Bank Specialization within Production Networks*

Olivier De Jonghe† Yushi Peng‡ Tong Zhao§

August 2026

Abstract

Using firm-to-firm transaction and credit registry data from Belgium, we show that banks' common lending to supply chain partners is persistent and widespread. To study the benefits and costs of this lending specialization along supply chains, 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. Exploiting the closure of a large manufacturing plant as an exogenous shock, we show that common lending also creates costs: the shock propagates through the production network, reducing credit demand along the supply chain and among common lenders, with banks more exposed to the affected network experiencing significantly larger declines in lending. A simulated counterfactual shows that the preference for borrowing from common lenders shapes how the losses are distributed across banks, concentrating them on the banks that lend directly to the disrupted firm and have a high exposure to the network.

JEL classification: E32, D57, L14, Q54

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

*The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Bank of Belgium, the European Central Bank, or the Eurosystem. We thank Ramin Baghai (discussant), Emmanuel Caiazzo (discussant), Matteo Benetton, Marie Hoerova, Adair Morse, Nicola Pavanini, Farzad Saidi for their helpful comments and suggestions, and seminar and conference participants at EARIE, SGF, Tilburg University, University of Bonn, the 15th MoFiR workshop on banking. All errors are our own.

†European Central Bank and National Bank of Belgium, olivier.dejonghe@nbb.be.

‡Tilburg University, y.peng@tilburguniversity.edu.

§KU Leuven, tong.zhao@kuleuven.be.

1 Introduction

Banks have a comparative advantage in producing information about borrowers. Their screening and monitoring are central to the efficient allocation of credit, which further affects real economic activity and financial stability. Through repeated interactions with borrowers who share the same industry or geography, banks accumulate an information advantage that improves their screening and monitoring and allows them to offer better credit terms. That is, banks specialize in lending (Berger et al., 2017; Blickle et al., 2026). This paper documents a further form of specialization: banks specialize within production networks, lending to firms along the same supply chain. These relationships often cut across industries and regions, going beyond conventional boundaries. We investigate the prevalence, drivers, and consequences of this form of specialization.

Whether bank specialization within production networks brings benefits or costs to borrowers and banks is not obvious ex ante. Understanding this requires looking at the bank that lends to both sides of a trading relationship, a practice we refer to as common lending. For borrowers, a preference for common lending cuts both ways on price. It could soften competition and give the bank market power, as in the hold-up logic of relationship lending (Sharpe, 1990; Rajan, 1992). Or it could discipline the bank, since its appeal to each borrower rests on its position with the others: raising one firm's rate erodes its standing with that firm's entire supply chain. A bank that lends to both sides of a trading relationship observes the flow of goods and payments between its borrowers, information that neither firm's balance sheet reveals. But this position also exposes the bank to correlated risk: because shocks travel along production networks (Acemoglu et al., 2012; Carvalho et al., 2021), a disruption at one firm also affects credit demand at that firm's suppliers and customers. Which force dominates for borrowers and for banks is an empirical question.

This paper asks three 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?

To answer these questions, 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. We then exploit the closure of General Motors' Antwerp plant as an exogenous real-sector shock to trace the impact of supply-chain disruptions and shock transmission. Our approaches are combined with several administrative datasets from Belgium, which offer key advantages. Our Belgian B2B dataset is drawn from VAT filings and records the annual sales of every domestic firm-to-firm trading relationship above €250 from 2002 to 2023.[1] As a result, we observe the full domestic production network. We merge B2B data with the corporate credit register maintained by the National Bank of Belgium, which covers every bank exposure above €25,000 and records interest rates and banks' assessments of borrower default risk in recent years. The balance-sheet data includes the universe of Belgian

[1] Only 19% of Belgian firms import directly (Dhyne et al., 2021).

limited-liability firms and thus extends the coverage to the small and medium-sized enterprises that could be overlooked in previous studies.

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. The analysis exploiting the closure of GM Antwerp shows that common lending also creates costs: the shock propagates through the production network, reducing credit demand along the supply chain and among common lenders, with banks more exposed to the affected network experiencing significantly larger declines in lending. A simulated counterfactual shows that the preference for borrowing from common lenders shapes how the losses are distributed across banks, concentrating them on the banks that lend directly to the disrupted firm and have high exposure to the network.

We begin by presenting three motivating facts. First, common lending is prevalent across industries, geographical locations, and banks of all sizes, and has become increasingly important over time. Conditional on operating in the same industry and the same province, a firm and its trading partner borrow from the same bank 30% to 35% of the time, whereas two randomly paired firms in the same industry and province do so only 10% to 15% of the time. The pattern spans nearly every sector, province, and bank. Second, borrowers prefer to borrow from common lenders. First-time borrowers, whose bank choice no prior lending relationship can explain, disproportionately choose the banks of their trading partners. This effect is stronger the more important the partner is: a one-percentage-point increase in the share of a firm's purchases coming from a supplier raises the probability of choosing that supplier's bank by 0.181 percentage points. Third, common lenders offer better credit terms. Firms borrowing from a common lender pay lower interest rates and obtain larger loans, but are also assigned higher default probabilities by banks. Therefore, both demand and supply push firms toward common lenders. How much each force contributes and what banks' market power does with the borrower preference are questions that require a model.

We develop a structural model that embeds an imperfectly competitive credit market in the production network, joining two workhorse traditions: discrete-choice demand for differentiated financial products (e.g., Berry, 1994; Berry et al., 1995; Crawford et al., 2018) and production networks with financial frictions (e.g., Bigio and La'o, 2020; Baqaee and Farhi, 2020; Huremovic et al., 2026). Firms produce with inputs bought from upstream suppliers and finance their input costs with bank credit, so each firm's loan demand is pinned down by its production plan rather than assumed. Given that demand, firms choose a bank, valuing its interest rate, any existing lending relationship, and the object of interest here: the bank's weight as a lender to their suppliers and customers. Banks compete on rates firm by firm, pricing each borrower's default risk. This structure delivers what we call the common lending channel. Because borrowers prefer banks that serve their trading partners, the rate a bank sets for one firm shifts the borrowing of firms up and down that firm's supply chain, and banks internalize this when they price. Relative to existing frameworks, the model makes extensions in three respects: by allowing firms to benefit from common lenders while banks can price that specialization, it sep-

arates borrowers' preference for common lenders from banks' supply of credit to supply chains; by integrating firm production into the credit model, it derives loan size endogenously, so financing costs feed back into input choices; and by embedding the credit market in a production network, it lets real-sector shocks move credit demand, and banks' responses to it, inside the model rather than by assumption.

We estimate the model using a control-function approach that addresses the endogeneity of two variables in credit demand, namely the interest rate and the bank's position among a firm's trading partners. The interest rate is instrumented with a standard cost-shifter, measured by the average rate that the same bank charges on term loans for similar firms in the same year and market. For the bank's common lender position, we use merger and acquisition events among a firm's trading partners, which change banks' common lending exposure to the firm but are unrelated to the firm's own credit demand. The estimation delivers the paper's central result: firms prefer to borrow from common lenders. Controlling for credit terms and credit supply, a 1% increase in the share of a firm's suppliers' and customers' credit held by a bank raises the firm's probability of borrowing from that bank by 0.11%.

This preference has two opposing effects on banks' pricing power. On average, it disciplines pricing: a higher rate for one firm erodes the bank's common lender position along that firm's entire chain, and this network effect lowers effective markups by about 5 basis points. In the cross-section, it rewards position: banks that are more important common lenders charge higher effective markups and have lower effective marginal costs, consistent with cheaper screening and monitoring of borrowers the bank observes from both sides of their transactions (e.g., Berger et al., 2017; De Jonghe et al., 2025). The discipline effect and the cost advantage together account for the pattern in the raw data: banks in a preferred position charge less, not more.

A second channel operates through production itself. Firms borrow to finance inputs, so a higher interest rate raises a firm's costs and prices, and through them its customers' input costs, propagating along the network and back into credit demand. This cost pass-through gives banks additional market power, but it is quantitatively modest, and we interpret its magnitude with caution given the modeling assumptions involved.

We illustrate the costs of common lending by examining how shocks in the real sector can propagate through the production network and spill over into the financial sector. We exploit the closure of General Motors' Antwerp plant, a large manufacturing plant with more than 5,000 workers and an annual output of about 400,000 cars. The analysis shows that the shock propagated along the production network with a clear distance gradient: sales fell by roughly a fifth for firms trading directly with GM, with smaller but still significant declines for firms two and three links removed. The shock was then transmitted into the financial sector. Controlling for credit supply with bank-time fixed effects, we find that firms in GM's network used less credit from their existing banks and became less likely to form new banking relationships, implying that they could not substitute toward new lenders. In particular, second-level customers (customers of GM's customers) became 3.7 percentage points less likely to use credit, an effect that fades with network distance. The results also reveal a decline in common lending. Trading pairs within GM's network, which had previously been more likely than comparable pairs to borrow

from the same bank, became less likely to do so after the closure. This finding suggests that the value of sharing a partner's bank falls when that partner's credit demand falls. The reduction in common lending also shows up on bank balance sheets. Banks with high exposure to GM's network saw committed credit in the affected sectors fall by approximately 20%, and they could not offset this elsewhere.

Finally, we use the estimated model and the insights from the GM reduced-form analysis for a counterfactual that quantifies the role of common lending in transmitting a real-sector shock. Specifically, we simulate the closure of a large network firm and compare the equilibrium credit allocation with and without the common lender preference. While common lending has only a small effect on the aggregate credit contraction, its defining role is to concentrate that contraction on particular banks. In partial equilibrium, the common lending channel reallocates the credit and profit losses onto the banks that act as direct lenders to the shocked firm. In general equilibrium, letting banks re-optimize their interest rates shifts the amplification toward the banks with the largest exposure to the shocked firm's production network. The counterfactual is the structural counterpart of our reduced-form finding that more exposed banks suffer larger declines, and it reveals two things. First, the common lending channel plays a different role across banks, depending on their specialization within the production network and their relationship with the shocked firm. Second, in either case the losses concentrate on the banks most connected to the shocked firm and its supply chain – its direct lenders at fixed rates, and the banks with the largest supply-chain exposure once rates adjust – rather than being spread evenly across the banking system. Thus, the benefits of common lending in normal times come with concentrated costs when the production network is disrupted.

Related Literature and Contribution. This paper connects several strands of literature on empirical banking, financial intermediation using structural IO methods, and production networks.

There is a large literature in empirical banking on the benefits and costs of lending concentration. While lending diversification can reduce delegated monitoring costs (Diamond, 1984), specialization can provide banks with informational advantages and industry-specific expertise. When specialization is defined by industry or geography, specialized banks screen and monitor better (Berger et al., 2017; Casado and Martinez Miera, 2025; De Jonghe et al., 2025), offer cheaper and more generous credit (Duquerroy et al., 2022; Paravisini et al., 2023; Blickle et al., 2025, 2026), and face lower individual and systemic risk (Acharya et al., 2006; Beck et al., 2022). A smaller branch of the literature studies bank specialization within production networks and documents its positive effects. Such specialization softens product-market competition among competing borrowers (Saidi and Streitz, 2021; Asai et al., 2024), strengthens vertical trading relationships and alliances (Giacomini et al., 2024; Frattaroli and Herpfer, 2023), boosts lending along supply chains (Hasan et al., 2020; Martins et al., 2023), and supports connected borrowers through transitory distress (Giannetti and Saidi, 2019; dos Santos and Ferreira, 2026). While these studies mainly focus on banks' lending behavior, we emphasize the demand side and disentangle the supply and demand channels. 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, we provide

the first structural quantification of the demand-side and supply-side mechanisms underlying lending along supply chains and of 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.

Following the seminal work of Berry (1994) and Berry et al. (1995), a growing literature applies structural IO methods to estimate demand for differentiated products in financial markets with applications to deposits, corporate loans, mortgages, insurance, and asset demand.[2] We are closest to Crawford et al. (2018), who estimate corporate credit demand and supply under asymmetric information, with loan size specified in reduced form. Our paper builds on but differs from the existing 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.

A large body of work examines shock propagation through production networks and the role of input-output linkages in amplifying micro-level shocks into macro-level economic fluctuations (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021), as well as allocation inefficiencies in production networks with frictions (Baqaee, 2018; Bigio and La'o, 2020; Baqaee and Farhi, 2020).[3] More recent studies incorporate financial frictions to study the interplay between production and credit networks, highlighting how financing frictions shape shock transmission along supply chains (Costello, 2020; Alfaro et al., 2021; Huremovic et al., 2026). While existing studies focus on the transmission of credit shocks to the real sector, we examine how supply-chain disruptions amplify real-sector shocks and 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.

Structure. The remainder of the paper proceeds as follows. Section 2 describes the data, and Section 3 documents the motivating facts on common lending. Section 4 presents the model, Section 5 its econometric implementation and identification, and Section 6 the estimation results. Section 7 traces the closure of GM Antwerp through the production network and into bank balance sheets, and Section 8 presents the counterfactual. Section 9 concludes.

2 Data and Sample

We combine three datasets from Belgium for years 2002-2023: (i) a firm-to-firm (B2B) transaction dataset, (ii) a credit registry that provides detailed information on firm-bank credit rela-

[2] 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 (Benetton, 2021), insurance (Koijen and Yogo, 2016), social security (Hastings et al., 2017), and investors' demand for assets (Koijen and Yogo, 2019).

[3] On broader corporate outcomes and international transmission: Bernard et al., 2019; Alfaro-Urena et al., 2022; Dhyne et al., 2021, 2025; Di Giovanni and Hale, 2022; Huo et al., 2025. For a review, see Carvalho and Tahbaz-Salehi (2019).

tionships, and (iii) firm balance sheet data containing financial and operational variables.

2.1 B2B Transaction Dataset

The Belgian B2B transaction dataset records every domestic firm-to-firm trading relationship whose annual value exceeds €250. An observation is the total sales from seller i to buyer j in a calendar year, with both firms identified by VAT number. Duprez et al. (2023) describes the data in detail, and Dhyne et al. (2021); Bernard et al. (2022) use them.

The data have three advantages for our purposes. First, we observe the whole domestic production network rather than a sample of it. Few datasets anywhere match this coverage: Japan's TSR data, for instance, cap the number of sellers and buyers a firm may report (Carvalho et al., 2021). Second, we observe the value of each seller-buyer link, taken from official VAT filings, which the tax authorities enforce with pecuniary sanctions for late or erroneous reporting. Third, the data span 2002 to 2023, long enough to study propagation through the network over time.

Panel A of Table A1 describes the B2B data, after dropping links below €1,000. Sales is the value of all transactions between a buyer and a seller in a given year, in thousands of euro. The median link is worth about €4 thousand, so the data capture a large number of small transactions, and a small share of very large links pulls the mean up to about €60 thousand. The median number of buyers per firm is 155, and of sellers 42.

2.2 Credit Registry

We use two vintages of the Belgian corporate credit register. Together they cover almost three decades, but the transition between them changed reporting requirements, granularity, and documentation practices, and induces a structural break. We therefore never pool them. The CCCR supports the motivating facts and the reduced-form analysis, and BECRIS the structural estimation.

CCCR. The Central Corporate Credit Register,[4] administered by the National Bank of Belgium, records monthly bank-firm credit from 1998 until its discontinuation in 2020, so it overlaps almost the entire B2B sample. Coverage is close to complete: every financial institution established in Belgium must report each debtor to which it has an aggregate exposure above €25,000.[5] The register gives authorized and used amounts, loan type, and maturity, but not interest rates, which is why we estimate the structural model on BECRIS instead.

Panel B of Table A1 summarizes the CCCR. The average committed amount per firm-bank pair is €738 thousand and the average used amount €487 thousand. Firms borrow from few banks: the average firm has 1.42 relationships, half have one, and three quarters have no more than two. On average 83% of firms have a main bank.

BECRIS. BECRIS is the Belgian input to AnaCredit, the harmonized euro-area credit register. It reports every loan granted by credit institutions resident in Belgium from November 2018

[4]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. (2025), among others.

[5]There is a structural change in the reporting threshold in 2012. To ensure consistency over time, we apply a constant reporting threshold of €25,000 throughout the entire sample period from 2002 to 2020.

onward, and from 2020 it is the only credit register in operation. An instrument is reportable if the borrower is a legal entity and the committed amount at the creditor-debtor level reaches €25,000 at any point in the reference period. BECRIS is loan-level: it records commitment and outstanding nominal amounts, maturity, loan type, the interest rate, and the borrower's probability of default as estimated by the bank's internal model. The last two are what the CCCR lacks and what the structural model requires.

We consolidate exposures at the firm-bank-loan type-year level and extract 2018 to 2023. The structural model is estimated on the 2020-2023 subsample, where interest-rate reporting is more complete, and on working-capital credit lines alone, identified by instrument type and loan purpose, since these are the loans that finance production.[6] Panel C of Table A1 reports the resulting statistics. The average firm-bank credit amount is €396 thousand, the average interest rate 2.44%, and the estimated probability of default is low, with a mean of 0.05 and a median of 0.01.

2.3 Firm Balance Sheets

We take firm balance sheets and income statements from the annual accounts that every limited-liability firm in Belgium files with the Central Balance Sheet Office, and supplement them with confidential VAT declarations, which give more accurate measures of sales, investment, input costs, and employment. The coverage of small firms matters for what we do with these data: balance-sheet information of this kind is routine for large listed firms and scarce for small businesses, and small and medium-sized firms are most of the Belgian production network.

Panel D of Table A1 describes the sample. Most firms are small or micro. Leverage has a median of 0.62 and a mean above one, a right-skewed distribution driven by a small number of highly leveraged firms. Profitability has a median of 0.03 and a negative mean, so a minority of firms record large losses.

2.4 Samples

The paper uses two samples. The motivating facts and the reduced-form analysis use the CCCR merged with the B2B data for 2002-2020, restricted to firms' main banks, to banks with at least 0.3% market share in a given year, and to trading links above €1,000. The structural model uses BECRIS merged with the B2B data for 2020-2023, restricted to working-capital credit lines and excluding overdrafts, credit card debt, and trade receivables. Appendix A.2 documents the treatment of factoring.

3 Motivating Facts

This section documents how common lending has evolved over time and how it varies across industries and markets, and characterizes its key features on both the demand and the supply side of credit.

[6] We also exclude factoring and trade receivables, given their small size and incomplete recording in the credit registry. More details see Appendix A.2.

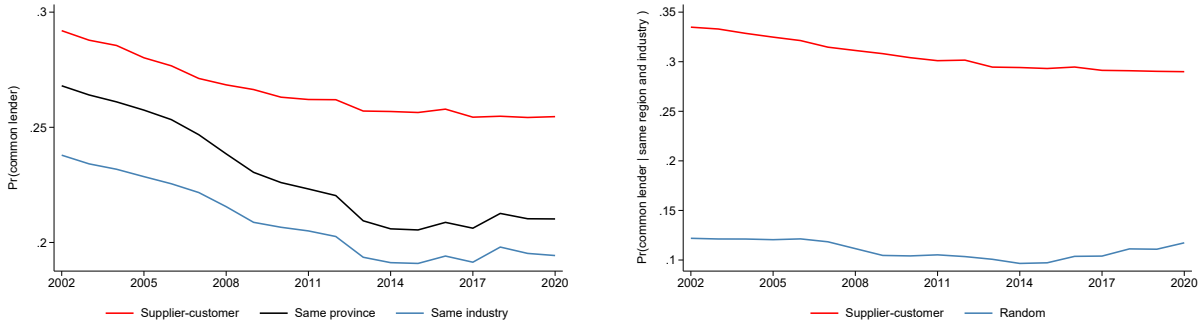
- **Fact 1: Common lending is prevalent.**

We document the prevalence of banks acting as common lenders along supply chains in Belgium and mainly focus here on the longer CCCR sample covering 2002-2020 to document the trend and patterns of common lending.[7]

Figure 1a shows the time series of the probability that two firms borrow from the same bank in a given year. The red line gives the probability that a buyer-seller pair shares a bank, while the blue (black) line gives the probability that two random firms in the same industry (province) borrow from the same bank. Throughout the sample period, trading partners are more likely to borrow from the same bank than firms matched on industry or province alone. This divergence suggests that bank specialization along supply chains has become increasingly important relative to traditional specialization by industry or geographical market.

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 pairs of firms within the same industry and province. During 2002-2020, the probability ranges between 10-15% for random firm pairs and between 30-35% for trading partners. This persistent gap indicates that common lending along supply chains cannot be explained solely by industry or geographic specialization.

Figure 1: Trend of Borrowing from Common Lenders



(a) Probability of Borrowing from Same Bank

(b) Conditional Probability

Notes: This figure presents the trend of borrowing from common lenders in Belgium from 2002 to 2020. Figure 1a shows the unconditional probability of borrowing from the same bank for three types of firm pairs. The red line represents the probability that two firms with trading relationships borrowing from the same bank. The blue (black) line shows the probability two random firms in the same industry (province) borrowing from the same bank. Figure 1b shows the conditional probability of borrowing from the same bank, conditional on firms being from the same industry and province. The red line represents firms with trading relationships, while the blue line shows purely random firms.

Beyond the importance of common lending and the persistence of common lending over time, we also find that this phenomenon is widespread across banks, industries and geographical locations. Figure B1 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

[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. We focus on firms' main bank only.

likelihood that trading partners borrow from the same bank, indicating that common lending is a pervasive feature of supply chain financing across the economy. Similarly, as illustrated by Figure B2, common lending is widely observed in all Belgian provinces. Furthermore, common lending is not concentrated among a few specialized banks but is distributed broadly across the whole banking sector. As illustrated in Figure B3, 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.

- **Fact 2: Firms prefer to borrow from common lenders, showing the demand side factor.**

After documenting the prevalence of common lending, we explore demand-side explanations for this pattern. We begin by examining whether firms prefer banks that (i) also serve their trading partners and (ii) have larger exposures to the firm's supply chain. 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 and a bank 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 of whether a first-time borrower chooses a bank that is also the bank of either its supplier or its customer. The independent variable in Column (1) 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. The independent variable in Column (2) is the trading-volume-weighted share of a bank's lending to a focal firm's trading partners relative to the total lending by all banks to the firm's supply chain partners.[8] This measure captures the importance of a bank within the focal firm's production network. The unit of observation is a buyer(seller)-seller(buyer) bank-year. To jointly control for firm-specific, bank-specific, and time-varying factors, all specifications include firm fixed effects, trading partner bank fixed effects, and year fixed effects.

The results show that firms borrowing for the first time are significantly more likely to borrow from the same bank as their important trading partners. In Column (1), a 10 percentage point increase in the share of purchases from a trading partner increases the probability of borrowing from the partner's bank by 1.81 percentage points. Column (2) suggests that a 10 percentage point increase in a bank's exposure to the supply chain increases that probability by 2.54 percentage points. We interpret this as evidence of firms' preference for common lenders, which is the key focus we formalize in the structural model presented in Section 4.[9]

- **Fact 3: Banks supply more credit, and at a lower price, to firms that share a lender with their trading partners, showing the supply side factor.**

We now turn to the intensive margin and ask whether loan contracting terms depend on how

[8] For a focal firm i, this variable is computed from the equation: $\frac{\sum_j \text{weight}_{i,j} \times \text{lending amount}_{j,b}}{\sum_{j,b} \text{weight}_{i,j} \times \text{lending amount}_{j,b}}$, and $\text{weight}_{i,j} = \frac{\text{trading volume}_{i,j}}{\sum_j \text{trading volume}_{i,j}}$, where b and j index bank and trading partners, respectively.

[9] We also report results for downstream and upstream firms separately in Appendix Table B1.

Table 1: First-Time Borrower Bank Choice

	𝟙(Common Lender)	
	(1)	(2)
Partner Importance to Supply Chain	0.181***	
	(0.003)	
Partner's Bank Importance to Supply Chain		0.254***
		(0.005)
Firm FE	✓	✓
Partner Bank FE	✓	✓
Year FE	✓	✓
N	9493005	1232180
R^2	0.11	0.13

Notes: 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 2002-2020. The dependent variable is an indicator equal to one if the firm chooses a bank that is also the bank of its trading partner. The independent variable in Column (1) is the share of the firm's total sales or purchases that goes to or comes from the respective trading partner, capturing the importance of that trading partner in the firm's production network. The independent variable in Column (2) is the trading-volume-weighted share of a bank's lending to a focal firm's trading partners relative to the total lending by all banks to the firm's supply chain partners. Robust standard errors clustered at the firm level are in parentheses. ***p<0.001, **p<0.01, *p<0.05.

much of the borrower's trade is with partners that borrow from the same bank. For this, we use BECRIS data recording contract terms and the bank's one-year-ahead assessment of the borrower's probability of default. We focus only on the main bank of a firm. The regressor, Common Lender, is the share of the firm's trade conducted with partners whose main bank is also its own. To distinguish supply-chain specialization from industry and geographic specialization, we construct measures of the latter two and include them as controls. This allows us to assess whether specialization within production networks matters for credit contracts conditional on other forms of bank specialization.

Columns (1) and (2) of Table 2 show that firms trading more heavily with partners at their own bank pay less for credit. The coefficient of -0.112 in Column (1) implies that a one-standard-deviation increase in Common Lender is associated with a 2.2 basis point reduction in loan rates, and Column (2) implies that the same increase is associated with a 2.5 percent increase in borrowing. These results are consistent with a credit supply effect, as also documented by Martins et al. (2023). Column (3) shows that the same increase raises the one-year-ahead PD forecast by 4.4 basis points. All estimates are statistically significant and economically sizable. Price and quantity point to an outward supply shift, while the last column suggests that banks may judge these borrowers riskier.

Banks' industry and local specialization do not affect the price of credit, but they exert larger effects on the amount lent than supply chain specialization does. One explanation is that locally specialized banks lend at longer maturities, and that banks specialized along either dimension assess their borrowers as safer (De Jonghe et al., 2025; Casado and Martinez Miera, 2025). The industry and province coefficients are economically large except in Column (1), and excluding

these controls leaves the sign and significance of the common lender coefficients unchanged. Common lending is therefore a distinct channel through which banks supply credit, not a proxy for sectoral or regional expertise.[10]

Altogether, these three facts indicate that common lending is widespread and that both demand-side and supply-side factors contribute to it, which is why we turn to a structural model to disentangle their respective roles. That is the focus of the next section.

Table 2: Importance of Common Lenders and Credit Terms

	Rate	ln(Amount)	PD
	(1)	(2)	(3)
Common Lender	-0.112***	0.124***	0.218***
	(0.012)	(0.016)	(0.042)
Industry Specialization	0.049	0.502***	-1.067***
	(0.083)	(0.095)	(0.359)
Province Specialization	-0.043	0.433***	-1.165***
	(0.064)	(0.079)	(0.373)
Bank-Year FE	✓	✓	✓
Industry-Size-Year FE	✓	✓	✓
Province-Year FE	✓	✓	✓
N	495788	512098	480911
R^2	0.23	0.43	0.02

Notes: This table reports how credit terms and default risk vary with the importance of a firm's common lender using BECRIS data. The unit of observation is a firm-year, measured at the firm's main bank, defined as its largest lender in that year. The dependent variable in Column (1) is the annualized interest rate in percentage points, in Column (2) is the euro value of credit, in Column (3) is the one-year-ahead probability of default estimated by the bank in percentage points. The independent variable Common Lender is the share of the firm's total business-to-business trade that is accounted for by trading partners whose own main bank is the firm's main bank, summing purchases and sales. It ranges from zero to one. Industry and province specialization are the shares of the main bank's portfolio lent to the firm's industry and to the firm's province. Standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4 The Model

We consider 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.

[10]Our results hold across various specifications, as shown in the Appendix Table B2. Dropping the two specialization measures or using lagged independent variables does not affect our results. We also weight partners by their borrowing rather than by their trade, and results remain. We also report results by splitting partners by direction in the supply chain.

4.1 Production

We model firm production in line with the recent literature on production networks, considering firms $i = 1, ..., N$ operating in the market, each producing a single distinct product. Following Huremovic et al. (2026), 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:

$$y_i = \zeta_i k_i^{\rho} \ell_i^{\beta} M_i^{\lambda}. \tag{1}$$

Firms use two primary input factors —physical capital k_i and labor ℓ_i— and an intermediate input bundle 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:

$$M_i = \left(\sum_{j=1}^{N} a_{ji}^{\frac{1}{\sigma}} x_{ji}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

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 a 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.

Following Bigio and La'o (2020) and Huremovic et al. (2026), 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 set prices as a markup μ_i over marginal cost to account for product market competition, which is not explicitly modeled. Like Baqaee and Farhi (2020) and Baqaee (2018), we thus also assume that competition in product markets is exogenously given.

Then, firms' profit is given by

$$\pi_i = p_i y_i - (1 + \theta_i) \left(\sum_{j=1}^{N} p_j x_{ji} + w\ell_i + rk_i \right), \tag{3}$$

where $p_i = \mu_i mc_i$ is the price of firm i's output product, and $\theta_i = \chi_i \bar{R}_i$ denotes the financing cost of firm i, which depends on the fraction of intermediate inputs requiring bank credit χ_i and the interest rate firm i expects to pay, $\bar{R}_i$. Because firms have imperfect information on the interest rates offered by different banks before searching the market, they first choose a production plan which determines the amount of credit needed based on their expected financing cost, and only then choose which bank to borrow the required amount from. The financing cost therefore depends on the *expected* market rate $\bar{R}_i = \left(\sum_b \Pr_{i,b}^{\tau} R_{i,b}^{\tau} \right) / \left(\sum_b \Pr_{i,b}^{\tau} \right)$, the probability-weighted average of the rates offered by all active banks (defined in Section 5.2), rather than the rate of

any single bank. The amount of credit required by firm i is

$$L_i = \chi_i \left(\sum_{j=1}^{N} p_j x_{ji} + w\ell_i + rk_i \right), \tag{4}$$

which is determined by the cost of all input factors.

4.2 Credit Market

Demand. We index firms by their observable type τ, defined by firm characteristics such as industry, size, and location, and we let $\mathcal{S}^\tau$ denote the set of firms of type τ. Banks price loans based on these firm characteristics, so that bank b offers a type-τ specific interest rate $R^\tau_{i,b}$ to firms in $\mathcal{S}^\tau$. Given their credit needs L_i, firms of type τ 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 if the decision $d_i = b$ yields the highest utility compared to other available options. The indirect utility of this decision takes the following form:

$$U^D_{i,b} = \alpha^D_P R^\tau_{i,b} + \alpha^D_C C_{i,b} + \alpha^D_Z Z_{i,b} + X'_b \alpha^D_X + \xi^D_b + \varepsilon^D_{i,b} \tag{5}$$

where $R^\tau_{i,b}$ is the interest rate offered by bank b to firm i of type τ. The rate is firm-bank specific: it depends on the firm's type τ capturing pricing on firm characteristics, as well as on bank-firm observables. Among other bank characteristics, firms have a 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 weighted by trading importance before making the discrete borrowing decision:

$$C_{i,b} = \sum_{j \neq i} w_{ij} \mathrm{Pr}_{j,b}, \tag{6}$$

where $w_{ij} = (s_{ji} + s_{ij}) L_j / \sum_{k \neq i} (s_{ki} + s_{ik}) L_k$. This weight indicates the importance of the trading partner j to firm i, where s_{ji} is the sale of firm j to firm i while s_{ij} is the purchase of firm j from firm i. $\mathrm{Pr}_{j,b}$ denotes the probability of firm j borrowing from bank b. The underlying assumption is that firm i's 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 have an existing lending relationship, and zero otherwise. X_b indicates observed bank-market characteristics, while ξ^D_b captures unobserved bank-market characteristics. $\varepsilon^D_{i,b}$ are type I extreme value distributed idiosyncratic demand shocks.

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

Default. Banks compete in a Bertrand-Nash framework, setting a separate interest rate for each firm type τ to maximize expected profits, taking firms' default risk into account for pricing. We model firms' loan performance as governed by the indirect utility of default:

$$U^F_{i,b} = \alpha^F_P R^\tau_{i,b} + \alpha^F_C C_{i,b} + \alpha^F_Z Z_{i,b} + X'_b \alpha^F_X + Y'_i \alpha^F_Y + \varepsilon^F_{i,b} \tag{7}$$

Similar to the demand model, we allow the firm-bank specific interest rate $R^\tau_{i,b}$, the bank-firm network common lending relationship $C_{i,b}$ and the firm-bank lending relationship $Z_{i,b}$, and observed bank characteristics X_b to affect a firm's default risk. Moreover, firms characteristics Y_i are included to account for their impact on firms' 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 price loans at the firm-bank level. For each firm i of type τ, bank b chooses the interest rate $R^\tau_{i,b}$ to maximize the expected profit it earns from that firm:

$$\Pi^\tau_{i,b} = \left(\left(1 - F^\tau_{i,b}\right) R^\tau_{i,b} - MC^\tau_{i,b}\right) Q^\tau_{i,b}, \qquad Q^\tau_{i,b} \equiv \Pr_{i,b} L_i, \tag{8}$$

where $F^\tau_{i,b}$ is the expected probability of default for firm i of type τ borrowing from bank b, $MC^\tau_{i,b}$ is bank b's marginal cost of lending one euro to firm i (allowed to vary at the firm-bank level to reflect firm-specific monitoring, screening, and relationship costs), and $Q^\tau_{i,b}$ is the expected loan volume from firm i, equal to firm i's borrowing probability times its loan size. When pricing firm i, bank b accounts for the direct effect of $R^\tau_{i,b}$ on firm i's borrowing probability and on its loan size through the production network, taking the interest rates on all other firm-bank pairs as given. The effect of $R^\tau_{i,b}$ on firm i's borrowing probability is embedded in the common lender feedback that loops back into its own demand in equilibrium, capturing the network effect.[11]

4.3 Consumption and Equilibrium

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

$$u(c) = \frac{c^{1-\delta}}{1-\delta} - \frac{L^{1+\eta}}{1+\eta}, \tag{9}$$

[11] This decentralizes the bank's problem into a separate first-order condition per firm. The common lender and production-network feedback is retained in each firm's demand response and reconciled across firms at the equilibrium fixed point.

subject to budget constraint

$$\sum_{i=1}^{N} p_i c_i \leqslant E, \tag{10}$$

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 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 $\{(p_i^*)_{i=1}^N, w^*, r^*, (R_{i,b}^{\tau *})_{i,b}\}$ and 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 of type τ chooses a 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 chooses a firm-bank specific pricing schedule $R_{i,b}^{\tau}$, depending on firm type and on bank-firm observables, to maximize profit on each firm-type segment; (iv) households choose their consumption plan to maximize utility; (v) credit markets for each firm type τ clear, as well as markets for intermediate inputs, capital, and labor.

5 Econometric Model

5.1 Production Shock

To estimate the production function of firms, we exploit the closure of the GM Antwerp plant and its propagation 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 approach in Huremovic et al. (2026) to approximate the changes in sales from firm j to firm i relative to firm i's total sales after the shock, using the following linear relationship

$$\begin{aligned} d\log s_{ji} - d\log s_i = -(\sigma-1) \underbrace{d\log(1+\theta_j)}_{\text{Supplier direct effect}} - \underbrace{d\log(1+\theta_i)}_{\text{Customer direct effect}} \\ -(\sigma-1)\underbrace{\lambda e_j' \mathbf{A}'(I-\lambda\mathbf{A}')^{-1} d\log(1+\theta)}_{\text{Supplier higher-order effect}} + (\sigma-1)\underbrace{e_i'\mathbf{A}'(1-\lambda\mathbf{A}')^{-1} d\log(1+\theta)}_{\text{Customer higher-order effect}} \end{aligned} \tag{11}$$

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 $\theta_i = \chi_i \bar{R}_i$ denotes the financing cost of firm i, where $\bar{R}_i = \left(\sum_b \Pr_{i,b}^{\tau} R_{i,b}^{\tau}\right) / \left(\sum_b \Pr_{i,b}^{\tau}\right)$ is its expected interest rate, the probability-weighted average of the rates offered by all active banks, formed before it chooses a bank. The detailed proofs are provided in Appendix E.

The shock to firm k propagates through the production network, changing the financing costs of i's suppliers and customers, their production and product prices, and hence its link-level sales. The two rows of equation (11) gives the direct and higher-order effects, with signs determined by the substitution elasticity σ. On the supplier side, both effects share one sign: a rise in j's cost θ_j makes i buy less from j when inputs are substitutes ($\sigma > 1$), and more when they are

complements ($\sigma < 1$). On the customer side the two diverge. The direct effect is a scale effect, independent of σ: a rise in i's cost θ_i shrinks its output, so it buys less of every input, including j's. The higher-order effect works through the cost of i's other inputs: when they become more costly and inputs are substitute ($\sigma > 1$), j becomes relatively cheaper and i shifts toward it.

We empirically estimate equation (11) using the following regression model

$$\Delta \log\left(\frac{s_{ji}}{s_i}\right) = \psi_1^s \Delta\widehat{\log(1+\theta_j)} + \psi_1^c \Delta\widehat{\log(1+\theta_i)} + \psi_2^s \widehat{Net}_j + \psi_2^c \widehat{Net}_i + \psi x_{ji} + \varepsilon_{ji}, \tag{12}$$

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

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 (4). Assuming that the fraction of production costs requiring credit χ_i is exogenous, reflecting the stringency of each firm's financial constraint, the change in credit demand after a physical capital shock satisfies

$$d\log L_i = e_i'(I - \lambda \mathbf{A}')^{-1}\left[\beta d\log w + \rho d\log r\right] + \lambda e_i' \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} d\log(1+\theta) \tag{13}$$

5.2 Credit Demand

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

$$\Pr_{i,b}^{\tau} = \frac{\exp(\alpha_P^D R_{i,b}^{\tau} + \alpha_C^D C_{i,b} + \alpha_Z^D Z_{i,b} + X_b' \alpha_X^D + \xi_b^D)}{\sum_{b=1}^{B} \exp(\alpha_P^D R_{i,b}^{\tau} + \alpha_C^D C_{i,b} + \alpha_Z^D Z_{i,b} + X_b' \alpha_X^D + \xi_b^D)}, \tag{14}$$

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

$$\mathcal{L}^D(\alpha^D) = \sum_{i=1}^{N} \sum_{b=1}^{B} 1\{d_i = b\} \log \Pr_{i,b}^{\tau} \tag{15}$$

5.3 Credit Supply

Banks compete by setting firm-bank specific interest rates to maximize expected profit. Because banks price loans at the firm level based on observable firm and bank-firm characteristics, the bank's pricing problem decentralizes across firms: bank b chooses $R_{i,b}^{\tau}$ for each firm i to maximize $\Pi_{i,b}^{\tau}$ in equation (8), taking other banks' pricing as given. The first-order condition of equation (8) suggests that the equilibrium interest rates satisfy

$$R_{i,b}^{\tau} = \frac{MC_{i,b}^{\tau}}{1 - F_{i,b}^{\tau} + F_{i,b,R}^{\tau} \mathcal{M}_{i,b}^{\tau}} + \frac{(1 - F_{i,b}^{\tau}) \mathcal{M}_{i,b}^{\tau}}{1 - F_{i,b}^{\tau} + F_{i,b,R}^{\tau} \mathcal{M}_{i,b}^{\tau}}, \tag{16}$$

where $\mathcal{M}_{i,b}^{\tau} = -Q_{i,b}^{\tau}/Q_{i,b,R}^{\tau}$, and $F_{i,b,R}^{\tau}$ and $Q_{i,b,R}^{\tau}$ denote the derivatives of firm i's default probability and expected loan volume with respect to its own rate $R_{i,b}^{\tau}$. 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 adds two extensions to the 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:

$$Q^{\tau}_{i,b,R} = \left(\alpha^{D}_{P,i}\left(1-\Pr_{i,b}\right)\Pr_{i,b} - \alpha^{D}_{C} N^{\tau}_{i,b}\right) L_i + \Pr_{i,b}\, L_{i,R^{\tau}_{i,b}}. \tag{17}$$

The first term in equation (17) 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. Specifically, $N^{\tau}_{i,b}$ ($N^{\tau}_{i,k}$) 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 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 E, the marginal common lender effects satisfy

$$N^{\tau}_{i,b} = -\sum_{k\neq b}\Pr_{i,k}\sum_{j\neq i} w_{ij}\alpha^{D}_{P,j}\Pr_{j,k}\Pr_{j,b} - \alpha^{D}_{C}\sum_{k\neq b}\Pr_{i,k}\sum_{j\neq i} w_{ij}N^{\tau}_{j,k}. \tag{18}$$

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 $\widehat{\Pr}_{i,b}$, and $\widehat{w}_{ij}$ observable from data, we can solve $\widehat{N}^{\tau}_{i,b}$ numerically.

Finally, the second term in equation (17) represents the price impact on the intensive margin, given that firm i's probability of borrowing from bank b is $\Pr_{i,b}$, and $L_{i,R^{\tau}_{i,b}}$ denotes the derivative of loan size demanded by firm i with respect to a marginal change in its own interest rate $R^{\tau}_{i,b}$ at bank b. The financing cost contributes to firms' marginal cost of production, influencing their production plan and credit demand. As detailed in Appendix E, the derivative of credit demand with respect to interest rates satisfies

$$L_{i,R^{\tau}_{i,b}} = L_i \cdot \Pr_{i,b} \cdot \lambda e_i' \mathbf{A}'(I-\lambda\mathbf{A}')^{-1}\widehat{\boldsymbol{\omega}}, \tag{19}$$

where $\widehat{\boldsymbol{\omega}}$ is a vector with the jth element equal to $\widehat{\chi}_j/(1+\widehat{\theta}_j)$. The term $\Pr_{i,b}\cdot\lambda e_i'\mathbf{A}'(I-\lambda\mathbf{A}')^{-1}\widehat{\boldsymbol{\omega}}$ represents the log-derivative $d\log L_i/dR$, which captures how the production network amplifies the effect of interest rate changes on firms' cost structures. Multiplying by L_i converts this to the level derivative dL_i/dR.

We obtain $\widehat{Q}^{\tau}_{i,b,R}$ and $\widehat{\mathcal{M}}^{\tau}_{i,b}$ at the firm-bank level from equation (17), and $\widehat{F}^{\tau}_{i,b,R}$ from

$$F^{\tau}_{i,b,R} \;=\; \phi^{F}_{i,b}\left[\,\alpha^{F}_{P} \;+\; \alpha^{F}_{C}\cdot T^{\tau}_{i,b}\,\right], \tag{20}$$

which combines the direct price effect with the network feedback on firm i's own common lender variable at bank b through $T^{\tau}_{i,b} \equiv \partial C_{i,b}/\partial R^{\tau}_{i,b}$. As shown in Appendix E, $T^{\tau}_{i,b}$ and the

demand-side network term $N^{\tau}_{i,b}$ are linear functionals of the same firm-bank probability response vector and can be obtained jointly from a single linear fixed-point system. With these estimates, we back out the marginal cost of bank b lending to firm i by inverting the firm-level pricing equation (16):

$$\widehat{MC}^{\tau}_{i,b} = \left(1 - \hat{F}^{\tau}_{i,b} - \hat{F}^{\tau}_{i,b,R}\widehat{\mathcal{M}}^{\tau}_{i,b}\right)\hat{R}^{\tau}_{i,b} - \left(1 - \hat{F}^{\tau}_{i,b}\right)\widehat{\mathcal{M}}^{\tau}_{i,b}, \tag{21}$$

which we keep fixed in counterfactual analyses.

5.4 Identification

Endogeneity and Control Function. Two key regressors, interest rates and the common lender variable, in the credit demand model are potentially endogenous. Interest rates are set by banks in response to unobservables that may also affect demand, and the common lender variable reflects equilibrium borrowing decisions of trading partners, which may be correlated with unobserved firm-bank specific demand. We adopt the control function approach (Petrin and Train, 2010) to address both sources of endogeneity.

For interest rates, we predict the interest rate each bank would offer to each firm using a linear prediction model with a rich set of fixed effects, including bank-year-province fixed effects, bank-firm-type fixed effects, and firm size and profitability quintiles interacted with bank fixed effects, consistent with banks pricing loans based on observable firm characteristics. We use the average rate that the same bank offers in the same year on term loans to firms with similar observable characteristics as an instrumental variable for credit-line interest rates. This is a price that moves with the bank's contemporaneous funding costs and pricing conditions but is plausibly unrelated to the firm's own credit-line demand.

For the common lender variable, we construct an instrument that exploits mergers and acquisitions (M&A) among firms' trading partners as a supply-side shock to the common lender structure. When a trading partner of firm i undergoes an M&A event, the resulting change in bank relationships is plausibly exogenous to firm i's own demand for credit. We construct the M&A instrument as

$$\text{IV}^{\text{MA}}_{i,b} = \frac{\sum_{j \neq i}(s_{ji} + s_{ij}) \cdot L^{\text{post-MA}}_{j,b}}{\sum_{j \neq i}(s_{ji} + s_{ij}) \cdot L_j}, \tag{22}$$

where $L^{\text{post-MA}}_{j,b}$ denotes the credit of partner j at bank b after an M&A event, using the same trade-volume weights as in the common lender variable. The instrument switches on when a trading partner completes an M&A, which is positive only for banks lending to the post-M&A partner, and varies across banks and over time. Because the first stage includes firm-bank fixed effects, identification comes from within-firm-bank changes in common lending around partners' M&A events. The exclusion restriction requires that the M&A events of firm i's trading partners be unrelated to firm i's bank-specific credit demand. This assumption is plausible because (1) M&A events are corporate-control decisions made by the merging partners rather than firm i; (2) although a partner's M&A may affect firm i directly, any resulting firm-level shocks are common to all bank alternatives and therefore cancel out in the choice probabilities, whereas the instrument's variation is firm-bank-specific by construction; and (3) bank-level supply re-

sponses are absorbed by bank-year fixed effects, with firm-bank rate responses captured by the interest-rate control function. The common lender residual from the first stage is included in the demand model as a second control function term.

The demand model is then estimated by maximum likelihood with both control function residuals $\hat{\nu}_{i,b}$ (interest rate) and $\hat{e}_{i,b}$ (common lender) included as additional regressors:

$$U_{i,b}^{D} = \alpha_{P,i}^{D}\widehat{R}_{b}^{\tau} + \alpha_{C}^{D}\widehat{C}_{i,b} + \alpha_{Z}^{D}Z_{i,b} + X_{b}'\alpha_{X}^{D} + \xi_{b}^{D} + \alpha_{\nu}^{D}\hat{\nu}_{i,b} + \alpha_{e}^{D}\hat{e}_{i,b} + \varepsilon_{i,b}^{D}. \tag{23}$$

Under the control function assumption, the coefficients α_{ν}^{D} and α_{e}^{D} on the residuals absorb the endogeneity bias, and the remaining coefficients are consistently estimated. Statistical significance of $\hat{\alpha}_{\nu}^{D}$ or $\hat{\alpha}_{e}^{D}$ provides a test for endogeneity of the corresponding variable. The first-stage regression results are reported in Appendix Table C18.

6 Estimation Results

Table 3 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 indicates a downward-sloping demand curve: a one percentage point increase in the interest rate decreases the utility of borrowing by 0.68, corresponding to an average own-price elasticity of 1.65, 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 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 0.19, with a standard deviation of 0.29. This suggests that on average 19% 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 0.11% 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 3 reports the estimation results for the default model as specified in Eq(7), controlling for bank, year, industry, and firm-size fixed effects. To address the endogeneity of the realized interest rate and the common lender variable in the default equation, we include control function residuals for both variables, constructed from the first-stage predictions used in the demand model. The results suggest that firms that borrow more from common lenders along the supply chain, and firms that borrow from a bank with which they already had a relationship, have a higher estimated probability of default. The realized interest rate, by contrast, is positive but statistically insignificant after using control functions to address endogeneity.[12]

[12]Estimated without the control-function correction, the realized rate enters the default probit positively and significantly, suggesting that riskier borrowers are charged more. Once the first-stage residual is included to purge this selection, the coefficient on the rate falls close to zero and loses significance.

Table 3: Credit Demand and Default

	Demand	Prob. Default
	(1)	(2)
Interest Rate	-0.68***	0.05
	(0.01)	(0.05)
Common Lender	0.73***	0.11***
	(0.01)	(0.02)
Pre-Existing Relationship	3.23***	0.13***
	(0.01)	(0.02)
Bank-Year FE	✓	✓
Industry & Size FE		✓
Control Function	Interest Rate, Common Lender	Interest Rate, Common Lender
Model	Logit	Probit
N	491140	182373

Notes: 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(6). Pre-Existing Relationship is a dummy variable that takes the value of one if the bank and the firm have a previous borrowing-lending relationship, and zero otherwise. The demand model includes control function residuals for both the interest rate and the common lender variable to address endogeneity, as described in Section 5.4. Interest rates are predicted using bank-year-province and firm-type fixed effects. The common lender variable is instrumented using M&A-induced partner bank switches. ***p<0.001, **p<0.01, *p<0.05.

Although the common lending channel in principle introduces an additional network feedback loop, since a bank raising rates to firm i can change the default probabilities of i's trading partners through common-lender spillovers, our estimates suggest that this feedback is quantitatively negligible. The network object $T_{i,b}$ yields a contribution of less than 0.1% of the direct own-default response. Therefore, the network effect of common lending operates almost entirely through credit demand, with the default channel almost negligible.

Based on the estimates from the demand and default models, we compute firms' price elasticity and effective markup for the period 2020-2023. Column (1) of Table 4 reports the estimated average price elasticity, accounting for both the common-lender effect and the intensive-margin channel. The price elasticity ranges from 1.33 to 3.52 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, suggesting that the common lender channel raises borrowers' price elasticity. Because a bank that raises its rate loses not only the focal borrower but also that borrower's trading partners through the erosion of its common-lender position, demand is more elastic where the channel is active. As shown in Columns (4) and (5), this higher elasticity coincides with a lower markup. The common lender channel simultaneously reduces the effective markup through the

Table 4: 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)
2020	1.34	1.28	1.36	1.73	1.78	1.59
2021	1.33	1.27	1.34	1.71	1.76	1.59
2022	2.03	1.94	2.05	1.73	1.78	1.59
2023	3.52	3.38	3.55	1.70	1.74	1.59

Notes: This table reports the estimated price elasticity of demand (Columns (1)-(3)) and the effective markups (Columns (4)-(6)) over the period 2020-2023. 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.

network spillover: when a bank raises rates, it reduces its borrowers' probability of remaining with the bank, which in turn diminishes its role as a common lender to their trading partners, triggering further demand losses across the supply chain. This network externality disciplines banks' pricing. Moreover, since the network effect operates almost entirely through the credit-demand margin, we report only the baseline and the "no common lender effect" scenario, without a further decomposition between demand- and default-side.

Column (3) shows the result without the cost pass-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 effect lowers price elasticity, making credit demand less sensitive to interest rate changes.

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 1.7 percentage points and remains stable across the four-year period. Comparing Column (4) with Column (5) shows that the common-lender channel reduces the effective markup by about 0.05 percentage points on average, while the cost pass-through channel raises it by about 0.13 percentage points. This pass-through contribution should be interpreted with caution, as it rests on the modeling assumptions that firms rely on bank credit to finance production and firms anchor their financing cost on the rate they expect to pay across all active banks, which may cause us to overestimate the strength of the channel in the former case and underestimate in the latter.

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 lending relationships, can leverage their market position to affect their borrow-

Table 5: Effective Markup and Marginal Costs

	Effective Markup	Effective Marginal Cost
	(1)	(2)
Common Lender	0.14***	-0.13***
	(0.00)	(0.00)
Pre-Existing Relationship	3.69***	-3.68***
	(0.00)	(0.00)
Bank-Year FE	✓	✓
Firm Type-Year FE	✓	✓
N	2321517	2321517
Adj. R^2	0.54	0.76

Notes: This table reports the results of regressing the estimated 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(6). 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.

ers' price elasticity, effective markup, and the implied marginal costs. We focus on our baseline model, incorporating both the common-lender channel and the cost pass-through channel. We compute firms' effective markup and effective marginal cost for each bank, and regress the effective markup and marginal cost 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 5 relates each firm-bank pair's estimated effective markup and marginal cost to the two measures. Both greater common-lender importance and a prior borrowing-lending relationship are associated with higher markups and lower effective marginal costs: common lenders and relationship lenders charge higher markups and enjoy lower marginal costs along the supply chain, consistent with greater market power and the cost advantages of specialized lending. 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 borrowers prefer. By exploiting borrowers' preference for common lenders, 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 Costs of Common Lending: The GM Antwerp Shock

Our previous sections document the benefits of common lending and quantify the mechanisms through which it shapes credit markets. In this section, we examine its potential costs. Because common lending concentrates bank exposures along supply chains, disruptions in the real sector can propagate through the production network and spill over into the financial sector. To illustrate this risk, we exploit the closure of GM Antwerp, a large car manufacturing company, as an exogenous shock to the production network. GM Antwerp was a prominent car manufacturing plant in Belgium. In the 2000s, GM suffered a $40 billion loss in 2007 (Goolsbee and Krueger, 2015) and implemented a restructuring plan across its European operations, including freezes in wages and benefits. 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). In 2010, GM Antwerp was shut down as part of these cost-cutting measures. The firm-specific nature, its temporary effect, and its significant implications for the supply chain and local economy make the GM closure a suitable shock. This setting is well suited for identification because the closure was firm-specific rather than economy-wide, and its effects were largely temporary, and it generated disruptions to the production network and local economy.[13] We study the impact of GM closure on firm sales and credit demand in Sections 7.1 and 7.2.[14]

7.1 Shock Propagation and Firm Sales

We start by analyzing shock propagation in the production network focusing on firm sales. The goal is to examine the impact of the GM closure that hit firms at different distances within GM's supply chain on the sales of those firms. For the sake of brevity, we discuss only the results. More details on the empirical specification and additional robustness checks can be found in the Appendix Section C.2.

To trace how the GM Antwerp closure propagated through the supply chain, we classify firms by their network distance from GM using pre-shock relationships following Carvalho et al. (2021). Direct buyers and sellers of GM are "Level 1" firms. Connected to Level 1 firms, but not to GM directly, are Level 2 firms, and so on through Level 3. Firms with no such connection to GM serve as the control group. Each firm is assigned to a single level based on its closest tie to GM, so a firm's transactions with more distant tiers are not double-counted.[15] We compare transaction-level sales between seller-buyer pairs before and after 2006, separately tracing propagation downstream (from GM to its buyers, and outward) and upstream (from GM's suppliers, and inward), to keep the estimates for each direction separate.

Table C3 Columns (1) and (2) report the transaction-level estimation results for the shock propagation. Panel A reports results for downstream propagation and Panel B for upstream propagation. The dependent variable is the log of annual transaction amounts between a seller and a

[13]The effect of the GM closure is temporary, which differs substantially from the effects of natural disasters, where the impact can be long-lasting or even permanent. Such a clean setting allows us to isolate the short-run transmission of supply chain shocks without confounding structural changes in productive capacity.

[14]Summary statistics of the sample for the GM analysis are reported in Appendix Table C2.

[15]We also address the concern that Level 1 firms might simply be GM subsidiaries: almost all of them transact with multiple counterparties beyond GM, and only about 1% share GM's postal code, so shadow-subsidiary status is unlikely to explain the results.

buyer.[16] 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 generally 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's buyers experienced a decline in sales of approximately 37.6% after 2006, compared to their sales trend before the shock and relative to non-treated pairs. The magnitude is reduced to 13.6% for Level 2 seller-buyer pairs and 18.9% for Level 3 seller-buyer pairs.

We further perform an analysis at the firm level by aggregating transaction-level data. Accordingly, the outcome variable is defined at the firm level, i.e., the sales from all transactions of a firm in a year.[17] The aim is to show that the reduction in sales is significant at the firm level. The regression results are reported in Columns (3) and (4) of Table C3 with the dependent variable being logarithm of firm sales. Column (3) suggests that direct downstream firms experienced a sales drop of roughly 21.5%, while Level 2 and Level 3 downstream firms saw reductions of approximately 15.1% and 11.7%, respectively. Upstream effects show a similar pattern. 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. These results suggest that the shock propagated both downstream and upstream, with stronger effects for firms closer to GM in the production network.

7.2 Shock Propagation and Firm Credit Demand

Our previous section documents that GM's closure propagated through the production network, negatively affecting the sales of direct and indirect customers and suppliers, with impacts decreasing for firms further 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 credit amounts, among other factors. As a result, our sample is restricted to firms that appear in the B2B dataset and that have borrowed from banks. This means that for our downstream analysis, we only include firms that have appeared in the B2B dataset at least once between 2002 and 2011 and who have engaged in borrowing from banks.[18] We study the impact of GM closure on firm credit demand in Section 7.2.1. Section 7.2.2 analyzes the effects on common lending, and Section 7.2.3 examines the aggregate effects at the bank level.

[16] For the downstream, the transaction is between GM→GM's buyer, GM's buyer→GM's buyers' buyers, GM's buyers' buyers→GM's buyers' buyers' buyers. For the upstream, the transaction is between GM's sellers→GM, GM's sellers' sellers→GM's sellers, GM's sellers' sellers' sellers→GM's sellers' sellers.

[17] We calculate sales for both downstream and upstream firms. That is, for downstream firms of GM, we compute total sales in which they act as sellers.

[18] 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 firms do not have borrowing relationships with banks.

7.2.1 Firm Credit Demand

We begin by estimating the following firm-bank-time level specification:

$$\text{Credit}_{i(j),b,t} = \beta_k \text{Level}^k_{i(j)} \times \text{Post}_t + \delta \mathbf{X}_{i(j),t} + \text{FE} + \epsilon_{i(j),b,t}, \tag{24}$$

where b and t denote bank and year, respectively. We first investigate how the credit usage amounts of firms, i.e., firm credit demand, with *existing banks* respond to the GM closure. Specifically, we construct $\mathbb{1}(\text{New use})$, a dummy variable that takes the value of one 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 zero otherwise. We then examine whether firms affected by the GM closure seek to establish *new bank relationships*. For this, we construct $\mathbb{1}(\text{New bank})$, a dummy variable that takes the value of one if bank b is new to firm i (j) in year t, and zero otherwise.[19] Accordingly, we aim to understand the probability of having a new firm-bank relationship before and after the shock. $\text{Level}^k_{i(j)}$ equals one for firms that are k-level buyers (sellers) of GM, and zero otherwise. The control group consists of firms that are buyers (sellers) but never appear in GM's supply chain.

To account for variation in firm fundamentals, we control for time-varying firm characteristics, including firm size, leverage, and profitability. In particular, we compute the Altman Z-score and include it as a control variable to capture firms' default risk, which may affect how they utilize credit.[20] To address endogenous matching between firms and banks, we incorporate bank-firm fixed effects. This approach assumes that non-random matching is driven by unobserved factors that remain constant over time. We mitigate concerns of credit supply by using bank-sector-province-time fixed effects, which is a stringent way to control for credit supply shocks. Standard errors are clustered at the firm level.

Table 6 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 all three levels of downstream and upstream firms, suggesting reduced credit demand after the GM closure. In Column (2), the outcome is a dummy for establishing a new bank relationship. We observe significantly negative effects for all three levels of upstream firms, indicating that affected firms are less likely to form new banking relationships, which is consistent with reduced financing needs after supply chain disruptions.[21]

To further show that the drop in credit demand detected from firm-bank level analysis is significant at the firm level, we examine the effects on firms' overall credit behavior by aggregating

[19] 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.

[20] Variable definitions are in Table A2.

[21] Table C15 reports results in which we use the change in credit demand at the intensive margin as the outcome variable. $\Delta \log(\text{Use})$, defined as $\log(\text{used amount})_{i(j),t} - \log(\text{used amount})_{i(j),t-1}$. We detect similar results. Table C16 further presents results using alternative model specifications when the outcome variable is $\mathbb{1}(\text{New bank})$, and the findings remain similar. For example, to isolate the effects of credit supply from credit demand, we include bank-province-year fixed effects, which allow us to control for unobserved, time-varying factors affecting credit supply specific to a bank operating in a 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., 2026; Paravisini et al., 2023; De Jonghe et al., 2025), we incorporate bank-province-sector-time fixed effects in some specifications.

Table 6: Shock Propagation and Credit Demand: Firm-Bank and Firm-Level Evidence

	Firm-Bank Level		Firm Level	
	$\mathbb{1}$(New use)	$\mathbb{1}$(New bank)	$\mathbb{1}$(New use)	$\mathbb{1}$(New bank)
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.112***	0.002	-0.015	0.015
	(0.024)	(0.007)	(0.029)	(0.011)
Level 2 × Post	-0.124***	-0.007***	-0.037***	-0.003
	(0.006)	(0.002)	(0.007)	(0.003)
Level 3 × Post	-0.103***	0.000	-0.034***	-0.002
	(0.005)	(0.002)	(0.007)	(0.003)
N	1114204	1593378	951910	959763
R^2	0.06	0.12	0.27	0.19
Panel B. Upstream				
Level 1 × Post	-0.039***	-0.011***	0.027*	-0.004
	(0.012)	(0.003)	(0.014)	(0.007)
Level 2 × Post	-0.056***	-0.010***	0.003	-0.003*
	(0.004)	(0.001)	(0.005)	(0.002)
Level 3 × Post	-0.042***	-0.005***	-0.000	-0.003
	(0.004)	(0.001)	(0.004)	(0.002)
N	1049723	1505686	894831	901981
R^2	0.06	0.12	0.26	0.19
Firm controls	✓	✓	✓	✓
Firm FE			✓	✓
Bank FE			✓	✓
Sector-Time FE	✓	✓		
Bank-Firm FE	✓	✓		
Province-Sector-Time FE			✓	✓
Bank-Province-Sector-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 use), a dummy equal to one if the credit used increases from the previous year; (ii) $\mathbb{1}$(New bank), a dummy equal to one if the firm forms a new bank relationship in year t. The independent variable $\text{Level}^k_{i(j)}$ 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, profitability and Altman Z-score. Robust standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

firm-bank level credit to the firm-level. We use two dependent variables. First, $\mathbb{1}$(New use), a dummy variable that takes the value of one if the difference in the used credit amount of firm i (j) from the previous year to year t is positive, and zero otherwise. Second, $\mathbb{1}$(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. Given the unit of observation is firm-year, we cannot incorporate bank-year fixed effects to control for credit supply shocks. Instead, we

include bank fixed effects by using the main bank of each firm. We combine it with sector-year fixed effects or province-sector-year fixed effects. The coefficient of interest 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 6 Columns (3) and (4) present firm-level results for downstream and upstream firms. 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, suggesting reduced credit demand after the GM shock. Column (4) examines whether firms establish new bank relationships. However, we do not detect significant effects for affected firms. The results for upstream firms are modest, showing significant declines in new bank formation among GM's Level 2 suppliers. These findings confirm that supply chain disruptions translate into reduced credit demand at the firm level. Additional model specifications are reported in Table C17 and yield consistent results.

A key concern in our setting is the overlap of the sample period with the Global Financial Crisis. In addition, one may be concerned that firms substitute bank credit with trade credit to finance their production. We address these concerns in Appendix C.3 and C.4. We confirm that our results are driven by a reduction in credit demand rather than a contraction in credit supply. We rule out substitution between bank credit and trade credit. We also perform a dynamic difference-in-differences estimation to validate the parallel trend assumption for our analysis on firm credit demand. Figure C3 shows that there is no significant pre-trend.

7.2.2 Firm Credit Demand and Role of Common Lenders

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 affects the production of its direct and indirect suppliers and customers, which in turn hinders their credit demand. What remains unclear is how common lenders shape firms' credit demand. As demonstrated by our model, production networks directly influence firms' borrowing decisions. In this section, we investigate the prevalence of common lenders within GM's production network and examine how the disruption affects firms' decisions to borrow from a common lender.

We focus on Level 1 and Level 2 firms in the production network of GM. First, we construct a complete mapping between Level 1 and Level 2 firms using 2006 B2B data and identify 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. The complete mapping of each Level 1 and Level 2 firm based on 2006 data is then replicated for the years 2004-2005 and 2007-2009, implying that the network structure is fixed. Firm-bank relationships are time-varying and are obtained by merging the data with the credit registry. We then estimate the following regression specification:

$$\text{Common lender}_{i,j} = \beta \mathbb{1}(\text{Trade})_{i,j} \times \text{Post}_t + \text{FE} + \epsilon_{i,j}. \tag{25}$$

We have two outcome variables: (i) $\mathbb{1}$(Common lender), which equals one if a Level 1 firm and

a Level 2 firm share a common lender, and zero otherwise. (ii) Number of common lender, a continuous variable indicating the number of common lenders between a Level 1 firm and a Level 2 firm. The explanatory variable, $\mathbb{1}(\text{Trade})$, equals one if a Level 1 firm and a Level 2 firm had a transaction in 2006, and zero otherwise. We include seller fixed effects and buyer fixed effects.

Table 7 presents the results. Columns (1) and (2) show the results on the extensive margin, where the outcome variable is an indicator variable for having common lenders. The coefficient estimate of $\mathbb{1}(\text{Trade})$ is positive and statistically significant, suggesting that firms with a direct transaction are more likely to share common lenders. Strikingly, the estimate of the interaction term, $\mathbb{1}(\text{Trade}) \times \text{Post}$, is negative and statistically significant in all four specifications. Column (1) suggests that, following the shock, affected firms are 5.6 percentage points less likely to borrow from common lenders when they have a direct transaction relationship, relative to firms without direct transactions. As shown in Column (2), the result remains robust when seller-buyer fixed effects are included, allowing us to exploit within-pair variation. We find similar results at the intensive margin, with the outcome variable being the number of common lenders. Together, these results highlight that the value of common lenders may depend on the financing decisions of suppliers and customers. Given that supply chain disruptions reduce credit demand along the chain, firms are more likely to terminate pre-existing relationships with common lenders since the benefits of borrowing from them diminish.

7.2.3 Firm Credit Demand and Bank Loan Portfolio

Our previous sections uncover a decline in firms' credit demand following the supply chain disruption triggered by the GM closure. The underlying mechanism is that the GM closure negatively affects the production of its direct and indirect suppliers and customers, which in turn reduces their credit demand. We also find that the role of common lending is dampened. Next, we examine the overall effects on bank loan portfolios. We are interested in whether banks that are more exposed to the shock are more affected. A negative impact would suggest that specialized banks suffer from reduced credit demand from both direct borrowers and borrowers' suppliers and customers due to the existence of common lending. We begin by dividing banks into two groups: banks with high or low exposures to the GM closure. The exposure is calculated using the following equation:

$$\text{Exposure}_b = \frac{\text{Amounts committed to affected firms in 2006}}{\text{Amounts committed to all firms in 2006}}. \tag{26}$$

Here, affected firms include Level 1 to Level 3 firms identified on 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. We choose to use committed credit amounts to capture the extent to which banks are exposed to the shock because it should better capture the credit supply determined by banks. We are interested in credit outcomes at the (i) bank-province level and (ii) bank-sector level.[22]

[22] There are ten provinces and the Brussels-Capital Region: Brussels, Walloon Brabant, Flemish Brabant, Antwerp, Limburg, Liège, Namur, Hainaut, Luxembourg, West Flanders, East Flanders. Sector is defined by 2-digit NACE

Table 7: Common Lender and Production Networks

	𝟙(Common lender)		Number of common lenders	
	(1)	(2)	(3)	(4)
Panel A: Downstream				
𝟙(Trade)× Post	-0.056***	-0.056***	-0.094***	-0.104***
	(0.002)	(0.002)	(0.008)	(0.006)
𝟙(Trade)	0.060***		0.395***	
	(0.002)		(0.015)	
N	20690397	20103976	20690397	20103976
R^2	0.26	0.86	0.38	0.96
Panel B: Upstream				
𝟙(Trade)× Post	-0.015***	-0.016***	-0.025***	-0.045***
	(0.001)	(0.001)	(0.005)	(0.004)
𝟙(Trade)	0.020***		0.285***	
	(0.001)		(0.008)	
N	113167392	109808976	113167392	109808976
R^2	0.31	0.84	0.47	0.96
Seller FE	✓		✓	
Buyer FE	✓		✓	
Seller-Buyer FE		✓		✓
Year FE	✓	✓	✓	✓

Notes: This table shows the estimation results of Eq(25). The dependent variables are (i) 𝟙(Common lender), which equals one if a Level 1 firm and a Level 2 firm share a common lender, and zero otherwise. (ii) Number of common lenders, a continuous variable indicating the number of common lenders between a Level 1 firm and a Level 2 firm. 𝟙(Trade), equals one if a Level 1 firm and a Level 2 firm had a transaction in 2006, and zero otherwise. Post_t is an indicator variable taking a value of one for the years 2007-2011, and 0 for the years 2002-2006. Robust standard errors clustered at the seller-buyer level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We investigate the influence of supply chain disruption on banks' credit outcomes by estimating the following equation:

$$\text{Credit}_{b,p(s),t} = \beta \text{Exposure}_b \times \text{Post}_t + \text{FE} + \epsilon_{b,p(s),t}, \tag{27}$$

where b, p, s, and t denote bank, province, sector, and year, respectively. The outcome variable is the logarithm of (1) authorized amounts and (2) used amounts of a bank in a province (sector) in a year. Exposure_b equals one if a bank's exposure to the shock is above the median, and zero otherwise. Since the interaction term is at the bank-year level, we cannot 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. We address this concern by including 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(24).[23] This captures shocks to bank-level credit supply that are common

code.

[23]The bank-year fixed effects are estimated from regressions for downstream firms. We show that using estimates

across all borrowers.[24] Bank fixed effects are also included to account for time-invariant bank characteristics that might affect the outcome variables.

Table 8 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 logarithm of 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 a 20.3 percent decrease in loan committed amounts at the bank-sector level. Columns (3)-(4) present similar results. Table 8 Panel B reports the results on banks' credit balances at the 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 or used amounts as the dependent variable. These results are consistent with the simple illustration in Figure C4 and Figure C5. Figure C6 shows that there is no pre-trend in authorized and used amounts at both the bank-sector and bank-province level. We conclude that specialized banks are unable to fully compensate for the reduced credit demand of affected firms, leading to an overall negative impact. Our evidence together indicates that a shock originating in the real sector can propagate to the financial sector through the production network.

The bank-level results can be attributed to the reduced role of common lending documented in Section 7.2.2. Due to lower demand for common lending, credit demand decreases for banks that are concentrated in the supply chain, which explains the significantly larger decline in lending volume for highly exposed banks compared to less exposed banks. These findings underscore an amplification channel through which common lenders propagate shocks, consistent with the structural model's prediction that common lending creates correlated exposures in banks' portfolios. The structural estimates presented in Section 6 quantify the market power that banks derive from their common-lender position. The GM shock evidence shows that this same concentration can amplify real-sector disruptions into the financial sector. In Section 8, we use the estimated model to quantify this mechanism directly, simulating the closure of a major network firm and comparing the equilibrium credit allocation with and without the common-lender preference.

8 Counterfactual: Common Lending and the Transmission of a Network Shock

The empirical evidence in Section 7 shows that the closure of a large firm propagates through the production network and reduces bank lending, with banks more exposed to the affected supply chain experiencing larger declines. However, these reduced-form estimates cannot sep-

from regressions for downstream firms does not change the level of statistical significance, but slightly affects the coefficient magnitude.

[24] It is more common in the literature to isolate credit demand. See, e.g., Federico et al. (2025).

Table 8: Shock Propagation to the Financial Sector: Bank Level Outcome

	log(CMT)		log(USE)	
	(1)	(2)	(3)	(4)
Panel A: Bank-Sector Level				
Exposure × Post	-0.219*	-0.227***	-0.237***	-0.214***
	(0.118)	(0.059)	(0.064)	(0.067)
Credit supply		✓		✓
Bank FE	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓
N	16506	13720	15998	13453
R^2	0.70	0.73	0.69	0.72
Panel B: Bank-Province Level				
Exposure × Post	-0.500**	-0.530**	-0.422*	-0.337
	(0.231)	(0.240)	(0.251)	(0.259)
Credit supply		✓		✓
Bank FE	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓
N	4384	3343	4299	3325
R^2	0.72	0.74	0.69	0.73

Notes: This table shows the estimation results of Eq(27). The dependent variables are natural logarithm of authorized amounts in a year in Columns (1) and (2), and used amounts of a bank in a province (sector, 2-digit NACE) in a year in Columns (3) and (4). Exposure_b equals one if a bank's exposure to the shock is above the median, and zero otherwise, as defined in Eq(26). Post_t is an indicator variable taking a value of one 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.

arately identify shock propagation through banks' correlated lending portfolios from the common lending channel driven by borrowers' preference for common lenders. In this section, we use the estimated model to perform this decomposition directly. We simulate the closure of a major firm in the production network and compute the equilibrium credit allocation under two scenarios: one with the estimated common-lender preference ($\alpha_C^D > 0$) and one with the preference switched off ($\alpha_C^D = 0$), holding all other parameters fixed. The difference between the two scenarios isolates what common lending contributes to the transmission of the shock from the real sector to bank balance sheets. We want to understand whether common lending amplifies or dampens the transmission of the shock, and how it shapes the reallocation of credit across banks.

We simulate the full closure of a large manufacturing firm in the 2021 production network. To illustrate the role of the common-lender channel, we select the largest seller in the manufacturing sector whose borrowing is concentrated on dominant banks, so that the closure has sharply defined direct lenders and common lenders. The selected firm is, however, considerably smaller than GM Antwerp, with fewer direct suppliers and customers, which is one reason the counterfactual effects reported below are modest relative to the historical GM episode.[25] The two

[25]The GM Antwerp closure is outside our 2020–2023 sample period. We therefore simulate the closure of a con-

firms occupy comparable positions in the production network. In the 2003–2006 network, GM Antwerp had 1,440 direct suppliers and 263 direct customers among Belgian firms, against 485 direct suppliers and 20 direct customers for the simulated firm in 2021: both are large manufacturing sellers whose upstream network is far larger than their downstream network. The closure removes the firm's entire output. The loss then propagates through the production network in both directions: (i) downstream, customers lose an input and reduce production, and (ii) upstream, suppliers lose their orders and scale down. In addition, each firm's credit demand falls one-for-one with its production because firms finance input purchases with bank credit. The propagation runs through the pre-closure network structure, using the production-network parameters estimated from the GM episode and the intermediate-input cost share calibrated from the firm accounts, which we assume to be stable over time. The production network itself is held fixed: firms can neither replace the closed supplier with new suppliers nor redirect sales to new customers, so the counterfactual captures the intensive margin of adjustment. Appendix D provides more details of the estimation and calibration of production function parameters.

8.1 Bank-Level Effects: Amplification versus Reallocation

We report the counterfactual in general equilibrium, letting banks re-optimize their prices. Each bank re-sets its firm-specific interest rates from the pricing first-order condition in equation (16), holding its estimated marginal cost fixed. Firms choose banks according to the estimated demand model, which changes choice probabilities, common-lender measures, and default risk, and the change in each firm's expected market rate feeds back into its production cost and loan size through the cost pass-through channel of equation (13). We iterate these responses jointly until they converge. We report the partial-equilibrium benchmark that holds rates fixed in Table C1 of Appendix D and discuss it where the comparison is informative.

One caveat is that the counterfactual magnitudes are not directly comparable to the reduced-form GM estimates of Section 7.1, which concern a different firm, a different network, and a different period. We use the reduced form only as a qualitative benchmark, to confirm that the model reproduces the observed pattern: production and credit decline at every network tier, in both directions, fading with network distance. The purpose of the exercise is accordingly not to replicate the reduced-form magnitudes but to study the role of the common lending channel within the transmission. Appendix D examines the model's qualitative and quantitative performance under the shock in detail.

Given firms' new credit demands after the simulated closure, we recompute the allocation of credit across banks using the estimated demand model. As the credit of a firm's suppliers and customers contracts, the common lender measure $C_{i,b}$ defined in equation (6) falls for the banks lending to the affected supply chain, and firms reallocate their borrowing according to the estimated preference α_C^D. We compare two scenarios: the *baseline* scenario with the estimated common-lender preference, and the *no-common-lending* scenario with $\alpha_C^D = 0$. We summarize the contribution of common lending for each bank using the amplification ratio, Amp_b. It is the difference in the bank's credit change between the baseline and no-common-lending

temporary counterpart in the manufacturing sector.

scenarios, capturing the portion of the response attributable to borrowers' preference for common lenders, expressed as a percentage of its decline under pure network propagation (the no-common-lending scenario). A negative Amp_b means common lending makes bank b's lending fall by more than network propagation alone (amplification); a positive Amp_b means common lending shelters the bank.

Table 9 reports the counterfactual. Panel A describes each bank's position before the shock; Panels B and C report the credit and profit responses to the closure, each under the model-estimated baseline scenario and the no-common-lending scenario.

Panel A characterizes the banks before the closure. The four dominant banks, A through D, hold about 90 percent of the total credit to the sample firms, while the many small banks are pooled into a single group. They differ along two dimensions that turn out to matter separately. The first is exposure to the closed firm's supply chain: Bank A holds the largest common-lender credit to the firms within three network levels of the closed firm (€5.6 billion) and the highest closed-firm common-lender measure ($C_{s,b} = 0.42$), even though it barely lends to the closed firm itself. The second is direct lending to the closed firm: here Banks B and D are the two large direct lenders (€4.9 and €4.5 million, with $C_{s,b}$ of 0.27 and 0.29), whereas Banks A and C and the pooled remainder each lend it at most €0.2 million. The two dimensions are far from collinear. Bank A is the broad common lender with negligible direct exposure, Bank B combines a direct relationship with the closed firm with sizeable supply-chain positions, Bank C is neither a large supply-chain lender nor a direct lender, and Bank D is mainly a direct lender.

Panel B reports the credit response. Columns (1) and (2) give the change in each bank's credit under the baseline scenario, Columns (3) and (4) the same under the no-common-lending scenario, and Column (5) the amplification ratio. Two distinct forces show up in different columns, and separating them resolves what would otherwise look like a puzzle. The *level* of the loss, in Columns (1) to (4), is governed by size and supply-chain exposure: the closure reduces total credit by €65.3 million, and the banks that lose most in euros are the large lenders to the affected supply chain, led by Bank A (-€24.7 million) and Bank B (-€16.4 million). This loss is almost entirely network propagation, which is present in the no-common-lending column too, so in the aggregate common lending is close to neutral, changing the total loss by only about one percent.

The contribution of common lending, illustrated in Column (5), depends on two features of each bank: whether it lends to the closed firm directly, and how large its common-lender exposure to the closed firm's supply chain is. When rates are fixed in the partial-equilibrium benchmark presented in Appendix Table C1, the channel is a pure demand-side reallocation, and only the *direct* lenders bear more than pure propagation: Banks B and D are amplified, while every bank without a direct tie to the closed firm is sheltered. Once banks re-optimize their rates, the incidence shifts toward *supply-chain exposure*: the amplification falls on the two banks with the largest common-lender positions in the affected chain, Banks A and B, while the banks with little exposure are sheltered.

Reading the two benchmarks bank by bank gives a coherent picture. Bank B, both a direct lender and a large supply-chain lender, is amplified under both and bears the deepest amplification once rates adjust. Bank A, the broad common lender that barely lends to the closed firm directly,

Table 9: Counterfactual: bank credit and profit response to the closure of a major network firm

Panel A: Pre-shock bank characteristics

	Total credit	CL credit to supply chain	Lending to closed firm	
			Credit	$C_{s,b}$
Bank A	11.68	5.59	0.2	0.42
Bank B	6.90	1.96	4.9	0.27
Bank C	5.63	1.12	0.2	0.02
Bank D	4.79	1.07	4.5	0.29
Other banks	3.26	0.34	0.2	0.00

Panel B: Credit response to the closure

	Baseline		No common lending		Amp_b
	Δ Credit	% of credit	Δ Credit	% of credit	(%)
	(1)	(2)	(3)	(4)	(5)
Bank A	-24.7	-0.21	-24.7	-0.21	-0.3
Bank B	-16.4	-0.24	-15.7	-0.23	-4.3
Bank C	-6.6	-0.12	-7.6	-0.14	+13.7
Bank D	-12.6	-0.26	-13.0	-0.27	+3.2
Other banks	-5.1	-0.16	-5.1	-0.16	+1.1
All banks	-65.3	-0.20	-66.1	-0.20	+1.2

Panel C: Profit response to the closure

	Baseline		No common lending		Amp_b
	Δ Profit	% of profit	Δ Profit	% of profit	(%)
	(1)	(2)	(3)	(4)	(5)
Bank A	-1.06	-0.24	-1.05	-0.24	-1.2
Bank B	-0.67	-0.25	-0.63	-0.24	-7.3
Bank C	-0.22	-0.12	-0.25	-0.13	+10.2
Bank D	-0.40	-0.26	-0.41	-0.27	+3.1
Other banks	-0.13	-0.15	-0.13	-0.15	-1.2
All banks	-2.49	-0.22	-2.46	-0.22	-0.8

Notes: This table reports the general-equilibrium effects of the closure of a large manufacturing firm with a concentrated banking relationship in the 2021 network, allowing each bank to re-optimize its firm-specific interest rates. Banks are anonymized and ordered by size; "Other banks" pools those with market share below 1%. *Panel A* reports the pre-shock characteristics, including total credit to the sample firms (€ bn), common-lender credit to the closed firm's supply chain (firms within three network levels, € bn), credit to the closed firm (€ mn), and the closed firm's common-lender measure $C_{s,b}$ (Eq.(6)). *Panel B* reports the credit change (€ mn, and % of pre-shock credit) under the baseline (Columns (1)-(2)) and no-common-lending ($\alpha_C^D = 0$, Columns (3)-(4)) scenarios; Column (5) is the amplification ratio Amp_b, Column (1) minus Column (3) as a percentage of the decline under pure propagation (Column (3)). *Panel C* reports the change in expected profit (Eq.(8); € mn, and % of baseline profit). In general equilibrium the per-bank amplification ratios in Column (5) also absorb small bank-specific interest-rate adjustments and are therefore noisier than the euro changes in Columns (1)-(4); the cross-bank incidence of common lending is read most cleanly from the fixed-rate benchmark in Table C1 of Appendix D, where the baseline and the no-common-lending scenario are computed at the same rates.

is sheltered at fixed rates but becomes amplified once rates adjust, because its large supply-chain position exposes it to the reallocation. Bank C, exposed on neither dimension, receives the largest shelter. Bank D, a direct lender with only a small supply-chain position, is amplified at fixed rates but modestly sheltered once rates adjust. And the pooled remainder, exposed on neither dimension, is sheltered throughout. The mechanism behind both benchmarks is the same reallocation: when the closed firm disappears, its trading partners lose the common-lender tie to its direct lenders and shift borrowing toward banks already well placed in the same supply chain. Once banks adjust interest rates, low-exposure banks are more able to mitigate the shock, and thus the loss concentrates on the banks most embedded in the shocked firm's production network.

Allowing banks to reprice changes the results only slightly, so the general-equilibrium counterfactual stays close to the fixed-rate benchmark. The equilibrium interest-rate adjustments are small for two reasons. First, the shock we simulate is itself modest, so the reallocation of borrowing across banks gives limited repricing pressure. Second, the estimated markup is relatively flat, and the estimated default response to the interest rate is small, so banks have little room to move their rates in response to the reallocation.

Although common lending has only a modest effect on the aggregate transmission of the shock, its defining role is to concentrate the loss on the banks that serve as common lenders to the shocked firm and its supply chain. This amplifying role of common lending contrasts with the stabilizing one that common lenders play after transitory shocks, where informed lenders forbear and support connected borrowers (Giannetti and Saidi, 2019; dos Santos and Ferreira, 2026). The difference is threefold. First, our quantification focuses on the demand-driven common lending channel rather than the credit-supply response. Second, we study the *permanent* closure of a focal firm in the production network rather than a transitory shock, so that there is no recovery of the shocked firm for lenders to support. Third, those studies rely on difference-in-differences designs that identify a local treatment effect by comparing the responses of more- versus less-connected firms, while our structural counterfactual recovers the general-equilibrium aggregate response. In Appendix D, we report the firm-bank-level evidence on this concentration mechanism, which is the structural counterpart of the reduced-form finding in Section 7. We show that, at the firm-bank level, the credit decline is systematically larger where a firm strongly tied to the closed firm borrows from one of the closed firm's own lenders.

9 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.

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 0.11%. This preference increases a bank's market power, allowing banks that are more central as common lenders charge higher markups and have lower marginal lending costs. This result explains banks' incentives to specialize along the 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 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. Quantitatively, however, we find the cost pass-through channel to be modest.

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.

Finally, we use the estimated model to quantify how common lending amplifies or dampens credit reallocation in this transmission, simulating the closure of a major network firm with and without the common-lender preference. Common lending changes the aggregate credit contraction only modestly, but it acts as a risk-concentration mechanism, channeling the credit and profit losses onto the banks that serve as direct lenders to the shocked firm; allowing banks to reprice in general equilibrium shifts this concentration onto common lenders with high exposure to the production network of the shocked firm. Common lending thus offers firms cheaper credit in normal times, but exposes its specialized lenders to concentrated losses when the supply chain they serve is disrupted.

Common lending is a form of portfolio concentration that industry and regional classifications do not reveal. A bank whose exposures are spread evenly across sectors and provinces can still be concentrated on a single supply chain, and our results show that such a bank bears the full force of a disruption to that chain. Measuring bank concentration along the production network, and not only across industries and regions, would identify exposures that these classifications leave invisible.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Acharya, V. V., Hasan, I., and Saunders, A. (2006). Should banks be diversified? evidence from individual bank loan portfolios. *The Journal of Business*, 79(3):1355–1412.

Alfaro, L. and Chen, M. X. (2012). Surviving the global financial crisis: Foreign ownership and establishment performance. *American Economic Journal: Economic Policy*, 4(3):30–55.

Alfaro, L., García-Santana, M., and Moral-Benito, E. (2021). On the direct and indirect real effects of credit supply shocks. *Journal of Financial Economics*, 139(3):895–921.

Alfaro-Urena, A., Manelici, I., and Vasquez, J. P. (2022). The effects of joining multinational supply chains: New evidence from firm-to-firm linkages. *The Quarterly Journal of Economics*, 137(3):1495–1552.

Asai, K., Hoang, T., and Yamada, T. (2024). Common lender, ex-banker director, and corporate investment. *Journal of Financial and Quantitative Analysis*, 59(8):3959–3993.

Baqaee, D. R. (2018). Cascading failures in production networks. *Econometrica*, 86(5):1819–1838.

Baqaee, D. R. and Farhi, E. (2020). Productivity and misallocation in general equilibrium. *The Quarterly Journal of Economics*, 135(1):105–163.

Barrot, J.-N. (2016). Trade credit and industry dynamics: Evidence from trucking firms. *The Journal of Finance*, 71(5):1975–2016.

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

Beck, T., De Jonghe, O., and Mulier, K. (2022). Bank sectoral concentration and risk: Evidence from a worldwide sample of banks. *Journal of Money, Credit and Banking*, 54(6):1705–1739.

Benetton, M. (2021). Leverage regulation and market structure: A structural model of the UK mortgage market. *The Journal of Finance*, 76(6):2997–3053.

Bentolila, S., Jansen, M., and Jiménez, G. (2018). When credit dries up: Job losses in the great recession. *Journal of the European Economic Association*, 16(3):650–695.

Berger, P. G., Minnis, M., and Sutherland, A. (2017). Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Journal of Accounting and Economics*, 64(2-3):253–277.

Bernard, A. B., Dhyne, E., Magerman, G., Manova, K., and Moxnes, A. (2022). The origins of firm heterogeneity: A production network approach. *Journal of Political Economy*, 130(7):1765–1804.

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 25(2):242–262.

Bigio, S. and La'o, J. (2020). Distortions in production networks. *The Quarterly Journal of Economics*, 135(4):2187–2253.

Blickle, K., He, Z., Huang, J., and Parlatore, C. (2025). Information-based pricing in specialized lending. *Journal of Financial Economics*, 172:104135.

Blickle, K., Parlatore, C., and Saunders, A. (2026). Specialization in banking. *The Journal of Finance*, n/a(n/a).

Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics*, 101(1):60–75.

Campello, M., Graham, J. R., and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97(3):470–487.

Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics*, 136(2):1255–1321.

Carvalho, V. M. and Tahbaz-Salehi, A. (2019). Production networks: A primer. *Annual Review of Economics*, 11(1):635–663.

Casado, A. and Martinez Miera, D. (2025). Banks' specialization and private information. *Banco de Espana WPS*, 2539.

Cingano, F., Manaresi, F., and Sette, E. (2016). Does credit crunch investment down? new evidence on the real effects of the bank-lending channel. *The Review of Financial Studies*, 29(10):2737–2773.

Cornett, M. M., McNutt, J. J., Strahan, P. E., and Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101(2):297–312.

Costello, A. M. (2020). Credit market disruptions and liquidity spillover effects in the supply chain. *Journal of Political Economy*, 128(9):3434–3468.

Crawford, G. S., Pavanini, N., and Schivardi, F. (2018). Asymmetric information and imperfect competition in lending markets. *American Economic Review*, 108(7):1659–1701.

De Haas, R. and Van Horen, N. (2013). Running for the exit? International bank lending during a financial crisis. *The Review of Financial Studies*, 26(1):244–285.

De Jonghe, O., Dewachter, H., Mulier, K., Ongena, S., and Schepens, G. (2019). Some borrowers are more equal than others: Bank funding shocks and credit reallocation. *Review of Finance*, 24(1):1–43.

De Jonghe, O., Mulier, K., and Samarin, I. (2025). Bank specialization and zombie lending. *Management Science*, 71(2):1260–1286.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., and Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40:100813.

Dhyne, E., Kikkawa, A. K., Komatsu, T., Mogstad, M., and Tintelnot, F. (2025). Firm responses and wage effects of foreign demand shocks with fixed labor costs and monopsony. *American Economic Review*, 115(12):4328–68. doi:10.1257/aer.20220948.

Dhyne, E., Kikkawa, A. K., Mogstad, M., and Tintelnot, F. (2021). Trade and domestic production networks. *The Review of Economic Studies*, 88(2):643–668.

Di Giovanni, J. and Hale, G. (2022). Stock market spillovers via the global production network: Transmission of us monetary policy. *The Journal of Finance*, 77(6):3373–3421.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

dos Santos, A. R. and Ferreira, M. A. (2026). Lending relationships within supply chains. *Working Paper, Banco de Portugal and Nova School of Business and Economics*.

Duprez, C., Dhyne, E., and Komatsu, T. (2023). The belgian business-to-business transactions dataset 2002-2021. *National Bank of Belgium WPS*, 444.

Duquerroy, A., Mazet-Sonilhac, C., Mésonnier, J.-S., and Paravisini, D. (2022). Bank local specialization. *Banque de France WPS*, 865.

Egan, M., Hortaçsu, A., and Matvos, G. (2017). Deposit competition and financial fragility: Evidence from the US banking sector. *American Economic Review*, 107(1):169–216.

Egan, M., Lewellen, S., and Sunderam, A. (2022). The cross-section of bank value. *The Review of Financial Studies*, 35(5):2101–2143.

Federico, S., Hassan, F., and Rappoport, V. (2025). Trade shocks and credit reallocation. *American Economic Review*, 115(4):1142–1169.

Frattaroli, M. and Herpfer, C. (2023). Information intermediaries: How commercial bankers facilitate strategic alliances. *Journal of Financial and Quantitative Analysis*, 58(2):543–573.

Garcia-Appendini, E. and Montoriol-Garriga, J. (2013). Firms as liquidity providers: Evidence from the 2007–2008 financial crisis. *Journal of Financial Economics*, 109(1):272–291.

Giacomini, E., Kumar, N., and Naranjo, A. (2024). Inter-firm relationships and the special role of common banks. *Journal of Financial Intermediation*, 58:101084.

Giannetti, M. and Saidi, F. (2019). Shock propagation and banking structure. *The Review of Financial Studies*, 32(7):2499–2540.

Giannetti, M., Serrano-Velarde, N., and Tarantino, E. (2021). Cheap trade credit and competition in downstream markets. *Journal of Political Economy*, 129(6):1744–1796.

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

Goolsbee, A. D. and Krueger, A. B. (2015). A retrospective look at rescuing and restructuring general motors and chrysler. *Journal of Economic Perspectives*, 29(2):3–24.

Hasan, I., Minnick, K., and Raman, K. (2020). Credit allocation when borrowers are economically linked: An empirical analysis of bank loans to corporate customers. *Journal of Corporate Finance*, 62:101605.

Hastings, J., Hortaçsu, A., and Syverson, C. (2017). Sales force and competition in financial product markets: the case of mexico's social security privatization. *Econometrica*, 85(6):1723–1761.

Honka, E., Hortaçsu, A., and Vitorino, M. A. (2017). Advertising, consumer awareness, and choice: Evidence from the US banking industry. *The RAND Journal of Economics*, 48(3):611–646.

Huber, K. (2018). Disentangling the effects of a banking crisis: Evidence from german firms and counties. *American Economic Review*, 108(3):868–898.

Huo, Z., Levchenko, A., and Pandalai-Nayar, N. (2025). International comovement in the global production network. *Review of Economic Studies*, 92(1):365–403.

Huremovic, K., Jiménez, G., Moral-Benito, E., Peydró, J.-L., and Vega-Redondo, F. (2026). Production and financial networks in interplay. *American Economic Review*, 116(5):1611–47.

Ioannidou, V., Pavanini, N., and Peng, Y. (2022). Collateral and asymmetric information in lending markets. *Journal of Financial Economics*, 144(1):93–121.

Ivashina, V. and Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3):319–338.

Jacobs, A. and Jacobs, A. (2019). General Motors in Belgium. *The Automotive Industry and European Integration: The Divergent Paths of Belgium and Spain*, pages 89–119.

Kahle, K. M. and Stulz, R. M. (2013). Access to capital, investment, and the financial crisis. *Journal of Financial Economics*, 110(2):280–299.

Koijen, R. S. and Yogo, M. (2016). Shadow insurance. *Econometrica*, 84(3):1265–1287.

Koijen, R. S. and Yogo, M. (2019). A demand system approach to asset pricing. *Journal of Political Economy*, 127(4):1475–1515.

Mariathasan, M., Mulier, K., and Okatan, N. G. (2024). How credit availability and production technologies shape hiring: Evidence from a plant closure. *Unpublished manuscript*.

Martins, T. C., Schiozer, R., and de Menezes Linardi, F. (2023). The information content from lending relationships across the supply chain. *Journal of Financial Intermediation*, 56:101057.

Murfin, J. and Njoroge, K. (2015). The implicit costs of trade credit borrowing by large firms. *The Review of Financial Studies*, 28(1):112–145.

Paravisini, D., Rappoport, V., and Schnabl, P. (2023). Specialization in bank lending: Evidence from exporting firms. *The Journal of Finance*, 78(4):2049–2085.

Paravisini, D., Rappoport, V., Schnabl, P., and Wolfenzon, D. (2015). Dissecting the effect of credit supply on trade: Evidence from matched credit-export data. *The Review of Economic Studies*, 82(1):333–359.

Petrin, A. and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research*, 47.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance*, 47(4):1367–1400.

Saidi, F. and Streitz, D. (2021). Bank concentration and product market competition. *The Review of Financial Studies*, 34(10):4999–5035.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance*, 45(4):1069–1087.

Xiao, K. (2020). Monetary transmission through shadow banks. *The Review of Financial Studies*, 33(6):2379–2420.

Online Appendix:

Bank Specialization within Production Networks

Olivier De Jonghe Yushi Peng Tong Zhao

A Data Details **A1**

A.1 More Details on the Data and Sample A1

A.2 Factoring and Trade Receivables A2

B Motivating Facts **A6**

B.1 Additional Tables A6

B.2 Additional Figures A8

C Cost of Common Lending **A10**

C.1 More Details on the GM shock A10

C.2 Shock Propagation and Firm Sales A12

C.3 Concerns of Global Financial Crisis A20

C.4 Concerns of Trade Credit A25

C.5 Additional Tables A28

C.6 Additional Figures A32

D Counterfactual: Derivation and Implementation Details **A34**

D.1 Production-network parameters A34

D.2 Derivation of the propagation equation A34

D.3 Model performance under the shock A35

D.4 Partial-equilibrium counterfactual A36

D.5 Firm-bank incidence of the common lending channel A38

E Proofs **A40**

E.1 Propagation of a Production Shock A40

E.2 Credit Supply A42

A Data Details

A.1 More Details on the Data and Sample

Table A1: Summary Statistics

	Mean	p25	p50	p75	SD	N
Panel A. B2B						
Sales	59.64	1.88	4.00	12.62	4369.75	152554857
log(Sales)	8.67	7.54	8.29	9.44	1.48	152554857
N. buyers	2027.50	42.00	155.00	587.00	8301.35	152554857
N. sellers	124.09	17.00	42.00	111.00	287.52	152554857
Panel B. CCCR						
Committed amounts	738.13	57.00	143.23	365.29	11233.29	4183547
Used amounts	486.75	39.77	106.13	280.00	9208.22	3894651
N. Firm-bank relationship	1.42	1.00	1.00	2.00	0.73	4183547
$\mathbb{1}$(Have a main bank)	0.83	1.00	1.00	1.00	0.38	4176446
Panel C. BECRIS						
Credit amounts	396.15	22.68	94.69	300.36	2027.22	1170388
Interest rates	2.44	1.43	1.98	3.08	1.50	1170388
PD	0.05	0.00	0.01	0.02	0.17	1071100
Panel D. Firm balance sheet						
log(Total assets)	12.47	11.37	12.47	13.55	1.82	8422679
Leverage	1.21	0.32	0.62	0.88	4.96	8422679
Profitability	-0.02	-0.02	0.03	0.11	0.59	8422680
Altman Z-score	2.43	0.20	1.03	2.43	24.65	7912116
log(Receivable)	10.11	8.85	10.12	11.44	2.18	6389383
log(Payable)	9.37	7.77	9.31	10.92	2.35	7705412

Notes: This table shows the summary statistics of datasets. Panel A reports the summary statistics of B2B data for years 2002-2023. Sales is in thousand euro. Panel B shows the summary statistics of CCCR for years 2002-2020. We impose the threshold €25,000 for years 2012-2020. Panel C reports the summary statistics of BECRIS for years 2018-2023. We limit to banks with market share higher than 0.3%. Credit amounts are in thousand euro. Panel D shows the summary statistics of balance sheet characteristics for years 2002-2023. Variable definitions are in Table A2.

Table A2: Variable Definitions

Variable	Definition
Panel A. Transaction level variables	
Sales	The bilateral sales between a buyer and a seller in a year
log(Sales)	The logarithm of bilateral sales between a buyer and a seller in a year
Panel B. Firm-bank level credit variables	

$\mathbb{1}$(New use)	A dummy equal to one if the change in used amounts between a firm and a bank from year $t-1$ to t is strictly positive, and zero otherwise.
Δlog(Use)	The change in the logarithm of used amounts between a firm and a bank from year $t-1$ to t
$\mathbb{1}$(New bank)	A dummy equal to one if there is a new firm-bank relationship in year t, and zero otherwise.
Panel C. Firm level variables	
log(Total assets)	The logarithm of firm total assets
Leverage	Total liabilities scaled by total assets
Profitability	Profit after tax scaled by total assets
Altman Z-score	$\text{Altman Z-score} = 0.717\frac{\text{working capital}}{\text{total assets}} + 0.847\frac{\text{retained earnings}}{\text{total assets}} + 3.107\frac{\text{earnings before interest and tax}}{\text{total assets}} + 0.42\frac{\text{book value of equity}}{\text{total debt}} + 0.998\frac{\text{operating revenue}}{\text{total assets}}$
log(Receivable)	The logarithm of firm total receivables
log(Payable)	The logarithm of firm total payables
Down Level 1	A dummy equal to one if a firm is a Level 1 buyer of GM, and zero otherwise
Down Level 2	A dummy equal to one if a firm is a Level 2 buyer of GM, and zero otherwise
Down Level 3	A dummy equal to one if a firm is a Level 3 buyer of GM, and zero otherwise
Up Level 1	A dummy equal to one if a firm is a Level 1 seller of GM, and zero otherwise
Up Level 2	A dummy equal to one if a firm is a Level 2 seller of GM, and zero otherwise
Up Level 3	A dummy equal to one if a firm is a Level 3 seller of GM, and zero otherwise

A.2 Factoring and Trade Receivables

In a factoring arrangement a firm transfers receivables arising from sales of goods or services to a financial institution in exchange for pre-financing. Factoring is therefore a credit relationship whose collateral is a trading relationship, so it is the one instrument that spans both networks this paper studies. The credit registers record it under a separate instrument type, trade receivables, whenever the financing institution is itself a reporting agent. We exclude it from the estimation sample, mainly because a trade-receivable exposure does not reveal which of the firm's buyers stand behind it. This appendix sets out what each vintage of the register records, how large the product is in Belgium and relative to the euro area, and the full basis for excluding

it.

What the registers record. The reporting population changed between the two register vintages. The Act of 4 March 2012, which governed the CCCR, required five categories of institution to report: credit institutions, leasing companies, factoring companies, surety insurers, and credit insurers. Specialized factoring companies were therefore visible in the CCCR. The Act of 28 November 2021, which governs the current Corporate Credit Register, narrows the reporting population to resident credit institutions and resident leasing companies, and factoring companies no longer report.

The transition also changed the instrument taxonomy. Reporting credit institutions now book factoring exposures explicitly as trade receivables, whereas the CCCR had no separate instrument type for them. Because BECRIS is the Belgian input to AnaCredit, the euro-area data inherit this perimeter, which lets us benchmark Belgium against other euro-area countries.

The size of the product in Belgium. Table A3 reports the composition of Belgian corporate credit across the seven instrument types that make up credit to firms. Trade receivables are 1.11% of outstanding credit and 0.05% of instruments, and only 0.04% of borrowers in BECRIS are counterparty to one, or about one Belgian borrower in 2,500. The product is therefore a small number of large positions, unlike overdrafts or credit card debt, which are held widely in small amounts. Participation on the lender side is equally narrow: the 5.56% of lenders that lend against trade receivables is the lowest share of any instrument type.

Table A3: Composition of Belgian corporate credit by instrument type

Type	Description	In sample	Outstanding	Borrowers	Lenders	Instruments
1002	Credit lines other than revolving	Yes	51.46	29.07	28.40	25.12
1004	Loans, residual category	Yes	28.68	33.43	33.95	23.35
1001	Revolving credit	Yes	10.52	14.96	22.84	8.13
20	Overdrafts	No	6.20	40.47	40.12	18.23
80	Financial leases	Yes	1.99	12.97	53.70	11.35
71	Trade receivables	No	1.11	0.04	5.56	0.05
51	Credit card debt	No	0.03	32.87	6.79	13.77

Notes: The table reports the composition of Belgian corporate credit in December 2023, across all reporting agents in BECRIS. Each figure is a percentage of the total for the seven instrument types shown. Outstanding is the share of the outstanding nominal amount; Borrowers, Lenders and Instruments are shares of the distinct counts of debtors, reporting agents and instruments. The Outstanding and Instruments columns sum to 100. The Borrowers and Lenders columns do not, because a firm holding both an overdraft and a loan enters the denominator once but appears in two rows. "In sample" marks the instrument types retained for the structural estimation.

Belgium in euro-area perspective. AnaCredit applies one instrument taxonomy across the euro area, so trade receivables carry the same definition in every country and the comparison does not depend on national reporting conventions. Figure A1 shows the trade-receivable share of each of the four margins for the twenty euro-area countries.

Belgium ranks in the middle of the euro area on the value of factoring and at the bottom on its breadth. Its 1.50% share of outstanding credit ranks eleventh of twenty, close to Croatia, Cyprus, and France; most countries fall below 2.50 percent, with Spain, Ireland, Portugal, and Italy the exceptions. Lender participation is likewise mid-ranked. On the two breadth margins Belgium

is near-last: nineteenth of twenty on the share of borrowing firms holding a trade receivable, at 0.11 percent, and twentieth on the share of instruments, at 0.08 percent.

Dividing the share of outstanding credit by the share of borrowers summarizes the difference. Belgium's ratio is 13.6, against 2.3 for Luxembourg, 2.0 for Ireland, and 0.2 for Italy, which makes Belgian factoring the most concentrated in the euro area by close to a factor of six over the next country. In Italy, where 22.82% of borrowing firms hold a trade receivable, the product is a small line for each of them; in Belgium a small number of firms hold large ones. This is the same pattern Table A3 shows in the Belgian register.

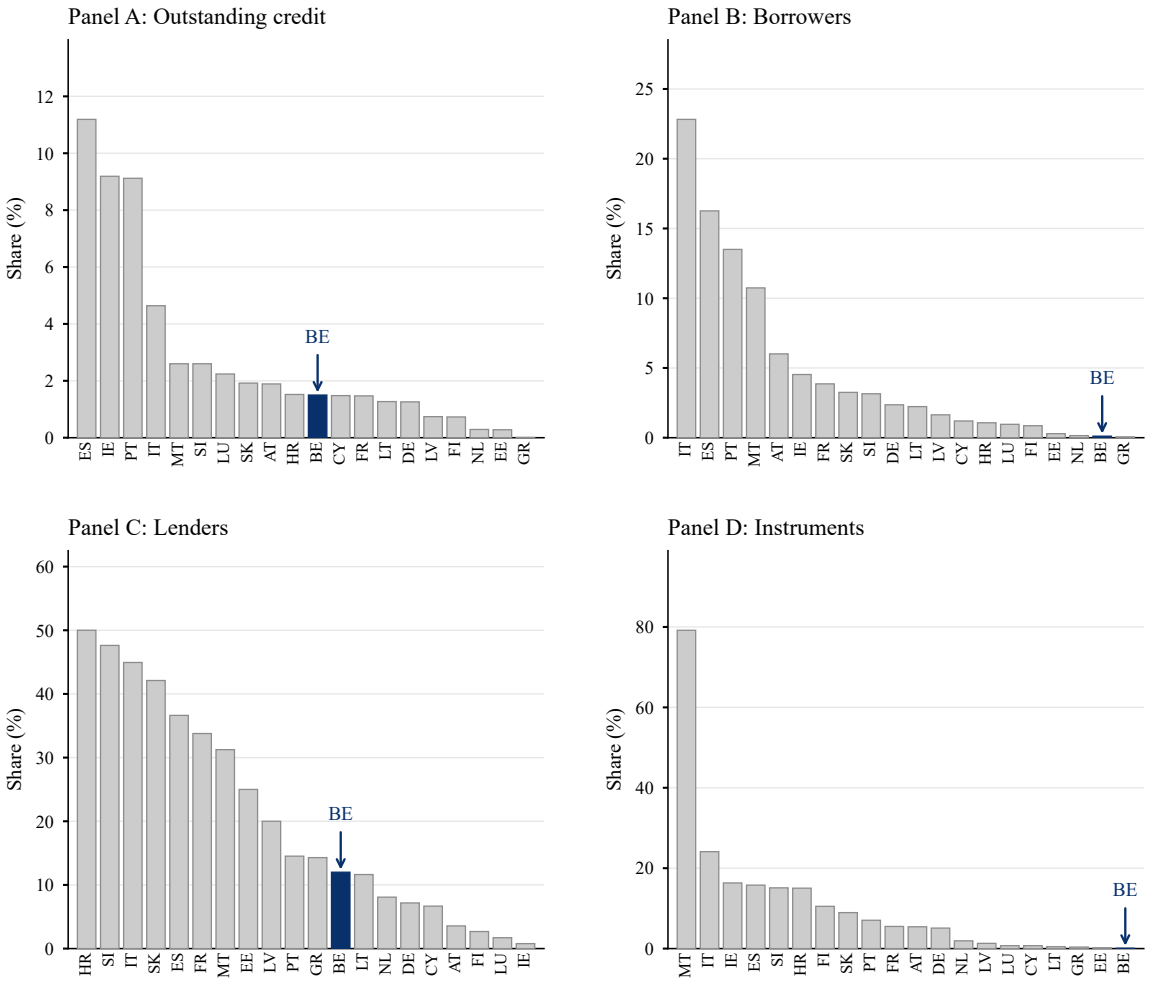
The numbers in Table A3 and Figure A1 differ because of filters applied to BECRIS before the data are passed to AnaCredit. The AnaCredit threshold of €25,000 at the borrower-lender level removes small exposures from the denominator while leaving large trade receivables in place, and AnaCredit receives only the credit-institution leg, so exposures booked by leasing companies drop out. Both the outstanding-credit share and the lender share are therefore lower in Table A3 than in Figure A1.

Why the estimation sample excludes factoring. We exclude trade receivables for three reasons. The first concerns the link this paper needs. A trade-receivable exposure cannot be mapped onto the production network. A creditor reporting such a credit does not reveal what fraction of the financed receivables is owed by buyers that are themselves in our sample. A firm may factor its receivables portfolio in whole or in part, so we cannot observe which trading relationships, or whose repayment behavior, the creditor actually sees. The model requires exactly that mapping.

What the register does show is only part of the product. Specialized factoring companies do not report to BECRIS. From the CCCR we know that the unobserved part consists of exposures booked by independent factoring companies, which offer no other products, and by factoring companies affiliated with banking groups. Counting the trade receivables that banks report while missing those routed through (un)affiliated factoring companies would introduce measurement error.

The exclusion is also immaterial for the sample. The estimation sample retains instrument types 80, 1001, 1002, and 1004, which together are 92.65% of outstanding credit and 67.95% of instruments. Overdrafts and credit card debt, the other two excluded types, are numerous but small in amount, and are generally detached from operational and investment purposes.

Figure A1: Trade receivables as a share of corporate credit, euro area, December 2023



Notes: Each panel plots the share of one margin accounted for by trade receivables (instrument type 71) within the seven instrument types that constitute credit to firms, for each of the twenty euro-area countries in December 2023. Panel A uses outstanding nominal amounts; Panels B, C and D use distinct counts of borrowers, lenders and instruments. Bars are sorted independently in each panel, so the ordering of countries differs across panels; Belgium is shown in blue and marked with an arrow. Shares are computed by creditor country.

B Motivating Facts

B.1 Additional Tables

Table B1: First-Time Borrower Bank Choice: Downstream and Upstream Firms

	$\mathbb{1}$(Common lender)		
	Downstream	Upstream	Both
	(1)	(2)	(3)
Panel A. Partner			
Partner importance to supply chain	0.100***	0.109***	0.181***
	(0.004)	(0.003)	(0.003)
N	3737626	5755379	9493005
R^2	0.144	0.126	0.114
Panel B. Bank			
Partner's bank importance to supply chain	0.143***	0.124***	0.254***
	(0.005)	(0.005)	(0.005)
N	639651	1080801	1232180
R^2	0.234	0.127	0.126
Firm FE	✓	✓	✓
Partner Bank FE	✓	✓	✓
Year FE	✓	✓	✓

Notes: 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 2002-2020. The dependent variable is an indicator equal to one if the firm chooses a bank that is also the bank of its trading partner. The independent variable in Panel A is the share of the firm's total sales or purchases that goes to or comes from the respective trading partner, capturing the importance of that trading partner in the firm's production network. The independent variable in Panel B is the trading-volume-weighted share of a bank's lending to a focal firm's trading partners relative to the total lending by all banks to the firm's supply chain partners. Robust standard errors clustered at the firm level are in parentheses. ***p<0.001, **p<0.01, *p<0.05.

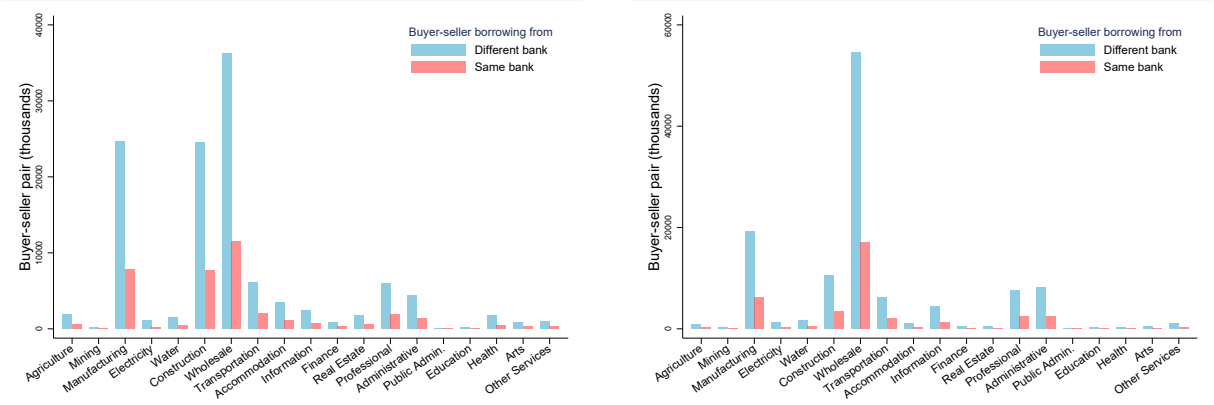
Table B2: Importance of Common Lenders and Credit Terms: Robustness

	Rate	ln(Amount)	PD
	(1)	(2)	(3)
Panel A. No specialization controls			
Common lender	-0.112***	0.130***	0.207***
	(0.012)	(0.016)	(0.042)
N	495788	512098	480911
R^2	0.229	0.428	0.018
Panel B. Common lender: weight partners by borrowing rather than by trade			
Common lender	-0.038***	0.092***	0.176***
	(0.010)	(0.012)	(0.037)
Observations	492781	508979	478088
R^2	0.230	0.428	0.018
Panel C. All right-hand-side variables lagged one year			
Common lender, $t-1$	-0.095***	0.126***	0.249***
	(0.013)	(0.017)	(0.046)
N	388517	395486	373043
R^2	0.178	0.430	0.018
Panel D. Upstream - common lending with suppliers			
Common lender	-0.102***	0.055***	0.151***
	(0.012)	(0.016)	(0.041)
N	495595	511891	480726
R^2	0.229	0.428	0.018
Panel D. Downstream - common lending with customers			
Common lender	-0.068***	0.150***	0.156***
	(0.009)	(0.012)	(0.034)
N	434119	448034	422059
R^2	0.227	0.420	0.016
Industry and geography specialization controls		Panel B, C, D	
Bank-Year FE	✓	✓	✓
Industry-Size-Year FE	✓	✓	✓
Province-Year FE	✓	✓	✓

Notes: This table reports four robustness checks on the baseline estimates in Table 2. Panel A drops the two bank specialization controls. Panel B replaces the trade-weighted common lender measure with its credit-weighted counterpart, in which trading partners are weighted by their own borrowing rather than by the volume of trade. Panel C measures every right-hand-side variable in the year before the credit outcome. Panels D splits the measure by position in the supply chain: upper Panel D counts only partners that sell to the firm, and lower Panel D only partners that buy from it. The coefficients on the specialization controls and the constant are estimated but not reported. Standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.2 Additional Figures

Figure B1: Common Lenders across Industry

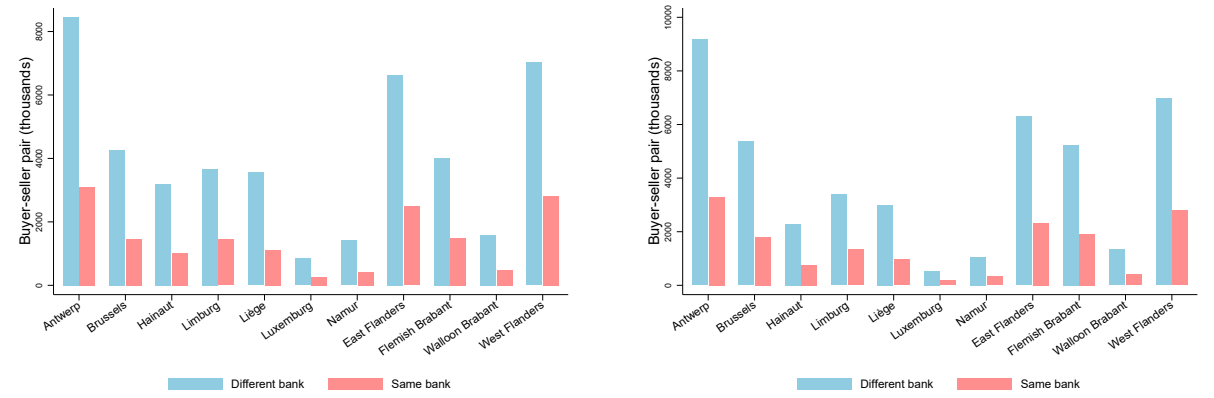


(a) Downstream Firms' Industry

(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. Figure B1a 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). Figure B1b presents the corresponding distribution for seller industries. Only main banks are included for the computation.

Figure B2: Common Lenders across Province

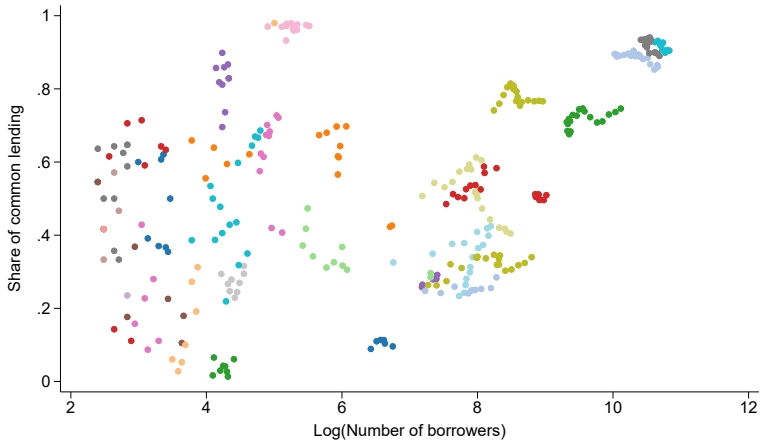


(a) Downstream Firms' Region

(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. Figure B2a displays the distribution of buyer provinces, distinguishing whether the buyer-seller pair borrows from the same bank (red bars) or from different banks (blue bars). Figure B2b presents the corresponding distribution for seller provinces. Only main banks are included for the computation.

Figure B3: 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. Only main banks are included for the computation.

C Cost of Common Lending

C.1 More Details on the GM shock

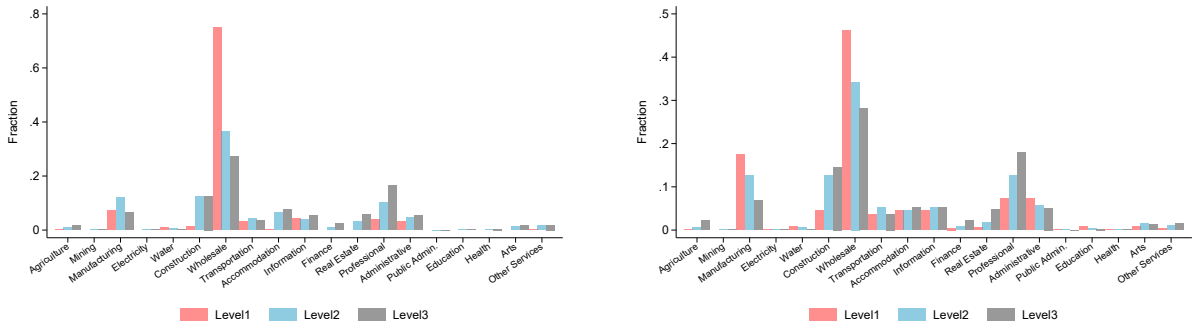
GM Antwerp was a prominent car manufacturing plant in Belgium with more than 5,000 employees, including approximately 4,700 production workers by 2005. It produced around 400,000 vehicles annually before the closure, with approximately 90% of these being exported across Europe (Mariathasan et al., 2024). In the 2000s, rising energy costs began to strain the global automotive industry, since they reduced demand for vehicles. This led to a $40 billion loss of GM in 2007 (Goolsbee and Krueger, 2015). In response, GM implemented a restructuring plan across its European operations, which included freezes in wages and benefits. 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 2008 global financial crisis further weakened GM, leading to a loss of $70 billion 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.

Table C1: Same postcode

	GM's buyers		GM's sellers	
	Number of Firms	Percent	Number of Firms	Percent
Different postcode	1665	98.99	7319	98.68
Same postcode	17	1.01	98	1.32
Total	1682	100.00	7417	100.00

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

Figure C1: Industry Distribution



(a) Downstream (b) Upstream

Notes: This figure plots the industry distribution of GM's supply chain network. Figure C1a plots the industry distribution of the downstream customers of GM. Figure C1b plots the industry distribution of the upstream suppliers of GM. Industry is denoted by one-digit NACE code.

Table C2: Summary Statistics of Sample for GM Analysis

	Mean	p25	p50	p75	SD	N
Panel A. Transaction level variables						
Sales	16121.26	602.00	1579.31	5705.33	68465.19	93174042
log(Sales)	7.71	6.40	7.36	8.65	1.66	93174042
Panel B. Firm-bank level credit variables						
$\mathbb{1}$(New use)	0.29	0.00	0.00	1.00	0.45	1407004
Δlog(Use)	-0.04	-0.23	-0.08	0.05	0.65	1300436
$\mathbb{1}$(New bank)	0.04	0.00	0.00	0.00	0.19	1816349
Panel C. Firm level variables						
log(Total assets)	12.36	11.24	12.34	13.43	1.80	2790884
Leverage	1.13	0.39	0.69	0.91	3.77	2790884
Profitability	-0.04	-0.03	0.02	0.08	0.54	2790884
Altman Z-score	1.33	0.13	0.86	1.95	16.68	2589143
log(Receivable)	10.24	8.93	10.24	11.60	2.20	2270328
log(Payable)	9.72	8.15	9.73	11.26	2.33	2607196
Down Level 1	0.00	0.00	0.00	0.00	0.03	2790887
Down Level 2	0.29	0.00	0.00	1.00	0.45	2790887
Down Level 3	0.60	0.00	1.00	1.00	0.49	2790887
Up Level 1	0.01	0.00	0.00	0.00	0.08	2790887
Up Level 2	0.31	0.00	0.00	1.00	0.46	2790887
Up Level 3	0.42	0.00	0.00	1.00	0.49	2790887

Notes: This table shows the summary statistics of datasets used for GM analysis. The sample period is from 2002 to 2011. Panel A reports the summary statistics of B2B data. Sales is in euro. Panel B shows the summary statistics of firm-bank level credit variables for firms appearing in the B2B dataset. Panel C shows the summary statistics of balance sheet characteristics of firms appearing in the B2B dataset. All continuous variables are winsorized at 0.5% and 99.5%. Variable definitions are in Table A2.

C.2 Shock Propagation and Firm Sales

For the transaction level analysis, we exploit the exact sales amounts between a seller-buyer pair at the end of the year. We follow 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 treated as unconnected firms to GM. We estimate the following specification:

$$\text{Sales}_{i,j,t} = \beta_k \text{Level}^k_{i,j} \times \text{Post}_t + \delta_1 \mathbf{X}_{i,t} + \delta_2 \mathbf{X}_{j,t} + \text{FE} + \epsilon_{i,j,t}, \tag{28}$$

where i, j, t denote seller, buyer, and year, respectively. The outcome variable $\text{Sales}_{i,j,t}$ is the logarithm of sales between a seller i and a buyer j in year t. $\text{Level}^k_{i,j}$ is an indicator equal to one for a buyer-seller pair in which the buyer (seller) is at distance k from GM in the supply chain during 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.[1] 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.[2]

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 one for the years 2007-2011, and zero for the years 2002-2006. To control for firm fundamentals, we add firm characteristics $\mathbf{X}_{i,t}$ and $\mathbf{X}_{j,t}$, 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(28). 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 in each direction separately. Accordingly, β_k captures the extent to which a seller (buyer) reduces its sales to

[1] 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.

[2] 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. We validate the distribution of number of non-GM suppliers (customers) of Level 1 firms who are direct buyers (sellers) of GM. The results show 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 C1 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.

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.

The firm-level regression takes the following form:

$$\text{Sales}_{i(j),t} = \beta_k \text{Level}^k_{i(j)} \times \text{Post}_t + \delta \mathbf{X}_{i(j),2006} \times \text{Year}_t + \text{FE} + \epsilon_{i(j),t}. \tag{29}$$

The outcome variable $\text{Sales}_{i(j),t}$ is transaction-level sales aggregated to the firm $(i(j))$ level in year t. $\text{Level}^k_{i(j)}$ is an indicator to indicate if a firm is at distance k of GM's supply chain.[3] Depending on the specifications, we also interact ex-ante firm characteristics with Year_t dummies. 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.

Additional Robustness Checks. Given the granularity of the data, we are able to include rich fixed effects, which we present in Tables C4 and C5. 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 per firm per year to examine whether firms affected by the GM closure adjust their production networks. Table C6 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 at least one full-time equivalent following Bernard et al. (2022). The results reported in Table C7 indicate that our findings remain largely unchanged. For our firm-level analysis using sales aggregated from production networks, one might be concerned that some transactions are omitted from the network since they fall below reporting requirements. Alternatively, firms might support their production entirely through importing or exporting, which will not be reflected in the domestic networks. We address these concerns using sales from balance sheet data and we again find a negative impact on firm sales as shown in Table C8.

Identification Assumption. To validate the parallel trend assumption, we conduct a dynamic difference-in-differences estimation. 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 1-digit NACE level. We apply the analogous specification for upstream propagation. Estimation results are illustrated in Figure C2. 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

[3] 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) is a *direct* seller (buyer) of GM.

Table C3: Shock Propagation and Firm Sales: Transaction-Level and Firm-Level Evidence

	log(Sales)			
	Transaction Level		Firm Level	
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.472***	-0.485***	-0.243***	-0.194***
	(0.012)	(0.012)	(0.060)	(0.061)
Level 2 × Post	-0.146***	-0.049*	-0.164***	-0.157***
	(0.032)	(0.028)	(0.032)	(0.033)
Level 3 × Post	-0.209***	-0.021	-0.124***	-0.130***
	(0.013)	(0.013)	(0.032)	(0.032)
N	15562870	18365455	1748200	1682912
R^2	0.81	0.43	0.85	0.86
Panel B. Upstream				
Level 1 × Post	-0.484***	-0.503***	-0.255***	-0.243***
	(0.011)	(0.016)	(0.022)	(0.022)
Level 2 × Post	-0.043***	0.183***	-0.215***	-0.214***
	(0.015)	(0.013)	(0.012)	(0.012)
Level 3 × Post	-0.038***	0.179***	-0.140***	-0.138***
	(0.010)	(0.011)	(0.012)	(0.012)
N	5346869	6498532	2053957	2049081
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(28). Columns (1) and (2) are at the transaction level, while Columns (3) and (4) are at the firm level. The dependent variable in Columns (1) and (2) is the logarithm of sales between a seller i and a buyer j in year t, while in Columns (3) and (4) is the logarithm of sales of transaction level aggregated at firm $(i(j))$ level in year t. In Columns (1) and (2), $\text{Level}_{i,j}$ is an indicator variable that indicates whether a buyer-seller pair, in which the buyer (seller) is at distance k of the GM supply chain during the years 2002-2006. k takes the values 1, 2, and 3. In Columns (3) and (4), $\text{Level}_{i(j)}$ is an indicator variable that indicates whether a firm is at distance k of the GM supply chain during the years 2002-2006. Post_t is an indicator variable taking a value of one for the years 2007-2011, and zero for the years 2002-2006. Columns (3) and (4) include the interactions between ten quantiles of firm controls at 2006 and year dummies. Firm controls include: 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 are in parentheses, clustered at the seller and buyer levels in Columns (1) and (2), at firm level in Column (3) and (4). *** p<0.01, ** p<0.05, * p<0.1.

firms do experience a decline compared to control firms in the post-period.

Table C4: Shock propagation and sales: Transaction level

	log(Sales)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.472***	-0.485***	-0.243***	-0.194***
	(0.012)	(0.012)	(0.060)	(0.061)
Level 2 × Post	-0.146***	-0.049*	-0.164***	-0.157***
	(0.032)	(0.028)	(0.032)	(0.033)
Level 3 × Post	-0.209***	-0.021	-0.124***	-0.130***
	(0.013)	(0.013)	(0.032)	(0.032)
N	15562870	18365455	1748200	1682912
R^2	0.81	0.43	0.85	0.86
Panel B. Upstream				
Level 1 × Post	-0.484***	-0.503***	-0.255***	-0.243***
	(0.011)	(0.016)	(0.022)	(0.022)
Level 2 × Post	-0.043***	0.183***	-0.215***	-0.214***
	(0.015)	(0.013)	(0.012)	(0.012)
Level 3 × Post	-0.038***	0.179***	-0.140***	-0.138***
	(0.010)	(0.011)	(0.012)	(0.012)
N	5346869	6498532	2053957	2049081
R^2	0.84	0.56	0.87	0.87
Seller controls		✓		✓
Buyer controls		✓		✓
Seller-Buyer FE	✓	✓		
Seller FE			✓	✓
Buyer FE			✓	✓
Year FE	✓	✓	✓	✓

Notes: This table shows the estimation results associated with Table C3.

Table C5: Shock propagation and sales: Firm level

	log(Sales)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.243***	-0.194***	-0.240***	-0.194***
	(0.060)	(0.061)	(0.058)	(0.054)
Level 2 × Post	-0.164***	-0.157***	-0.148***	-0.157***
	(0.032)	(0.033)	(0.036)	(0.036)
Level 3 × Post	-0.124***	-0.130***	-0.122***	-0.130***
	(0.032)	(0.032)	(0.029)	(0.031)
N	1748200	1682912	1682919	1682912
R^2	0.85	0.86	0.86	0.86
Panel B. Upstream				
Level 1 × Post	-0.255***	-0.243***	-0.256***	-0.243***
	(0.022)	(0.022)	(0.047)	(0.042)
Level 2 × Post	-0.215***	-0.214***	-0.216***	-0.214***
	(0.012)	(0.012)	(0.034)	(0.026)
Level 3 × Post	-0.140***	-0.138***	-0.142***	-0.138***
	(0.012)	(0.012)	(0.021)	(0.017)
N	2053957	2049081	2049088	2049081
R^2	0.87	0.87	0.87	0.87
Firm control × Year	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓		✓	
Sector-Year FE		✓		✓
Cluster	Firm	Firm	Sector	Sector

Notes: This table shows the estimation results associated with Table C3.

Table C6: Shock propagation and sales: Firm level number of buyers

	log(Number of buyers)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.099**	-0.083*	-0.095***	-0.083***
	(0.044)	(0.045)	(0.031)	(0.030)
Level 2 × Post	-0.132***	-0.116***	-0.127***	-0.116***
	(0.017)	(0.018)	(0.019)	(0.021)
Level 3 × Post	-0.087***	-0.080***	-0.089***	-0.080***
	(0.017)	(0.017)	(0.019)	(0.021)
N	1748200	1682912	1682919	1682912
R^2	0.89	0.90	0.90	0.90
Panel B. Upstream				
Level 1 × Post	-0.349***	-0.338***	-0.350***	-0.338***
	(0.020)	(0.020)	(0.028)	(0.029)
Level 2 × Post	-0.296***	-0.293***	-0.297***	-0.293***
	(0.006)	(0.006)	(0.021)	(0.019)
Level 3 × Post	-0.181***	-0.178***	-0.182***	-0.178***
	(0.006)	(0.006)	(0.018)	(0.017)
N	2053957	2049081	2049088	2049081
R^2	0.91	0.91	0.91	0.91
Firm control × Year	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓		✓	
Sector-Year FE		✓		✓
Cluster	Firm	Firm	Sector	Sector

Notes: This table shows the estimation results associated with Table C3.

Table C7: Shock propagation and sales: Firm level with restricted sample

	log(Sales)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.356***	-0.105	-0.163	-0.105
	(0.119)	(0.136)	(0.166)	(0.162)
Level 2 × Post	-0.321***	-0.086	-0.113	-0.086
	(0.111)	(0.130)	(0.153)	(0.153)
Level 3 × Post	-0.264**	-0.060	-0.081	-0.060
	(0.111)	(0.130)	(0.151)	(0.150)
N	825502	778531	778541	778531
R^2	0.90	0.91	0.91	0.91
Panel B. Upstream				
Level 1 × Post	-0.267***	-0.241***	-0.268***	-0.241***
	(0.037)	(0.037)	(0.045)	(0.049)
Level 2 × Post	-0.226***	-0.206***	-0.227***	-0.206***
	(0.033)	(0.033)	(0.037)	(0.039)
Level 3 × Post	-0.152***	-0.140***	-0.153***	-0.140***
	(0.033)	(0.033)	(0.043)	(0.043)
N	881842	880912	880923	880912
R^2	0.92	0.92	0.92	0.92
Firm control × Year	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓			
Sector-Year FE		✓		
Province-Year FE			✓	
Sector-Province-Year FE				✓

Notes: This table shows the estimation results associated with Table C3. Sample is restricted to firms with at least one full-time-equivalent (FTE).

Table C8: Shock propagation and sales: Firm level balance sheet data

	log(Sales)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.098**	-0.079**	-0.161***	-0.068*
	(0.038)	(0.039)	(0.039)	(0.041)
Level 2 × Post	-0.069***	-0.050***	-0.086***	-0.006
	(0.005)	(0.008)	(0.006)	(0.009)
Level 3 × Post	-0.080***	-0.054***	-0.089***	-0.013
	(0.005)	(0.008)	(0.005)	(0.009)
N	2116371	2085599	1879064	1858206
R^2	0.79	0.79	0.75	0.75
Panel B. Upstream				
Level 1 × Post	-0.062***	-0.041**	-0.030*	-0.028*
	(0.018)	(0.019)	(0.015)	(0.016)
Level 2 × Post	-0.046***	-0.024***	0.006*	0.005
	(0.004)	(0.006)	(0.003)	(0.005)
Level 3 × Post	-0.061***	-0.036***	-0.003	-0.001
	(0.004)	(0.005)	(0.003)	(0.004)
Observations	2116371	2085599	2116371	2085599
R-squared	0.79	0.79	0.88	0.88
Time-varying Firm control	✓		✓	
Ex-ante Firm control × Year		✓		✓
Firm FE	✓	✓	✓	✓
Year FE	✓		✓	
Sector-Year FE		✓		✓

Notes: This table shows the estimation results associated with Table C3. The sample is based on firm balance sheets.

C.3 Concerns of Global Financial Crisis

We address the concern that our setting overlaps with the global financial crisis, which can raise several confounding factors.

First, our outcome variable regarding used amounts may capture both credit demand and supply. To overcome this, we replace used amounts with utilization ratio that better measures credit demand. The ratio is defined as used amounts scaled by commitment amounts. The advantage of this variable is that it isolates firms' credit usage behavior conditional on credit availability. Then we construct a dummy equal to one if the utilization ratio increases from year $t-1$ to t, and zero otherwise. A decrease of the ratio would suggest that the reduction of used amounts is larger than the reduction in commitment amounts. We re-estimate Eq(24) and report results in Table C9. In line with previous findings, after the GM shock, affected firms in both downstream and upstream sectors of GM are less likely to use credit relative to unaffected firms, holding other factors constant. These results suggest that our findings are more likely to be demand-driven.

Second, our baseline results might be driven by the possibility that some firms reduced production after the crisis, which in turn lowered their credit demand (Kahle and Stulz, 2013). To address this concern, we exclude the years 2008–2010 and keep only 2007 as the post period. This setting allows us to examine whether the effects of the GM shock are already present in 2007. If so, we can be more confident that the results are attributable to the GM shock rather than the financial crisis. In line with this expectation, Table C10 shows that firms indeed reduce utilized credit amounts, and this reduction is largely driven by the GM shock rather than the financial crisis.

Another concern is that our results may be driven by a contraction in credit supply during the crisis. A large body of literature shows that banks hit by the financial crisis curtailed lending (Ivashina and Scharfstein, 2010; Campello et al., 2010; Cornett et al., 2011; De Haas and Van Horen, 2013), which in turn affected firm investment, employment, exports, and other outcomes (Alfaro and Chen, 2012; Paravisini et al., 2015; Cingano et al., 2016; Huber, 2018; Bentolila et al., 2018). To address this concern, we use committed amounts as the outcome variable to assess whether there were changes in credit supply already in 2007. Table C11 suggests that this is not the case. We do not find evidence that banks reduced lending in 2007, mitigating the concern that our results are driven by a contraction in credit supply.

Third, we investigate the role of industry specialization in credit supply. De Jonghe et al. (2019) find that credit supply contraction is more pronounced for firms when banks are less specialized in their industries after the GFC. Their results imply that, if the credit supply channel holds, we should observe less negative effects on credit supply for affected firms in sectors where banks are more specialized. Table C12 reports the results. We find no significant evidence to support the credit allocation mechanism.

Table C9: Propagation financial sector: Firm-bank level utilization ratio

	𝟙(Utilization ratio increase)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.099***	-0.081***	-0.083***	-0.079***
	(0.025)	(0.025)	(0.026)	(0.026)
Level 2 × Post	-0.092***	-0.071***	-0.072***	-0.074***
	(0.005)	(0.006)	(0.006)	(0.006)
Level 3 × Post	-0.080***	-0.061***	-0.062***	-0.064***
	(0.005)	(0.006)	(0.006)	(0.006)
N	1126368	1125275	1124764	1108663
R^2	0.03	0.04	0.04	0.07
Panel B. Upstream				
Level 1 × Post	-0.032***	-0.023**	-0.023**	-0.022*
	(0.011)	(0.011)	(0.011)	(0.011)
Level 2 × Post	-0.038***	-0.029***	-0.029***	-0.030***
	(0.003)	(0.004)	(0.004)	(0.004)
Level 3 × Post	-0.030***	-0.023***	-0.023***	-0.024***
	(0.003)	(0.003)	(0.003)	(0.004)
N	1062073	1061340	1060849	1045074
R^2	0.03	0.04	0.04	0.07
Firm controls	✓	✓	✓	✓
Bank-Time FE	✓	✓		
Firm-Bank FE	✓	✓	✓	✓
Sector-Time FE		✓	✓	✓
Bank-Province-Time FE			✓	
Bank-Province-Sector-Time FE				✓

Notes: This table shows the estimation results associated with Table 6.

Table C10: Propagation financial sector: Firm level no crisis period

	𝟙(New use)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	0.024	-0.007	-0.010	-0.008
	(0.049)	(0.050)	(0.051)	(0.051)
Level 2 × Post	-0.015*	-0.025**	-0.024**	-0.024**
	(0.009)	(0.010)	(0.010)	(0.010)
Level 3 × Post	-0.021**	-0.025**	-0.026**	-0.026**
	(0.009)	(0.010)	(0.010)	(0.010)
N	483497	482608	482265	482262
R^2	0.33	0.33	0.34	0.34
Panel B. Upstream				
Level 1 × Post	0.038*	0.032	0.036	0.036
	(0.023)	(0.023)	(0.023)	(0.023)
Level 2 × Post	0.014**	0.008	0.010	0.010
	(0.006)	(0.007)	(0.007)	(0.007)
Level 3 × Post	0.006	0.005	0.006	0.005
	(0.006)	(0.006)	(0.006)	(0.006)
N	454489	453860	453515	453510
R^2	0.33	0.33	0.33	0.34
Firm Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓			
Bank FE				✓
Sector-Time FE		✓	✓	
Province-Sector-Time FE			✓	✓

Notes: This table shows the estimation results associated with Table 6.

Table C11: Propagation financial sector: Firm level credit supply

	$\mathbb{1}$(New CMT)			Δlog(CMT)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Downstream						
Level 1 × Post	0.200			-0.037		
	(0.170)			(0.140)		
Level 2 × Post		-0.031**			-0.012	
		(0.015)			(0.019)	
Level 3 × Post			-0.018			-0.009
			(0.013)			(0.015)
N	8755	208057	282095	8703	206919	280183
R^2	0.38	0.32	0.34	0.37	0.27	0.29
Panel B. Upstream						
Level 1 × Post	0.025			0.026		
	(0.033)			(0.035)		
Level 2 × Post		-0.000			0.007	
		(0.010)			(0.012)	
Level 3 × Post			-0.003			-0.003
			(0.009)			(0.011)
N	18405	225692	224732	18255	224439	223158
R^2	0.41	0.32	0.34	0.35	0.28	0.29
Firm controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Province-Sector-Time FE	✓	✓	✓	✓	✓	✓

Notes: This table shows the estimation results associated with Table 6.

Table C12: Propagation financial sector: Firm level bank specialization

	$\mathbb{1}$(New CMT)			Δlog(CMT)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Downstream						
Level 1 × Post	0.249			-0.028		
	(0.180)			(0.143)		
Level 1 × Post × High	-0.139			-0.134		
	(0.104)			(0.093)		
Level 2 × Post		-0.035**			-0.014	
		(0.017)			(0.021)	
Level 2 × Post × High		0.022			0.010	
		(0.026)			(0.028)	
Level 3 × Post			-0.021			-0.012
			(0.014)			(0.018)
Level 3 × Post × High			0.013			0.011
			(0.025)			(0.027)
N	8648	206636	279636	8599	205511	277747
R^2	0.38	0.32	0.34	0.37	0.27	0.29
Panel B. Upstream						
Level 1 × Post	0.025			0.031		
	(0.034)			(0.036)		
Level 1 × Post × High	-0.010			-0.063		
	(0.087)			(0.086)		
Level 2 × Post		-0.002			0.005	
		(0.010)			(0.013)	
Level 2 × Post × High		0.011			0.001	
		(0.026)			(0.026)	
Level 3 × Post			-0.003			-0.006
			(0.010)			(0.012)
Level 3 × Post × High			0.002			0.010
			(0.025)			(0.025)
N	18243	224251	222773	18091	223011	221212
R^2	0.41	0.32	0.34	0.35	0.28	0.29
Firm controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Province-Sector-Time FE	✓	✓	✓	✓	✓	✓

Notes: This table shows the estimation results associated with Table 6. High is a dummy variable that takes the value of one if a bank is in the top 25% of the distribution of sector specialization in 2006, and zero otherwise. Bank sector specialization is measured as the share of total committed amounts that a bank lends to a given sector in a year, scaled by the bank's total committed amounts in that year.

C.4 Concerns of Trade Credit

One concern in our current setting 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. While there is debate about the substitutability and complementarity between the two types of credit, several studies emphasize the importance of trade credit in facilitating firm activities (Garcia-Appendini and Montoriol-Garriga, 2013; Murfin and Njoroge, 2015; Barrot, 2016; Giannetti et al., 2021; Gofman and Wu, 2022).

To address this concern, we estimate firm-level regressions using accounts payable and accounts receivable as outcome variables. The results in Table C13 and C14 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.

Table C13: Propagation financial sector: Firm level receivable

	Δlog(Receivable)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	0.086*	0.056	0.065	-0.150***
	(0.045)	(0.047)	(0.048)	(0.046)
Level 2 × Post	0.008	0.008	0.010	-0.085***
	(0.026)	(0.029)	(0.029)	(0.026)
Level 3 × Post	0.010	0.016	0.018	-0.069***
	(0.026)	(0.029)	(0.029)	(0.025)
N	771236	771101	770441	879661
R^2	0.13	0.13	0.14	0.12
Panel B. Upstream				
Level 1 × Post	-0.025	-0.035*	-0.029	-0.012
	(0.020)	(0.021)	(0.021)	(0.020)
Level 2 × Post	-0.038**	-0.045***	-0.041***	-0.021*
	(0.015)	(0.015)	(0.015)	(0.012)
Level 3 × Post	-0.043***	-0.046***	-0.043***	-0.007
	(0.015)	(0.015)	(0.016)	(0.012)
N	751501	751411	750737	835898
R^2	0.13	0.13	0.14	0.13
Firm controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓			
Bank FE				✓
Sector-Time FE		✓		
Province-Sector-Time FE			✓	✓

Notes: This table shows the estimation results associated with Table 6.

Table C14: Propagation financial sector: Firm level payable

	Δlog(Payable)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.124***	-0.156***	-0.150***	-0.150***
	(0.043)	(0.045)	(0.045)	(0.046)
Level 2 × Post	-0.087***	-0.088***	-0.085***	-0.085***
	(0.022)	(0.025)	(0.026)	(0.026)
Level 3 × Post	-0.074***	-0.071***	-0.069***	-0.069***
	(0.022)	(0.025)	(0.025)	(0.025)
N	880586	880272	879667	879661
R^2	0.12	0.12	0.12	0.12
Panel B: Upstream				
Level 1 × Post	-0.011	-0.012	-0.013	-0.012
	(0.019)	(0.020)	(0.020)	(0.020)
Level 2 × Post	-0.024**	-0.021*	-0.021*	-0.021*
	(0.012)	(0.012)	(0.012)	(0.012)
Level 3 × Post	-0.011	-0.005	-0.007	-0.007
	(0.012)	(0.012)	(0.012)	(0.012)
N	836727	836554	835904	835898
R^2	0.12	0.12	0.13	0.13
Firm controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓			
Bank FE				✓
Sector-Time FE		✓		
Province-Sector-Time FE			✓	✓

Notes: This table shows the estimation results associated with Table 6.

C.5 Additional Tables

Table C15: Propagation financial sector: Firm-bank level credit

	$\mathbb{1}$(New use)				Δlog(Use)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Downstream								
Level 1 × Post	-0.113***	-0.110***	-0.112***	-0.112***	-0.101***	-0.112***	-0.113***	-0.110***
	(0.023)	(0.024)	(0.024)	(0.024)	(0.031)	(0.031)	(0.031)	(0.032)
Level 2 × Post	-0.132***	-0.120***	-0.121***	-0.124***	-0.101***	-0.106***	-0.106***	-0.107***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Level 3 × Post	-0.115***	-0.100***	-0.101***	-0.103***	-0.085***	-0.086***	-0.086***	-0.087***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
N	1132027	1130931	1130403	1114204	1059088	1058077	1057566	1041539
R^2	0.02	0.03	0.03	0.06	0.01	0.02	0.02	0.05
Panel B. Upstream								
Level 1 × Post	-0.042***	-0.037***	-0.037***	-0.039***	-0.036**	-0.039**	-0.037**	-0.041**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.018)	(0.018)	(0.018)	(0.018)
Level 2 × Post	-0.059***	-0.055***	-0.056***	-0.056***	-0.040***	-0.044***	-0.043***	-0.042***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Level 3 × Post	-0.047***	-0.041***	-0.042***	-0.042***	-0.029***	-0.029***	-0.029***	-0.029***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
N	1066783	1066048	1065556	1049723	997111	996436	995962	980257
R^2	0.02	0.03	0.03	0.06	0.01	0.02	0.02	0.05
Firm controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector-Time FE		✓	✓	✓		✓	✓	✓
Bank-Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank-Time FE	✓	✓			✓	✓		
Bank-Province-Time FE			✓				✓	
Bank-Province-Sector-Time FE				✓				✓

Notes: This table shows the estimation results associated with Table 6.

Table C16: Propagation financial sector: Firm-bank level relationship

	𝟙(New bank)			
	(1)	(2)	(3)	(4)
Panel A. Downstream				
Level 1 × Post	-0.002	-0.001	-0.001	0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Level 2 × Post	-0.005***	-0.006***	-0.006***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Level 3 × Post	0.003	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
N	1621598	1618134	1617373	1593378
R^2	0.07	0.07	0.09	0.12
Panel B. Upstream				
Level 1 × Post	-0.012***	-0.011***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Level 2 × Post	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Level 3 × Post	-0.004***	-0.004***	-0.004***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
N	1532499	1529926	1529161	1505686
R^2	0.07	0.07	0.09	0.12
Firm controls	✓	✓	✓	✓
Sector-Time FE		✓	✓	✓
Bank-Firm FE	✓	✓	✓	✓
Bank-Time FE	✓	✓		
Bank-Province-Time FE			✓	
Bank-Province-Sector-Time FE				✓

Notes: This table shows the estimation results associated with Table 6.

Table C17: Propagation financial sector: Firm-level

	𝟙(New use)			𝟙(New bank)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Downstream						
Level 1 × Post	-0.017	-0.017	-0.015	0.016	0.014	0.015
	(0.029)	(0.029)	(0.029)	(0.011)	(0.011)	(0.011)
Level 2 × Post	-0.039***	-0.038***	-0.037***	-0.003	-0.003	-0.003
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Level 3 × Post	-0.034***	-0.034***	-0.034***	-0.002	-0.002	-0.002
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
N	952506	951914	951910	960366	959766	959763
R^2	0.26	0.27	0.27	0.18	0.19	0.19
Panel B. Upstream						
Level 1 × Post	0.021	0.025*	0.027*	-0.005	-0.004	-0.004
	(0.014)	(0.014)	(0.014)	(0.007)	(0.007)	(0.007)
Level 2 × Post	0.001	0.002	0.003	-0.004**	-0.003*	-0.003*
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Level 3 × Post	-0.002	-0.001	-0.000	-0.003	-0.002	-0.003
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
N	895448	894835	894831	902601	901984	901981
R^2	0.25	0.26	0.26	0.18	0.19	0.19
Firm Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Bank FE			✓			✓
Sector-Time FE	✓	✓		✓	✓	
Province-Sector-Time FE			✓			✓

Notes: This table shows the estimation results associated with Table 6.

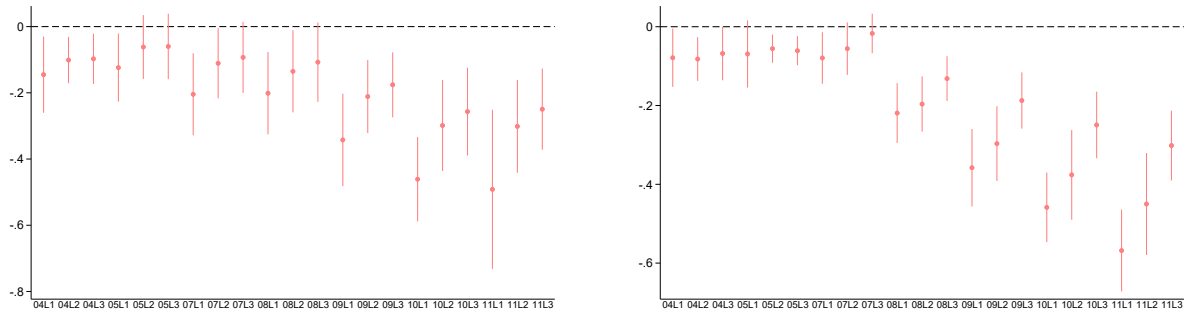
Table C18: First-Stage Regressions for Instrumental Variables

	Common Lender	Interest Rate
	(1)	(2)
Panel A. Excluded Instruments		
M&A-Weighted IV	2.10***	
	(0.13)	
Average Interest Rate IV		0.25***
		(0.05)
Panel B. Diagnostics		
N	3286879	3676120
Estimation Method	GLM (Quasibinomial)	OLS
Firm-Bank FE	Y	
Bank-Year FE	Y	Y
Firm-Type FE		Y
Adj. R^2		0.91
Within R^2		0.09
Squared Correlation	0.57	
Partial F-statistic	589.4	
Wald Statistic	276.7	

Notes: This table reports first-stage regression results for the instrumental variables used in the control function approach. Column (1) reports the first stage for the common lender variable, estimated via GLM with a quasibinomial family. The excluded instrument is an M&A-weighted instrument exploiting mergers and acquisitions among trading partners as exogenous shocks to common lender relationships. Standard errors are clustered at the firm-bank level. Column (2) reports the first stage for the interest rate, estimated via OLS. The average interest rate IV is constructed from leave-one-out average rates at the bank-year-province level. Standard errors are clustered at the bank-year level. ***p<0.01, **p<0.05, *p<0.1.

C.6 Additional Figures

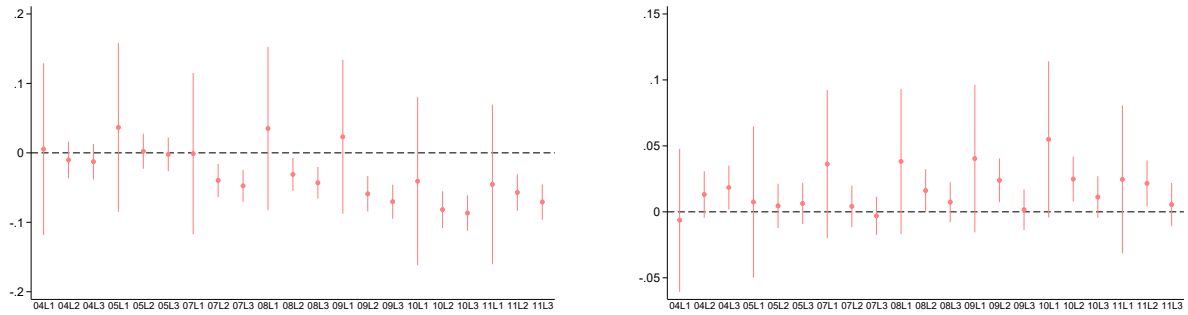
Figure C2: Parallel trend on firm sales - Firm level



(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 is for upstream propagation. "04L1", "04L2", "04L3" refer 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.

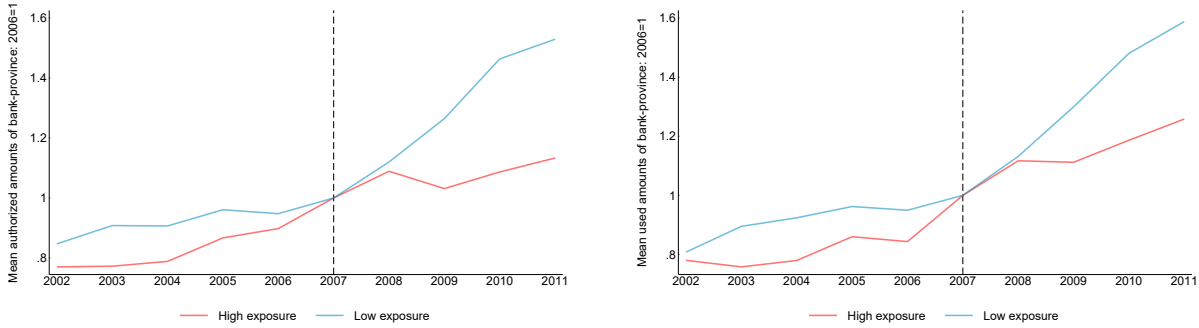
Figure C3: Parallel trend on firm credit demand - Firm level



(a) Downstream (b) Upstream

Notes: This figure validates the parallel trend assumption of estimating firm-level credit demand. The estimated dynamic difference-in-difference specification is at the firm level with the outcome variable being $\mathbb{1}(\text{New bank})$. We control for firm characteristics by interacting firm size, leverage, and profitability in 2006 with year dummies. We add firm fixed effects, bank fixed effects, and province-sector-year fixed effects. Robust standard errors are clustered at the firm level. We apply the analogous specification for upstream propagation. The left panel plots coefficient estimates for downstream propagation. The right panel is for upstream propagation. "04L1", "04L2", "04L3" refer 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.

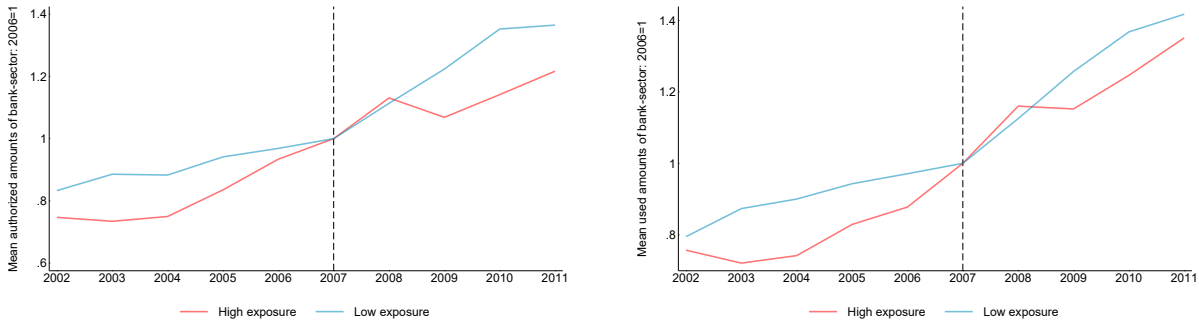
Figure C4: Credit Outcome at Bank-market Level



(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(26).

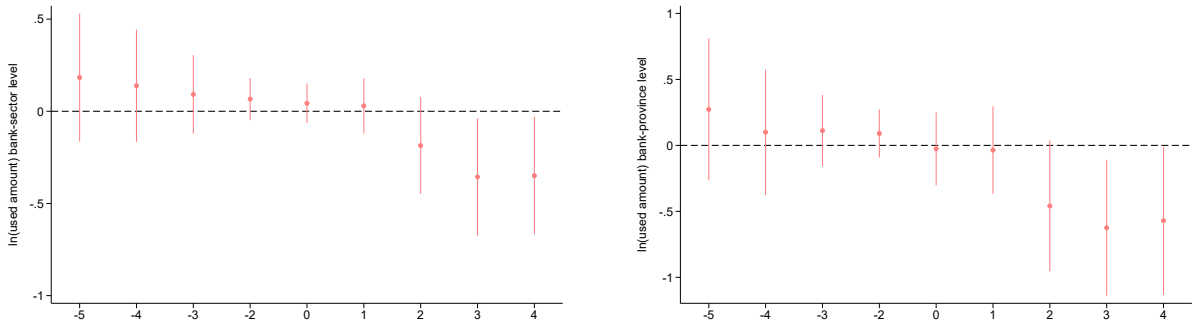
Figure C5: Credit Outcome at Bank-sector Level



(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-digit NACE code. Exposure is defined as in Eq(26).

Figure C6: Parallel trend on credit demand - 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.

D Counterfactual: Derivation and Implementation Details

D.1 Production-network parameters

The counterfactual uses two production-network parameters: the elasticity of substitution between intermediate inputs, σ, and the intermediate-input cost share, λ. Both are obtained before the counterfactual is run, and the counterfactual treats them as given.

The elasticity of substitution is estimated from the GM episode. As described in Section 7, the closure of GM Antwerp provides an exogenous production shock whose propagation through input shares identifies σ via the link-level regression in equation (12); the estimate is $\sigma = 1.18$, indicating that intermediate inputs are mild substitutes.

The cost share λ is calibrated from the universe of Belgian firm accounts over 2018–2023 as the ratio of material purchases to total input costs, where total input costs comprise materials, labor costs, and the user cost of capital (computed with a rental rate of 10 percent). We aggregate the firm-level cost shares to NACE sections and take the gross-output-weighted average across sections, excluding wholesale and retail trade: for these distribution sectors, the accounting margin between purchases and sales does not reflect a production technology, and including them would overstate the economy-wide input share. The resulting value is $\lambda = 0.63$, close to the benchmark of 0.55 implied by the National Bank of Belgium input-output tables; the calibration moves by less than 0.03 when the rental rate varies between 8 and 12 percent.

Both are technology parameters: σ describes how easily firms substitute across intermediate inputs and λ the share of intermediates in production costs. We therefore assume they are stable over time, so that parameters identified from the GM episode and calibrated on the recent firm accounts can be applied to the 2021 production network in which the counterfactual closure is simulated. The remaining ingredient, the product-market markup μ, is exogenous in the model; we set $\mu = 1$, the value most favorable to upstream transmission, since a higher markup would only dampen the upstream cascade below.

D.2 Derivation of the propagation equation

We model the closure as a direct output loss $\boldsymbol{\delta} = \delta_s e_s$ at the closed firm s, where δ_s is the proportional change in the firm's output and $\delta_s = -1$ removes the firm's entire output – the linearized representation of a complete shutdown. The derivation proceeds in three steps: we first link credit demand to sales, then derive the downstream and upstream cascades, and finally combine them into the propagation equation used in the counterfactual.

Step 1: credit demand tracks sales. From equation (4), firm i's credit demand is $L_i = \chi_i \mathcal{C}_i$, where $\mathcal{C}_i = \sum_j p_j x_{ji} + w\ell_i + rk_i$ is the input bill. Under constant returns to scale and markup pricing, $p_i = \mu_i\, mc_i$, total revenue satisfies $s_i = p_i y_i = \mu_i(1+\theta_i)\,\mathcal{C}_i$, since the marginal cost inclusive of financing is $(1+\theta_i)$ times the unit input cost. Combining,

$$L_i = \frac{\chi_i\, s_i}{\mu_i(1+\theta_i)} \qquad \Longrightarrow \qquad d\log L_i = d\log s_i - d\log(1+\theta_i), \tag{30}$$

so in the partial-equilibrium counterfactual, where interest rates are held fixed ($d\log(1+\theta_i)=0$), credit demand moves one-for-one with sales. When interest rates are allowed to adjust, as in the repricing counterfactual of Section 8.1, the financing-cost terms no longer drop out: each firm's financing wedge moves with its expected market rate, $d\log(1+\theta_i)=\chi_i\, d\bar{R}_i/(1+\theta_i)$, and the change propagates to other firms' credit demand through input prices. We incorporate this through the credit-demand response in equation (13), whose financing-cost term $\lambda e_i'\mathbf{A}'(I-\lambda\mathbf{A}')^{-1}d\log(1+\boldsymbol{\theta})$ adds the network pass-through of the equilibrium rate changes to the loan sizes; this is the production-feedback step of the repricing counterfactual.

Step 2: downstream cascade. When supplier s shuts down, customer i loses the input x_{si}, which enters the CES bundle with weight a_{si} (the entry of the input-share matrix $\mathbf{A}$ defined in Section 3), and the bundle enters production with cost share λ. To first order, and treating input proportions as fixed at the shock horizon (the CES substitution response is second order for σ close to one, and our estimate is $\sigma=1.18$), firm i's output falls by $\lambda\, a_{si}\,|\delta_s|$. The same logic applies to each subsequent link: a tier-2 customer loses output in proportion to its input share of the tier-1 firm, again damped by λ. Stacking all firms and all orders of the cascade,

$$d\log\mathbf{y}^{\text{down}}=\lambda\mathbf{A}'\,d\log\mathbf{y}^{\text{down}}+\boldsymbol{\delta}\qquad\Longrightarrow\qquad d\log\mathbf{y}^{\text{down}}=(\mathbf{I}-\lambda\mathbf{A}')^{-1}\boldsymbol{\delta}. \tag{31}$$

Step 3: upstream cascade. Supplier i's sales are the sum of its customers' purchases plus final demand, $s_i=\sum_k\omega_{ik}E_k^M+f_i$, where $\omega_{ik}=s_{ik}/s_i$ is the share of i's sales going to customer k (the entry of the output-share matrix $\boldsymbol{\Omega}$) and E_k^M is customer k's total spending on intermediate inputs. Under the Cobb-Douglas structure of equation (1), intermediate spending is the share λ of total cost, and by markup pricing total cost is s_k/μ_k, so $E_k^M=(\lambda/\mu)s_k$: each euro of a customer's sales generates λ/μ euros of demand for its suppliers. A customer's sales decline therefore reaches supplier i in proportion to ω_{ik}, damped by λ/μ; stacking,

$$d\log\mathbf{s}^{\text{up}}=\tfrac{\lambda}{\mu}\,\boldsymbol{\Omega}\,d\log\mathbf{s}^{\text{up}}+\boldsymbol{\delta}\qquad\Longrightarrow\qquad d\log\mathbf{s}^{\text{up}}=\left(\mathbf{I}-\tfrac{\lambda}{\mu}\boldsymbol{\Omega}\right)^{-1}\boldsymbol{\delta}. \tag{32}$$

Combining. Adding the two cascades counts the direct loss $\boldsymbol{\delta}$ at the closed firm twice (it is the zeroth-order term of both inverses), so we subtract $\boldsymbol{\delta}$ once. The total sales response to the closure is therefore

$$d\log\mathbf{s}\;=\;\underbrace{(\mathbf{I}-\lambda\mathbf{A}')^{-1}\boldsymbol{\delta}}_{\text{downstream (customers)}}\;+\;\underbrace{\left(\mathbf{I}-\tfrac{\lambda}{\mu}\boldsymbol{\Omega}\right)^{-1}\boldsymbol{\delta}}_{\text{upstream (suppliers)}}\;-\;\boldsymbol{\delta}, \tag{33}$$

and combining with Step 1 gives the credit-demand response $d\log L_i=d\log s_i$ used in the partial-equilibrium counterfactual.

D.3 Model performance under the shock

This appendix records how the propagation in equation (33) performs against the reduced-form evidence, both qualitatively and quantitatively. We apply the same closure as in Section 8 and compare the model-implied change in firms' credit demand, $d\log L_i=d\log s_i$, by network

tier and direction, with the difference-in-differences estimates of the GM closure in Section 7.1.

Qualitatively, the model reproduces the observed pattern. Credit demand falls at every network tier, in both directions, and the decline fades monotonically with network distance. Downstream, the closed firm's direct customers (tier 1) lose on average 18.4 percent of their credit demand, tier-2 firms 0.30 percent, and tier-3 firms 0.18 percent; upstream, the direct suppliers (tier 1) lose 6.6 percent, tier-2 firms 0.41 percent, and tier-3 firms 0.15 percent. The effect is negative at every tier in both directions and declines monotonically with distance, which is the same qualitative pattern as the reduced form, and the asymmetry between the broader upstream network and the narrower downstream one mirrors the structure of the firm's trading relationships.

Quantitatively, the model-implied magnitudes are smaller than the reduced form, and increasingly so with network distance. The natural benchmark is the firm-level difference-in-differences estimates of the GM closure in Table C3, Columns (3)-(4), whose tier coefficients give the average change in log sales for firms at each network distance: there, direct (tier-1) customers and suppliers lose about 21.5 and 22.5 percent, with the downstream effect declining to roughly 15 and 12 percent at the second and third tiers. Because in the model credit demand moves one-for-one with sales ($d \log L_i = d \log s_i$), these are the comparable magnitudes. The model's direct (tier-1) effects are of the same order: 18.4 percent downstream and 6.6 percent upstream. However, its propagation to the indirect tiers is more muted, fading faster with distance. This is expected: the counterfactual holds the production network fixed and linearizes around the pre-shock equilibrium, so firms scale output along existing links but cannot exit, sever relationships, or form new ones, and higher-order propagation is damped, whereas the reduced-form estimates additionally absorb extensive-margin adjustment, relationship destruction, and the broader downturn that coincided with the closure. The model should therefore be read as a conservative structural lower bound: it captures the architecture of the propagation, i.e., its direction, its monotone decay with distance, and which firms and banks are exposed, rather than its full magnitude, which is what matters for isolating the common lending channel in Section 8.

D.4 Partial-equilibrium counterfactual

Table C1 reports the partial-equilibrium version of the counterfactual in Table 9, holding all interest rates fixed at their pre-shock values. Because the equilibrium rate adjustments in general equilibrium are very small, the aggregate credit decline barely differs across the two, €66.0 million at fixed rates against €65.3 million with repricing, and the ordering of banks is preserved. The amplification ratios in Column (5) are easier to read here, because the no-common-lending benchmark and the baseline are computed at the same fixed rates: the closed firm's two direct lenders, Banks B and D, are amplified, at -0.6 and -1.8 percent, and every bank without a direct lending relationship to the closed firm is sheltered, by +1.4 percent for Bank A, +0.8 for Bank C, and +0.4 for the pooled remainder. The magnitude of the sheltering lines up with each bank's common-lender credit to the closed firm's supply chain: Bank A, the largest supply-chain common lender, is sheltered the most.

Table C1: Partial equilibrium: bank credit and profit response to the closure with fixed interest rates

Panel A: Pre-shock bank characteristics

	Total credit	CL credit to supply chain	Lending to closed firm	
			Credit	$C_{s,b}$
Bank A	11.68	5.59	0.2	0.42
Bank B	6.90	1.96	4.9	0.27
Bank C	5.63	1.12	0.2	0.02
Bank D	4.79	1.07	4.5	0.29
Other banks	3.26	0.34	0.2	0.00

Panel B: Credit response to the closure (fixed rates)

	Baseline		No common lending		Amp_b
	Δ Credit	% of credit	Δ Credit	% of credit	(%)
	(1)	(2)	(3)	(4)	(5)
Bank A	-24.3	-0.21	-24.7	-0.21	+1.4
Bank B	-15.8	-0.23	-15.7	-0.23	-0.6
Bank C	-7.6	-0.13	-7.6	-0.14	+0.8
Bank D	-13.2	-0.28	-13.0	-0.27	-1.8
Other banks	-5.1	-0.16	-5.1	-0.16	+0.4
All banks	-66.0	-0.20	-66.1	-0.20	+0.1

Panel C: Profit response to the closure (fixed rates)

	Baseline		No common lending		Amp_b
	Δ Profit	% of profit	Δ Profit	% of profit	(%)
	(1)	(2)	(3)	(4)	(5)
Bank A	-1.02	-0.23	-1.04	-0.24	+1.2
Bank B	-0.63	-0.24	-0.62	-0.24	-0.1
Bank C	-0.25	-0.13	-0.25	-0.13	+1.2
Bank D	-0.42	-0.27	-0.41	-0.27	-1.4
Other banks	-0.12	-0.15	-0.13	-0.15	+0.3
All banks	-2.44	-0.22	-2.45	-0.22	+0.4

Notes: This table reports the partial-equilibrium counterpart of Table 9: the same closure of a large manufacturing firm with a concentrated banking relationship in the 2021 network, with all interest rates held fixed at their pre-shock values, so that the response reflects demand-side reallocation alone. Panel A reports the pre-shock characteristics – total credit to the sample firms and common-lender credit to the closed firm's supply chain (both in € bn), credit to the closed firm (€ mn), and the closed firm's common-lender measure $C_{s,b}$ – as in Table 9. Panel B reports the credit change (€ mn, and % of pre-shock credit) and Panel C the change in expected profit (€ mn, and % of baseline profit), under the baseline (Columns (1)-(2)) and no-common-lending ($\alpha_C^D = 0$, Columns (3)-(4)) scenarios, with the amplification ratio Amp_b in Column (5). Comparing the two tables shows that allowing banks to re-optimize their rates leaves both the aggregate decline and the cross-bank pattern essentially unchanged.

D.5 Firm-bank incidence of the common lending channel

Section 8 states that, within the affected supply chain, the credit decline concentrates where exposed firms are tied to common lenders. To show this, we relate the change in credit at the firm-bank level to the importance of the bank as a common lender for the firm before the closure. On the firm-bank pairs of affected firms (firms within three network steps of the closed firm), we run

$$\frac{\Delta L_{i,b}}{L_{i,b}} = \gamma_0 + \gamma_1 C_{i,b} + \varepsilon_{i,b}, \tag{34}$$

where the dependent variable is the relative change in firm i's credit at bank b between the pre-closure equilibrium and the counterfactual ($L_{i,b} = \Pr_{i,b} L_i$ is the pre-closure expected credit), and the regressor $C_{i,b}$ is the bank's common lender measure for the firm before the closure, as defined in equation (6). A negative γ_1 would mean that, among the affected firms, credit falls by more at the banks that were more important common lenders for them. In the model, however, the closure changes a firm's common-lender exposure only where that exposure ran through the closed firm itself; the overall level of $C_{i,b}$, which mostly reflects the firm's other trading partners, is therefore close to orthogonal to the credit cuts. To capture the operative dimension, we also estimate a second specification that adds the *closed-firm component* of common lending,

$$C^s_{i,b} = \exp^s_i \times \Pr_{s,b}, \tag{35}$$

the product of firm i's transaction share with the closed firm ($\exp^s_i$) and the closed firm's probability of borrowing from bank b ($\Pr_{s,b}$): it is large exactly where a firm strongly tied to the closed firm borrows from one of the closed firm's own banks, the pairs where the closure erodes the common-lender position. We expect the coefficient on the level $C_{i,b}$ to be close to zero: a bank's overall common-lender importance for a firm says little about how that firm's credit changes (Columns (1) and (3)). We expect the coefficient on the closed-firm component $C^s_{i,b}$ to be negative and large: a firm heavily tied to the closed firm that borrows from one of the closed firm's lenders cuts that credit by more. This coefficient combines two forces: the firm's loss of business with the closed firm itself (the network-propagation effect, present whether or not borrowers value common lenders), and the erosion of the common-lender tie. To separate them, we estimate the specification under both scenarios. In the no-common-lending scenario borrowing no longer responds to the common-lender measure, so the $C^s_{i,b}$ coefficient (Column (4)) reflects only the propagation effect and is smaller in magnitude; in the baseline (Column (2)) it also carries the common-lender channel. The difference between the two coefficients is therefore the incidence of the common lending preference. Table C2 reports the estimates.[4]

[4] These regressions describe the incidence of the channel within the model rather than providing an independent test: the dependent variable is generated by the same model that produces the bank-level reallocation in Table 9.

Table C2: Firm-bank incidence of the common lending channel in the closure counterfactual

	$\Delta L_{i,b}/L_{i,b}$			
	Baseline		No common lending	
	(1)	(2)	(3)	(4)
Common Lender $C_{i,b}$	-0.00003	-0.00003	-0.00003	-0.00003
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Closed-firm component $C^s_{i,b}$		-2.391***		-2.238***
		(0.006)		(0.006)
Constant	-0.0011***	-0.0010***	-0.0011***	-0.0010***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
N	566,211	566,211	566,211	566,211
R^2	0.000	0.195	0.000	0.175

Notes: This table reports the estimates of equation (34), with and without the closed-firm component of equation (35), on the firm-bank pairs of affected firms (within three network steps of the closed firm) in the closure counterfactual. The dependent variable is the relative change in the firm-bank credit between the pre-closure equilibrium and the counterfactual. $C_{i,b}$ is the bank's pre-closure common lender measure for the firm, as defined in Eq(6); $C^s_{i,b}$ is its closed-firm component, the firm's transaction share with the closed firm interacted with the closed firm's borrowing probability at the bank. Columns (1)-(2) use the baseline scenario (common-lender preference active); Columns (3)-(4) the no-common-lending scenario ($\alpha^D_C = 0$), in which any remaining relationship reflects only the correlation between the closed-firm tie and the production-cascade exposure; the difference between the $C^s_{i,b}$ coefficients across the two scenarios (-2.39 versus -2.24) is the incidence of the common lending channel itself. Standard errors in parentheses. $***p < 0.001$; $**p < 0.01$; $*p < 0.05$.

E Proofs

E.1 Propagation of a Production Shock

According to Huremovic et al. (2026) Lemma 1 to 3, we obtain the following results similar to Lemma 4 and Corollary 1:

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

$$\frac{\partial \log \boldsymbol{P}}{\partial k_k} = \mathbf{A}' \left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \left[\frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k} + \frac{\partial \log w}{\partial k_k}\boldsymbol{\beta} + \frac{\partial \log r}{\partial k_k}\boldsymbol{\rho}\right] \tag{37}$$

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

$$P_i = \left(\sum_{k=1}^{N} a_{ki} p_k^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{38}$$

The amount of credit required by firm i satisfies

$$L_i = \frac{\chi_i}{\kappa_i} r^{\rho} w^{\beta} P_i^{\lambda}, \tag{39}$$

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

$$\log L_i = \log \chi_i - \log \kappa_i + \beta \log w + \rho \log r + \lambda \log P_i \tag{40}$$

$$\frac{\partial \log L_i}{\partial k_k} = \left[\beta \frac{\partial \log w}{\partial k_k} + \rho \frac{\partial \log r}{\partial k_k} + \lambda \frac{\partial \log P_i}{\partial k_k}\right] \tag{41}$$

The matrix representation is

$$\frac{\partial \log \mathbf{L}}{\partial k_k} = \left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \left[\beta \frac{\partial \log w}{\partial k_k} + \rho \frac{\partial \log r}{\partial k_k}\right] + \lambda \mathbf{A}' \left[\mathbf{I} - \lambda \mathbf{A}'\right]^{-1} \frac{\partial \log(1+\boldsymbol{\theta})}{\partial k_k} \tag{42}$$

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

$$d \log L_i = e_i'(I - \lambda \mathbf{A}')^{-1} \left[\beta d \log w + \rho d \log r\right] + \lambda e_i' \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} d \log(1+\boldsymbol{\theta}) \tag{43}$$

$$d \log \mathbf{L} = (I - \lambda \mathbf{A}')^{-1} \left[\beta d \log w + \rho d \log r\right] + \lambda \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} \boldsymbol{\omega}\, d\bar{R} \tag{44}$$

where $\boldsymbol{\omega}$ is a vector with the jth element $\omega_j = \chi_j/(1+\theta_j)$, capturing the pass-through of interest rate changes to firm j's financing cost. Since $dL_i = L_i \cdot d \log L_i$, we obtain

$$L_{i,R} = L_i \cdot \mathrm{Pr}_i \cdot \lambda e_i' \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} \boldsymbol{\omega}, \tag{45}$$

where L_i is firm i's own credit (a scalar) multiplied outside the Leontief sum. The term $\mathrm{Pr}_i \cdot \lambda e_i' \mathbf{A}'(I - \lambda \mathbf{A}')^{-1} \boldsymbol{\omega}$ is the log-derivative $d \log L_i / dR$, which is dimensionless and captures the network-amplified sensitivity of firm i's cost structure to interest rates.

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

$$\log s_{ji} = (1-\sigma)\log(1+\theta_j) - \log(1+\theta_i) + \log a_{ji} + (1-\sigma)(\log\mu_j - \log\kappa_j + \beta\log w + \rho\log r) + \log\lambda + \log s_i - \log\mu_i + (1-\sigma)\lambda\log P_j + (\sigma-1)\log P_i. \tag{46}$$

Taking differentiation with respect to k_k:

$$\begin{aligned}\frac{\partial\log s_{ji}}{\partial k_k} = &-\frac{\partial\log(1+\theta_i)}{\partial k_k} - (\sigma-1)\frac{\partial\log(1+\theta_j)}{\partial k_k} + \frac{\partial\log s_i}{\partial k_k} \\ &- (\sigma-1)\lambda\boldsymbol{e}_j'\mathbf{A}'(\mathbf{I}-\lambda\mathbf{A})^{-1}\frac{\partial\log(1+\boldsymbol{\theta})}{\partial k_k} + (\sigma-1)\boldsymbol{e}_i'\mathbf{A}'\left(\mathbf{I}-\lambda\mathbf{A}'\right)^{-1}\frac{\partial\log(1+\boldsymbol{\theta})}{\partial k_k}.\end{aligned} \tag{47}$$

Noting that $d\log s_{ji} = \sum_k \frac{\partial\log s_{ji}}{\partial k_k} dk_k$, equation (12) holds.

E.2 Credit Supply

The derivative of firm i's expected loan volume at bank b with respect to its own firm-bank interest rate $R^{\tau}_{i,b}$ consists of an extensive margin (changes in firm i's borrowing probability) and an intensive margin (changes in firm i's loan size):

$$Q^{\tau}_{i,b,R} = \frac{\partial \Pr_{i,b}}{\partial R^{\tau}_{i,b}} L_i + \Pr_{i,b} \frac{\partial L_i}{\partial R^{\tau}_{i,b}}. \tag{48}$$

The intensive margin term $\partial L_i / \partial R^{\tau}_{i,b} = L_{i,R^{\tau}_{i,b}}$ is derived above in equation (19). Since interest rates affect firms' production costs through the financing cost $\theta_i = \chi_i \bar{R}_i$, changes in $R^{\tau}_{i,b}$ propagate through the production network, altering input prices and thus firm i's credit requirement.

$$\frac{\partial \Pr_{i,b}}{\partial R^{\tau}_{i,b}} = \alpha^{D}_{P,i} \left(1 - \Pr_{i,b}\right) \Pr_{i,b} - \alpha^{D}_{C} N^{\tau}_{i,b}, \tag{49}$$

$$\frac{\partial \Pr_{i,k}}{\partial R^{\tau}_{i,b}} = -\alpha^{D}_{P,i} \Pr_{i,k} \Pr_{i,b} - \alpha^{D}_{C} N^{\tau}_{i,k} \tag{50}$$

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

$$N^{\tau}_{i,b} = \sum_{k \neq b} \Pr_{i,k} \frac{\partial C_{i,k}}{\partial R^{\tau}_{i,b}} = \sum_{k \neq b} \Pr_{i,k} \sum_{j \neq i} w_{ij} \frac{\partial \Pr_{j,k}}{\partial R^{\tau}_{i,b}} \tag{51}$$

$$N^{\tau}_{i,k} = \sum_{l \neq k} \Pr_{i,l} \frac{\partial C_{i,l}}{\partial R^{\tau}_{i,b}} = \sum_{l \neq k} \Pr_{i,l} \sum_{j \neq i} w_{ij} \frac{\partial \Pr_{j,l}}{\partial R^{\tau}_{i,b}} \tag{52}$$

Combining above definitions of the common lender effect (51) and (52) with equations (49) and (50), we get the relationship between the common lender effect across banks and borrowers.

$$N^{\tau}_{i,b} = -\sum_{k \neq b} \Pr_{i,k} \sum_{j \neq i} w_{ij} \alpha^{D}_{P,j} \Pr_{j,k} \Pr_{j,b} - \alpha^{D}_{C} \sum_{k \neq b} \Pr_{i,k} \sum_{j \neq i} w_{ij} N^{\tau}_{j,k} \tag{53}$$

With the probit link $F^{\tau}_{i,b} = \Phi(\alpha^{F}_{P} R^{\tau}_{i,b} + \alpha^{F}_{C} C_{i,b} + \alpha^{F}_{Z} Z_{i,b} + X'_b \alpha^{F}_{X} + Y'_i \alpha^{F}_{Y})$, a change in firm i's own rate at bank b affects $F^{\tau}_{i,b}$ both directly and indirectly through $C_{i,b}$. Applying the chain rule,

$$F^{\tau}_{i,b,R} = \frac{\partial F^{\tau}_{i,b}}{\partial R^{\tau}_{i,b}} = \phi^{F}_{i,b} \left[\alpha^{F}_{P} + \alpha^{F}_{C} \cdot \frac{\partial C_{i,b}}{\partial R^{\tau}_{i,b}} \right] = \phi^{F}_{i,b} \left[\alpha^{F}_{P} + \alpha^{F}_{C} \cdot T^{\tau}_{i,b} \right], \tag{54}$$

where $\phi^{F}_{i,b}$ is the standard normal density evaluated at the default index. The first term in brackets is the direct price effect; the second is the network channel, with

$$T^{\tau}_{i,b} \equiv \frac{\partial C_{i,b}}{\partial R^{\tau}_{i,b}} = \sum_{j \neq i} w_{ij} \frac{\partial \Pr_{j,b}}{\partial R^{\tau}_{i,b}}. \tag{55}$$

The sign of the correction is governed by $\alpha_C^F \cdot T_{i,b}^{\tau}$. Under the empirically relevant case $\alpha_C^F < 0$ (common lending reduces default) and $T_{i,b}^{\tau} < 0$ (an own-rate hike erodes the common-lender variable), the product is positive and $F_{i,b,R}^{\tau}$ is larger in magnitude than the direct-effect benchmark. Substituted into the FOC (16), a larger default derivative shrinks the effective denominator and raises the equilibrium rate, so the bank optimally prices higher to internalize the erosion of its common-lender role with firm i.