Bank Specialization within Production Networks*

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Abstract

This paper studies the benefits and costs of lending specialization along supply chains, where banks serve as common lenders. Using firm-to-firm transaction and credit registry data from Belgium, we show that common lending is persistent and widespread. Exploiting an exogenous manufacturing shock, we find that it negatively affects firm production, credit demand along the supply chain and among common lenders. We develop and estimate a structural model of credit demand and supply in imperfectly competitive markets, where firms are connected through the production network. Our estimation results reveal that firms prefer to borrow from the same bank as their suppliers or customers, which gives common lenders market power and enables them to charge higher markups. At the same time, the network effects of common lending give banks an incentive to offer lower interest rates to maintain their role as common lenders.

JEL classification: E32, D57, L14, Q54

Keywords: Common lenders, Production network, Credit demand, Shock propagation

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1 Introduction

Banks often specialize in lending to particular industries or regions, which allows them to build expertise, reduce information asymmetries, and better monitor borrowers (e.g., Berger et al., 2017; Blickle et al., 2023, 2025a). Existing literature has largely focused on bank specialization by industry and geography (e.g., Duquerroy et al., 2022; Paravisini et al., 2023; De Jonghe et al., 2024). An important but less studied form of bank specialization involves lending to multiple firms along the supply chain; these relationships often span industries and regions, going beyond traditional scopes. Despite its potential significance, we know little about the prevalence, drivers, or consequences of this form of specialization.

Recent literature on common lenders, where banks lend to both suppliers and customers, offers two main perspectives. One line of research highlights common lenders' role in reducing information frictions, allowing for more favorable credit terms and greater credit supply (Hasan et al., 2020; Martins et al., 2023). Another suggests that common lenders provide substantive benefits by strengthening existing trading relationships and facilitating new ones (Giacomini et al., 2024; Frattaroli and Herpfer, 2023). While the former emphasizes supply-side advantages and the latter the demand-side, both suggest the benefits of common lending. However, bank specialization within production networks also comes with potential costs. Because firms are embedded in complex production networks, shocks affecting one firm can propagate to upstream and downstream partners, influencing their production, investment, and financing decisions (e.g., Acemoglu et al., 2012; Carvalho et al., 2021). When banks act as common lenders, disruptions in the real sector can spill over through them, affecting credit allocation to directly and indirectly connected firms.

In this paper, we investigate three main questions. First, how prevalent is common lending in terms of scope, trends, and key characteristics? Second, why do we observe common lending–is it driven by supply-side factors or demand-side preferences? Third, what are the consequences of common lending, in particular, how do shocks originating in the real sector transmit to the financial sector through common lending? Our findings support both supply- and demand-side views: while common lenders offer cheaper credit, firms also prefer borrowing from them not only for favorable loan terms but for value-added services. This preference reveals a mechanism we refer to as the *common lending channel*: although firms' preferences give common lenders market power, the network effects from serving both suppliers and customers incentivize banks to lower interest rates and increase their importance in the production networks they specialize in. This helps explain why banks offering valuable services may still charge lower rates.

This paper contributes to the literature by leveraging the universe of firm-to-firm transaction data merged with credit registry data from Belgium over two decades. We first provide empirical evidence on the prevalence of common lending: firms with trading relationships are significantly more likely to borrow from the same bank. This pattern has become increasingly important over time, surpassing industry- and region-based specialization. It is widely observed across industries, regions, and banks, and we find evidence consistent with both demand- and supply-side motives for common lending. We further show that an exogenous shock in the manufacturing sector propagates through the production network, affecting production output and credit demand along the supply chain, with stronger impacts on upstream and downstream firms closer to the origin of the shock. At the aggregate level, banks with greater exposure to the affected network experience significantly larger declines in credit growth, highlighting how real-sector disruptions can amplify into the financial sector, potentially due to the concentrated exposures created by common lending.

To disentangle the effects of credit demand and supply, and to account for general equilibrium effects on firms' production and financing decisions, we develop a structural model of firm production with credit demand and supply in imperfectly competitive lending markets, where borrowers are interconnected through the production network. The model integrates two key frameworks: imperfect competition in differentiated financial products (Berry, 1994; Berry et al., 1995) and production networks with financial frictions (Bigio and La'o, 2020; Baqaee and Farhi, 2020; Huremovic et al., 2024). On the credit side, banks exercise market power in setting loan prices based on product differentiation, such as contract terms, bank specialization, and lending relationships, while firms exhibit preferences over these differentiated banking products, following Crawford et al. (2018), with particular emphasis on bank specialization within firms' production networks. On the production side, we build on Huremovic et al. (2024), modeling firms that use upstream inputs in production and rely on bank credit to finance input costs.

This paper makes three key extensions to existing frameworks. First, by allowing firms to obtain benefits from borrowing through common lenders along the supply chain and allowing banks to exercise market power in this form of specialization, we disentangle the effects of credit supply driven by bank specialization from borrower preferences for common lenders. This provides new insights into how lender concentration within production networks shapes credit allocation and availability. Second, by integrating firm production into a structural model of credit demand and supply, we endogenize loan size decisions, capturing price effects through cost pass-through at the intensive margin of credit demand, with a microfoundation.[1] This enables

[1]Existing research on corporate credit demand often models loan size as a function of firm characteristics, macroe-

us to study general equilibrium effects in credit markets. Third, by embedding a micro-founded model of credit demand and supply into a production network framework, we endogenize banks' responses to demand shocks originating in the real sector, which are typically treated as exogenous in existing models. This allows us to analyze how real-sector shocks propagate into the financial sector, offering insights into financial risks arising from common lending.

Our paper relies on several administrative datasets from Belgium. We have access to the Belgium Transactions Dataset (B2B), which records the universe of domestic firm-to-firm transactions within Belgium for sales above €250.[2] Compared to existing datasets used in the literature, ours not only encompasses nearly all business relationships between Belgian enterprises but also provides transaction values. This feature ensures the completeness of the firm production network. We combine B2B data with the corporate credit register administered by the National Bank of Belgium (NBB). The credit register is highly comprehensive, as all financial institutions in Belgium are required to report information on any debtor to which they have an aggregate exposure exceeding €25,000. This dataset includes details on authorized loans, used loan amounts, loan types, and loan maturity. In addition to these two core datasets, we have access to detailed balance sheet and income statement data, meaning our data covers large public firms as well as small and medium sized enterprises.

Leveraging detailed data on firm production and credit networks, we document the phenomenon of common lending along supply chains.[3] First, we show that a large share of firms borrow from the same bank as their suppliers or customers. This pattern is pervasive across industries, regions, and banks, and has become increasingly common over time, surpassing traditional forms of bank specialization based on industry or geographical markets. Second, we document evidence consistent with a demand-driven mechanism: first-time borrowers are more likely to choose banks that also serve their important trading partners, and borrowing from common lenders helps sustain trading relationships over time (Giacomini et al., 2024). Third, we show that borrowing from a common lender is associated with favorable credit terms, especially for upstream firms. They receive lower interest rates, obtain larger loans, and exhibit lower estimated default risk, consistent with evidence that lending specialization can increase credit

conomic factors, and loan terms, e.g., Crawford et al. (2018); Ioannidou et al. (2022). In the context of mortgage lending, Benetton (2021) applies Roy's identity to a household utility function to model the size of mortgage demand.

[2]Domestic suppliers and customers are crucial for firms' production processes. Dhyne et al. (2021) show that only 19% of firms import directly, while other firms obtain foreign inputs either directly or indirectly through domestic suppliers that themselves use foreign inputs.

[3]Prior studies have shown that borrowing from common lenders increases credit availability and reduces loan pricing (Martins et al., 2023), reinforces trading relationships (Giacomini et al., 2024), and reduces competition for competing borrowers in product markets (Asai et al., 2024).

availability (Martins et al., 2023; Blickle et al., 2023) and improve screening and monitoring (Berger et al., 2017; De Jonghe et al., 2024).

To illustrate potential costs of common lending, we exam how shocks in the real sector can propagate through the production network and spill over into the financial sector. We use the 2007 closure of GM Antwerp as an exogenous shock, which had major repercussions for the local economy and supply chain (Jacobs and Jacobs, 2019). At the transaction level, affected firms significantly reduced trade with their suppliers and customers relative to unaffected firms, with the effect fading for firms further from GM in the supply chain, consistent with the evidence of a cascading effect Carvalho et al. (2021). At the firm level, we find that total sales declined significantly for firms closely connected to GM in the production network.

In addition to its impact on production, the shock affects firms' credit demand from three perspectives. First, we find that direct and indirect customers and suppliers of GM reduce credit usage with *existing banks* and are less likely to establish *new firm–bank relationships*, controlling for credit supply using bank–time fixed effects following Khwaja and Mian (2008). Second, at the bank-firm level, we find a decline in credit usage with existing banks. However, firms may offset this by borrowing from other banks. Finally, we examine firms' likelihood of establishing new firm-bank relationships and detect a significant decline. Direct customers of GM experience an approximately 5.4 percentage point (pp) decrease in the probability of forming new banking relationships, while the magnitude decreases to 3.1 pp for firms further away from GM in the supply chain.

To assess the impact on banks' lending portfolio, we aggregate credit data at the bank-province and bank-sector levels. We find that banks more exposed to GM-related firms experience significantly larger reductions in lending, especially at the sector level. Highly exposed banks see a 34.5% drop in committed loan amounts post-shock. These effects persist even after controlling for credit supply, suggesting that banks cannot fully offset the decline in demand, resulting in an overall negative lending impact. We also show that firms with direct transactions in GM's production network are more likely to share common lenders and have a higher number of common lending relationships. However, the supply chain disruption significantly reduces the likelihood of borrowing from common lenders. This pattern is consistent with the spillover effect of common lending: as the credit demand of suppliers and customers declines, the value of maintaining shared banking relationships diminishes, reducing firms' incentive to continue borrowing from the same bank.

To further understand the underlying mechanism, we develop a structural model that incorporates the crucial features we documented. In the model, each firm produces a single product within a production network. Firms employ a nested CES production technology with constant returns to scale, requiring capital, labor, and intermediate inputs from upstream suppliers. Due to working capital constraints, firms rely on bank credit to finance production costs and make production plans that maximize profit while factoring in financing costs. Consequently, a firm's credit demand depends on its production plan and the required levels of capital, labor, and intermediate inputs purchased from suppliers.

Given their required credit, firms choose which bank to borrow from based on their preferences for bank characteristics, credit terms, and lending relationships. In particular, we consider two types of borrowing-lending relationships: (1) direct relationships, where a firm borrows from a bank with which it has a pre-existing relationship, reflecting the information advantage in relationship lending; and (2) indirect relationships, where a firm prefers banks that also serve its suppliers or customers, capturing the spillover effects within the production network. Firms make a discrete choice to select a bank that maximizes their utility. Banks engage in Bertrand-Nash competition on interest rates, maximizing expected utility while considering borrowers' credit demand and default risk. Due to firms' preference for borrowing from common lenders within the supply chain, a bank's pricing strategy affects not only its direct borrowers but also their suppliers and customers, influencing credit demand propagation through the network, which we refer to as the *common lending channel*.

The model also features a *cost pass-through channel*: higher interest rates raise production costs, which in turn increase product prices. These higher prices elevate the cost of intermediate inputs for other firms, propagating through the production network. When production relies on bank credit, this pass-through channel boost credit demand and strengthening banks' market power during economic booms. Conversely, in downturns, falling prices reduce credit demand. This downward spiral, when combined with common lending, leads to correlated declines in credit demand across a bank's portfolio, both at the intensive and extensive margins, amplifying an idiosyncratic shock across sectors.

Structural estimation shows that borrowers prefer to borrow from common lenders even controlling for credit supply. A 1% increase in the common lender measure (the share of credit of a firm's suppliers and customers coming from a bank) raises the probability of borrowing from that bank by 0.1%. This preference gives rise to two effects. First, it creates a common lender effect that limits banks' ability to raise interest rates. Higher rates reduce demand not only from the focal borrower but also from its trading partners, weakening the bank's common lender position and diminishing its market power. We estimate that this channel reduces banks' effective markup by 23 basis points on average. As a result, banks are more inclined to offer favorable pricing to firms along the supply chain, consistent with our and existing empirical evidence that common lending is associated with lower interest rates. Second, conditional on this common lender effect, borrower preferences increase market power for banks with greater exposure along the supply chain. A one standard deviation increase in the common-lender measure decreases borrowers' price elasticity by 0.08, raises the effective markup by 6.8 basis points, and lowers the effective marginal cost by 8.6 basis points on average. These findings are consistent with the view that bank specialization reduces monitoring and screening costs. Moreover, when firms face capital constraints and rely on bank credit to finance production, banks gain additional market power. The cost pass-through channel accounts for an average effective markup of 23 basis points. However, if firms were financially unconstrained, this effect would likely be smaller.

1.1 Related Literature

This paper contributes to three strands of literature. First, this paper contributes to the debate on the benefits and costs of lending concentration within production networks. While lending diversification can reduce delegated monitoring costs (Diamond, 1984), specialization also provides banks with informational advantages and industry-specific expertise. Recent studies show that banks specializing in specific industries can accumulate superior knowledge in their area of focus, improve screening and monitoring (Berger et al., 2017; De Jonghe et al., 2024), offer cheaper and more generous credit (Blickle et al., 2023, 2025a), reduce individual bank and systemic risk (Acharya et al., 2006; Beck et al., 2022), and provide stewardship in corporate lending (Blickle et al., 2025b). We contribute to this discussion by highlighting a specific form of lending specialization – acting as common lenders along the supply chain, which is different from the existing bank specialization literature focusing on industry and geography.[4] Recent research on common lenders shows that borrowing from the same bank can reduce horizontal competition in product markets (Asai et al., 2024), strengthen vertical trading relationships (Giacomini et al., 2024), and facilitate strategic alliances (Frattaroli and Herpfer, 2023). Common lenders also extend more credit with more generous terms especially to suppliers (Hasan et al., 2020; Martins et al., 2023), and provide additional liquidity to firms in distressed industries (Giannetti and Saidi, 2019). While these studies mainly focus on banks' lending behavior, we emphasize the demand side and disentangle the supply and demand channels. Specifically,

[4] See e.g., Berger et al., 2017; Duquerroy et al., 2022; Paravisini et al., 2023; Blickle et al., 2023; De Jonghe et al., 2024.

we examine how banks' specialization influences borrowers' willingness to borrow from specialized common lenders, and how common lending shapes lenders' market power and credit supply. To the best of our knowledge, this is the first paper to structurally quantify both the benefits that firms gain from borrowing from common lenders and the costs they face from common lender exposure during adverse shocks in the production network.

Second, this paper contributes to the growing literature that applies structural IO methods to estimate demand for differentiated products in financial markets, following the seminal work of Berry (1994); Berry et al. (1995).[5] Our paper is particularly close to Crawford et al. (2018), which models corporate credit demand in markets with asymmetric information. In their framework, credit demand is specified in reduced form as a function of firm characteristics and credit conditions. This paper builds on and extends this literature in two key ways. First, we model credit demand based on firms' financing needs for production, endogenizing the amount of credit required with a micro-founded approach. Second, we incorporate firm-to-firm production linkages into a structural model of credit demand and supply, allowing banks to act as common lenders and quantifying how this interaction influences credit market outcomes.

Third, it contributes to the literature on production networks and their impact on corporate decisions and economic activity,[6] with a focus on their interaction with credit networks. Existing studies examine shock propagation through production networks and the role of input-output linkages in amplifying micro-level shocks to macro-level economic fluctuations (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). A growing body of work explores allocation inefficiencies in production networks when frictions are present (Baqaee, 2018; Bigio and La'o, 2020; Baqaee and Farhi, 2020). More recently studies have explicitly incorporated financial frictions to study the interplay between production and credit networks, highlighting how financing frictions shape shock transmission along supply chains. For example, Costello (2020) shows that exogenous credit shocks spill over through supply chains, affecting downstream firms via trade credit and sales channels. Alfaro et al. (2021) investigate how buyer-supplier linkages mediate the transmission of credit supply shocks across the economy. Huremovic et al. (2024) examines how bank credit supply shocks propagate through firm production networks, influencing aggregate outcomes. While existing studies

[5]Previous applications to financial markets include deposits, see e.g., Egan et al. (2017); Honka et al. (2017); Xiao (2020); Egan et al. (2022), corporate loans, see e.g., Crawford et al. (2018); Ioannidou et al. (2022), mortgages, see e.g., Benetton (2021), insurance see e.g., Koijen and Yogo (2016), social security, see e.g., Hastings et al. (2017), and investors' demand for assets, see e.g., Koijen and Yogo (2019).

[6]Existing literature has examined the role of production network in shaping firm productivity and performance (Bernard et al., 2019; Alfaro-Urena et al., 2022), access to the international markets (Dhyne et al., 2021), and the transmission of shocks across countries (Boehm et al., 2019; Dhyne et al., 2022; Di Giovanni and Hale, 2022; Huo et al., 2024). For a review of the production network literature, see Carvalho and Tahbaz-Salehi (2019).

focus on the transmission of credit shocks to the real sector, this paper examines how supply chain disruptions not only amplify real-sector shocks but also feed back into the financial sector through firms' borrowing decisions. This analysis requires a careful characterization of credit markets within a general equilibrium model incorporating the production network.

2 Data and Institutional Background

2.1 Data

We combine three datasets from Belgium during 2002 and 2023 in our analysis: (i) a firm-to-firm (B2B) transaction dataset, (ii) a credit registry that provides detailed information on firm-bank credit relationships, and (iii) firm balance sheet data containing financial and operational variables.

2.1.1 B2B Transaction Dataset

The Belgium Transactions Dataset records the universe of domestic firm-to-firm transactions within Belgium whose sales are above €250. The unit of observation in the dataset is the total sales from a seller i to a buyer j in a calender year. Each firm in the dataset is uniquely identified with a VAT number. A detailed description of this dataset is provided by Duprez et al. (2023).

The dataset has several advantages. First, we observe the whole domestic production network. Few datasets globally provide this level of coverage and completeness for inter-firm trade. For example, Japan's TSR data limit the number of reported sellers and buyers (Carvalho et al., 2021). Second, we observe the value of transactions for each seller-buyer pair, sourced from official VAT filings, which are highly reliable and standardized. Third, the time period spans from 2002 to 2023, enabling the study of dynamic relationships, such as the propagation of shocks through supply chains. The Belgium B2B data set has been used in previous studies, including Dhyne et al. (2021) and Bernard et al. (2022), among others.

Table B1 describes our B2B dataset. Sales are the amounts of transactions between a buyer and a seller, and are winorized at 0.5% and 99.5%. The table shows that the dataset captures a large amount of transactions among small firms, since the median is only around 1600 euros. Moreover, it appears that a small fraction of firms engage in exceptionally large transaction amounts, which ultimately skews the mean to approximately €16000.

2.1.2 Credit Registry

CCCR. For the empirical analysis, we use a comprehensive dataset on monthly bank-firm level credit from the Central Corporate Credit Register (CCCR), administered by the National

Bank of Belgium (NBB). The data is available for the entire period covered by the B2B transaction dataset. The credit register is very comprehensive, as all financial institutions established in Belgium are obliged to provide information to the credit register on all debtors to which they have an aggregate exposure exceeding €25,000. It includes details on authorized loans, used loans, loan types, and loan maturity. However, the dataset lacks information on loan interest rates for our sample period 2002-2020. The Belgian credit register has been used in previous studies, including De Jonghe et al. (2019), Degryse et al. (2019) and De Jonghe et al. (2024), among others.

BECRIS. To estimate our model, we need data with information on loan rates and default. Therefore, we employ corporate loan data from BECRIS, which is part of the euro area corporate credit registry AnaCredit established by the European Central Bank. BECRIS reports all loans granted by credit institutions residing in Belgium. A credit instrument is subject to reporting if the borrower is a legal entity and if the total committed amounts at the creditor-debtor level is greater than or equal to €25,000 at any point within the reference period. We extract yearly data from 2018 to 2023. The dataset provides detailed information at the individual loan level, including loan commitment amounts, outstanding amounts (ONA), maturity, loan rate, and loan type. It also contains information on borrowers, including the probability of default estimated by banks using internal risk modeling frameworks. A significant advantage of using such a dataset is its ability to disentangle credit demand from credit supply through the analysis of firms that engage with multiple banks. For our objectives, we consolidate the credit exposures at the level of firm-bank-loan type-year.

Table B2 presents summary statistics of the loan data at the firm-bank-time level. The average probability of increasing used credit is 23.8%, while the probability of establishing a new firm-bank relationship is only around 6.9%. The mean logarithmic difference is -0.031, suggesting that on average the amounts used decreased by approximately 3% compared to the previous year.

2.1.3 Firm Balance Sheets

We collect balance sheet and income statement data for every limited liability firm in Belgium from the annual accounts reported annually to the Central Balance Sheet Office (CBSO) of the NBB. The dataset contains rich information on firm characteristics, including size, industry, age, leverage, and employment. We supplement these data with confidential VAT declarations to obtain more accurate measures of firm sales, investment and input costs, and employment. Although such data is commonly available for large public firms, data on small business finances are rarely available. We take advantage of these firm characteristics to control for observable differences between borrowers and firms in the supply chain. Table B3 presents statistics on firm fundamentals. A large fraction of firms consists of small and micro firms, as evidenced by the median value of total assets being only 0.2 million. The median leverage is around 0.6, while the mean is above 1, suggesting that larger firms tend to have higher leverage ratios. The median profitability ratio is 0.017, while the mean is negative, indicating a negatively skewed distribution where losses are frequent, but some firms achieve substantial profitability.

2.2 Institutional Background – The Closure of GM Antwerp

To examine how a shock propagates through the production network and affects common lenders, we exploit the 2007 closure of GM Antwerp. GM Antwerp was a prominent car manufacturing plant in Belgium, employing over 5,000 people by 2005, including approximately 4,700 production workers by 2005. It produced around 400,000 vehicles annually before the closure, with about 90% of these being exported across Europe (Mariathasan et al., 2024). In the 2000s, rising energy costs began to strain the global automotive industry since it reduced demand for vehicles. This lead to $40 billion loss of GM in 2007 (Goolsbee and Krueger, 2015). To deal with it, GM's global response involved implementing a restructuring plan across its European operations, which included wage and benefit freezes. However, Belgian labor regulations prevented GM Antwerp from adopting these measures, making the facility one of GM's most expensive to operate (Jacobs and Jacobs, 2019). The financial crisis of 2008 further weakened GM, leading to a $70 billion loss and necessitating a US government bailout. In 2010, GM Antwerp was shut down as part of these cost-cutting measures. This closure had significant implications for the supply chain and local economy.

This setting offers two key advantages. First, the closure of GM Antwerp was firm-specific rather than system-wide, allowing us to distinguish between firms affected by the shock and unaffected firms. While the closure coincided with the global financial crisis, our identification relies on the production network before 2006 that prior to major macroeconomic disruptions, where GM's closure disproportionately impacted firms along its supply chain. Second, although the shock originated from a single firm, GM was a large and influential player in the local economy, with substantial real effects on the manufacturing sector. In 2006, GM's direct buyers and sellers accounted for 0.1% and 0.5% of all firms in our sample, respectively. These shares rise to 30.3% and 28.1% for second-tier downstream and upstream firms, and further to 57.3% and 40.4% at the third tier. Moreover, as shown in Figures A1 and A2, GM Antwerp's direct trading partners spanned all major industries and regions in Belgium, highlighting the broad economic impact of the closure through the production network, extending beyond industry and geographic locations.

3 Empirical Evidence

In this section, we first document common lending patterns over time across industries and markets, and characterize key features of common lending from both the credit demand and supply sides, providing evidence consistent with mechanisms documented in the literature (Section 3.1). Next, we examine how a shock originating in the real sector can be amplified through production networks (Section 3.2) and how it transmits to lending markets (Section 3.3).

3.1 Common Lenders along the Supply Chain

3.1.1 The Rising Trend of Common Lending

We first document the pervasive phenomenon of banks acting as common lenders along supply chains in Belgium. Our analysis draws on two phases of credit registry data covering more than two decades, from 2002 to 2023. The earlier period between 2002 and 2020 relies on the CCCR, while the later period uses BECRIS, which provides more granular loan-level information including interest rates and probabilities of default. The transition between the two registry systems occurred between 2018 and 2020, reflecting changes in reporting requirements and documentation practices. To maintain consistency, we first focus on the longer 2002-2020 sample to document the trend and patterns of common lending.[7]

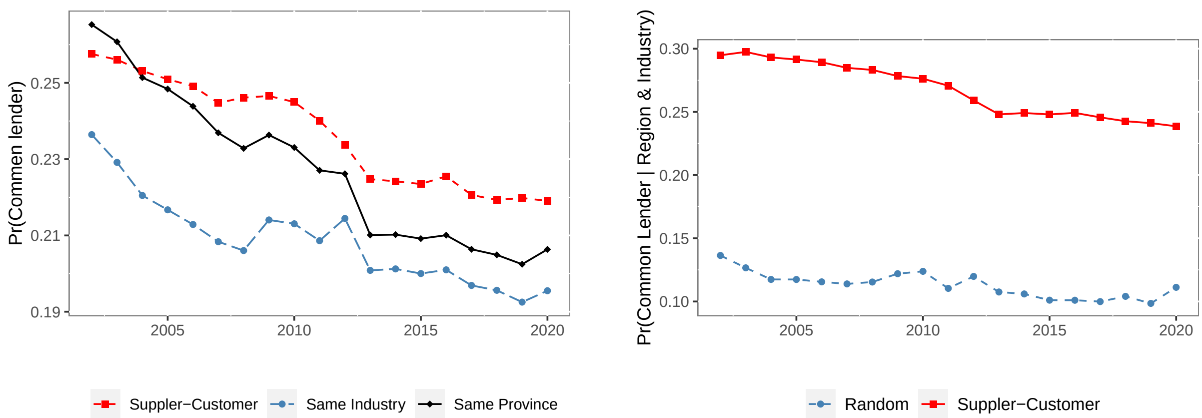
Figure 1a shows the probability that two firms borrow from the same bank over the sample period. The red dashed line represents buyer–seller pairs with trading relationships, the blue dotted line represents firms in the same industry, and the black solid line represents firms located in the same province. At the beginning of the sample period, both trading partners and firms in the same industry exhibited similar probabilities of borrowing from the same bank. Over time, however, this probability declined more sharply for industry-based lending. By the mid-2000s, trading partners became more likely to borrow from the same bank than firms from the industry or province. This divergence suggests that bank specialization along supply chains has become increasingly important relative to traditional specialization by industry or geographical markets. Figure 1b further examines the probability of borrowing from the same bank conditional on firms being in the same industry and province. Trading partners remain substantially more likely to share a lender than randomly matched firm pairs. During 2000-2020, the probability

[7] To avoid noise from very small banks or transactions, we restrict the sample to banks with at least 0.3% market share in each year, which yields on average 19 banks per year. We also exclude firm-to-firm transactions below €1,000. Our results remain qualitatively unchanged when these restrictions are relaxed.

ranges from about 10–15% for random firm pairs and 25–30% for trading partners. This persistent gap indicates that common lending along supply chains cannot be explained solely by industry or geographic specialization.

In addition to the persistent trend of common lending over time, we also find that this phenomenon is widespread across industries and geographical locations. Figure A5 illustrates the number of buyer–seller pairs borrowing from the same bank versus different banks, broken down by industry. In nearly all major sectors, there is a high likelihood that trading partners borrow from the same bank, indicating that common lending is a widespread feature of supply chain financing across the economy. Similarly, as illustrated by Figure A6, common lending is widely observed in all Belgian provinces. Furthermore, common lending is not concentrated among a few specialized banks but is widespread across the whole banking sector. As illustrated in Figure A7, while larger banks tend to exhibit higher levels of common lending, the pattern is present across banks of different sizes. Moreover, substantial variation exists even among banks of similar size, suggesting that supply chain specialization reflects strategic lending choices rather than being mechanically driven by bank scale.

Figure 1: The Trend of Borrowing from Common Lenders



(a) Probability of Borrowing from Same Bank

(b) Conditional Probability

Notes: This figure presents the empirical trend of borrowing from common lenders in Belgium from 2002 to 2020. Subfigure (a) shows the unconditional probability of borrowing from the same bank for three types of firm pairs. The red dashed line represents firms with trading relationships; the blue dotted line shows firms in the same industry; and the black solid line shows firms in the same province. Subfigure (b) shows the conditional probability of borrowing from the same bank, conditional on firms being from the same industry and province. The red solid line represents firms with trading relationships, while the blue dashed line shows purely random firms.

3.1.2 Demand Side Evidence

After documenting the increasing prevalence of common lending, we explore both supply- and demand-side explanations for this pattern. We begin with evidence on the demand side by examining whether firms prefer banks that also serve their trading partners. To identify this preference, we focus on first-time borrowers whose bank choices are not influenced by prior lending relationships. A firm is defined as a first-time borrower if its first credit record appears after 2002 and it has no prior record in the credit registry in 2000 or 2001. We then examine whether the importance of a trading partner in a firm's production network affects the likelihood of choosing a common lender. Table 1 reports the results.

The dependent variable is an indicator for whether a first-time borrower chooses a bank that is also the bank of its supplier, customer, or both. The key independent variable is the share of the firm's total sales that comes from (or goes to) the respective trading partner, capturing the importance of that trading partner in the firm's production network. All specifications include firm fixed effects, trading partner bank fixed effects (supplier bank, customer bank, or partner bank fixed effects depending on the specification), and year fixed effects to control for firm-specific, bank-specific, and time-varying factors.

The results show that firms with more important trading partners are significantly more likely to choose from the same bank of that trading partner when entering the credit market for the first time. In Column (1), a one percentage point increase in the share of purchases from a supplier increases the probability of borrowing from the supplier's bank by 0.10 percentage points. Similarly, in Column (2), a one percentage point increase in the share of sales to a customer increases the probability of borrowing from the customer's bank by 0.08 percentage points. When considering both upstream and downstream relationships together (Column 3), the effect is even stronger at 0.15 percentage points.

Having shown that firms, especially first-time borrowers, are more likely to choose banks that also serve their trading partners, we next examine whether borrowing from the same bank helps sustain trading relationships. Table 2 investigates whether common lending contributes to the persistence of supplier–customer relationships over time. We focus on firms that initiated a trading relationship during the sample period and trace the survival of these relationships over the following years. The dependent variable is an indicator for whether the trading relationship survives after 1, 2, 3, 4, or 5 years from the initial transaction. The key explanatory variable is an indicator for whether both firms borrow from the same bank. All specifications control for total trade value to capture the economic importance of the relationship and include buyer bank fixed effects, seller bank fixed effects, and first trade year fixed effects to account for bank characteristics and time trends.

The results show that trading partners with a common lender are significantly more likely to

Table 1: First-Time Borrower Bank Choice and Trading Partner Importance

	Upstream	Downstream	Both
	(1)	(2)	(3)
Share of Trade	0.10***	0.08***	0.15***
	(0.00)	(0.00)	(0.00)
Firm FE	✓	✓	✓
Supplier Bank FE	✓		
Customer Bank FE		✓	
Partner Bank FE			✓
Year FE	✓	✓	✓
N	5,808,833	3,950,305	9,759,138
Adj. R^2	0.09	0.11	0.09

Note: This table reports the relationship between the importance of trading partners and the probability of choosing a common lender for first-time borrowers. The sample includes firms entering the credit registry for the first time during 2000-2020. The dependent variable is an indicator equal to one if the firm chooses a bank that is also the bank of its supplier (Column 1), customer (Column 2), or trading partner (Column 3). The key independent variable is the share of the firm's total sales (for upstream) or purchases (for downstream) that goes to or comes from the respective trading partner, capturing the importance of that trading partner in the firm's production network. All specifications include firm fixed effects, trading partner bank fixed effects, and year fixed effects. $***p < 0.001$; $**p < 0.01$; $*p < 0.05$

continue their relationship in the following year, conditional on having traded in the previous year. The effect is positive and statistically significant across all horizons, with the largest effect at the two-year horizon. Borrowing from the same bank increases the probability that the trading relationship remains active in the third year by 0.3 percentage points, corresponding to a 6% increase relative to the average continuation probability. These findings suggest that common lending provides benefits beyond credit terms by helping firms maintain more stable trading relationships over time, consistent with (Giacomini et al., 2024). Together with the earlier evidence that firms are more likely to borrow from the same bank as their important trading partners, the results support a demand-side motive for common lending. Firms value common lenders for material benefits that sustain economically important trading relationships.

3.1.3 Supply Side Evidence

Next, we examine whether borrowing from common lenders is associated with differences in loan contract terms using the BECRIS data, which contains information on interest rates and default risk measures. In Table 3, we regress loan characteristics, specifically interest rates, loan amounts, and lenders' estimation of default risk, on an indicator variable that equals one if both the buyer and seller in a trading relationship borrow from the same bank. The unit of observation is a buyer–seller trading pair with an active borrowing relationship. All regressions

Table 2: Common Lending and Trading Relationship Persistence

	1-Year	2-Year	3-Year	4-Year	5-Year
	(1)	(2)	(3)	(4)	(5)
Common Lender	0.001***	0.003***	0.002***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading Control	✓	✓	✓	✓	✓
Buyer Bank FE	✓	✓	✓	✓	✓
Seller Bank FE	✓	✓	✓	✓	✓
First Trade Year FE	✓	✓	✓	✓	✓
N	30,702,702	12,609,884	7,478,276	5,202,024	3,848,044
Adj. R^2	0.024	0.094	0.145	0.183	0.205

Note: This table examines whether common lending helps sustain trading relationships over time. The sample includes firm pairs that initiated a trading relationship during 2002-2020 and also have credit relationships with banks. Column (1) includes relationships that began one year earlier, while Column (2) includes relationships that began two years earlier and survived for one year. Columns (3)–(5) follow the same structure for longer horizons. The dependent variable is an indicator equal to one if the trading relationship survives after 1, 2, 3, 4, and 5 years from the initial transaction. The key independent variable is an indicator for whether both firms in the trading pair borrow from the same bank (common lender). All specifications include total trade value to control for the economic importance of the relationship, buyer bank fixed effects, seller bank fixed effects, and first trade year fixed effects. $***p < 0.001$; $**p < 0.01$; $*p < 0.05$

include firm-type fixed effects (defined by industry and size category), region fixed effects, and bank–year fixed effects to control for both credit supply and demand shocks. For downstream analyses, we include seller fixed effects, comparing customers of the same supplier who borrow from the supplier's common lender with those who do not, thereby controlling for unobservables that affect loan terms through trading partners. Similarly, for upstream analyses, we include buyer fixed effects.

Columns (1) and (2) report results for interest rates. We find that upstream firms (sellers) pay 0.73 percentage points lower interest rates when borrowing from common lenders, compared to firms borrowing from different banks, conditional on trading with the same customer. The effect for downstream firms (buyers) is not statistically significant. Columns (3) and (4) show the results for credit amounts. Both buyers and sellers borrowing through common lenders receive larger loans, approximately 33,400 Euro more for buyers and 260,100 Euro more for sellers. These results suggest that borrowing from common lenders is associated with better loan terms and credit availability, with particularly pronounced effects for upstream firms, which is consistent with Martins et al. (2023). As shown in Columns (5) and (6), sellers borrowing from the same bank as their trading partners receive lower estimated default risk, whereas no such effect is observed for downstream firms. This finding is consistent with the view that specialized banks' information advantages enhance screening and monitoring (Berger et al., 2017;

De Jonghe et al., 2024)

Table 3: Interest Rate and Loan Size Borrowing from Common Lenders

	Interest Rate		Loan Size		Prob Default	
	Down	Up	Down	Up	Down	Up
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Common Lender)	0.22	-0.73***	33.39*	260.13***	0.02	-0.07***
	(0.12)	(0.11)	(15.62)	(6.09)	(0.01)	(0.01)
Seller FE	✓		✓		✓	
Buyer FE		✓		✓		✓
Firm Type, Region FE	✓	✓	✓	✓	✓	✓
Bank-Year FE	✓	✓	✓	✓	✓	✓
N	5,710,929	5,710,929	5,710,929	5,710,929	5,451,057	5,536,630
Adj. R^2	0.25	0.44	0.08	0.12	0.02	0.03

Note: This table reports how interest rates and loan sizes vary depending on whether firms borrow from common lenders. The unit of observation is a buyer–seller trading pair with active borrowing in the credit registry. The key independent variable, $\mathbb{1}$(Common Lender), is a dummy equal to one if both firms borrow from the same bank, and zero otherwise. Columns (1) and (2) show the interest rate (in percentage points) for buyers and sellers, respectively. Columns (3) and (4) report loan size (in thousands of euros) for buyers and sellers. Columns (5) and (6) report lenders' estimation of probability of default (in percentage points) for buyers and sellers. All regressions include firm-type fixed effects (defined by industry and firm size), region fixed effects, and bank–year fixed effects. For downstream analyses, seller fixed effects are included. For upstream analyses, buyer fixed effects are included. $***p < 0.001$; $**p < 0.01$; $*p < 0.05$

3.2 GM Closure Propagation in Production Network

3.2.1 Transaction Level Evidence

To investigate the shock propagation in the production network, we start the analysis at the transaction level, where we are able to observe the exact sales amounts between a seller-buyer pair at the end of the year. The goal is to examine the impact of the GM closure hitting firms at different distances within its supply chain on the sales of those firms. We adopt a similar approach as Carvalho et al. (2021) to measure firms distance to GM in the production network using data from 2002–2006. First, we define direct buyers of GM as downstream level 1 firms. A firm is classified as downstream level 2 if it is a customer of at least one level 1 firm but is not itself a level 1 firm. Using the same method, we define downstream level 3 firms. Similarly, we classify upstream level 1, 2, and 3 firms based on their supplier relationships. All remaining firms are categorized as unconnected firms to GM. Our specification focuses on the transaction between a seller-buyer pair. We estimate the following specification:

$$\text{Sales}_{i,j,t} = \beta_k \text{Level}^k_{i,j} \times \text{Post}_t + \delta_1 \mathbf{X}_{i,t} + \delta_2 \mathbf{X}_{j,t} + \text{FE} + \epsilon_{i,j,t}, \tag{1}$$

where i, j, t denote seller, buyer, and year, respectively. The outcome variable $\text{Sales}_{i,j,t}$ is the natural logarithm of sales between a seller i and a buyer j in year t. $\text{Level}_{i,j}$ is an indicator variable that indicates whether a buyer-seller pair, in which the buyer (seller) is in distance k of the GM supply chain during the years 2002-2006. k takes the values 1, 2, and 3. For instance, $\text{Level}^1_{i,j}$ refers to a buyer-seller pair in which the buyer (seller) is a direct buyer (seller) of GM, and $\text{Level}^2_{i,j}$ refers to a buyer-seller pair in which the buyer (seller) is a buyer (seller) of GM's direct buyers (sellers). Importantly, each firm is assigned to one level *only* to simplify the interpretation,[8] and we show that direct buyers or sellers of GM are unlikely to be shadow subsidiaries, as they engage in transactions beyond GM and have different geographical locations.[9]

The control group includes seller-buyer pairs in which sellers (buyers) are not linked with any firms in level 1, level 2, or level 3 for the years 2002-2006. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. To control for firm fundamentals, we add $\mathbf{X}_{i,t}$ and $\mathbf{X}_{j,t}$, which are firm characteristics, including firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets) of sellers and buyers, respectively. The main coefficient of interest is β_k.

We estimate two versions of Eq(1). In the first one, we examine the downstream of shock propagation by looking at GM's buyers, GM's buyers' buyers, and so on. In the second version, we examine the upstream of shock propagation by looking at GM's sellers, GM's sellers' sellers, and so on. We omit cases such as shock propagation to a buyer of a GM's seller for simplicity. Doing so allows us to have a clean setting on studying the propagation toward either downstream or upstream. Consequently, β_k captures the extent to which a seller (buyer) reduces its sales to its two counterparts that are closer or further away from the GM supply chain, controlling for unobserved and observed characteristics of the seller and the buyer and other factors.

Table 4, Columns (1) and (2), report the transaction-level estimation results for the shock propagation, where Panel A reports results for downstream propagation (seller→buyer) and Panel B for upstream (seller←buyer) propagation. The dependent variable is the log of annual sales

[8] It is likely that $\text{Level}^1_{i,j}$ firms have transactions with $\text{Level}^2_{i,j}$ firms. Such transactions are not included in either the treated or control group. In addition, we use the distance of the highest-order appearance of firms in the supply chain of GM and omit any later appearance. For instance, Firm A is (i) a direct buyer of GM, and (ii) a buyer of GM's buyer's buyer Firm C. In this case, Firm A will be identified as a level 1 firm only. Its transactions with Firm C will not be included in the sample.

[9] Unfortunately, we do not have ownership data to verify, but we address this concern by two steps. First, we count the number of non-GM suppliers (customers) of level 1 firms who are direct buyers (sellers) of GM. Figure A3 plots the distribution of number of non-GM suppliers (customers) of level 1 firms who are direct buyers (sellers) of GM. We see that almost all firms purchase from multiple suppliers (customers), suggesting that they are very unlikely subsidiaries of GM. Second, we examine whether GM is located in the same postcode area as its suppliers and customers. Table B4 shows that among GM's suppliers and customers, only 1% of firms are in the same postal codes as GM. This again supports the notion that level 1 firms are unlikely to be subsidiaries of GM.

between a seller and a buyer. In Column (1), with seller–buyer fixed effects, we find significant declines in sales for Level 1, 2, and 3 pairs after the GM Antwerp closure, with the effect size in general decreasing with distance in the supply chain, consistent with the cascading pattern documented in Carvalho et al. (2021). For instance, within level 1 seller-buyer pairs, GM and its buyers experienced a decline in sales of approximately 47.2% after 2006, compared to their sales trend before the shock and relative to non-treated pairs. The magnitude reduced to 14.6% for level 2 seller-buyer pairs and 20.9% for level 3 seller-buyer pairs. In Column (2), with seller and buyer fixed effects, the estimates remain negative and significant for Level 1 and 2 pairs, though smaller in magnitude. These results suggest that the shock propagated both downstream and upstream, with stronger effects for firms closer to GM in the production network.

3.2.2 Firm Level Evidence

After showing GM's supply chain reduce transactions with downstream or upstream counterparties after the GM closure, one remaining question is whether such a sales reduction is significant at the aggregate firm level. For instance, sales to a specific buyer might not represent a large fraction of a firm's total sales in a year. If this is the case, the aggregate effects might not be apparent. Moreover, firms could mitigate the negative impacts by supplementing the reduction with alternative buyers. To address these concerns, we conduct an analysis at the firm level. The goal is to examine whether the shock propagation is evident at the firm level. To this end, we use firm-level data to estimate the following specification:

$$\text{Sales}_{i(j),t} = \beta_k \text{Level}^k_{i(j)} \times \text{Post}_t + \delta \mathbf{X}_{i(j),2006} \times \text{Post}_t + \text{FE} + \epsilon_{i(j),t}. \tag{2}$$

The outcome variable $\text{Sales}_{i(j),t}$ is the sales of transaction level aggregated at firm $(i(j))$ level in year t. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain.[10] Depending on the specifications, we also interact ex-ante firm characteristics with Post_t dummy. As indicated above, the control group contains firms that are k distance away from the chain of GM before the shock. To control for unobserved firm characteristics, we incorporate seller (buyer) fixed effects and year fixed effects. Therefore, our specification exploits within-firm variation over time. Alternatively, we saturate the specification with seller (buyer) fixed effects and sector-year fixed effects, meaning that we are comparing outcomes of firms in the same sector in the same year. The coefficient of interest is β_k.

Similarly with what we do at the transaction level, we estimate Eq(2) for downstream and upstream separately. In addition, since the sales is at the firm level, the value can include sales

[10]Note the difference between $\text{Sales}^k_{i(j),t}$ and $\text{Sales}_{i,j,t}$. $\text{Sales}^1_{i(j),t}$ means a level 1 firm is a *direct* seller (buyer) of GM. $\text{Sales}^1_{i,j,t}$ means level 1 seller-buyer pair where the seller (buyer) it is a *direct* seller (buyer) of GM.

Table 4: Shock Propagation: Transaction-Level and Firm-Level Estimates

	(1)	(2)	(3)	(4)
	Transaction Level		Firm Level	
	ln(sales)			
Panel A: Downstream				
Level 1 × Post	-0.4718***	-0.4852***	-0.2428***	-0.1947***
	(0.0122)	(0.0122)	(0.0602)	(0.0537)
Level 2 × Post	-0.1460***	-0.0489*	-0.1637***	-0.1568***
	(0.0319)	(0.0276)	(0.0321)	(0.0355)
Level 3 × Post	-0.2093***	-0.0209	-0.1243***	-0.1299***
	(0.0128)	(0.0127)	(0.0319)	(0.0307)
N	15,563,114	18,365,775	1,748,206	1,682,951
R^2	0.81	0.43	0.85	0.86
Panel B: Upstream				
Level 1 × Post	-0.4842***	-0.5031***	-0.2541***	-0.2426***
	(0.0109)	(0.0158)	(0.0217)	(0.0410)
Level 2 × Post	-0.0434***	0.1825***	-0.2149***	-0.2143***
	(0.0150)	(0.0135)	(0.0119)	(0.0260)
Level 3 × Post	-0.0383***	0.1793***	-0.1403***	-0.1388***
	(0.0104)	(0.0110)	(0.0118)	(0.0167)
N	5,347,025	6,498,781	2,053,999	2,049,123
R^2	0.84	0.56	0.87	0.87
Seller-Buyer FE	✓			
Seller FE		✓		
Buyer FE		✓		
Firm FE			✓	✓
Year FE	✓	✓	✓	
Sector-Year FE				✓

Notes: This table shows the estimation results of Eq(1) in Columns (1) and (2) and Eq(2) in Columns (3) and (4). The dependent variables are the natural logarithm of sales between a seller i and a buyer j in year t (Columns (1) and (2)) and the sales of transaction level aggregated at firm ($i(j)$) level in year t (Columns (3) and (4)). Level$_{i,j}$ is an indicator variable that indicates whether a buyer-seller pair, in which the buyer (seller) is in distance k of the GM supply chain during the years 2002-2006. k takes the values 1, 2, and 3. Post$_t$ is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Columns (1) and (2) include time-varying control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets) of sellers and buyers. Columns (3) and (4) include the interactions between ten quantiles of firm controls at 2006 and year dummies. Robust standard errors are in parentheses, clustered at the seller and buyer levels in Columns (1) and (2), at firm level in Column (3), at 2-digit NACE code level in Column (4). *** p<0.01, ** p<0.05, * p<0.1.

from couterparties outside the B2B network. It might be less concerned if transaction amounts are below €250 and thus are not subject to reporting requirements. Alternatively, firms might support their production entirely through importing or exporting, which will also be reflected in their total sales.

The regression results are reported in Columns (3) and (4) of Table 4 present firm-level estimates of downstream and upstream shock propagation. The unit of observation is a firm-year, and the dependent variable is log sales. To eliminate the concern that pre-shock firm characteristics may drive the outcomes, we include interactions between ten quantiles of firm controls in 2006 and year dummies. We add firm fixed effects together with either year fixed effects or sector–year fixed effects. The results show significant sales declines for firms directly and indirectly connected to GM, with the magnitude decreasing by distance in the supply chain. For example, direct downstream firms experienced a sales drop of roughly 24%, while second-level and third-level downstream firms saw reductions of around 16% and 12%, respectively. Upstream effects show a similar pattern. Direct suppliers experienced a sales decline of approximately 25%, with smaller but still significant effects for firms further upstream. The consistent magnitude across both downstream and upstream effects suggests that firms were unable to fully offset the disruption by switching to new trading partners.

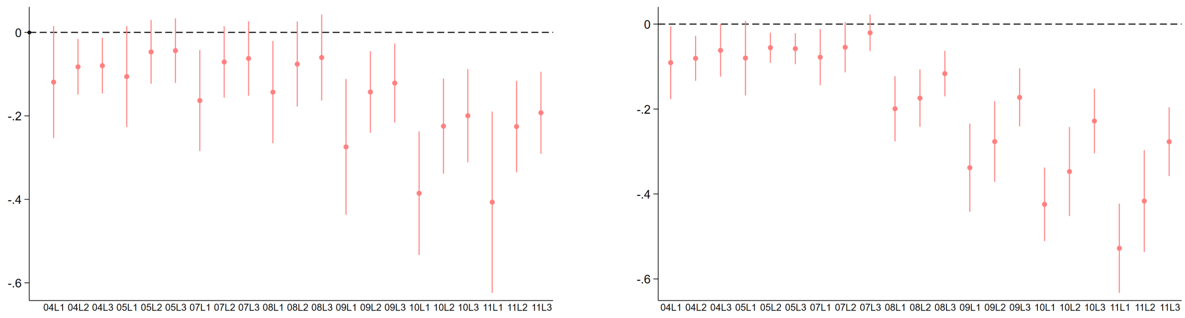
Additional Results. Given the granularity of the data, we are able to include rich fixed effects, which we present in Tables B5 and B6. The results remain consistent across specifications, confirming that our findings are not driven by the choice of fixed effects. Moreover, firm-level sales declines may reflect fewer transactions, fewer trading partners, or both. To explore this, we replace the outcome variable with the log number of buyers (sellers) per firm per year to examine whether firms affected by the GM closure adjust their production networks. Table B7 shows that affected firms reduce their number of buyers after the shock, with stronger effects for Level 1 and 2 firms, consistent with shock propagation along the supply chain. To eliminate the concern that our results are driven by very small firms, we repeat the exercises at both the transaction level and the firm level using samples that include only firms with positive full-time equivalents. The results reported in Table B8 indicate that our findings remain largely unchanged.

Identification Assumption. To validate the parallel trend assumption, we conduct a dynamic difference-in-differences estimation.[11] We use 2006 as the base year and interact the $\text{Level}^k_{i(j)}$ with year dummies. The specification controls for firm characteristics by interacting firm size, leverage, and profitability in 2006 with year dummies. We add firm fixed effects and sector-year fixed effects. Robust standard errors are clustered at the location and 1-digit NACE

[11] The results at the transaction level are shown in Figure A4.

level. We apply the analogous specification for upstream propagation. Estimation results are illustrated in Figure 3. Coefficients prior to the GM closure are not statistically significant, which suggests that the sales between treated and control firms are not statistically different. However, the sales of treated firms do experience a decline compared to control firms in the post-period.

Figure 2: Parallel trend - Firm level



(a) Downstream (b) Upstream

Notes: This figure validates the parallel trend assumption at the firm level. The left panel plots coefficient estimates in a dynamic difference-in-difference setting for downstream propagation. The right panel plots coefficient estimates in a dynamic difference-in-difference setting for upstream propagation. "04L1", "04L2", "04L3" refers to (i) year 2004 and level 1 firms, (ii) year 2004 and level 2 firms, (iii) year 2004 and level 3 firms. Year 2006 is omitted as the reference year. Hence, "06L1", "06L2", "06L3" are not reported.

3.3 GM Closure and Firm Credit Demand

In the previous section, we documented how GM's closure propagated through the production network, negatively affecting the sales of direct and indirect customers and suppliers, and the impact decreases as firms are further away from GM in the supply chain. Next, we examine how firms respond to this negative production shock, focusing on its effects on credit demand.

To investigate this, we link firm production networks to their credit networks by combining B2B data with credit register data. This integration allows us to observe all firm-bank relationships. For each firm, we track its banks, along with the corresponding committed and utilized loan amounts, among other factors. As a result, our sample is restricted to firms that appear in the B2B dataset and have borrowed from banks. This means that for our downstream (seller→buyer) analysis, we only include sellers that have appeared in the B2B dataset at least once between 2002 and 2011 and who have engaged in borrowing from banks. It is important to note that some firms in the B2B dataset will be excluded. One reason for this exclusion could be that the total exposure between a firm and its bank does not exceed €25,000. Another reason could be that the firm does not have borrowing relationships with the bank.[12]

[12] We do not aim to explain why some firms do not borrow from banks. Instead, the focus of our research is on understanding the broader implications of production shocks on credit demand and credit allocation.

3.3.1 Credit Demand at Firm-Bank Level

To investigate the impact of the closure of GM on credit demand, we estimate the following specification:

$$\text{Credit}_{i(j),b,t} = \beta_k \text{Level}^k_{i,j} \times \text{Post}_t + \delta \mathbf{X}_{i(j),t} + \text{FE} + \epsilon_{i(j),b,t}, \tag{3}$$

where i, j, b, and t denote seller, buyer, bank, and year, respectively. We first investigate how the credit usage amounts of firms with *existing banks* respond to the GM closure. To do so, we employ outcome variables that better reflect firms' credit demand than "authorized amounts." Specifically, we use: $\mathbb{1}$(New credit), a dummy variable that takes the value of 1 if the difference in the used credit amount of firm i (j) at bank b from the previous year to year t is positive, and 0 otherwise. We then examine whether firms affected by the GM closure seek to establish *new bank relationships*. For this, the outcome variable is $\mathbb{1}$(New bank), a dummy variable that takes the value of 1 if bank b is new to firm i (j) in year t, and 0 otherwise.[13] Accordingly, we aim to understand the probability of having a new firm-bank relationship before and after the shock.

To account for variations in firm fundamentals, we include time-varying firm characteristics in our analysis. Additionally, we incorporate bank-firm fixed effects to address the issue of endogenous matching between firms and banks. This approach assumes that non-random matching is driven by unobserved factors that remain constant over time. Standard errors are clustered at the firm level. One concern is that the time of GM closure coincides with the financial crisis, which induces credit supply shock documented extensively in the literature (e.g., De Jonghe et al., 2019). One could argue that a potential reduction in credit demand is driven by lower credit supply. We can mitigate such concerns by using bank-time fixed effects, which is a standard way to control credit supply shocks. Furthermore, we use "used amounts" rather than "authorized amounts". This is crucial to tease out credit supply.

Table 5, Columns (1) and (2), present firm-bank level results for downstream and upstream propagation. In Column (1), the dependent variable is a dummy equal to one if a firm increases its used credit with an existing bank relative to the previous year. We find negative and statistically significant effects for Level 2 and 3 downstream firms, suggesting reduced credit demand following the GM closure. In Column (2), where the outcome is a dummy for establishing a new bank relationship, we observe significantly negative effects for Level 2 and 3 firms both downstream and upstream, indicating that affected firms are less likely to form new banking relationships, which is consistent with reduced financing needs following supply chain

[13] The first-year appearance is not counted as a new firm-bank relationship. For example, if firm A borrows from bank A in 2020 and from both bank A and bank B in 2021, only bank B is considered a new bank.

disruptions. In Table B9, we also report results where we use the change in credit demand at the intensive margin as the outcome variable. In particular, we create the variable $\Delta \ln(\text{Credit})$, defined as $\ln(\text{used amount})_{i(j),t} - \ln(\text{used amount})_{i(j),t-1}$. Again, we detect a negative impact on firm credit demand for downstream firms. Table B9 further presents results using alternative model specifications, and the findings remain similar.[14]

3.3.2 Credit Demand at Firm Level

The results from the previous section show a consistent negative impact of supply chain disruptions on the credit demand of affected firms. One remaining question is whether the drop in credit demand is significant at the firm level. Although we observe a reduction in credit demand at the firm-bank level, it is possible that firms substitute credit sources, leaving no effect at the aggregate level.

To address this, we conduct exercises to examine the effects on firms' overall credit behavior. Similar to the previous section, we are interested in (i) changes in the total amount of credit used and (ii) firm-bank relationships. Specifically, we estimate the following firm-year level specification:

$$\text{Credit}_{i(j),t} = \beta_k \text{Level}^k_{i,j} \times \text{Post}_t + \delta \mathbf{X}_{i(j),t} + \text{FE} + \epsilon_{i(j),t}. \tag{4}$$

We again use two dependent variables in our analysis. First, $\mathbb{1}(\text{New credit})$, a dummy variable that takes the value of 1 if the difference in the used credit amount of firm i (j) from the previous year to year t is positive, and 0 otherwise. Second, $\mathbb{1}(\text{New bank})$ is a binary variable that equals one if the change in the number of firm-bank relationships from year $t-1$ to t is strictly positive and zero otherwise. Note that the unit of observation is firm-year, and thus we cannot incorporate bank-year fixed effects to control for credit supply shocks. Instead, we include sector-year fixed effects or province-sector-year fixed effects. Hence, β_k captures the overall effect on firm credit demand, assuming that credit supply changes are accounted for by these fixed effects. Robust standard errors are clustered at the firm level.

Table 5, Columns (3) and (4), present firm-level results for downstream and upstream propagation. In Column (3), the dependent variable is a dummy equal to one if there is a strictly positive increase in used credit from the previous year. We find negative and statistically significant effects for Level 2 and 3 downstream firms, indicating reduced credit demand after GM

[14] For example, to further isolate the effects of credit supply from credit demand, we include bank-location-year fixed effects, which allow us to control for unobserved, time-varying factors affecting credit supply specific to a bank operating in a particular location during a given year. To address the concern that banks specialize in certain industries, enabling them to accumulate information advantages over time (Blickle et al., 2023; Paravisini et al., 2023; De Jonghe et al., 2024), we incorporate bank-location-sector-time fixed effects in some specifications.

Table 5: Shock Propagation to the Financial Sector: Firm-Bank and Firm-Level Outcomes

	(1)	(2)	(3)	(4)
	Firm–Bank Level		Firm Level	
	$\mathbb{1}$(New Credit)	$\mathbb{1}$(New Bank)	$\mathbb{1}$(New Credit)	$\mathbb{1}$(New Bank)
Panel A: Downstream				
Level 1 × Post	-0.0076	0.0061	0.0065	-0.0538***
	(0.0200)	(0.0068)	(0.0218)	(0.0141)
Level 2 × Post	-0.0326***	-0.0084***	-0.0412***	-0.0766***
	(0.0061)	(0.0026)	(0.0062)	(0.0032)
Level 3 × Post	-0.0255***	-0.0046*	-0.0350***	-0.0307***
	(0.0061)	(0.0026)	(0.0062)	(0.0031)
N	1,197,945	1,964,472	1,040,220	1,145,609
R^2	0.2662	0.4836	0.2416	0.2154
Panel B: Upstream				
Level 1 × Post	0.0019	-0.0037	0.0122	-0.1110***
	(0.0092)	(0.0031)	(0.0106)	(0.0063)
Level 2 × Post	-0.0039	-0.0086***	-0.0082**	-0.0719***
	(0.0041)	(0.0016)	(0.0042)	(0.0020)
Level 3 × Post	-0.0021	-0.0060***	-0.0081*	-0.0243***
	(0.0041)	(0.0016)	(0.0032)	(0.0015)
N	1,134,265	1,878,026	980,980	1,081,924
R^2	0.2640	0.4868	0.2374	0.2165
Firm controls	✓	✓	✓	✓
Bank–Firm FE	✓	✓		
Bank–Time FE	✓	✓		
Firm FE			✓	✓
Time FE			✓	✓

Notes: This table reports the regression results of how credit demand affected by the shock at the firm–bank-level and the firm-level. The dependent variables are: (i) $\mathbb{1}$(New Credit), a dummy equal to 1 if the credit used increases from the previous year; (ii) $\mathbb{1}$(New Bank), a dummy equal to 1 if the firm forms a new bank relationship in year t. $\text{Level}^k_{i(j)}$ indicates a firm's distance k from GM in the supply chain. Post equals 1 for 2007–2011 and 0 for 2002–2006. All specifications control for firm size, leverage, and profitability. Robust standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

closure. Column (4) examines whether firms establish new bank relationships. Again, the coefficient estimates are negative and statistically significant for affected firms, with the effects weakening as distance from GM increases. The results for upstream firms are similar, showing significant declines in credit usage and new bank formation among GM's direct and indirect suppliers. These findings confirm that supply chain disruptions translate into reduced credit demand. Additional model specifications are reported in Table B10 and yield consistent results.

One concern is that affected firms may substitute bank credit with trade credit to finance their production. For example, downstream firms can increase accounts payable, while upstream firms can increase accounts receivable. To address this concern, we re-estimate Eq(4) using accounts payable and accounts receivable as outcome variables. The results in Table B11 and Table B12 indicate no increase in trade financing. By contrast, trade financing for affected firms is significantly reduced after the shock relative to non-affected firms. This finding is consistent with our expectation, suggesting a contraction in production after the shock, which further reduces firms' credit demand from banks. Another concern is that the decrease in credit demand is driven by reductions from non-main banks while leaving credit from the main bank unaffected. We re-estimate Eq(4) using a sample that includes only firm borrowing from main banks. We identify main banks by calculating the fraction of the used amount obtained from each bank. The results in Table B13 remain similar.

3.3.3 Credit Demand at Bank Level

We have consistently shown that the drop in credit demand follows the supply chain disruption triggered by the GM closure at both the firm-bank level and the firm level. The underlying mechanism is that the GM closure negatively impacts the production of its direct and indirect suppliers and customers, which in turn hinders their credit demand. However, we cannot draw conclusions about the overall effects on bank loan portfolios. It is possible that banks reallocate the available credit from affected firms to unaffected firms, resulting in no aggregate effect on total bank credit balances.

To start with, we divide banks into two groups: banks with high or low exposures of GM closure, and look at their credit outcomes at (i) bank-province level and (ii) bank-sector level by aggregating firm-bank data.[15] The exposure is calculated using the following equation:

$$\text{Exposure}_b = \frac{\text{Amounts committed to affected firms in 2006}}{\text{Amounts committed to all firms in 2006}}. \tag{5}$$

Here, affected firms include level 1 to level 3 firms identified on either the buyer or seller side. That is, we do not differentiate between downstream or upstream relationships relative to GM. Ultimately, what matters is whether a firm is impacted by the GM closure. Additionally, we use authorized or committed credit amounts to capture the extent to which banks are exposed to the shock, as this measure accounts for the potential decline in credit demand.

[15] There are 11 provinces: Brussels, Walloon Brabant, Flemish Brabant, Antwerp, Limburg, Liège, Namur, Hainaut, Luxembourg, West Flanders, East Flanders. Sector is defined by 2-digit NACE code.

Figure A8 illustrates the average credit outcome of each bank-province combination. We normalize the lending volume in 2006 equal to one for both high exposure and low exposure banks. The figures indicate that high exposure banks experienced slower lending growth in committed and utilized loan amounts after the shock compared to low-exposure banks, suggesting that banks more concentrated in the supply chain faced a larger decline in credit demand. Figure A9 plots the average credit outcome of each bank-sector. Similarly, the results suggest a difference between banks with high or low exposure.

To formally investigate the influence of supply chain disruption on banks credit outcomes, we estimate following specification:

$$\text{Credit}_{b,p(s),t} = \beta \text{Exposure}_b \times \text{Post}_t + \text{FE} + \epsilon_{b,p(s),t}, \tag{6}$$

where b, p, s, and t denotes bank, province, sector, and year respectively. The outcome variable is the natural logarithm of (i) authorized amounts and (2) used amounts of a bank in a province (sector) in a year. Exposure_b equals 1 if a bank's exposure to the shock is above the 75 quantile, and 0 otherwise. Since the exposure variable is defined at the bank level, we cannot fully saturate the specification with bank-year fixed effects to control for credit supply. In this case, one could argue that the results may be driven by credit supply rather than demand. To address this concern, we include sector-year or province-year fixed effects to account for credit supply fluctuations at the sector or province level. Furthermore, we add a control variable, the bank-year fixed effects estimated from Eq(3). This captures shocks to bank-level credit supply that are common across all borrowers.[16] Bank fixed effects are also included to account for time-invariant bank characteristics that might affect the outcome variables. Standard errors are clustered at the bank level.

Table 6, Panel A reports the results on the effects of the GM closure on banks' credit balances at the bank-sector level. The dependent variable in Columns (1)-(2) is the committed amount. The coefficients of the interaction term are negative and statistically significant, suggesting that banks that ex-ante lent more to firms along GM's supply chain experience a greater reduction in credit demand at the bank-sector level after the GM closure, relative to banks that were ex-ante less exposed to the shock. After controlling for estimated bank-time fixed effects in Column (2), the results remain significant. In terms of economic magnitude, it suggests that ex-ante highly exposed banks experience 34.5% decrease in loan committed amounts at the bank-sector level. Columns (3)-(4) present similar results, with negative estimated coefficients while the significance disappears. Table 6, Panel B reports the results on banks' credit balances at the

[16] It is more common in the literature to isolate credit demand. See, e.g., Alfaro et al. (2021).

bank-province level. Consistent with expectations, we find that the drop in credit demand after the shock is significant for ex-ante more exposed banks compared to less exposed banks. The results hold when using either committed amounts as the dependent variable. Therefore, we conclude that banks are unable to fully compensate for the reduced credit demand of affected firms, resulting in an overall negative impact.

The results at the firm-bank, firm, and bank levels together indicate that a shock originating in the real sector can propagate to the financial sector through the production network.

Table 6: Propagation financial sector: Bank level

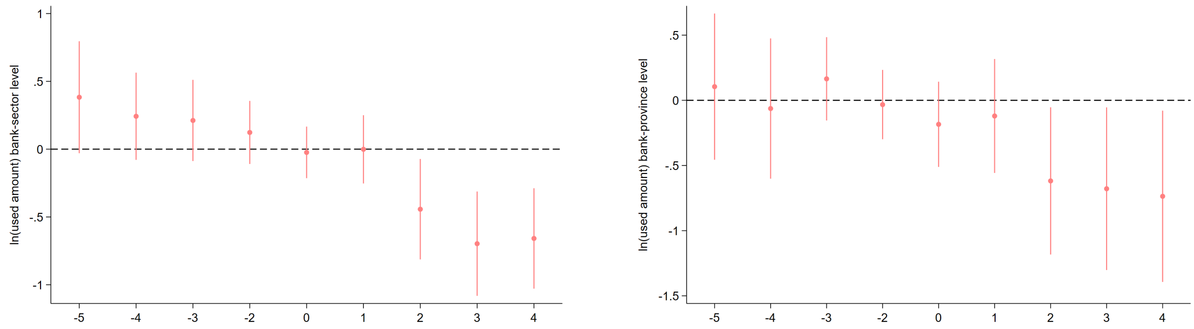
	(1)	(2)	(3)	(4)
	ln(CMT)		ln(USE)	
Panel A: Bank-Sector Level				
Exposure × Post	-0.4136***	-0.3447***	-0.5146***	-0.4472***
	(0.1432)	(0.1274)	(0.1539)	(0.1458)
Estimated Bank-Time FE		✓		✓
Bank FE	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓
N	16,379	14,501	15,867	14,083
R^2	0.70	0.70	0.70	0.70
Panel B: Bank-Province Level				
Exposure × Post	-0.5329**	-0.5255**	-0.4712*	-0.4450*
	(0.2545)	(0.2343)	(0.2775)	(0.2603)
Estimated Bank-Time FE		✓		✓
Bank FE	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓
N	4,920	4,161	4,761	4,045
R^2	0.72	0.72	0.71	0.71

Notes: This table shows the estimation results of Eq(6). The dependent variables are natural logarithm of (i) authorized amounts in a year in Columns (1) and (2), and (ii) used amounts of a bank in a province (sector, i.e., 2-digit NACE) in a year in Columns (3) and (4). Exposure_b equals 1 if a bank's exposure to the shock is above the 75 quantile, and 0 otherwise, as defined in Eq(5). Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Robust standard errors clustered at the bank level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.3.4 The Role of Common Lenders

This section investigates how prevalent common lenders are in GM's production network and how the disruption affects firms' decisions to borrow from a common lender. We focus on level 1 and level 2 firms to ensure they are at the same distance from GM in the production network.

Figure 3: Parallel trend - Bank level



(a) Bank-Sector Level

(b) Bank-Province Level

Notes: This figure validates the parallel trend assumption at the bank level. The left panel plots coefficient estimates in a dynamic difference-in-difference setting for bank-sector level used amounts. The right panel plots coefficient estimates in a dynamic difference-in-difference setting for bank-province level used amounts. Year 2006 is omitted as the reference year. Hence, "-1" are not reported.

The first exercise relies on cross-sectional variation, using a complete mapping of seller-buyer-bank relationships from 2006. First, we construct a complete mapping between level 1 and level 2 firms using 2006 B2B data, identifying firm pairs as linked in the supply chain if they have a transaction. Next, we use credit registry data to determine each firm's bank relationships, check whether they share common lenders, and count the number of common lenders. After that, we estimate the following regression specification:

$$\text{Common lender}_{i,j} = \beta \mathbb{1}(\text{Link})_{i,j} + \text{FE} + \epsilon_{i,j}. \tag{7}$$

We are interested in two outcome variables: (i) $\mathbb{1}(\text{CML})$, which equals 1 if a level 1 firm and a level 2 firm share a common lender, and 0 otherwise. (ii) #CML, a continuous variable indicating the number of common lenders between a level 1 firm and a level 2 firm. The explanatory variable, $\mathbb{1}(\text{Link})$, equals 1 if a level 1 firm and a level 2 firm had a transaction in 2006, and 0 otherwise. We include seller fixed effects and buyer fixed effects. Standard errors are clustered at the seller and buyer level.

Table 7 presents the results. We find that firms that have direct transactions are more likely to have common lenders. Regardless of the downstream or upstream, the estimated coefficients are positive and highly significant. Although the cross-sectional analysis suggests that trading partners are more likely to borrow from the same bank, it provides limited insight into how common lenders influence credit demand and allocation. To address this, we exploit the closure of GM as an exogenous shock to the importance of common lenders within GM's supply chain. We extend the cross-sectional sample into a multi-year panel dataset to examine how supply chain disruptions affect firms' decisions to borrow from common lenders. Specifically,

Table 7: Common lender and production links - Cross section

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(CML)		#CML	$\mathbb{1}$(CML)		#CML
	Downstream			Upstream		
$\mathbb{1}$(Link)	0.0333***	0.0333***	0.1080***	0.00860**	0.00860***	0.1180***
	(0.0121)	(0.0026)	(0.0039)	(0.0041)	(0.0009)	(0.0017)
Seller FE	✓	✓	✓	✓	✓	✓
Buyer FE	✓	✓	✓	✓	✓	✓
N	5,000,571	5,000,571	5,000,571	28,690,376	28,690,376	28,690,376
R^2	0.311	0.311	0.429	0.400	0.400	0.607
SE cluster	seller and buyer	seller-buyer		seller and buyer	seller-buyer	

Notes: This table shows the estimation results of Eq(7). The dependent variables are (i) $\mathbb{1}$(CML), which equals 1 if a level 1 firm and a level 2 firm share a common lender, and 0 otherwise. (ii) #CML, a continuous variable indicating the number of common lenders between a level 1 firm and a level 2 firm. $\mathbb{1}$(Link), equals 1 if a level 1 firm and a level 2 firm had a transaction in 2006, and 0 otherwise. Robust standard errors clustered at the seller and buyer level level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

the complete mapping of each level 1 and level 2 firm based on 2006 data is replicated for the years 2004–2005 and 2007–2009. The linkage between level 1 and level 2 firms is determined using 2006 B2B information. However, firm-bank relationships are time-varying and are obtained by merging the data with the credit registry.

Table 8 presents the results. Column (1) shows the results on the extensive margin, where the outcome variable is an indicator variable for having common lenders. The coefficient estimate is positive and statistically significant, indicating that firms with a direct transaction are more likely to share common lenders. Column (2) reports the results at the intensive margin, and the findings remain consistent. The predicted number of common lenders increases by 0.7 when the direct transaction indicator changes from 0 to 1, holding other factors constant. In Columns (3) and (4), we further interact the indicator variable with the Post dummy. The coefficient of the direct transaction indicator remains positive and statistically significant, with a slight increase in magnitude. Strikingly, the estimate of the interaction term is negative and statistically significant, suggesting that the number of common lenders for firms with direct transactions decreases after the shock, relative to firms without direct transactions. The results hold even when seller-buyer fixed effects are included, allowing us to exploit within-pair variations. Columns (5) and (6) report similar results.

These results highlight that the value of common lenders may depend on suppliers' and customers' financing decisions. As supply chain disruptions reduce credit demand along the supply chain, firms are more likely to terminate pre-existing relationships with common lenders, as the benefits of borrowing from them diminish. This further reduces credit demand for banks concentrated in the supply chain, explaining the significantly larger drop in lending volume for banks with high exposure to GM compared to low exposure banks. These findings underscore an amplification channel through which common lenders propagate shocks. To further investigate the role of common lenders in credit allocation and shock propagation, we build and estimate a structural model to quantify the benefits and costs of lending specialization as common lenders along the supply chain.

Table 8: Common lender and production links downstream

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(CML)	#CML	$\mathbb{1}$(CML)	$\mathbb{1}$(CML)	#CML	#CML
$\mathbb{1}$(Link)	0.0418***	0.700***	0.0564***		0.742***	
	(0.00994)	(0.213)	(0.0120)		(0.219)	
$\mathbb{1}$(Link) $\times$ Post			-0.0290***	-0.0323***	-0.0830*	-0.0891***
			(0.0100)	(0.0104)	(0.0433)	(0.0331)
Seller FE	✓	✓	✓		✓	
Buyer FE	✓	✓	✓		✓	
Seller-Buyer FE				✓		✓
Year FE	✓	✓	✓	✓	✓	✓
N	23,827,201	23,827,201	23,827,201	23,302,849	23,827,201	23,302,849
R^2	0.270	0.442	0.270	0.820	0.442	0.960

Notes: This table shows the estimation results of Eq(7). The dependent variables are (i) $\mathbb{1}$(CML), which equals 1 if a level 1 firm and a level 2 firm share a common lender, and 0 otherwise. (ii) #CML, a continuous variable indicating the number of common lenders between a level 1 firm and a level 2 firm. $\mathbb{1}$(Link), equals 1 if a level 1 firm and a level 2 firm had a transaction in 2006, and 0 otherwise. $Post_t$ is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Robust standard errors clustered at the seller and buyer level level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4 The Model

We consider Belgian manufacturing firms operating in a market defined by a given year t. In each period, firms first determine their production plans, which in turn determine the amount of credit needed to finance production. They then search across banks in the lending market to choose the credit offer that maximizes their utility. Banks compete by setting interest rates and leveraging their specialization to maximize profits. For simplicity of notation, we focus on a single year and omit the subscript t in the remainder of this section.

4.1 Production

We model firm production in line with recent literature on production network, considering firms $i = 1, ..., N$ operating in the market, each producing a single distinct product. Similar to Huremovic et al. (2024), we assume that firms have a nested CES production technology with constant returns to scale, the output of firm i is given by the following functional form:

$$y_i = \zeta_i k_i^{\rho} \ell_i^{\beta} M_i^{\lambda}. \tag{8}$$

Firms use two primary input factors physical capital k_i and labor ℓ_i, and intermediate input factors M_i for production. The positive parameters ρ, β, and λ denote input shares, and ζ_i represents the productivity parameter of firm i. For intermediate inputs, we define the following CES aggregate of inputs purchased from other firms:

$$M_i = \left(\sum_{j=1}^{N} a_{ji}^{\frac{1}{\sigma}} x_{ji}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{9}$$

where x_{ji} denotes the intermediate input that firm i purchases from firm j, σ represents the elasticity of substitution between different intermediate inputs, and a_{ji} is non-negative weight indicating the relative importance of input j for firm i's production. The weights satisfy $\sum_{j=1}^{N} a_{ji} = 1$ for all firms i. The matrix $\mathbf{A} = (a_{ji})_{j,i=1}^{N}$ captures the structure of the economy's production network, where a larger a_{ji} indicates a higher dependence of firm i on supplier j.

Similarly to Bigio and La'o (2020) and Huremovic et al. (2024), we assume that firms face working capital constraints in the production process. In each period, firms require bank credit to finance a fraction of intermediate inputs purchased from upstream suppliers, while revenues are generated at the end of the period through sales to downstream buyers. Firms are assumed to set their prices by applying a markup μ_i to marginal costs to account for competition in the product market, which is not explicitly modeled.[17] Thus, firms' profit is given by

$$\pi_i = p_i y_i - (1 + \theta_i) \left(\sum_{j=1}^{N} p_j x_{ji} + w\ell_i + rk_i \right), \tag{10}$$

where $p_i = \mu_i mc_i$ is the price of firm i's output product, and $\theta_i = \chi_i R_i$ denotes the financing cost of firm i, which depends on the fraction of intermediate input requiring bank credit χ_i and the interest rate applied to firm i, R_i. We assume that firms have imperfect information on interest rates offered by different banks before searching in the market. Therefore, they first make a decision on their production plan, which determines the amount of credit needed based

[17] Baqaee and Farhi (2020) and Baqaee (2018) also make a similar assumption taking the competition in product markets exogenously given.

on their estimation of the cost of financing, and then choose from which bank to borrow for the given amount of credit. The amount of credit required by firm i is

$$L_i = \chi_i \left(\sum_{j=1}^{N} p_j x_{ji} + w\ell_i + rk_i \right), \tag{11}$$

which is determined by the cost of all input factors.

4.2 Credit Market

Demand. We classify firms' credit demand into different types of loan products, denoted by τ, based on loan amount L_i and other loan characteristics. The set of firms requiring a type τ credit is represented by $\mathcal{S}^\tau$. Given their credit needs and desired loan type, firms can choose from banks $b = 1, \ldots, B$ that are actively operating in the market. Firms can shop around for banks and decide to borrow from bank b is the decision $d_i = b$ yields the highest utility compared to other available options. The indirect utility of this decision takes the following form:

$$U_{i,b}^D = \alpha_{P,i}^D R_b^\tau + \alpha_C^D C_{i,b} + \alpha_Z^D Z_{i,b} + X_b' \alpha_X^D + \xi_b^D + \varepsilon_{i,b}^D \tag{12}$$

where R_b^τ is the interest rate offered by bank b of loan type τ in this market. Among other bank characteristics, firms have preference regarding the lending relationship of the bank with themselves, their suppliers, and their customers. $C_{i,b}$ represents bank b's exposure to firm i's production network, measured by the share of loans granted by bank b among all credit used by i's suppliers or customers before making the descrete borrowing decision:

$$C_{i,b} = \sum_{j \neq i} w_{ij} \mathrm{Pr}_{j,b}, \tag{13}$$

where $w_{ij} = (a_{ji} + a_{ij})L_j / \sum_{j \neq i}(a_{ji} + a_{ij})L_j$, and $\mathrm{Pr}_{j,b}$ denotes the probability of firm j borrowing from bank b. The underlying assumption is that firm i' unobserved preference for bank b is orthogonal to that of other firms, given the observed firm and bank characteristics. A higher value of $C_{i,b}$ reflects a more significant role of bank b as a common lender in firm i's production network. $Z_{i,b}$ is a dummy variable that equals one if firm i and bank b had an existing lending relationship, and zero otherwise. X_b indicates observed bank-market characteristics, while ξ_b^D captures unobserved bank-market characteristics. $\varepsilon_{i,b}^D$ are type I extreme value distributed idiosyncratic demand shocks. We allow firms to have heterogeneous preferences over interest rates, which depends on previous lending relationship $Z_{i,b}$, as follows:

$$\alpha_{P,i}^D = \overline{\alpha}_P^D + \alpha_{PZ}^D Z_{i,b} + \varepsilon_{P,i}^D \tag{14}$$

where $\varepsilon^D_{P,i}$ is firms' unobserved preference for interest rates, assuming to be i.i.d. normally distributed.

The production network affects credit demand through two channels. First, shock propagation through production network influences the intermediate inputs used in production, and thus affecting the amount of credit L_i and the required type of credit product τ. Second, the borrowing decision of firms' suppliers and customers in the production network, combined with the changes their demand loan size, determines the convenience value firm can obtain from banks acting as a common lender of upstream and downstream firms.

Default. Banks compete in a Bertrand-Nash framework, setting interest rates to maximize expected profits across all types of loan products, taking firms' default risk into account for pricing. We model firms' loan performance been governed by the indirect utility of default:

$$U^F_{i,b} = \alpha^F_P R^\tau_b + \alpha^F_C C_{i,b} + \alpha^F_Z Z_{i,b} + X'_b \alpha^F_X + Y'_i \alpha^F_Y + \varepsilon^F_{i,b} \tag{15}$$

Similar to the demand model, we allow interest rates R^τ_b, the firm-bank lending relationship $C_{i,b}$ and $Z_{i,b}$, and observed bank characteristics X_b to affect a firm's default. Moreover, firms' productivity and profitability, such as sales shares, markups, are included to account for the impact of supply chain disruptions on firm's default risk. $\varepsilon^F_{i,b}$ represent the unobserved risk of default for firm i borrowing from bank b in this market, which is assumed to be i.i.d. normally distributed. The production network directly plays a role through the propagation of shocks affecting firms' productivity, and consequently financial soundness. Additionally, through its interaction with bank lending relationships, the production network influences the extent to which a bank acts as a common lender, potentially affecting firms' likelihood of default through strategic interactions.

Supply. Banks set interest rates R^τ_b for the type τ loan product to maximize their total expected profit

$$\Pi_b = \sum_\tau \left(\left(1 - F^\tau_b\right) R^\tau_b - MC^\tau_b\right) Q^\tau_b \tag{16}$$

where F^τ_b represents the expected probability of default for firms borrowing a type τ loan from bank b. MC^τ_b denotes the marginal cost of bank b lending one euro for a type τ credit, and Q^τ_b is the expected credit demand for a type τ loan from bank b in this market.

$$Q^\tau_b = \int_{i \in \mathcal{S}^\tau} \mathrm{Pr}_{i,b} L_i \mathrm{d}v(i) \tag{17}$$

where $v(\cdot)$ denotes the distribution of firms across their characteristics space.

4.3 Consumption and Equilibrium

In addition, the economy has a unit mass of households. They endogenously supply the total amount of L labor and inelastically supply K units of physical capital. Firms' production is either purchased by other firms as inputs or consumed by households, who derive utility from consuming products $c = (c_1, ..., c_N)$ across all goods. The representative household maximizes utility

$$u(c) = \frac{c^{1-\delta}}{1-\delta} - \frac{L^{1+\eta}}{1+\eta}, \tag{18}$$

subject to budget constraint

$$\sum_{i=1}^{N} p_i c_i \leqslant E, \tag{19}$$

where $c = \Pi_{i=1}^{N} c_i^{\gamma_i}$, γ_i represents the household's preference weight for good i, and δ and η determine the income elasticity of labor supply. Household income of households comes from labor income, capital income, firm profits, and earnings from the financial sector, that is, $E = wL + rK + \sum_{i=1}^{N} \pi_i + \sum_{i=1}^{N} \theta_i (\sum_{j=1}^{N} p_j z_{ji} + w\ell_i + rk_i)$.

Equilibrium. The equilibrium is characterized by a collection of prices $\{(p_i^*)_{i=1}^N, w^*, r^*, (R_b^{\tau *})_{b=1}^B\}$, quantities $\{(y_i^*)_{i=1}^N, (c_i^*)_{i=1}^N, (x_{ji}^*)_{i,j=1}^N, (\ell_i^*)_{i=1}^N, (k_i^*)_{i=1}^N, (Q_b^{\tau *})_{b=1}^B\}$, such that (i) each firm chooses a type τ credit product from bank b to finance production based on their preference; (ii) each firm i minimizes production costs and applies a markup μ_i to set prices; (iii) each bank sets the interest rate R_b^τ to maximize their profit; (iv) households choose their consumption plan to maximize utility; (v) markets for each type of credit product, intermediate input, capital, and labor clear.

5 Econometric Model

5.1 Production Shock

To estimate the production function of firms, we utilize the shock from the closure of GM and its propagation of the shock through the production network. Consider a shock dk_k that affects the physical capital of firm k and then propagates through the production network, influencing transactions among all firms connected within the network. We follow the same approach of Huremovic et al. (2024) to approximate the changes of sales from firm j to firm i relative to firm

i's total sale after the shock, using the following linear relationship

$$d\log s_{ji} - d\log s_i = -(\sigma-1)\ \underbrace{d\log(1+\theta_j)}_{\text{Supplier direct effect}} - \underbrace{d\log(1+\theta_i)}_{\text{Customer direct effect}} \tag{20}$$

$$-(\sigma-1)\underbrace{\lambda e_j'\mathbf{A}'(I-\lambda\mathbf{A}')^{-1}d\log(1+\theta)}_{\text{Supplier higher-order effect}} + (\sigma-1)\underbrace{e_i'\mathbf{A}'(1-\lambda\mathbf{A}')^{-1}d\log(1+\theta)}_{\text{Customer higher-order effect}}$$

where s_{ji} represents the total transaction from firm j to firm i, s_i represents the total sales of firm i, e_i is a column vector of length N with the ith element equal to one and zero otherwise. The variable $\theta_i = \chi_i R_b^\tau$ denotes the financing cost if firm i borrows a type τ credit from bank b. The detailed proofs are provided in Appendix C.

The shock to firm k affects its production, which in turn influences the demand for intermediate inputs and the supply of output products. This impact propagates through the production network, affecting both suppliers' and customers' production and product prices, which are reflected in the cost of intermediate inputs requiring credit financing. As a result, the impact of the shock on firms' sales can be divided into two parts. The first row of equation (20) corresponds to the direct impact of the production shock on link-level sales due to financing costs on suppliers and customers, while the second row corresponds to the higher-order impact resulting from financing costs incurred by suppliers and customers. The effects on suppliers and customers differ, depending on the magnitude of σ, which reflects the level of substitution among intermediate inputs. If $\sigma > 1$, suggesting that intermediate inputs are substitutes, a production shock that increases the financing cost of firm j leads to a reduction in firm i purchases from firm j. Conversely, when $\sigma < 1$, intermediate inputs are complements, meaning that firm i purchases more from j. The same argument applies to both direct and higher-order supplier effects. For customer effects, when the shock affects firm i's financing cost, it decreases the demand for all of its inputs, including those from firm j. In contrast, an increase in firm i's higher-order financing costs makes it more difficult to switch away from firm j if the intermediate inputs are substitutes (i.e. $\sigma > 1$).

We empirically estimate equation (20) using the following regression model

$$\Delta\log\left(\frac{s_{ji}}{s_i}\right) = \psi_1^s \Delta\widehat{\log(1+\theta_j)} + \psi_1^c \Delta\widehat{\log(1+\theta_i)} + \psi_2^s \widehat{Net}_j + \psi_2^c \widehat{Net}_i + \psi x_{ji} + \varepsilon_{ji}, \tag{21}$$

where $\widehat{Net}_i = e_i'\mathbf{A}'(I-\lambda\mathbf{A}')^{-1}\Delta\widehat{\log(1+\theta)}$. We obtain $\hat{\sigma} = 1 + \widehat{\psi_1^s}/\widehat{\psi_1^c}$, and $\hat{\lambda} = -\widehat{\psi_2^s}/\widehat{\psi_2^c}$.

Since firms use bank credit to finance production, a shock to production affects the amount of credit needed by firms. The amount of credit demanded by firm i is given by equation (11). Assuming that the fraction of production costs requiring credit χ_i is exogenous, reflecting the stringency of each firms' financial constraint, the change in credit demand after a physical capital shock satisfies

$$d\log L_i = e_i'(I-\lambda\mathbf{A}')^{-1}\left[\beta d\log w + \rho d\log r\right] + \lambda e_i'\mathbf{A}'(I-\lambda\mathbf{A}')^{-1}d\log(1+\theta) \tag{22}$$

5.2 Credit Demand

Given firms' credit demand L_i, the production network $\mathbf{A}$ and firms financing decisions $\mathrm{Pr}^{\tau}_{i,b}$, the probability of firm i borrowing from bank b is

$$\mathrm{Pr}^{\tau}_{i,b} = \int \mathrm{Pr}^{\tau}_{i,b,\varepsilon}\mathrm{d}\phi(\varepsilon^{D}_{P,i}) = \int \frac{\exp(\alpha^{D}_{P,i}R^{\tau}_{b} + \alpha^{D}_{C}C_{i,b} + \alpha^{D}_{Z}Z_{i,b} + X_b'\alpha^{D}_{X} + \xi^{D}_{b})}{\sum_{b=1}^{B}\exp(\alpha^{D}_{P,i}R^{\tau}_{b} + \alpha^{D}_{C}C_{i,b} + \alpha^{D}_{Z}Z_{i,b} + X_b'\alpha^{D}_{X} + \xi^{D}_{b})}\mathrm{d}\phi(\varepsilon^{D}_{P,i}), \tag{23}$$

where the second equality comes from the distributional assumption of $\varepsilon^{D}_{i,b}$. The log-likelihood function of firms credit demand choices is

$$\mathcal{L}^{D}(\alpha^{D}) = \sum_{i=1}^{N}\sum_{b=1}^{B} 1\{d_i = b\}\log \mathrm{Pr}^{\tau}_{i,b} \tag{24}$$

5.3 Credit Supply

Banks compete by setting interest rates to maximize their total expected profit. Since firms require a specific type of credit based on their production needs, banks effectively maximize their expected profit for each type of loan product. The first order condition of equation (16) suggests that the equilibrium interest rates satisfy

$$R^{\tau}_{b} = \frac{MC^{\tau}_{b}}{1-F^{\tau}_{b}+F^{\tau}_{b,R}\mathcal{M}^{\tau}_{b}} + \frac{(1-F^{\tau}_{b})\mathcal{M}^{\tau}_{b}}{1-F^{\tau}_{b}+F^{\tau}_{b,R}\mathcal{M}^{\tau}_{b}}, \tag{25}$$

where $\mathcal{M}^{\tau}_{b} = -\frac{Q^{\tau}_{b}}{Q^{\tau}_{b,R^{\tau}_{b}}}$, $F^{\tau}_{b,R}$ and $Q^{\tau}_{b,R^{\tau}_{b}}$ denote the derivative of the probability of default and demand with respect to interest rates. The first term corresponds to *effective marginal cost*, that is, the marginal cost of lending – including funding cost, operational and administrative cost – adjusted for the default. The second term corresponds to *effective markup*. In particular, our demand model added two extensions to standard credit demand model, allowing interest rates to affect credit demand through (i) the common lender effect along the supply chain, and (ii) the intensive margin through firms' production plans. This implies that:

$$Q^{\tau}_{b,R^{\tau}_{b}} = \int_{i\in\mathcal{S}^{\tau}} \left(\alpha^{D}_{P,i}\left(1-\mathrm{Pr}_{i,b}\right)\mathrm{Pr}_{i,b} - \alpha^{D}_{C}N^{\tau}_{i,b}\right)L_i + \mathrm{Pr}_{i,b}L_{i,R^{\tau}_{b}}\mathrm{d}v(i). \tag{26}$$

The first term in equation (26) represents the price impact on the extensive margin, where the first component corresponds to the standard own-price derivative on demand, while the second component captures the impact through the production network and the common lender effect.

In particular, $N^{\tau}_{i,b}$ ($N^{\tau}_{i,k}$) denotes the impact of marginal own-price (cross-price) changes in type τ credit from bank b on the credit demand of firm i for type τ credit from bank b (k) through the common lender effect. This effect arises from borrowers' preference for banks that serve as common lenders to their suppliers and customers. A change in the interest rate of one credit product affects the likelihood of firm i borrowing from other banks and the importance of those banks as common lenders to firm i and its suppliers and customers. As elaborated in Appendix C, the marginal common lender effects satisfy

$$N^{\tau}_{i,b} = -\sum_{k\neq b} \mathrm{Pr}_{i,k} \sum_{j\neq i} w_{ij}\alpha^{D}_{P,j}\mathrm{Pr}_{j,k}\mathrm{Pr}_{j,b} - \alpha^{D}_{C} \sum_{k\neq b} \mathrm{Pr}_{i,k} \sum_{j\neq i} w_{ij} N^{\tau}_{j,k}. \tag{27}$$

Given estimated credit demand preferences $\widehat{\alpha}^{D}_{P,i}$, $\widehat{\alpha}^{D}_{C}$, $\widehat{\alpha}^{D}_{Z}$, $\widehat{\alpha}^{D}_{X}$, estimated probability of borrowing from all banks $\widehat{\mathrm{Pr}}_{i,b}$, and $\widehat{w}_{ij}$ observable from data, we can solve $\widehat{N}^{\tau}_{i,b}$ numerically.

Finally, the second term in equation (26) represents the price impact on the intensive margin, given that firm i's probability of borrowing from bank b is $\mathrm{Pr}_{i,b}$, and $L_{i,R^{\tau}_{b}}$ denotes the derivative of loan size demanded by firm i with respect to a marginal change in the interest rate of type τ credit of bank b. The interest cost contributes to firms' marginal cost of production, influencing their production plan and credit demand. As detailed in Appendix C, we estimate the derivative of demand on prices $L_{i,R^{\tau}_{b}}$ using the ith element of $\lambda\mathbf{A}'(I-\lambda\mathbf{A}')^{-1}\widehat{\Omega}L$, where $\widehat{\Omega}$ is a diagonal matrix with each diagonal element equals to $\widehat{\chi}_i/(1+\widehat{\chi}_i\widehat{R}^{\tau}_{b})$.

And thus, we obtain $\widehat{Q}^{\tau}_{b,R}$ and $\widehat{\mathcal{M}}^{\tau}_{b}$. With these estimates, we can back out the marginal cost of bank b offering type τ product MC^{τ}_{b} from equation (25)

$$\widehat{MC}^{\tau}_{b} = \left(1 - \widehat{F}^{\tau}_{b} - \widehat{F}^{\tau}_{b,R}\widehat{\mathcal{M}}^{\tau}_{b}\right)\widehat{R}^{\tau}_{b} - \left(1 - F^{\tau}_{b}\right)\mathcal{M}^{\tau}_{b}, \tag{28}$$

which we keep fixed in counterfactual analyses.

6 Estimation Results

Table 9 presents the estimation results for the credit demand and default models. Using maximum likelihood estimation, we obtain the demand model parameters α^{D}, reported in Column (1). The negative coefficient on Interest Rate suggests a downward-sloping demand curve: a one percentage point increase in the interest rate decreases the utility of borrowing by 0.55, corresponding to an average own-price elasticity of 1.90, holding the production plan and financing demand fixed. In other words, this elasticity reflects only the extensive margin with given production and financing network; the intensive margin and network effect will be discussed later. The positive coefficient on Common Lender indicates that the more important a

Table 9: Credit Demand and Default

	Demand	Default
	(1)	(2)
Interest Rate	-0.55***	0.17***
	(0.01)	(0.00)
Common Lender	0.64***	0.06***
	(0.01)	(0.02)
Pre-Existing Relationship	3.81***	-0.07***
	(0.01)	(0.02)
Bank-Year FE	Y	Y
Firm Type-Year FE	N	Y
Control Function	Interest Rate	
Model	Mixed Logit	Probit
N	700,455	250,569

Note: This table reports the estimation results for credit demand and default in Columns (1) and (2), respectively. The demand model includes all firms in the sample, while the default model includes firms that have a positive balance on bank credit. Interest Rate is the annual interest rate of the bank credit line, expressed in percentage points. In the demand model, it corresponds to the predicted interest rate for each firm from each bank, while in the default model, it corresponds to the observed interest rate paid by each firm. Common Lender is a variable indicating the importance of a bank as a common lender for firms, as defined in Eq(13). Pre-Existing Relationship is a dummy variable that takes the value of 1 if the bank and the firm have a previous borrowing-lending relationship, and 0 otherwise. $***p < 0.001$; $**p < 0.01$; $*p < 0.05$.

bank is as a common lender within a firm's supply chain, the higher the firm's borrowing demand from that bank. In the sample, the mean of the Common Lender variable is 0.15, with a standard deviation of 0.26. This suggests that on average 15% of the total credit of a firm's direct customers and suppliers comes from the same bank. Based on the estimated elasticity of borrowing demand with respect to the common lender measure, a 1% increase in this measure raises the probability of borrowing from that bank by 0.1% on average. Finally, banks with a previous borrowing–lending relationship have a significant impact on firms' credit demand, highlighting the important role of relationship lending in Belgian credit markets.

Column (2) of Table 9 reports the estimation results for the default model as specified in Eq(15), controlling for bank-year fixed effects and firm type-year fixed effects. The results indicate that borrowers facing higher interest rates are more likely to default. A one percentage point increase in the interest rate raises the probability of default by 1.2 percentage points, corresponding to 0.55 standard deviations in the probability of default. Firms borrowing from common lenders along the supply chain are more likely to default: A one standard deviation increase in the Common Lender variable increases the probability of default by 0.1 percentage points. Whereas, firms with a previous borrow-lending relationship reduces the probability of default.

Table 10: Price Elasticity and Effective Markup

Year	Price Elasticity			Effective Markups		
	Baseline	No Common Lender Effect	No Cost Pass-Through	Baseline	No Common Lender Effect	No Cost Pass-Through
	(1)	(2)	(3)	(4)	(5)	(6)
2019	1.33	0.84	1.50	2.05	2.24	1.81
2020	0.83	0.75	0.99	2.02	2.31	1.71
2021	1.13	0.73	1.30	2.00	2.27	1.78
2022	1.85	1.10	2.12	2.02	2.18	1.89
2023	2.96	1.65	3.39	2.02	2.26	1.77

Note: This table reports the estimated price elasticity of demand (Columns (1)–(3)) and the effective markups (Columns (4)–(6)) over the period 2019–2023. Columns (1) and (4) present the estimates under the baseline model, where both the common lender channel and the cost pass-through channel are active. Columns (2) and (5) show the estimates when the common lender channel is excluded, while Columns (3) and (6) report the results when the cost pass-through channel is excluded.

Based on the estimates from the demand and default models, we compute firms' price elasticity and effective markup for the period 2019-2023. Column (1) of Table 10 reports the estimated average price elasticity, accounting for both the common-lender effect and the intensive-margin channel. The price elasticity ranges from 0.83 to 2.96 over the sample period, with an increasing trend that reflects the general rise in interest rates during these years.

Column (2) reports the estimated elasticities when the common-lender effect is excluded. Comparing Column (2) with Column (1) shows a lower price elasticity without the common lender channel, indicating that acting as a common lender increases borrowers' price elasticity and thus reduces banks' market power. This effect arises because increasing interest rates not only decreases the probability that a firm will borrow from the bank, but also reduces the likelihood that the firm's suppliers and customers will borrow from that same bank. As the bank becomes less central in the supply chain, the advantages of borrowing from it diminish further.

In contrast, Column (3) shows result without the cost path-through channel: ignoring the impact of financing costs on production and credit demand results in a higher estimated price elasticity. This implies that, under the assumption that the share of production costs requiring external financing is fixed, the pass-through of financing costs to product prices raises production costs–particularly the cost of intermediary inputs–and increases the amount of credit needed to finance production. This counteracting effect lowers price elasticity, making credit demand less sensitive to interest rate changes. Notably, if firms were financially unconstrained, this effect would likely be smaller. Therefore, we interpret this as an upper-bound estimate.

Table 11: Price Elasticity, Effective Markup, and Marginal Costs

	Price Elasticity	**Effective Markup**	**Effective Marginal Cost**
	(1)	(2)	(3)
Common Lender	-0.30***	0.26***	-0.33***
	(0.01)	(0.00)	(0.00)
Pre-Existing Relationship	-1.31***	1.15***	-0.83***
	(0.01)	(0.00)	(0.00)
Bank-Year FE	✓	✓	✓
Firm Type-Year FE	✓	✓	✓
N	3,639,273	3,639,273	3,639,273
Adj. R^2	0.08	0.10	0.34

Note: This table reports the results of regressing the estimated price elasticity of demand, effective markups, and effective marginal costs on the Common Lender variable and the Pre-Existing Relationship indicator. Each observation corresponds to a firm-bank pair. Common Lender measures the importance of a bank as a common lender for the firm, as defined in Eq(13). Pre-Existing Relationship is a dummy variable equal to one if the bank and the firm have a previous borrowing-lending relationship, and zero otherwise. Bank–year fixed effects and firm-type-year fixed effects are included. ***p<0.001; **p<0.01; *p<0.05

Columns (4) to (6) report the estimated effective markup over time in our model, as well as the results when excluding the common-lender channel and the cost pass-through channel. The estimated effective markup is approximately 2 percentage points and remains stable across the five-year period. Comparing Column (4) with Column (5) shows that the common-lender channel reduces the effective markup by about 0.23 percentage points on average, while the cost pass-through channel increases the markup by approximately 0.23 percentage points on average.

Knowing the important role of the common lender channel and cost pass-through channel in credit demand, we further examine how banks with different importance as common lenders, or with prior borrowing–lending relationships, can leverage their market position to affect their borrowers' price elasticity, effective markup, and the implied marginal costs. We focus on our baseline model, which incorporates both the common-lender channel and the cost pass-through channel.

We compute firms' price elasticity, effective markup, and effective marginal costs for each bank, and regress these outcomes on the Common Lender variable and a dummy indicating whether the firm and bank have a pre-existing borrowing–lending relationship. We include bank-year fixed effects and firm-type–year fixed effects to control for unobserved bank-time level supply shocks and industry–size–time level demand shocks.

Table 11 shows that banks with greater importance as common lenders in a firm's supply chain face less price-sensitive borrowing. A one standard deviation increase in the Common Lender variable reduces borrowers' price elasticity of demand by 0.08. Having a prior borrowing-lending relationship reduces price elasticity by 1.31, consistent with a hold-up in relationship lending. Lower price elasticity for common lenders and relationship lenders translates into higher markups (Column (2)) and lower effective marginal costs (Column (3)).

These results highlight banks' incentives to concentrate lending within supply chains. Although lending concentration introduces a network effect that can dampen market power by creating spillovers through suppliers and customers, greater concentration also increases the bank's role as a common lender, which is preferable by borrowers. By exploiting this preference from borrowers, banks can charge higher markups when they act more prominently as common lenders. In addition, sector-specific expertise and informational advantages obtained through suppliers and customers reduce screening and monitoring costs, lowering effective marginal costs and making lending to both suppliers and customers more profitable. Relationship lending generates a similar effect: while the role of relationship lending is well documented in the literature, our results show that lending concentration within supply chains works through a comparable mechanism, with a smaller but economically meaningful impact.

7 Conclusion

This paper studies the benefits and costs of lending specialization within production networks, with a particular focus on the role of common lenders along the supply chain. Using several administrative datasets from Belgium, including the universe of firm-to-firm transaction data merged with credit registry data, we provide the first empirical evidence on common lending, defined as banks simultaneously lending to both suppliers and customers. This phenomenon is pervasive and distinct from the existing literature on bank specialization by industry or geographic location: common lending along supply chains spans multiple sectors and regions. We document that firms with direct trading relationships are significantly more likely to borrow from the same bank. Credit from common lenders is associated with lower interest rates, larger loan sizes, and better credit ratings, and the effect is especially strong for suppliers, highlighting the benefits of borrowing from common lenders.

On the downside, we show that an exogenous shock to the manufacturing sector, the closure of a large manufacturing firm GM Antwerp, propagates along the production network, reducing output and credit demand for both upstream and downstream firms, with stronger effects for firms closer to GM Antwerp in the production network. At the aggregate level, banks with higher exposure to the shock experience a larger decline in credit growth, highlighting an amplification mechanism through which real-sector disruptions spill over to the financial sector via common lenders.

To separate credit demand from credit supply and to account for general-equilibrium effects on production and financing decisions, we develop a structural model of firm production embedded in an imperfectly competitive lending market, where borrowers are interconnected through the supply chain. Structural estimation shows that borrowers prefer to borrow from common lenders. A 1% increase in the common-lender measure (the share of credit of a firm's suppliers and customers coming from a bank) raises the probability of borrowing from that bank by 0.1%. This preference increases a bank's market power. Banks that are more central as common lenders face lower price elasticity of demand, charge higher markups, and have lower marginal lending costs. This result explains banks' incentives to specialize along supply chains. However, the same preference also generates a spillover effect that limits banks' ability to increase interest rates. Higher interest rates reduce demand not only for the focal borrower, but also for its suppliers and customers, weakening the bank's common-lender position and reducing market power. Hence, banks are more willing to offer favorable pricing to firms within the same supply chain.

The model further illustrates a cost pass-through channel: higher financing costs raise product prices by increasing intermediary-input costs. When production requires bank credit financing, this mechanism increases credit demand, making the pass-through channel pro-cyclical and strengthening banks' market power during booms. Conversely, in downturns, lower prices decrease credit demand, amplifying the transmission of real-sector shocks to the financial sector. Combined with borrowing from common lenders, this generates correlated declines in credit demand across a bank's portfolio.

Overall, our results highlight the crucial role of lending concentration along supply chain in amplifying economic shocks and demonstrate the close connection between supply-chain links and credit relationships. The importance of dynamics in firm–bank connections sheds light on broader implications for credit allocation, financial stability, and the design of macro-prudential regulation.

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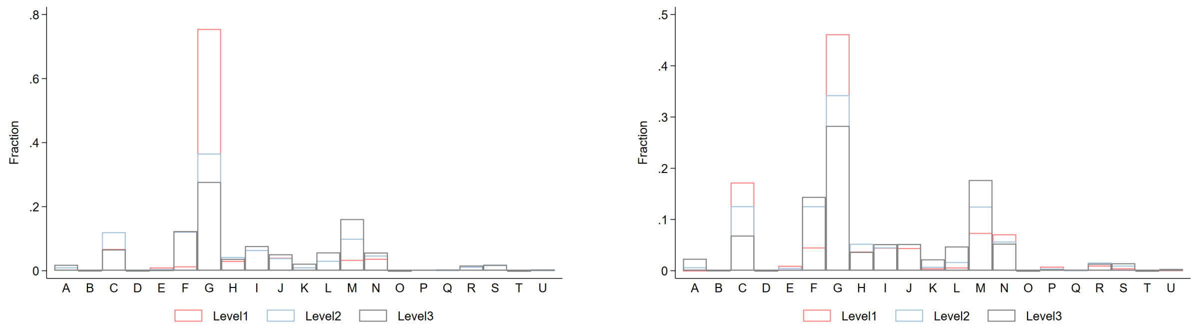
Appendices

A Figures

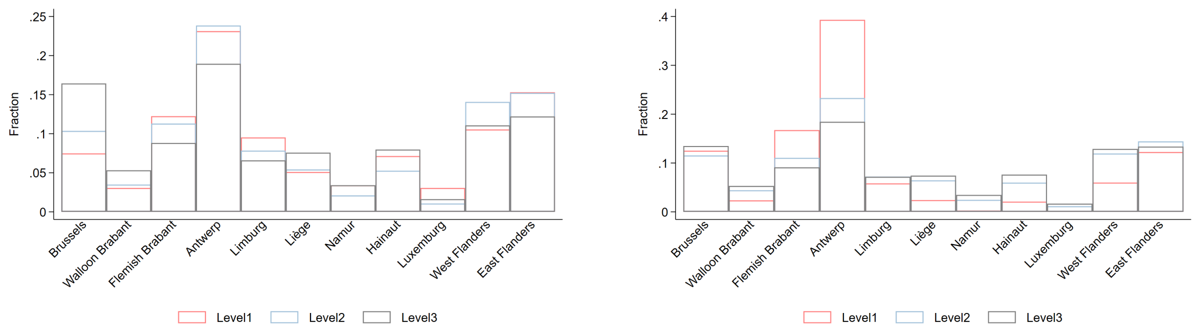
Figure A1: Industry Distribution



(a) Downstream (b) Upstream

Notes: This figure plots the industry distribution of GM's supply chain network. Figure A1a plots the industry distribution of the downstream customers of GM. Figure A1b plots the industry distribution of the upstream customers of GM. Industry is denoted by one-digit NACE code. A, Agriculture, Forestry and Fishing. B, Mining and Quarrying. C, Manufacturing. D, Electricity, Gas, Steam and Air Conditioning Supply. E, Water Supply; Sewerage, Waste Management and Remediation Activities. F, Construction. G, Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles. H, Transportation and Storage. I, Accommodation and Food Service Activities. J, Information and Communication. K, Financial and Insurance Activities. L, Real Estate Activities. M, Professional, Scientific and Technical Activities. N, Administrative and Support Service Activities. O, Public Administration and Defence; Compulsory Social Security. P, Education. Q, Human Health and Social Work Activities. R, Arts, Entertainment and Recreation. S, Other Service Activities. T, Activities of Households as Employers; Undifferentiated Goods- and Services-Producing Activities of Households for Own Use. U, Activities of Extraterritorial Organizations and Bodies.

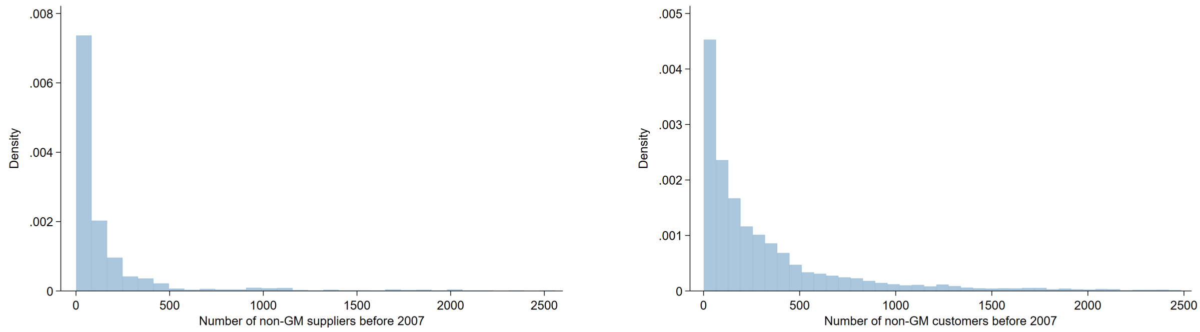
Figure A2: Geography Distribution



(a) Downstream (b) Upstream

Notes: This figure plots the geography distribution of GM's supply chain network. Figure A2a plots the geography distribution of the downstream customers of GM. Figure A2b plots the geography distributionn of the upstream customers of GM.

Figure A3: Number of non-GM suppliers and customers

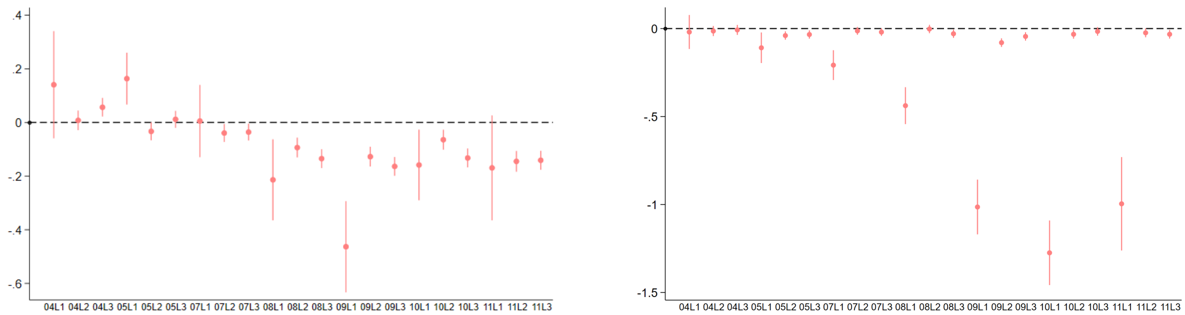


(a) Level 1 firms as GM's buyers

(b) Level 1 firms as GM's sellers

Notes: This figure shows the distribution of number of non-GM suppliers and customers of Level 1 firms.

Figure A4: Parallel trend - Transaction level

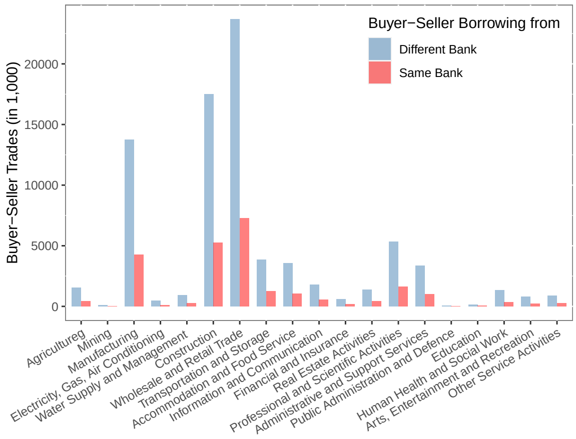


(a) Downstream

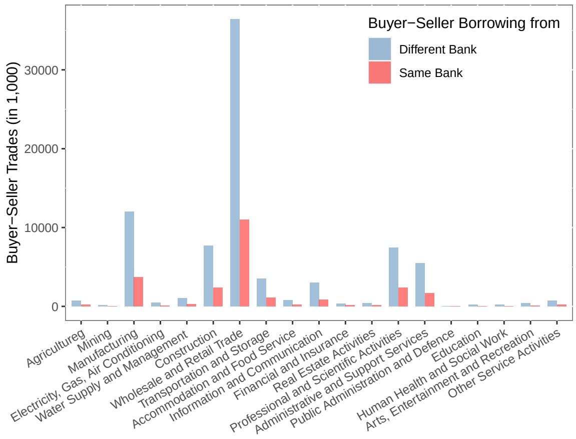
(b) Upstream

Notes: This figure validates the parallel trend assumption at the transaction level. The left panel plots coefficient estimates in a dynamic difference-in-difference setting for downstream propagation. The right panel plots coefficient estimates in a dynamic difference-in-difference setting for upstream propagation. "04L1", "04L2", "04L3" refers to (i) year 2004 and level 1 firms, (ii) year 2004 and level 2 firms, (iii) year 2004 and level 3 firms. Year 2006 is omitted as the reference year. Hence, "06L1", "06L2", "06L3" are not reported.

Figure A5: Common Lenders across Industry



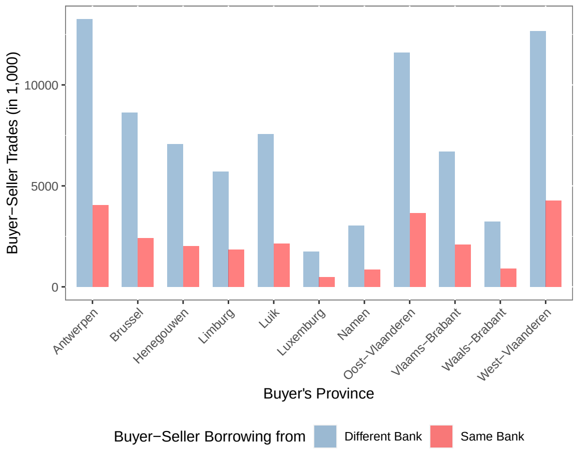
(a) Downstream Firms' Industry



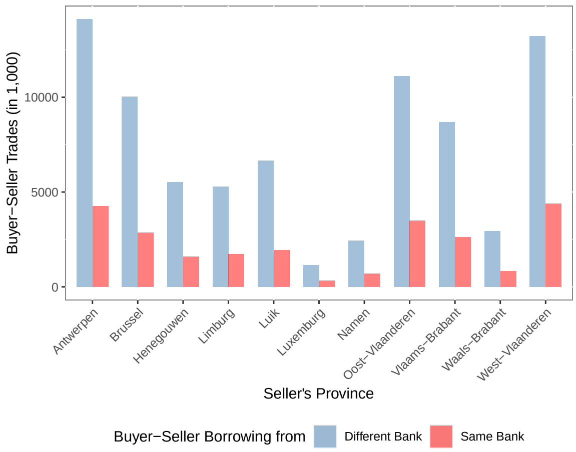
(b) Upstream Firms' Industry

Notes: This figure shows the distribution of buyer–seller trading pairs borrowing from the same bank versus different banks across industries and for both buyers and sellers. Subfigure (a) displays the distribution of buyer industries, distinguishing whether the buyer–seller pair borrows from the same bank (red bars) or from different banks (blue bars). Subfigure (a) presents the corresponding distribution for seller industries.

Figure A6: Common Lenders across Province



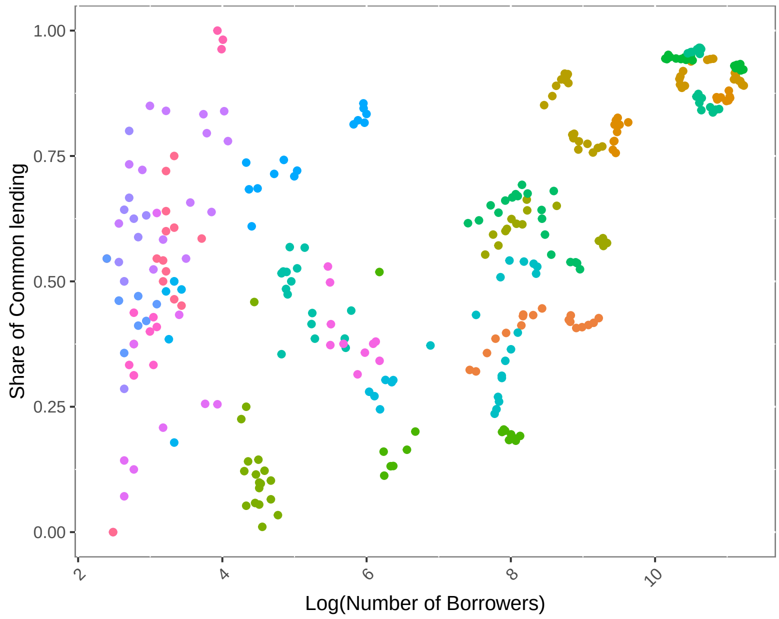
(a) Downstream Firms' Region



(b) Upstream Firms' Region

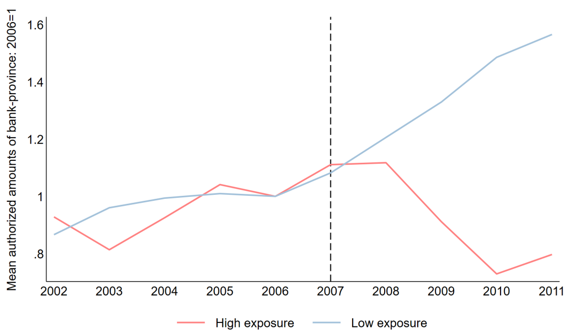
Notes: This figure shows the distribution of buyer-seller trading pairs borrowing from the same bank versus different banks across Belgium provinces and for both buyers and sellers. Subfigure (a) displays the distribution of buyer privinces, distinguishing whether the buyer-seller pair borrows from the same bank (red bars) or from different banks (blue bars). Subfigure (b) presents the corresponding distribution for seller provinces.

Figure A7: Common Lending by Bank

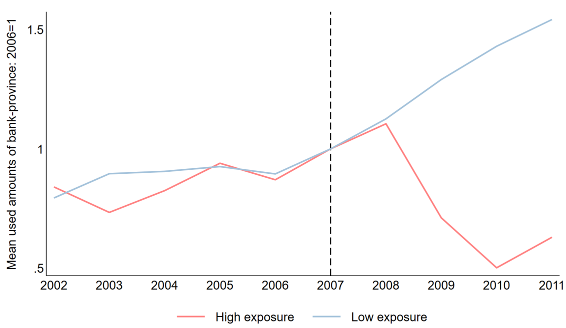


Notes: This figure shows the relationship between bank size and the extent of common lending across banks. The horizontal axis shows the total number of borrowers of each bank (log scale). The vertical axis shows the percentage of a bank's borrowers who have at least one trading partner that also borrows from the same bank. Each point represents one bank in a given year, and each color indicates a different bank. The figure demonstrates that common lending is widespread across banks of different sizes, with substantial heterogeneity in the degree of supply chain specialization even among banks of similar size.

Figure A8: Credit Outcome at Bank-market Level



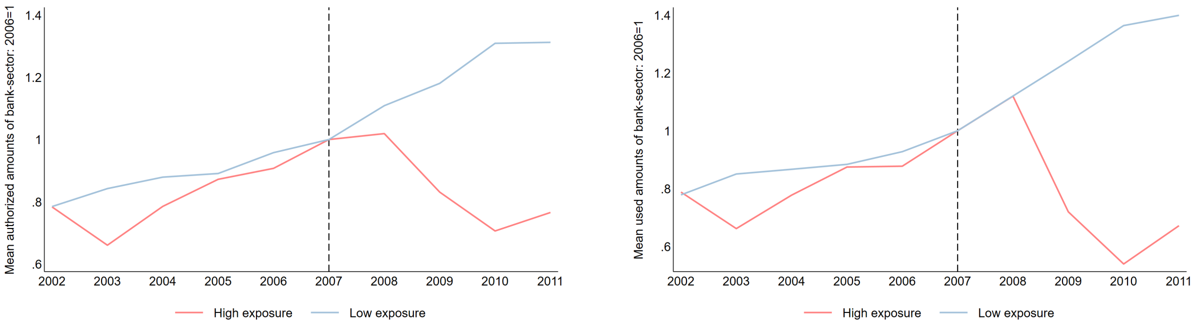
(a) Committed amounts



(b) Used amounts

Notes: This figure illustrates the credit outcome at the bank-market level. The market is defined as the province of Belgium. Exposure is defined as in Eq(5).

Figure A9: Credit Outcome at Bank-sector Level



(a) Committed amounts

(b) Used amounts

Notes: This figure illustrates the credit outcome at the bank-sector level. The sector is defined as the 2-digits NACE code. Exposure is defined as in Eq(5).

B Tables

Table B1: Summary Statistics: B2B

	N	Mean	SD	Min	p25	p50	p75	Max
Sales	93,177,390	16119.91	68458.26	251.76	602	1579.29	5705.03	726017
ln(Sales)	93,177,390	7.712	1.659	5.528	6.400	7.365	8.649	13.495

Notes: This table shows the summary statistics of B2B data. Sales is in EUR. The variables are winsorized at 0.5% and 99.5%.

Table B2: Summary Statistics: Credit Register at Bank-firm Level

	N	Mean	SD	Min	p25	p50	p75	Max
$\mathbb{1}$(New credit)	1,429,551	0.295	0.456	0	0	0	1	1
$\mathbb{1}$(New bank)	2,257,341	0.069	0.253	0	0	0	0	1
Δ(New credit)	1,320,825	-0.031	0.665	-10.342	-0.232	-0.079	0.064	10.707

Notes: This table shows the summary statistics of firm-bank level bank loan of firms appear in B2B dataset for years 2002-2011. $\mathbb{1}$(New credit) a dummy variable that takes the value of 1 if the difference in the used credit amount of a firm at a bank from the previous year to the current year is positive, and 0 otherwise. $\mathbb{1}$(New bank) is a dummy variable that takes the value of 1 if a bank is new to a firm in year the current year, and 0 otherwise. Δ(New credit) is the difference between natural logarithm of total used amount in the current year and the natural logarithm of total used amount in the previous year.

Table B3: Summary Statistics: Firm Balance Sheets

	N	Mean	SD	Min	p25	p50	p75	Max
Total assets	2,790,962	1610756	7579731	540	76479	227809	680301	90100000
Total liabilities	2,790,962	926990.6	4108742	0	38939	134855.5	430795	47600000
ln(Total assets)	2,790,962	12.363	1.806	6.292	11.245	12.336	13.430	18.316
$\frac{\text{Total liabilities}}{\text{Total assets}}$	2,790,962	1.101	3.531	0.000	0.393	0.685	0.911	46.075
$\frac{\text{Profit after taxes}}{\text{Total assets}}$	2,790,962	-0.029	0.446	-4.111	-0.031	0.017	0.083	1.172
Down Level 1	2,506,936	0.001	0.032	0	0	0	0	1
Down Level 2	2,506,936	0.303	0.460	0	0	0	1	1
Down Level 3	2,506,936	0.573	0.495	0	0	1	1	1
Up Level 1	3,434,510	0.005	0.074	0	0	0	0	1
Up Level 2	3,434,510	0.281	0.450	0	0	0	1	1
Up Level 3	3,434,510	0.404	0.491	0	0	0	1	1

Notes: This table shows the summary statistics of balance sheet characteristics of firms appear in B2B for years 2002-2011. Total assets and Total liabilities are in EUR. Down (Up) Level 1, 2, and 3 are dummy variables indicating whether a firm is a downstream (upstream) buyer (supplier) of GM at level 1, 2, or 3, respectively. The variables are winsorized at 0.5% and 99.5%.

Table B4: Same postcode

	GM's buyers		GM's sellers	
	#Firms	Percent	#Firms	Percent
Different postcode	1,665	98.99	7,319	98.68
Same postcode	17	1.01	98	1.32
Total	1,682	100.00	7,417	100.00

Notes: This table shows the number of firms that have same postcodes as GM among its direct customers and suppliers.

Table B5: Shock propagation: Transaction level

	(1)	(2)	(3)	(4)
	ln(sales)			
Panel A: Downstream				
Level 1 × Post	-0.4718***	-0.3158***	-0.4852***	-0.3349***
	(0.0122)	(0.0128)	(0.0122)	(0.0127)
Level 2 × Post	-0.1460***	-0.0616	-0.0489*	0.0525
	(0.0319)	(0.0452)	(0.0276)	(0.0355)
Level 3 × Post	-0.2093***	-0.1225***	-0.0209	0.0694***
	(0.0128)	(0.0132)	(0.0127)	(0.0131)
N	15,563,114	12,597,242	18,365,775	14,814,192
R^2	0.81	0.81	0.43	0.42
Panel B: Upstream				
Level 1 × Post	-0.4842***	-0.4749***	-0.5031***	-0.5030***
	(0.0109)	(0.0118)	(0.0158)	(0.0160)
Level 2 × Post	-0.0434***	-0.0032	0.1825***	0.2171***
	(0.0150)	(0.0156)	(0.0135)	(0.0153)
Level 2 × Post	-0.0383***	-0.0150	0.1793***	0.1976***
	(0.0104)	(0.0120)	(0.0110)	(0.0131)
N	5,347,025	4,357,982	6,498,781	5,234,259
R^2	0.84	0.84	0.56	0.55
Seller controls		✓		✓
Buyer controls		✓		✓
Seller-Buyer FE	✓	✓		
Seller FE			✓	✓
Buyer FE			✓	✓
Year FE	✓	✓	✓	✓

Notes: This table shows the estimation results of Eq(1). The dependent variable is the natural logarithm of sales between a seller i and a buyer j in year t. Level$_{i,j}$ is an indicator variable that indicates whether a buyer-seller pair, in which the buyer (seller) is in distance k of the GM supply chain during the years 2002-2006. k takes the values 1, 2, and 3. Post$_t$ is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets) of sellers and buyers. Robust standard errors clustered at the seller and buyer levels are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Shock propagation: Firm level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(sales)							
Panel A: Downstream								
Level 1 × Post	-0.3511***	-0.2428***	-0.2034***	-0.1947***	-0.3862***	-0.2548***	-0.2677***	-0.2496***
	(0.0562)	(0.0602)	(0.0575)	(0.0537)	(0.0747)	(0.0590)	(0.0666)	(0.0728)
Level 2 × Post	-0.2770***	-0.1637***	-0.2078***	-0.1568***	-0.3078***	-0.1695***	-0.2035***	-0.1522***
	(0.0229)	(0.0321)	(0.0417)	(0.0355)	(0.0580)	(0.0296)	(0.0380)	(0.0330)
Level 3 × Post	-0.2372***	-0.1243***	-0.2049***	-0.1299***	-0.2609***	-0.1244***	-0.1908***	-0.1182***
	(0.0228)	(0.0319)	(0.0372)	(0.0307)	(0.0578)	(0.0305)	(0.0335)	(0.0284)
N	2,445,160	1,748,206	2,049,123	1,682,951	2,444,780	1,748,206	2,048,037	1681798
R^2	0.85	0.85	0.86	0.86	0.85	0.85	0.86	0.87
Panel B: Upstream								
Level 1 × Post	-0.3287***	-0.2541***	-0.2123***	-0.2426***	-0.3290***	-0.2492***	-0.2469***	-0.2715***
	(0.0226)	(0.0217)	(0.0476)	(0.0410)	(0.0243)	(0.0287)	(0.0501)	(0.0503)
Level 2 × Post	-0.2879***	-0.2149***	-0.2108***	-0.2143***	-0.2933***	-0.2157***	-0.2278***	-0.2254***
	(0.0110)	(0.0119)	(0.0261)	(0.0260)	(0.0201)	(0.0189)	(0.0335)	(0.0313)
Level 3 × Post	-0.1819***	-0.1403***	-0.1442***	-0.1388***	-0.1854***	-0.1422***	-0.1485***	-0.1416***
	(0.0110)	(0.0118)	(0.0191)	(0.0167)	(0.0147)	(0.0152)	(0.0229)	(0.0199)
N	2,445,160	2,053,999	2,049,123	2,049,123	2,444,780	2,053,999	2,048,037	2,048,037
R^2	0.85	0.87	0.86	0.87	0.85	0.87	0.86	0.88
Firm control × Year		✓		✓		✓		✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓						
Sector-Year FE			✓	✓				
Location-Year FE					✓	✓		
Sector-Location-Year FE							✓	✓

Notes: This table shows the estimation results of Eq(2). The dependent variable is the sales of transaction level aggregated at firm $(i(j))$ level in year t. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Robust standard errors clustered at the firm levels in Columns (1) and (2), at 2-digit NACE code level in Columns (3) and (4), at 2-digit postcode level in Columns (5) and (6), at 2-digit NACE code and 2-digit postcode in Columns (7) and (8) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Shock propagation: Firm level number of buyers

	(1)	(2)	(3)	(4)
	#buyers			
Panel A: Downstream				
Level 1 × Post	-0.1015**	-0.0866***	-0.1097**	-0.0930**
	(0.0444)	(0.0302)	(0.0459)	(0.0460)
Level 2 × Post	-0.1307***	-0.1146***	-0.1343***	-0.1156***
	(0.0172)	(0.0212)	(0.0151)	(0.0171)
Level 3 × Post	-0.0870***	-0.0803***	-0.0873***	-0.0795***
	(0.0170)	(0.0205)	(0.0152)	(0.0168)
N	1,748,206	1,682,951	1,748,206	1,681,798
R^2	0.89	0.90	0.89	0.90
Panel B: Upstream				
Level 1 × Post	-0.3391***	-0.3286***	-0.3382***	-0.3426***
	(0.0209)	(0.0276)	(0.0259)	(0.0331)
Level 2 × Post	-0.2942***	-0.2923***	-0.2962***	-0.2984***
	(0.0060)	(0.0185)	(0.0076)	(0.0190)
Level 3 × Post	-0.1808***	-0.1776***	-0.1831***	-0.1815***
	(0.0058)	(0.0164)	(0.0072)	(0.0166)
N	2,053,999	2,049,123	2,053,999	2,048,037
R^2	0.91	0.91	0.91	0.91
Firm control × Year	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓			
Sector-Year FE		✓		
Location-Year FE			✓	
Sector-Location-Year FE				✓

Notes: This table shows the estimation results of Eq(2). The dependent variable is the number of buyers of firm $(i(j))$ level in year t. Level$^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post$_t$ is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Robust standard errors clustered at the firm levels in Columns (1), at 2-digit NACE code level in Columns (2), at 2-digit postcode level in Columns (3), at 2-digit postcode and 2-digit NACE code level in Columns (4) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Shock propagation: Firm level with restricted sample

	(1)	(2)	(3)	(4)
	ln(sales)			
Panel A: Downstream				
Level 1 × Post	-0.2643***	-0.0869	-0.2718***	-0.1709
	(0.1178)	(0.1623)	(0.1220)	(0.1628)
Level 2 × Post	-0.2317***	-0.0781	-0.2355***	-0.1148
	(0.1098)	(0.1534)	(0.1098)	(0.1458)
Level 3 × Post	-0.1801	-0.0542	-0.1750	-0.0789
	(0.1098)	(0.1517)	(0.1099)	(0.1440)
Observations	970,367	919,369	970,367	918,105
R-squared	0.89	0.91	0.89	0.91
Panel A: Downstream				
Level 1 × Post	-0.2619***	-0.2316***	-0.2668***	-0.2708***
	(0.0305)	(0.0509)	(0.0432)	(0.0450)
Level 2 × Post	-0.2249***	-0.2032***	-0.2326***	-0.2299***
	(0.0256)	(0.0351)	(0.0349)	(0.0290)
Level 3 × Post	-0.1475***	-0.1336***	-0.1551***	-0.1485***
	(0.0257)	(0.0336)	(0.0314)	(0.0308)
Observations	1,058,519	1,057,036	1,058,519	1,055,828
R-squared	0.91	0.91	0.91	0.91
Firm control × Year	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓			
Sector-Year FE		✓		
Location-Year FE			✓	
Sector-Location-Year FE				✓

Notes: This table shows the estimation results of Eq(2). The sample is restricted to firms with positive full-time-equivalent. The dependent variable is the sales of transaction level aggregated at firm ($i(j)$) level in year t. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Robust standard errors clustered at the firm levels in Columns (1), at 2-digit NACE code level in Columns (2), at 2-digit postcode level in Columns (3), at 2-digit postcode and 2-digit NACE code level in Columns (4) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B9: Propagation financial sector: Firm-bank level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\mathbb{1}$(New credit)			Δln(Credit)			$\mathbb{1}$(New bank)		
Panel A: Downstream									
Level 1 × Post	-0.0076	-0.0053	-0.0204	0.0228	-0.0101	0.0254	0.0061	0.0096	0.0059
	(0.0200)	(0.0199)	(0.0209)	(0.0336)	(0.0350)	(0.0332)	(0.0068)	(0.0067)	(0.0070)
Level 2 × Post	-0.0326***	-0.0322***	-0.0393***	-0.0173**	-0.0338***	-0.0159*	-0.0084***	-0.0078**	-0.0090***
	(0.0061)	(0.0061)	(0.0071)	(0.0086)	(0.0104)	(0.0085)	(0.0026)	(0.0030)	(0.0026)
Level 3 × Post	-0.0255***	-0.0258***	-0.0304***	-0.0034	-0.0165	-0.0010	-0.0046*	-0.0054*	-0.0042
	(0.0061)	(0.0061)	(0.0070)	(0.0085)	(0.0101)	(0.0084)	(0.0026)	(0.0030)	(0.0026)
N	1,197,945	1,196,648	1,175,754	1,118,240	1,098,229	1,119,482	1,964,472	1,932,785	1,966,191
R^2	0.2662	0.2676	0.2939	0.1806	0.2101	0.1787	0.4836	0.5112	0.4783
Panel B: Upstream									
Level 1 × Post	0.0019	0.0056	-0.0005	-0.0293	-0.0280	-0.0340*	-0.0037	0.0013	-0.0062**
	(0.0092)	(0.0098)	(0.0092)	(0.0189)	(0.0194)	(0.0189)	(0.0031)	(0.0033)	(0.0031)
Level 2 × Post	-0.0039	-0.0016	-0.0039	0.0046	0.0030	0.0039	-0.0086***	-0.0061***	-0.0092***
	(0.0041)	(0.0045)	(0.0041)	(0.0063)	(0.0071)	(0.0063)	(0.0016)	(0.0017)	(0.0016)
Level 3 × Post	-0.0021	0.0004	-0.0015	0.0085	0.0085	0.0089	-0.0060***	-0.0048***	-0.0058***
	(0.0041)	(0.0044)	(0.0041)	(0.0063)	(0.0069)	(0.0062)	(0.0016)	(0.0017)	(0.0016)
N	1,134,265	1,114,091	1,135,508	1,058,640	1,039,277	1,059,816	1,878,026	1,847,738	1,879,648
R^2	0.2640	0.2907	0.2626	0.1791	0.2090	0.1772	0.4868	0.5144	0.4816
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank-Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank-Province-Time FE	✓			✓			✓		
Bank-Province-Sector-Time FE		✓			✓			✓	
Bank-Time FE			✓			✓			✓

Notes: This table shows the estimation results of Eq(3). The dependent variables are (i) $\mathbb{1}$(New credit), a dummy variable that takes the value of 1 if the difference in the used credit amount of firm i (j) at bank b from the previous year to year t is positive, and 0 otherwise, (ii) $\mathbb{1}$(New bank), a dummy variable that takes the value of 1 if bank b is new to firm i (j) in year t, and 0 otherwise. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets). Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B10: Propagation financial sector: Firm-level

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(New credit)			$\mathbb{1}$(New bank)		
Panel A: Downstream						
Level 1 $\times$ Post	0.0065	-0.0097	-0.0064	-0.0538***	-0.0435***	-0.0444***
	(0.0218)	(0.0226)	(0.0229)	(0.0141)	(0.0141)	(0.0143)
Level 2 $\times$ Post	-0.0412***	-0.0468***	-0.0459***	-0.0766***	-0.0448***	-0.0460***
	(0.0062)	(0.0070)	(0.0071)	(0.0032)	(0.0036)	(0.0036)
Level 3 $\times$ Post	-0.0350***	-0.0370***	-0.0373***	-0.0307***	-0.0082**	-0.0078**
	(0.0062)	(0.0069)	(0.0070)	(0.0031)	(0.0034)	(0.0035)
N	1,040,220	1,039,150	1,038,081	1,145,609	1,144,478	1,143,405
R^2	0.2416	0.2432	0.2491	0.2154	0.2373	0.2439
Panel B: Upstream						
Level 1 $\times$ Post	0.0122	0.0170	0.0189*	-0.1110***	-0.0850***	-0.0866***
	(0.0106)	(0.0108)	(0.0109)	(0.0063)	(0.0064)	(0.0064)
Level 2 $\times$ Post	-0.0082**	-0.0074*	-0.0061	-0.0719***	-0.0506***	-0.0511***
	(0.0042)	(0.0045)	(0.0045)	(0.0020)	(0.0022)	(0.0022)
Level 3 $\times$ Post	-0.0081*	-0.0060	-0.0052	-0.0243***	-0.0126***	-0.0125***
	(0.0042)	(0.0043)	(0.0043)	(0.0020)	(0.0020)	(0.0020)
N	980,980	980,255	979,226	1,081,924	1,081,154	1,080,141
R^2	0.2374	0.2390	0.2452	0.2165	0.2378	0.2446
Firm Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Time FE	✓			✓		
Sector-Time FE		✓			✓	
Province-Sector-Time			✓			✓

Notes: This table shows the estimation results of Eq(4). The dependent variables are (i) $\mathbb{1}$(New credit), a dummy variable that takes the value of 1 if the difference in the used credit amount of firm i (j) at bank b from the previous year to year t is positive, and 0 otherwise, (ii) $\mathbb{1}$(New bank) is a binary variable that equals 1 if the change in the number of firm-bank relationships from year $t-1$ to t is strictly positive and 0 otherwise. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets). Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B11: Propagation financial sector: Firm level receivable

	(1)	(2)	(3)
		ln(receivable)	
Panel A: Downstream			
Level 1 × Post	-0.2851***	-0.2811***	-0.2772***
	(0.0463)	(0.0493)	(0.0494)
Level 2 × Post	-0.2091***	-0.1987***	-0.1916***
	(0.0336)	(0.0369)	(0.0370)
Level 3 × Post	-0.1838***	-0.1767***	-0.1717***
	(0.0337)	(0.0368)	(0.0369)
N	1,193,892	1,191,903	1,190,711
R^2	0.8746	0.8752	0.8762
Panel B: Upstream			
Level 1 × Post	-0.1747***	-0.1389***	-0.1304***
	(0.0226)	(0.0232)	(0.0235)
Level 2 × Post	-0.1302***	-0.1081***	-0.1047***
	(0.0164)	(0.0169)	(0.0170)
Level 3 × Post	-0.0930***	-0.0777***	-0.0742***
	(0.0167)	(0.0170)	(0.0170)
N	1,159,595	1,157,948	1,156,777
R^2	0.8754	0.8760	0.8769
Firm controls	✓	✓	✓
Firm FE	✓	✓	✓
Year FE	✓		
Sector-Time FE		✓	
Province-Sector-Time FE			✓

Notes: This table shows the estimation results of Eq(4). The dependent variable is the natural logarithm of account receivable of firm i (j) in year t. Level$^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post$_t$ is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets). Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B12: Propagation financial sector: Firm level payable

	(1)	(2)	(3)
		ln(payable)	
Panel A: Downstream			
Level 1 × Post	-0.3384***	-0.3083***	-0.2916***
	(0.0530)	(0.0555)	(0.0559)
Level 2 × Post	-0.3883***	-0.3575***	-0.3506***
	(0.0273)	(0.0309)	(0.0311)
Level 3 × Post	-0.3452***	-0.3241***	-0.3245***
	(0.0273)	(0.0308)	(0.0309)
N	1,315,796	1,312,825	1,311,601
R^2	0.8624	0.8633	0.8643
Panel B: Upstream			
Level 1 × Post	-0.1755***	-0.1081***	-0.0939***
	(0.0213)	(0.0218)	(0.0221)
Level 2 × Post	-0.1999***	-0.1525***	-0.1484***
	(0.0135)	(0.0141)	(0.0142)
Level 3 × Post	-0.1653***	-0.1329***	-0.1298***
	(0.0138)	(0.0141)	(0.0142)
N	1,249,427	1,247,162	1,245,966
R^2	0.8638	0.8646	0.8656
Firm controls	✓	✓	✓
Firm FE	✓	✓	✓
Year FE	✓		
Sector-Time FE		✓	
Province-Sector-Time FE			✓

Notes: This table shows the estimation results of Eq(4). The dependent variable is the natural logarithm of account payable of firm i (j) in year t. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets). Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B13: Propagation financial sector: Firm-bank level main banks

	(1)	(2)	(3)
		$\mathbb{1}$(New credit)	
Panel A: Downstream			
Level 1 × Post	-0.0130	-0.0296	-0.0156
	(0.0206)	(0.0216)	(0.0207)
Level 2 × Post	-0.0348***	-0.0414***	-0.0351***
	(0.0061)	(0.0072)	(0.0061)
Level 3 × Post	-0.0268***	-0.0311***	-0.0265***
	(0.0061)	(0.0070)	(0.0061)
N	1,180,130	1,159,329	1,181,416
R^2	0.2680	0.2945	0.2666
Panel B: Upstream			
Level 1 × Post	-0.0029	0.0013	-0.0050
	(0.0096)	(0.0102)	(0.0095)
Level 2 × Post	-0.0052	-0.0024	-0.0051
	(0.0041)	(0.0046)	(0.0041)
Level 3 × Post	-0.0022	0.0005	-0.0016
	(0.0041)	(0.0044)	(0.0041)
N	1,118,010	1,097,936	1,119,242
R^2	0.2643	0.2912	0.2629
Firm controls	✓	✓	✓
Bank-Firm FE	✓	✓	✓
Bank-Province-Time FE	✓		
Bank-Province-Sector-Time FE		✓	
Bank-Time FE			✓

Notes: This table shows the estimation results of Eq(3). The sample is restricted to main banks of firms. The dependent variables are (i) $\mathbb{1}$(New credit), a dummy variable that takes the value of 1 if the difference in the used credit amount of firm i (j) at bank b from the previous year to year t is positive, and 0 otherwise, (ii) $\mathbb{1}$(New bank), a dummy variable that takes the value of 1 if bank b is new to firm i (j) in year t, and 0 otherwise. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is in the k distance of GM's supply chain. k takes the values 1, 2, and 3. Post_t is an indicator variable taking a value of 1 for the years 2007-2011, and 0 for the years 2002-2006. Control variables includes firm size (natural logarithm of total assets), leverage ratio (liabilities scaled by total assets), and profitability (profit after tax scaled by total assets). Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C Proofs

C.1 Propagation of A Production Shock

According to Huremovic et al. (2024) Lemma 1 to 3, we obtain the following results similar to Lemma 4 and Corollary 1:

$$\frac{\partial \log \boldsymbol{p}}{\partial k_k} = \left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \left[\frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k} + \frac{\partial \log w}{\partial k_k}\boldsymbol{\beta} + \frac{\partial \log r}{\partial k_k}\boldsymbol{\rho}\right] \tag{29}$$

$$\frac{\partial \log \boldsymbol{P}}{\partial k_k} = \mathbf{A}'\left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \left[\frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k} + \frac{\partial \log w}{\partial k_k}\boldsymbol{\beta} + \frac{\partial \log r}{\partial k_k}\boldsymbol{\rho}\right] \tag{30}$$

where $\mathbf{P}$ is an $N \times 1$ vector with the ith element P_i the price of the input bundle of firm i,

$$P_i = \left(\sum_{k=1}^{N} a_{ji} p_k^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{31}$$

The amount of credit required by firm i satisfies

$$L_i = \frac{\chi_i}{\kappa_i} r^\rho w^\beta P_i^\lambda, \tag{32}$$

where $\kappa_i = \zeta_i \rho^\rho \lambda^\lambda \beta^\beta$. Taking logarithm and derivation with respect to physical capital of firm i yields

$$\log L_i = \log \chi_i - \log \kappa_i + \beta \log w + \rho \log r + \lambda \log P_i \tag{33}$$

$$\frac{\partial \log L_i}{\partial k_k} = \left[\beta \frac{\partial \log w}{\partial k_k} + \rho \frac{\partial \log r}{\partial k_k} + \lambda \frac{\partial \log P_i}{\partial k_k}\right] \tag{34}$$

The matrix representation is

$$\frac{\partial \log \mathbf{L}}{\partial k_k} = \left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \left[\beta \frac{\partial \log w}{\partial k_k} + \rho \frac{\partial \log r}{\partial k_k}\right] + \lambda \mathbf{A}'\left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k} \tag{35}$$

Since $d\log L = \sum_k \frac{\partial \log L}{\partial k_k} dk_k$,

$$d\log L_i = e_i'(I - \lambda \mathbf{A}')^{-1}\left[\beta d\log w + \rho d \log r\right] + \lambda e_i' \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} d\log(1+\boldsymbol{\theta}) \tag{36}$$

$$d\log \mathbf{L} = (I - \lambda \mathbf{A}')^{-1}\left[\beta d\log w + \rho d \log r\right] + \lambda \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} \boldsymbol{\Omega} dR \tag{37}$$

where $\Omega = \text{diag}(\chi_i/(1+\theta_i))$ is a diagonal matrix with each element equals to $\chi_i/(1+\theta_i)$. Thus, we obtain

$$L_{i,R} = \lambda e_i' \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} \boldsymbol{\Omega} L_i \tag{38}$$

The sales of firm j to i is $s_{ji} = p_j x_{ji}$

$$\log s_{ji} = (1-\sigma)\log(1+\theta_j) - \log(1+\theta_i) + \log a_{ji} + (1-\sigma)(\log \mu_j - \log \kappa_j + \beta \log w + \rho \log r) \tag{39}$$

$$+ \log \lambda + \log s_i - \log \mu_i + (1-\sigma)\lambda \log P_j + (\sigma - 1)\log P_i. \tag{40}$$

Taking differentiation with respect to k_i:

$$\frac{\partial \log s_{ji}}{\partial k_k} = -\frac{\partial \log(1+\theta_i)}{\partial k_k} - (\sigma-1)\frac{\partial \log(1+\theta_j)}{\partial k_k} + \frac{\partial \log s_i}{\partial k_k} \tag{41}$$

$$-(\sigma-1)\alpha \boldsymbol{e}_j' \mathbf{G}'(\mathbf{I} - \alpha \mathbf{G})^{-1} \frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k} + (\sigma-1)\boldsymbol{e}_i' \mathbf{G}'\left(\mathbf{I} - \alpha \mathbf{G}'\right)^{-1} \frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k}. \tag{42}$$

Noting that $d\log s_{ji} = \sum_k \frac{\partial \log s_{ji}}{\partial k_k} dk_k$, equation (21) holds.

C.2 Credit Supply

$$Q_{b,R}^{\tau} = \int_{i\in\mathcal{S}^{\tau}} \left(\frac{\partial \mathrm{Pr}_{i,b}}{\partial R_b^{\tau}} L_i + \mathrm{Pr}_{i,b} \frac{\partial L_i}{\partial R_b^{\tau}} \right) \mathrm{d}v(i) \tag{43}$$

$$= \int_{i\in\mathcal{S}^{\tau}} \frac{\partial \mathrm{Pr}_{i,b}}{\partial R_b^{\tau}} L_i \mathrm{d}v(i) \tag{44}$$

The second equality holds from the envelop theorem that the required amount of credit is determined by the cost of production given banks interest rate in equilibrium.

$$\frac{\partial \mathrm{Pr}_{i,b}}{\partial R_b^{\tau}} = \alpha_{P,i}^{D} \left(1 - \mathrm{Pr}_{i,b}\right) \mathrm{Pr}_{i,b} - \alpha_C^D N_{i,b}^{\tau}, \tag{45}$$

$$\frac{\partial \mathrm{Pr}_{i,k}}{\partial R_b^{\tau}} = -\alpha_{P,i}^{D} \mathrm{Pr}_{i,k} \mathrm{Pr}_{i,b} - \alpha_C^D N_{i,k}^{\tau} \tag{46}$$

where $N_{i,b}^{\tau}$ ($N_{i,k}^{\tau}$) denotes the common lenders effect of marginal change in bank b's interest rate of type τ credit on demand firm i's demand on the type τ product of bank b (k). More specifically, they are defined as

$$N_{i,b}^{\tau} = \sum_{k\neq b} \mathrm{Pr}_{i,k} \frac{\partial C_{i,k}}{\partial R_b^{\tau}} = \sum_{k\neq b} \mathrm{Pr}_{i,k} \sum_{j\neq i} w_{ij} \frac{\partial \mathrm{Pr}_{j,k}}{\partial R_b^{\tau}} \tag{47}$$

$$N_{i,k}^{\tau} = \sum_{l\neq k} \mathrm{Pr}_{i,l} \frac{\partial C_{i,l}}{\partial R_b^{\tau}} = \sum_{l\neq k} \mathrm{Pr}_{i,l} \sum_{j\neq i} w_{ij} \frac{\partial \mathrm{Pr}_{j,l}}{\partial R_b^{\tau}} \tag{48}$$

Combining above definitions of the common lender effect (47) and (48) with equations (45) and (46), we get the relationship between the common lender effect across banks and borrowers.

$$N_{i,b}^{\tau} = -\sum_{k\neq b} \mathrm{Pr}_{i,k} \sum_{j\neq i} w_{i,j} \alpha_{P,j}^{D} \mathrm{Pr}_{j,k} \mathrm{Pr}_{j,b} - \alpha_C^D \sum_{k\neq b} \mathrm{Pr}_{i,k} \sum_{j\neq i} w_{ij} N_{j,k}^{\tau} \tag{49}$$