activities (i.e., $D_{it} + D_{jt} > 0$) rises from 20% in 2013 to 45% in 2023. This indicates that the financing activities of paired firms are becoming more and more correlated over time.

Furthermore, when firms of a supplier-customer pair borrow simultaneously (i.e., the blue segment in Panel (a) of Figure 2), the simultaneous loans are likely from a common bank. This is shown in Figure 3, where we restrict the sample to loans for which the lending banks can be identified. As can be seen, for the supplier-customer pairs where both firms borrowed simultaneously, around half of these paired firms borrowed from their common banks. Notice that there are around 15 major banks in the loan market from which a firm can potentially borrow from (see Table 1). Thus, our result indicates that when firms of a supplier-customer pair borrow from the same bank, they are more likely to borrow simultaneously than when borrowing from different banks.

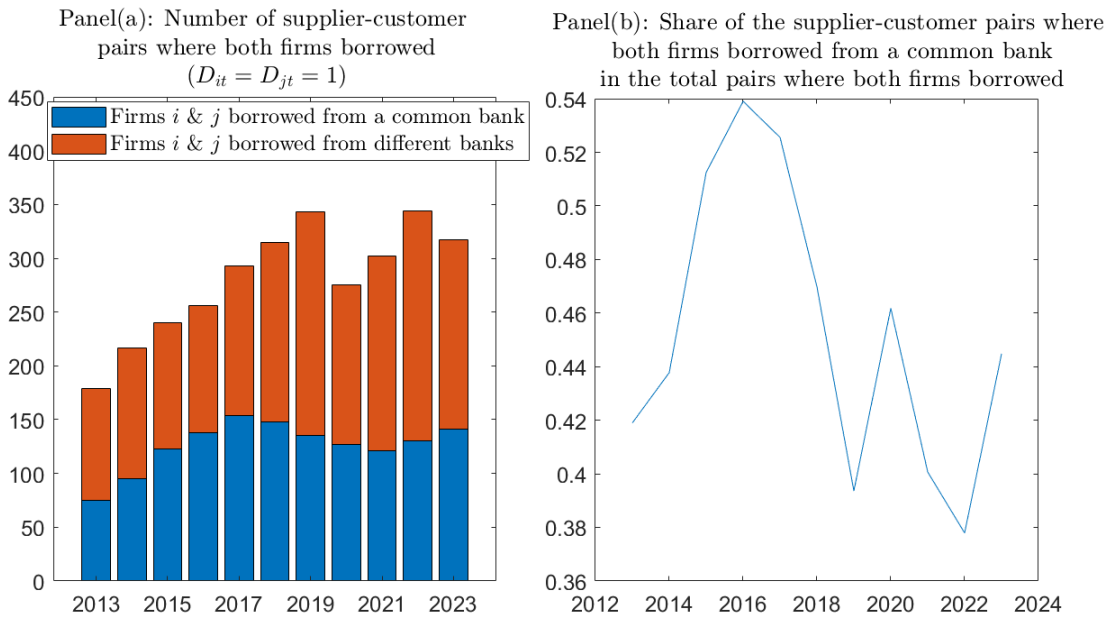


Figure 3: Supplier-customer pairs where both firms borrowed simultaneously (only loans from identified lending banks are included)

Notes: In Panel (a) the whole bar shows the number of supplier-customer pairs where both firms borrowed in year t ($D_{it} = D_{jt} = 1$). The blue segment represents the number of pairs where the two firms borrowed from a common bank, and the red segment represents the number of pairs where the two firms borrowed from different banks. Panel(b) shows the ratio of the number of pairs where the two firms borrowed from a common bank (the blue segment in Panel(a)) to the total number of pairs where both firms borrowed (the whole bar in Panel(a)).

To show the significance of the correlation between the financing activities of paired firms, we consider the following logit regression:

$$Prob(D_{it} = 1) = F_L(\beta D_{it}^C + \theta X_{i,t-1}), \tag{4}$$

where F_L is the cumulative logistic function, $F_L(z) = 1/(1+e^{-z})$. As before, D_{it} is the financing decision of firm i, and $D_{it} = 1$ if firm i borrows at least one loan in period t, and $D_{it} = 0$ otherwise. We denote by D_{it}^C the average financing decision of firm i's business partners (suppliers and customers), which is defined as

$$D_{it}^C = \frac{1}{N_i^C} \sum_{j \in \mathcal{I}_i^C} D_{jt}, \tag{5}$$

where D_{jt} is the financing decision of firm j, $\mathcal{I}_i^C$ is the set containing all the suppliers and customers of i, and N_i^C is the number of firms in set $\mathcal{I}_i^C$. Thus, D_{it}^C is essentially the fraction of firm i's business partners that borrowed in period t. X_{it} is a vector of firm-level control variables, including sales growth, leverage and ROA.

The results of regression 4 are reported in Table 3 below. As can be seen from Column (1) of Panel I, the financing activities of firms are significantly correlated with those of their business partners.

To investigate whether the financing activities of firms are more correlated with those of their business partners when they are connected with the same banks, we divide firms in our sample into two groups: (1) firms share more common banks with their business partners ($CB_i > 0.5$), and (2) those share less common banks with their business partners ($CB_i < 0.5$). As can be seen in Columns (2)-(4), the correlation is larger and more significant when the firm shares more common banks with its business partners.

Table 3: Results of regression (4)

	Firm i's financing decision (D_{it})						
	I. SOEs & Non-SOEs				II. Non-SOEs		
	(1) All	(2) $CB_i < 0.5$	(3) $CB_i \geq 0.5$	(4) $CB_i \geq 0.75$	(5) All	(6) $CB_i < 0.5$	(7) $CB_i \geq 0.5$
Borrowing of partner firms D_{it}^C	0.510**	0.389	0.794**	1.323***	0.725**	0.312	1.401***
	(0.224)	(0.272)	(0.362)	(0.448)	(0.338)	(0.399)	(0.516)
Observations	1888	1077	811	499	852	442	410
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results from logit regression (4). The dependent variable is a dummy D_{it} which takes the value of one if firm i borrowed at least one loan in year t and the value of zero otherwise. The key independent variable D_{it}^C defined by (5) is the share of firm i's business partners that borrowed at least one loan in year t. In Panel I, Column (1) reports the results when all the firms are included. Columns (2)-(4) report the results for the subgroups of firms with $CB_i < 0.5$, $CB_i \geq 0.5$ and $CB_i \geq 0.75$ respectively, where CB_i defined by (2) is the fraction of firm i's business partners that share at least one common bank with firm i. Panel II reports the results from the same regressions when we restrict the sample to non state-owned firms.

Also, as can be seen from Columns (5)-(7), the effect of sharing a common lender on the correlation between financing activities of firms and those of their business partners tends to be stronger for non state-owned firms than for state-owned firms. This is not surprising since coordination in the loan supply is important only when firms of a industrial chain are liquidity constrained. When liquidity is abundant, the optimal level of production can always be achieved with or without coordination in the loan supply.

Intensity of financing activities. We then investigate whether firms borrow more when they share more common banks with their business partners. To this end, we consider the following logit regression

$$Prob(D_{it} = 1) = F_L(\gamma CB_i + \theta X_{i,t-1}). \tag{6}$$

The key independent variable is CB_i, the fraction of firm i's business partners that share a common bank with from i, as defined by (2).

Table 4: Results of regression (6)

	I. Firm i's financing decision (D_{it})			II. Firm i's leverage (Lev_{it})		
	(1)	(2)	(3)	(4)	(5)	(6)
Common bank CB_i	1.559***			1.317**		
	(0.243)			(0.511)		
Common bank (Big) CB_i^B		1.670***			1.436**	
		(0.258)			(0.538)	
Common bank (Small) CB_i^S		0.478			-0.219	
		(0.506)			(0.387)	
Common bank (Up) CB_i^{UP}			1.680***			1.392***
			(0.287)			(0.507)
Common bank (Down) CB_i^{DW}			1.411***			1.200
			(0.298)			(0.871)
Observations	3605	3605	3605	3617	3617	3617
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel I reports the results from logit regression (6). Column (1) corresponds to the benchmark regression, where the key independent variable CB_i defined by (2) is the fraction of firm i's business partners that share a common bank with firm i. Columns (2) and (3) report the results for alternative specifications for CB_i. CB_i^B is the fraction of firm i's business partners that share a big common bank with firm i, and CB_i^S is the fraction that share only small common banks with i. CB_i^{UP} is the fraction of firm i's upstream partners (suppliers) that share a common bank with firm i, and CB_i^{DW} is the fraction of firm i's downstream partners (customers) that share a common bank with firm i. Panel II reports the results from the linear regression model where the independent variables are the same and the dependent variable is changed to firm i's leverage.

The results of regression (6) are reported in Table 4. As shown in Columns (1) and (4) of the table, firms tend to borrow more frequently and to have higher leverages when they share more common banks with their business partners. Figure 8 in Appendix A shows that firms that share common banks with their business partners not only borrow more frequently, but also borrow mostly from the common banks.

We then compare the effect of big common banks with the effect of small common banks on firms' financing activities. 'Large banks' include the five state-owned banks and the twelve joint stock banks, and all the other banks are considered as 'small banks'. As can be seen from Columns (2) and (5), firms tend to borrow more only when they share large common banks with their business partners, while sharing small common banks does not affect the firm's financing activities. This is not surprising since large banks with more branches and funds can better coordinate the loan supply to firms in supply chains.

Also, we compare the effect of common banks shared with upstream partners (suppliers) with the effect of common banks shared with downstream partners (customers) on firms. As shown in Columns (3) and (6), firms tend to borrow more frequently when they share more common banks with either their suppliers or customers. However, firms tend to have higher leverages only when they share more common banks with their suppliers. This indicates that coordination in the loan supply to industrial chains could be more beneficial for the downstream firms.

Responses to a negative collateral shock. Coordination failure is more likely to happen when the economic conditions are worsened, such as bank-run and fire-sale. To investigate if the likelihood of coordination failure between the lenders to firms in supply-chains is also higher during the periods of credit tightening, we now consider the firms' responses to the 2015 stock market crash. To this end, we consider the following regression:

$$Prob(D_{it} = 1) = F_L(\beta \cdot CB_i \cdot Y_{t-1}^{2016} + \theta X_{i,t-1}), \tag{7}$$

where Y_t^{2016} is a dummy for the stock market crash ($Y_t^{2016} = 1$ if $t >= 2016$).

Similarly, to investigate if the possibility of coordination failure rises after an adverse shock, we compare the group with more common banks to the group with less common bank. More specifically, we show that the coefficient of the interaction between Y_{t-1}^{2016} and the dummy indicating with more common banks is negative and statistically significant, while that of the interaction between Y_{t-1}^{2016} and the dummy indicating with less common banks is not significant.[3]

2.2 Loan-level evidence from supply chain finance

We have shown that when firms in supply chains are connected to the same banks, (i) their financing activities are more correlated with each other, and (ii) they borrow more frequently and have higher leverages (Subsection 2.1.2). A possible reason is that when the interconnected firms borrow from the same bank, the common lender can internalize the positive external effects associated with lending and coordinate the lending decisions. In this subsection, we provide an example on how a 'common bank' coordinates the loan supply to firms in supply chains though its internal management process. To this end, we use loan-level data from a major bank in China, which include detailed information on each loan extended to firms in and out of supply chains.

Among the borrowers of the bank, some of them are tagged with supply chain numbers, referred to as 'firms in supply chains', while the rest of them do not have a supply chain number, referred to as 'firms out of supply chains'. All the firms in a supply chain have a common supply-chain number.

For each supply chain, the largest leading company in the chain is labeled as the 'core firm', while the rest of the firms in the chain are labeled as the 'non-core firms', as illustrated in Figure 4.

When the bank lends to firms in supply chains, there can be two types of loans: (i) the loans lent through the bank's supply chain platform that are tagged with firms supply chain

[3]See the complete result in the appendix.

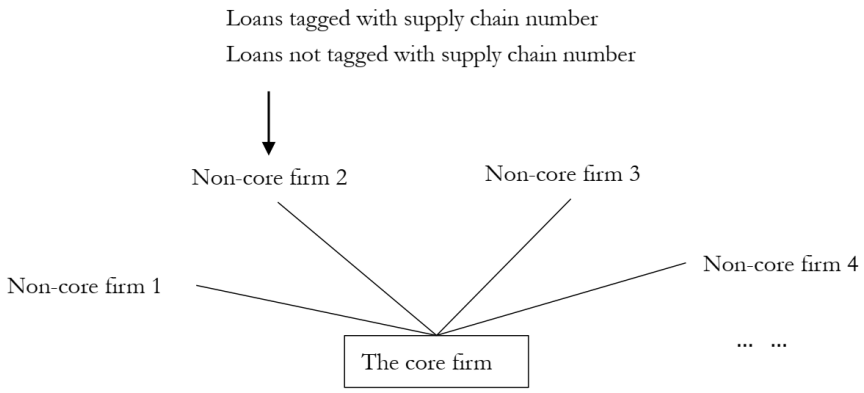


Figure 4: Core and non-core firms in a supply chain

number, and (ii) the regular loans without supply chain number. Obviously, a supply chain loan is supposed to be used for business operations related to the supply chain. Thus, when extending a supply chain loan, the bank is more likely to take into account the positive external effect of the loan on the other firms in the supply chain.

Figure 5 shows the amounts of the loans extended to the core and non-core firms in a specific supply chain. The red triangles represent loans to the core firm. The dots of the same color correspond to the loans to the same non-core firm. As can be seen, the loans to the core firm tend to be larger than the loans to the non-core firms. Also, the financing activities of the firms in this specific supply chain are correlated with each other.

We first focus on the non-core firms in supply chains and compare the supply chain loans (with supply chain number) versus the regular loans (without supply chain number) borrowed by these firms. To this end, we consider the following regression:

$$\ln L_{ijt} = \beta \ln L^{C}_{j,t-1} + \theta X_{j,t-1} + u_j + v_t + e_{ijt}, \tag{8}$$

where L_{ijt} is the total lending to non-core firm i in supply chain j in month t, which could be either (i) the total amount of supply chain loans (with supply chain number), or (ii) the total amount of regular loans (without supply chain number). L^{C}_{jt} is the total lending to the core firm of supply chain j in month t, X_{jt} is the vector of control variables for the core firm which are observed at the annual frequency.

The results of regression (8) are reported in Table 5. As can be seen, for the loans lent to the non-core firms, only those tagged with the firms' supply chain numbers is significantly correlated with the loans lent to the core firms. This indicates that more lending to the core firm is usually accompanied with more lending to the non-core firms through the bank's supply chain platform. In contrast, when the core firm gets more loans, the regular loans

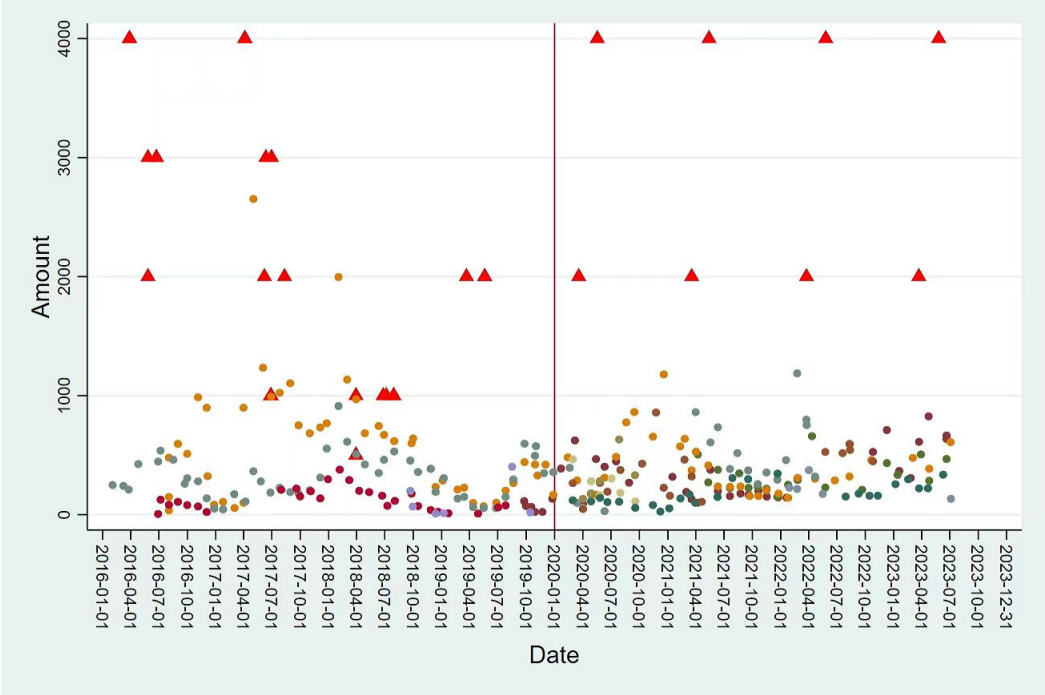


Figure 5: The loans to the core and non-core firms in a supply chain

Notes: The figure shows the amounts of loans lent to the core and the non-core firms in a specific supply chain. Each red triangle represents a loan to the core firm. Each dot represents a loan to a non-core firm. The dots of the same color correspond to the loans to the same non-core firm.

borrowed by non-core firms do not increase.

Table 5: Results of regression (8)

	I. Loans tagged with supply-chain number		II. Loans not tagged with supply-chain number	
	(1)	(2)	(3)	(4)
Log loans to the core firm, $\ln L_{jt}^{C}$	0.083***	0.040**	-0.023*	0.011
	[8.83]	[2.30]	[-1.86]	[0.51]
Log cash holding of the core firm		-0.066		0.181***
		[-0.84]		[2.61]
Log fixed assets of the core firm		0.041		0.033
		[0.44]		[0.53]
Log sales of the core firm		0.799***		-0.018
		[4.24]		[-0.19]
Observations	8665	6831	7588	4362
Supply chain FE	No	Yes	No	Yes
Moth FE	No	Yes	No	Yes

Notes: Robust t-statistics in parentheses: $***p < 0.01, **p < 0.05, *p < 0.1$.

Second, we compare the financing activities the firms in supply chains with those of the firms out of supply chains, following the credit stimulus in 2009-2010. To this end, we consider the following regression

$$\ln L_{it} = \beta \cdot S_t^{2010} \cdot SC_i + \theta X_{j,t-1} + u_i + v_t + e_{it}, \tag{9}$$

where L_{it} is the total amount of loans lent to firm i, S_t^{2010} is a dummy for the credit stimulus ($S_t^{2010} = 1$ if $t >= 2010$), and SC_i is an indicator for supply chain firm ($SC_i = 1$ if firm i is assigned with a supply chain number).

Table 6: Results of regression (9)

	$\ln loan_{it}$		
	(1)	(2)	(3)
$S_t^{2010} \cdot SC_i$	0.211***	0.134***	0.224***
	[16.71]	[6.62]	[3.77]
$\ln assets_{i,t-1}$		0.105***	0.049***
		[15.61]	[3.86]
$\ln liabilities_{i,t-1}$		0.165***	0.116***
		[38.76]	[15.01]
$\ln sales_{i,t-1}$			0.043***
			[7.68]
$\ln profits_{i,t-1}$			0.018***
			[6.31]
Observations	2140972	806322	241520
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Robust t-statistics in parentheses: $***p < 0.01, **p < 0.05, *p < 0.1$.

The results of regression (9) are reported in Table 6. As can be seen, following the credit expansion in 2009, firms in supply chains experienced around a 25% greater increase in loans, when compared with firms not in supply chains. This result is consistent with Fact 3 in subsection 2.1.

3 The Model

In this section, we develop a simple theoretical model of industrial chain with a banking sector that formalizes the key features of the firm-bank relationship in China. The model allows us to rationalize the empirical findings. The key empirical facts are the following.

1. On average each firm has banking relationship with a small number of banks and do not switch to new banks frequently.

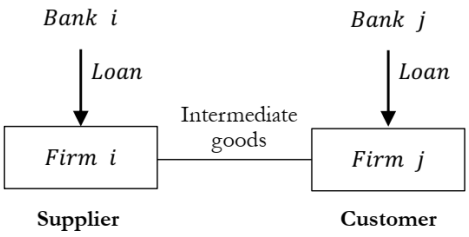
2. When a firm and its business partner(s) have banking relationship with the same bank, the firm's financing activities are more correlated with those of its partner(s).

3. Also, when a firm and its business partner(s) are connected to the same bank, that firm tends to borrow more frequently and to have a higher leverage.

The first fact informs us on how to set up the model, and the second and third facts are endogenously generated by the model. The model predicts that when firms of a supplier-customer pair are connected to the same bank, the common bank can coordinate the loan supply to the two firms. As results, the financing activities of the two firms are more synchronized and both of the two firms borrow more from the bank, when compared to the case where the two firms are connected to different banks.

3.1 Model set-up

We consider a simple model of industrial chain with two representative firms, i and j, with the former being the supplier and the latter being the customer. The two firms are connected to two banks (relationship banking), i and j, as shown in the figure below. In the benchmark model, we assume that banks i and j does not coordinate. Then, we allow for coordination by assuming that banks i and j are subsidiaries of a 'large' bank.



Each firm is endowed with C units of cash. In addition to the endowed cash, firms can borrow loans from their connected banks to meet the working capital requirement.

Each bank is endowed with one unit of funds, which can be either lent to the connected firm or invested on an alternative project.

The production sector is assumed to be competitive. Firms take as given the loan interest rates and choose the amounts they borrow from banks. In contrast, the two monopolistic banks, i and j, choose their loan supplies, and then the loan interest rates are determined by the market clearing conditions.

3.1.1 The production sector

Supplier. Firm i produces intermediate good Y_i using labor N_i, and the production function is given as

$$Y_i = N_i. \tag{10}$$

Firm i has to make the wage payment before production starts. The working capital requirement can be met by using the endowed cash C and borrowing a working capital loan D_i from

the connected bank i. The liquidity constraint is

$$\bar{w}N_i \leq D_i + C, \tag{11}$$

where $\bar{w}$ is the exogenously given wage rate in terms of the final good.

Firm i chooses labor inputs and the amount of working capital loans to maximize profits, while taking as given the price of intermediate good, q, and the loan interest rate r_i. The optimization problem of firm i is thus given as

$$\max_{N_i, D_i} \quad qY_i - \bar{w}N_i - r_i D_i, \quad \textit{subject to (10) and (11)}.$$

The profits are the operating revenue, qY_i, net of the direct cost, $\bar{w}N_i$, and the interests charged by the bank, $r_i D_i$.

Customer. Firm j produces final good Y_j using labor N_j and intermediate good Y_i. The production function is assumed to be Cobb-Douglas and given as

$$Y_j = Y_i^{\alpha} N_j^{1-\alpha}, \tag{12}$$

where $\alpha \in (0, 1)$ is the share of intermediate good.

Similarly, firm j can meet the working capital requirement by using the endowed cash C and by borrowing a working capital loan D_j from bank j. We assume that the pledgeability of intermediate goods is perfect, and thus the supplier (firm i) provides full trade credit and does not ask for any down payment. As a result, firm j does not need to pay for the intermediate good in advance. Therefore, the liquidity constraint faced by firm j is given as

$$\bar{w}N_j \leq D_j + C. \tag{13}$$

Firm j chooses labor and intermediate inputs and the amount of working capital loan to maximize profits, while taking as given the price of intermediate good, q, and the loan interest rate, r_j. Thus, the optimization problem of firm j is given as

$$\max_{N_j, D_j} \quad Y_j - qY_i - \bar{w}N_j - r_j D_j, \quad \textit{subject to (12) and (13)}.$$

Again, profits are the operating revenue, Y_j, net of the direct costs, $qY_i + \bar{w}N_j$, and the financial cost, $r_j D_j$.

Partial equilibrium given (D_i, D_j)**.** Before describing the optimization problems of the banks, we first characterize the partial equilibrium given the loan supplies, (D_i, D_j). We focus only on the cases where the firms' liquidity constraints, (11) and (13), bind.

Note that the optimization of firm i implies

$$q = \bar{w}(1 + r_i). \tag{14}$$

The left hand side is the marginal return of labor and the right hand side is its marginal cost, which is the wage rate, $\bar{w}$, augmented by a financial cost, $1 + r_i$.

Note also that the optimization of firm j implies

$$\frac{\partial Y_j}{\partial Y_i} = \alpha \left(\frac{N_j}{Y_i}\right)^{1-\alpha} = q, \tag{15}$$

$$\frac{\partial Y_j}{\partial N_j} = (1-\alpha)\left(\frac{Y_i}{N_j}\right)^{\alpha} = \bar{w}(1 + r_j). \tag{16}$$

The above two conditions say that the marginal returns of intermediate good and labor should be equal to their marginal costs. Again, the marginal cost of labor is the wage rate, $\bar{w}$, augmented by the financial cost, $1 + r_j$.

Thus, given the loan supplies of the two banks, (D_i, D_j), the firms' labor inputs and output, N_i, N_j, Y_i and Y_j, the price of intermediate good, q, and the interest rates of loans, r_i and r_j, are jointly determined by equations (10) - (16).

Complementarity. Note that by using the (binding) liquidity constraints, (11) and (13), in the production functions, (10) and (12), the firms' output can be expressed as functions of loan supplies:

$$Y_i = \frac{D_i + C}{\bar{w}},$$

$$Y_j = \left(\frac{D_i + C}{\bar{w}}\right)^{\alpha} \left(\frac{D_j + C}{\bar{w}}\right)^{1-\alpha}.$$

This is because the labor inputs of the two firms, N_i and N_j, are determined by the amounts of loans provided by the banks. By using the above conditions in the firms' optimizing conditions, (14), (15) and (16), we have the following *loan demand functions*

$$1 + r_i = \frac{\alpha}{\bar{w}} \left(\frac{D_j + C}{D_i + C}\right)^{1-\alpha}, \tag{17}$$

$$1 + r_j = \frac{1-\alpha}{\bar{w}} \left(\frac{D_i + C}{D_j + C} \right)^{\alpha}. \tag{18}$$

Condition (17) is the loan demand function faced by bank i. As can be seen, all else being equal, the return of lending, r_i, decreases with bank i's loan supply D_i. However, bank i's lending rate, r_i, also depends positively on bank j's loan supply D_j. The loan demand function (17) faced by bank i is shifted downward when D_j is low. This is because if the downstream firm j does not get any loans from bank j ($D_j = 0$), firm j's hiring is constrained and $N_j = C/\bar{w}$. In this case, firm j's demand for intermediate good is low (see (15)), making production less profitable for the upstream firm i. As a result, firm i's demand for working capital loan decreases.

Similarly, condition (18) is the loan demand function faced by bank j, which is shifted downward when bank i's loan supply D_i decreases. This is because if bank i does not lend any loan to the upstream firm i ($D_i = 0$), the supply of intermediate good is limited and $Y_i = C/\bar{w}$. Thus, the price of intermediate good tends to be high, making production less profitable for the downstream firm j's. As a result, firm j's demand for working capital loans tends to be low.

Lemma 1 (Partial equilibrium.)**.** *Given banks' loan supplies, D_i and D_j, the loan rates in the partial equilibrium are given by (17) and (18).*

3.1.2 Banks

We assume that banks make only discrete choice on how to use the endowed funds. We denote by D_i bank i's lending decision, and $D_i = 1$ if the one unit of endowed funds is lent to firm i, and $D_i = 0$ if it is invested on the alternative project. This assumption does not affect the complementarity in lending discussed above, but ensures that our theoretical analysis is consistent with the empirical facts.[4]

Bank i's optimization. The gross return of the alternative project, z_i, is assumed to be stochastic and uniformly distributed on $[0, \bar{z}_i]$. After observing realized z_i, bank i chooses D_i to maximize profits, while taking the loan demand function (17) as given. Notice that bank i takes as given bank j's decision D_j. Thus, bank i's optimization problem is given as

$$\max_{D_i \in \{0,1\}} \left[D_i(1 + r_i) - \kappa \cdot \frac{D_i(1 + r_i)}{qY_i} \right] + (1 - D_i)z_i, \quad \textit{subject to (17)}.$$

[4]Remember that the key empirical results are from the logit regressions ((4) and (6)).

The second term in the square bracket is the monitoring cost of lending to firm i, which is positively related to the ratio of debt, $D_i(1+r_i)$, to firm i's operating revenue, qY_i. It can be shown that in equilibrium[5]

$$\kappa \cdot \frac{D_i(1+r_i)}{qY_i} = \kappa \cdot \frac{D_i}{D_i + C}.$$

As can be seen from the loan demand function (17), the net return from bank lending ($D_i = 1$) given D_j is

$$1 + r_i(D_i = 1, D_j) = \frac{\alpha}{\bar{w}} \left(\frac{D_j + C}{1 + C} \right)^{1-\alpha}.$$

Thus, bank i' optimal choice is

$$D_i = \begin{cases} 1 & \textit{if} \quad \frac{\alpha}{\bar{w}} \left(\frac{D_j + C}{1 + C} \right)^{1-\alpha} - \frac{\kappa}{1+C} \geq z_i, \\ 0 & \textit{otherwise.} \end{cases} \tag{19}$$

Thus, bank i lends to the connected firm i only when the net return of lending is higher than the realized return of its alternative project, z_i.

Bank j's optimization. The gross return of bank j's alternative project, z_j, is assumed to be uniformly distributed on $[0, \bar{z}_j]$, and independent from that of bank i, z_i. After observing realized z_j, bank j chooses D_j to maximize profits, while taking the loan demand function (18) as given. As before, bank j takes as given bank i's decision D_i. Thus, bank j's optimization problem is given as

$$\max_{D_j \in \{0,1\}} \left[D_j(1+r_j) - \kappa \cdot \frac{D_j(1+r_j)}{Y_j - qY_i} \right] + (1 - D_j) z_j, \quad \textit{subject to (18).}$$

Again, it can also be shown that in equilibrium (see (12), (13), (15) and (16))

$$\kappa \cdot \frac{D_j(1+r_j)}{Y_j - qY_i} = \kappa \cdot \frac{D_j}{D_j + C}.$$

As can be seen from the loan demand function (18), the net return from bank lending ($D_j = 1$) given D_i is

$$1 + r_j(D_j = 1, D_i) = \frac{1-\alpha}{\bar{w}} \left(\frac{D_i + C}{1 + C} \right)^{\alpha}.$$

Thus, bank j's optimal choice is given as

[5] This can be derived from (10), (11) and (14).

$$D_j = \begin{cases} 1 & \text{if} \quad \frac{1-\alpha}{\bar{w}} \left(\frac{D_i + C}{1+C} \right)^{\alpha} - \frac{\kappa}{1+C} \geq z_j, \\ 0 & \text{otherwise.} \end{cases} \tag{20}$$

As can be seen, bank j lends to connected firm j only when the net return of lending is higher than the realized z_j.

Equilibrium. An *equilibrium* consists of banks' loan supply decisions, D_i and D_j, and loan interest rates, r_i and r_j, such that (i) given the loan interest rates, firms' borrowing decisions are optimal ((17) and (18)), and (ii) banks' decisions are optimal ((19) and (20)).

3.2 Multiple equilibria

Due to the interdependence of the two banks' lending decisions (see (19) and (20)), there could be multiple equilibria. In this subsection, we investigate the conditions for the existence of multiple equilibria.

Note first that for bank i, there are two thresholds for the return of the alternative project, z_i, such that if $z_i < \hat{z}_i^L$, bank i always lends the endowed funds to firm i regardless of bank j's lending decision D_j, and if $z_i > \hat{z}_i^H$, bank i always invests the endowed funds in the alternative project and does not lend to firm i, regardless of D_j. The two thresholds for z_i are given as

$$\hat{z}_i^L = \frac{\alpha}{\bar{w}} \left(\frac{C}{1+C} \right)^{1-\alpha} - \frac{\kappa}{1+C}, \tag{21}$$

$$\hat{z}_i^H = \frac{\alpha}{\bar{w}} - \frac{\kappa}{1+C}. \tag{22}$$

$\hat{z}_i^L$ is the net return of lending for bank i if bank j does not lend ($D_j = 0$), and $\hat{z}_i^H$ is the net return of lending if bank j lends ($D_j = 1$) (see (17)), with $\hat{z}_i^L < \hat{z}_i^H$. Thus, if $z_i < \hat{z}_i^L$, bank i always lends ($D_i = 1$) regardless of bank j's decision D_j, and it never lends ($D_i = 0$) if $z_i > \hat{z}_i^H$. However, when the realized z_i lies between $\hat{z}_i^L$ and $\hat{z}_i^H$, bank i lends ($D_i = 1$) if and only if bank j also lends ($D_j = 1$).

Thus, bank i's optimal decision (19) can be re-written as

$$D_i = \begin{cases} 1 & \text{if} \quad z_i \leq \hat{z}_i^L, \\ 1 & \text{if} \quad z_i \in (\hat{z}_i^L, \hat{z}_i^H) \text{ and } D_j = 1, \\ 0 & \text{if} \quad z_i \in (\hat{z}_i^L, \hat{z}_i^H) \text{ and } D_j = 0, \\ 0 & \text{if} \quad z_i \geq \hat{z}_i^H. \end{cases} \tag{23}$$

Similarly, for bank j, there are two thresholds for z_j, such that if $z_j < \hat{z}_j^L$, bank j always lends the endowed funds to firm j regardless of bank i's lending decision D_i, and if $z_j > \hat{z}_j^H$, bank j invests on the alternative project and does not lend regardless of D_i. The two thresholds for z_j are given as

$$\hat{z}_j^L = \frac{1-\alpha}{\bar{w}}\left(\frac{C}{1+C}\right)^{\alpha} - \frac{\kappa}{1+C}, \tag{24}$$

$$\hat{z}_i^H = \frac{1-\alpha}{\bar{w}} - \frac{\kappa}{1+C}. \tag{25}$$

As in the previous case of bank i, $\hat{z}_j^L$ is the net return of lending for bank j if bank i does not lend ($D_i = 0$), and $\hat{z}_j^H$ is the net return of lending if bank i lends ($D_i = 1$). When the realized z_j lies between $\hat{z}_j^L$ and $\hat{z}_j^H$, bank j lends ($D_j = 1$) if and only if bank i also lends ($D_i = 1$).

Thus, bank j's optimal decision (20) can be re-written as

$$D_j = \begin{cases} 1 & if \quad z_j \leq \hat{z}_j^L, \\ 1 & if \quad z_j \in (\hat{z}_j^L, \hat{z}_j^H) \text{ and } D_i = 1, \\ 0 & if \quad z_j \in (\hat{z}_j^L, \hat{z}_j^H) \text{ and } D_i = 0, \\ 0 & if \quad z_j \geq \hat{z}_j^H. \end{cases} \tag{26}$$

Figure 6 shows banks' decisions in equilibrium, conditional on the realized returns of the alternative projects, z_i and z_j. When the realized (z_i, z_j) falls in the blue area, the equilibrium is unique and both banks lend ($D_i = D_j = 1$). This is the case when the returns of the alternative projects (z_i, z_j) are both low.

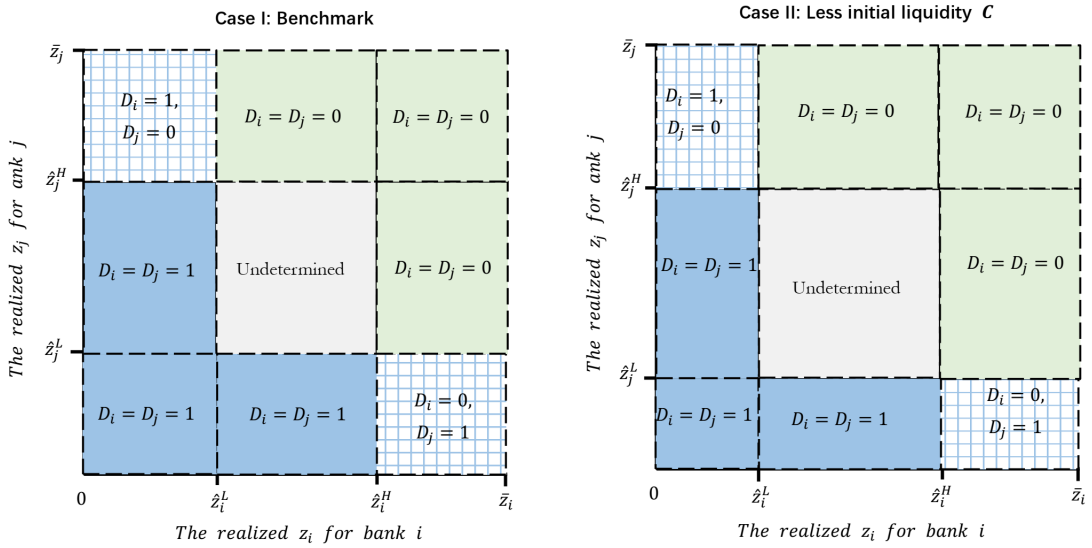


Figure 6: Banks' decisions in equilibrium (without coordination)

When the realized (z_i, z_j) falls in the green area, the equilibrium is unique and both banks do not lend ($D_i = D_j = 0$). This is the case when the returns of the alternative projects (z_i, z_j) are both high.

When the realized (z_i, z_j) falls in the areas with blue grid pattern on the two ends of the diagonal, the equilibrium is unique and only one bank lends ($D_i = 1, D_j = 0$ or $D_i = 0, D_j = 1$). This is the case when the return of the alternative project is high for one bank, but low for the other.

Most importantly, when the realized (z_i, z_j) falls in the gray area in the middle of the diagram, there could be two equilibria. In the 'Good' equilibrium, both banks lend ($D_i = D_j = 1$). In the 'Bad' equilibrium, none of the banks lend ($D_i = D_j = 0$). Obviously, coordination between the two banks eliminates the 'Bad' equilibrium, increasing the aggregate loan supply.

When multiple equilibria exist (i.e., the gray ares of Figure 6), the equilibrium is chosen by a sunspot shock, s. With probability τ, $s = 1$ and the 'Good' equilibrium is realized. With probability $1 - \tau$, $s = 0$ and the 'Bad' equilibrium is realized.

Proposition 1 (No coordination.)**.** *Without coordination, the lending decisions of banks i and j are not perfectly correlated.*

1. *If* $z_i < \hat{z}_i^L$ & $z_j < \hat{z}_j^H$ *or* $z_i < \hat{z}_i^H$ & $z_j < \hat{z}_j^L$*, both banks lend to the firms* ($D_i = D_j = 1$).
2. *If* $z_i > \hat{z}_i^L$ & $z_j > \hat{z}_j^H$ *or* $z_i > \hat{z}_i^H$ & $z_j > \hat{z}_j^L$*, neither of the banks lends to the firms* ($D_i = D_j = 0$).
3. *If* $z_i < \hat{z}_i^L$ & $z_j > \hat{z}_j^H$*, bank i lends to firm i and bank j does not lend* ($D_i = 1, D_j = 0$).
4. *If* $z_i > \hat{z}_i^H$ & $z_j < \hat{z}_j^L$*, bank j lends to firm j and bank i does not lend* ($D_i = 0, D_j = 1$).
5. *If* $z_i \in [\hat{z}_i^L, \hat{z}_i^H]$ & $z_j \in [\hat{z}_j^L, \hat{z}_j^H]$*, both banks lend to the firms* ($D_i = D_j = 1$) *when the sunspot shock s is one and otherwise neither of the banks lends* ($D_i = D_j = 0$).

Finally, the aggregate lending of the whole production sector, denoted by D_A, is simply the expected value of $D_i + D_j$:

$$D_A = \mathbb{E}_{z_i, z_j}[D_i + D_j]. \tag{27}$$

A negative liquidity shock. Suppose an adverse shock decreases firms' cash inflows, and thus each firm starts with less cash, C. This tends to raise the monitoring cost of banks, since the firms' net worth is lower. As a result, the thresholds $\hat{z}_i^L$, $\hat{z}_i^H$, $\hat{z}_j^L$ and $\hat{z}_j^H$ decrease, reducing the likelihood of bank lending (i.e., the blue area in Figure 6). Moreover, since $\hat{z}_i^L$ decreases more than $\hat{z}_i^H$, and $\hat{z}_j^L$ decreases more than $\hat{z}_j^H$, thus the likelihood for multiplicity (i.e., the gray area in Figure 6) becomes larger.

Proposition 2 (Low liquidity and fragility). *When firms' initial liquidity C declines, the likelihood for multiplicity increases and the aggregate lending to firms,* $\mathbb{E}_{z_i,z_j}[D_i + D_j]$*, decreases.*

3.3 Coordination

To investigate how coordination can affect the loan supply of the banks, we now consider the case where two banks i and j are subsidiaries of a large banking group, and the head office maximizes the total profits of the two banks. Thus, the optimization problem of the head office is given as

$$\max_{D_i\in\{0,1\},D_j\in\{0,1\}} \left[D_i(1+r_i) - \kappa\cdot\frac{D_i(1+r_i)}{qY_i}\right] + (1-D_i)z_i \\ + \left[D_j(1+r_j) - \kappa\cdot\frac{D_j(1+r_j)}{Y_j - qY_i}\right] + (1-D_j)z_j, \quad \textit{subject to (17) and (18)}$$

The total profits, denoted by π^H, is a function of lending decisions (D_i, D_j)

$$\pi^A(D_i,D_j) = \begin{cases} z_i + z_j & \textit{if} \quad D_i = 0, D_j = 0, \\ z_i + \hat{z}_j^L & \textit{if} \quad D_i = 0, D_j = 1, \\ \hat{z}_i^L + z_j & \textit{if} \quad D_i = 1, D_j = 0, \\ \hat{z}_i^H + \hat{z}_j^H & \textit{if} \quad D_i = 1, D_j = 1, \end{cases}$$

where $\hat{z}_i^L$, $\hat{z}_i^H$, $\hat{z}_j^L$ and $\hat{z}_j^H$ are given by (21), (22), (24) and (25).

Assumption 1. *Assume that* $\bar{z}_i$ *and* $\bar{z}_j$ *satisfy*

$$\bar{z}_i - \hat{z}_i^H < \hat{z}_j^H - \hat{z}_j^L \quad \textit{and} \quad \bar{z}_j - \hat{z}_j^H < \hat{z}_i^H - \hat{z}_i^L.$$

We assume that the positive externality of lending, $\hat{z}_j^H - \hat{z}_j^L$ and $\hat{z}_i^H - \hat{z}_i^L$, are large enough such that the conditions in Assumption 1 are satisfied. It can be shown that under coordination the lending decisions of the two banks are perfectly correlated. Both banks i and j lend to the firms ($D_i = D_j = 1$) if and only if the total return of the alternative projects is smaller than the total profits from lending, i.e., $z_i + z_j < \hat{z}_i^H + \hat{z}_j^H$, as illustrated in Figure 7. Otherwise, both banks i and j invest the endowed funds in the alternative projects rather than lending to the firms ($D_i = D_j = 0$).

In addition, under coordination banks are more likely to lend to the firms. As can be seen in Figure 7, the size of the no lending area (the green area) becomes strictly smaller, when

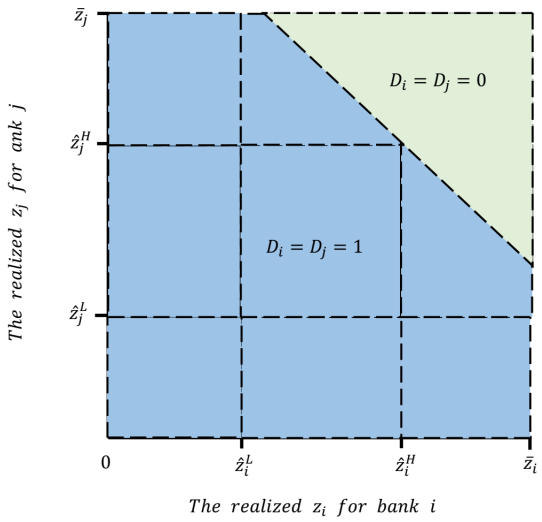


Figure 7: Banks' decisions in equilibrium under coordination

compared to the case where banks do not coordinate (Figure 6). This indicates that under coordination the aggregate lending of banks, $\mathbb{E}_{z_i,z_j}[D_i + D_j]$, is larger.

Proposition 3 (Coordination)**.** *Under coordination, the lending decisions of banks i and j are perfectly correlated. Both banks i and j lend to the firms ($D_i = D_j = 1$) if and only if the realized z_i and z_j satisfy*

$$z_i + z_j < \hat{z}_i^H + \hat{z}_j^H.$$

Otherwise, both banks invest in the alternative projects and do not lend to the firms ($D_i = D_j = 0$). In addition, under coordination the aggregate lending to firms, $\mathbb{E}_{z_i,z_j}[D_i + D_j]$, is larger, when compared to the case where banks do not coordinate.

4 Conclusion

This paper studies how coordination between lenders can affect the loan supply to firms in industrial chains. Using Chinese firm-level data, we find that the financing activities of firms in an industrial chain are more correlated with each other when those firms are connected to the same bank than when they are connected to different banks. We find also that when a firm and its business partners are connected to a common bank, they borrow more frequently and have higher leverages. We propose a model of industrial chain with relationship banking that can capture the empirical findings. In particular, we show that when the lenders are branches of the same bank and can coordinate their lending decisions, they lend more to the firms and the loan supply is more stable. We use granular loan-level data for supply chain

finance from a major bank in China to provide an example on how bank coordinates the loan supply to its customers in industrial chains through internal management process.

Our study highlights the crucial role that banking coordination plays in the development of industrial chains. By demonstrating that upstream and downstream firms connected to the same bank exhibit better financial coordination, our findings suggest significant policy implications. Policymakers should consider promoting relationship banking within industrial chains to enhance financial stability and efficiency. Encouraging banks to develop specialized internal management processes for supply chain finance could facilitate more synchronized lending decisions, ultimately supporting the growth and resilience of interconnected firms. This approach could be particularly beneficial in emerging markets, where industrial chains are often more vulnerable to financial disruptions.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2015) 'Networks and the macroeconomy: An empirical exploration.' In 'NBER Macroeconomics Annual 2015, Volume 30' NBER Chapters (National Bureau of Economic Research, Inc) pp. 276–335

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012) 'The network origins of aggregate fluctuations.' *Econometrica* 80(5), 1977–2016

Afrouzi, Hassan, and Saroj Bhattarai (2023) 'Inflation and GDP dynamics in production networks: A sufficient statistics approach.' NBER Working Papers 31218, National Bureau of Economic Research, Inc, May

Altinoglu, Levent (2021) 'The origins of aggregate fluctuations in a credit network economy.' *Journal of Monetary Economics* 117(C), 316–334

Barrot, Jean-Noel, and Julien Sauvagnat (2016) 'Input specificity and the propagation of idiosyncratic shocks in production networks.' *The Quarterly Journal of Economics* 131(3), 1543–1592

Bigio, Saki (2023) 'A Theory of Payments-Chain Crises.' NBER Working Papers 30859, National Bureau of Economic Research, Inc, January

Bigio, Saki, and Jennifer La'O (2020) 'Distortions in Production Networks.' *The Quarterly Journal of Economics* 135(4), 2187–2253

Bocola, Luigi, and Gideon Bornstein (2023) 'The Macroeconomics of Trade Credit.' NBER Working Papers 31026, National Bureau of Economic Research, Inc, March

Carvalho, Carlos, and Fernanda Nechio (2011) 'Aggregation and the PPP Puzzle in a sticky-price model.' *American Economic Review* 101(6), 2391–2424

Chod, Jiri, Evgeny Lyandres, and S. Alex Yang (2019) 'Trade credit and supplier competition.' *Journal of Financial Economics* 131(2), 484–505

Costello, Anna M. (2019) 'The value of collateral in trade finance.' *Journal of Financial Economics* 134(1), 70–90

Costello, Anna M. (2020) 'Credit Market Disruptions and Liquidity Spillover Effects in the Supply Chain.' *Journal of Political Economy* 128(9), 3434–3468

Devereux, Michael B, Karine Gente, and Changhua Yu (2023) 'Production networks and international fiscal spillovers.' *The Economic Journal* 133(653), 1871–1900

Ersahin, Nuri, Mariassunta Giannetti, and Ruidi Huang (2024) 'Trade credit and the stability of supply chains.' *Journal of Financial Economics*

Gabaix, Xavier (2011) 'The granular origins of aggregate fluctuations.' *Econometrica* 79(3), 733–772

Galí, Jordi (2015) *Monetary policy, inflation, and the business cycle: An introduction to the new keynesian framework and its applications second edition* number 10495. In 'Economics Books.' (Princeton University Press)

Ghassibe, Mishel (2021a) 'Endogenous production networks and non-linear monetary transmission.' Technical Report, Working paper

_ (2021b) 'Monetary policy and production networks: An empirical investigation.' *Journal of Monetary Economics* 119(C), 21–39

Giannetti, Mariassunta, and Farzad Saidi (2019) 'Shock Propagation and Banking Structure.' *The Review of Financial Studies* 32(7), 2499–2540

Giovanni, Julian Di, and Galina Hale (2022) 'Stock market spillovers via the global production network: Transmission of U.S. monetary policy.' *Journal of Finance* 77(6), 3373–3421

Gofman, Michael, and Youchang Wu (2022) 'Trade credit and profitability in production networks.' *Journal of Financial Economics* 143(1), 593–618

Grigoris, Fotis, Yunzhi Hu, Gill Segal, and Ralph Koijen (2023) 'Counterparty Risk: Implications for Network Linkages and Asset Prices.' *The Review of Financial Studies* 36(2), 814–858

Hertzel, Michael G, Zhi Li, Micah S Officer, and Kimberly J Rodgers (2008) 'Inter-firm linkages and the wealth effects of financial distress along the supply chain.' *Journal of Financial Economics* 87(2), 374–387

Houston, Joel F., Chen Lin, and Zhongyan Zhu (2016) 'The Financial Implications of Supply Chain Changes.' *Management Science* 62(9), 2520–2542

Jacobson, Tor, and Erik Schedvin (2015) 'Trade Credit and the Propagation of Corporate Failure: An Empirical Analysis.' *Econometrica* 83(4), 1315–1371

Kouvelis, Panos, Xiaole Wu, and Yixuan Xiao (2019) 'Cash Hedging in a Supply Chain.' *Management Science* 65(8), 3928–3947

La'O, Jennifer, and Alireza Tahbaz-Salehi (2022) 'Optimal monetary policy in production networks.' *Econometrica* 90(3), 1295–1336

Liu, Ernest (2019) 'Industrial Policies in Production Networks.' *The Quarterly Journal of Economics* 134(4), 1883–1948

Luo, Shaowen, and Daniel Villar (2023) 'Propagation of shocks in an input-output economy: Evidence from disaggregated prices.' *Journal of Monetary Economics* 137(C), 26–46

Martins, Theo Cotrim, Rafael Schiozer, and Fernando de Menezes Linardi (2023) 'The information content from lending relationships across the supply chain.' *Journal of Financial Intermediation*

Nakamura, Emi, and Jon Steinsson (2010) 'Monetary non-neutrality in a multisector menu cost model.' *The Quarterly Journal of Economics* 125(3), 961–1013

Pasten, Ernesto, Raphael Schoenle, and Michael Weber (2017) 'Price rigidity and the origins of aggregate fluctuations.' NBER Working Papers 23750, National Bureau of Economic Research, Inc, August

Pasten, Ernesto, Raphael Schoenle, and Michael Weber (2020) 'The propagation of monetary policy shocks in a heterogeneous production economy.' *Journal of Monetary Economics* 116(C), 1–22

Rubbo, Elisa (2023) 'Networks, phillips curves, and monetary policy.' *Econometrica* 91(4), 1417–1455

Saidi, Farzad, and Daniel Streitz (2021) 'Bank Concentration and Product Market Competition.' *The Review of Financial Studies* 34(10), 4999–5035

Schwert, Michael (2018) 'Bank Capital and Lending Relationships.' *Journal of Finance* 73(2), 787–830

Xu, Zhihao, and Changhua Yu (2025) 'Optimal monetary policy in production networks with distortions.' *Journal of Economic Theory* 225, 105979

A Empirical results

Table 7: The distribution of supplier-customer pairs

Rank	Code	Industry	No. of SC pairs	Share
1	C	Manufacturing	2745	59.7%
2	G	Transportation, warehousing and postal services	349	7.6%
3	D	Electricity, heat, gas and water production and supply	328	7.1%
4	I	Information transmission, software and technology	226	4.9%
5	K	Real estate	218	4.7%
6	B	Mining	189	4.1%
7	F	Wholesale and Retail	150	3.3%
8	S	Comprehensive	86	1.9%
9	N	Water conservancy, environment and public facilities	71	1.5%
10	E	Construction	63	1.4%
		Others	390	3.7%
Ownership			No. of SC pairs	Share
State-owned			2372	57.0%
Now state-owned			1786	43.0%

Table 8: The purpose of loans

Rank	Code	Loan purpose	No. of loans	Share
1	100	Business Operations	47612	59.2%
2	200	Replenishing liquidity	5483	6.7%
3	700	Project Construction	2185	2.7%
		Others	26562	31.4%

Table 9: Results of regression (7)

	$\ln loan_{it}$
	(1)
$S_t^{2016} \cdot CB_{50}$	-0.132
	[0.261]
$S_t^{2016} \cdot CB_{00}$	-0.843***
	[0.267]
Observations	1888
Controls	Yes
Firm FE	Yes
Year FE	Yes

Notes: Robust t-statistics in parentheses: $***p < 0.01, **p < 0.05, *p < 0.1$.

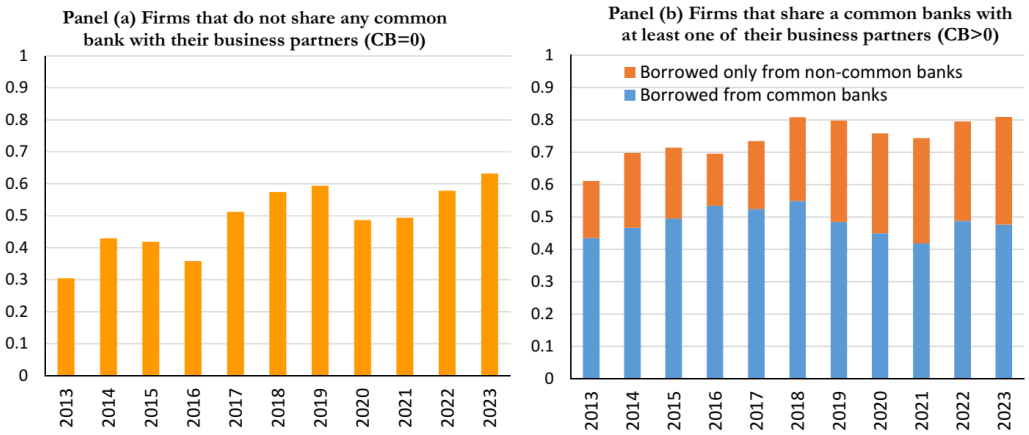


Figure 8: Fraction of firms with financing activities ($D_{it} = 1$) in each year

Notes: Panel (a) corresponds to the subgroup of firms that share no common bank with their business partners ($CB_i = 0$). Panel (b) corresponds to the subgroup of firms that share a common bank with at least one of their business partners ($CB_i > 0$). The whole bar represents the share of firms that borrowed in year t in all firms, in which the blue segment represents the share of firms that borrowed from a common bank and the yellow segment represents the share of firms that borrowed from non common banks.