Financial and Production Integration in the Macroeconomy*

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Abstract

We study how the integration between the financial sector and the production structure influences business cycle transmission. In a dynamic general equilibrium economy where banks finance supply chains, we find that a stronger integration between the banking sector and supply chains has ambiguous effects on macroeconomic stability. Integration along an extensive margin, in the form of greater ability to borrow from banks specialized in other supply chain segments, amplifies the impact of negative banking shocks. In contrast, integration between banks and supply chains along an intensive margin, in the form of greater diffusion of supply chain finance (factoring activities and bank invoice discounting), mitigates the transmission of banking shocks. The predictions of the model are consistent with bank-firm matched data from Italy.

Keywords: Banks, Financial integration, Production networks, Factoring

JEL Classification Codes: E23, E32, E44

1 Introduction

Recent decades have seen a dramatic intensification in firm production and commercial linkages, with supply chains becoming longer and production networks more ramified. These transformations in the production structure have been accompanied by equally important transformations in the mechanisms of

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firm financing, aimed at accommodating and promoting supply chains. Banks have become increasingly integrated with supply chains, tailoring financial products and services to their needs and leveraging financial instruments to facilitate supply chain operations. The growing integration between the banking sector and supply chains has resulted in the diffusion of supply chain financing, such as invoice discounting and factoring. Figure 1, for example, displays the significant increase in the use of factoring in nine advanced economies over the 2005-2024 period. In 2024, factoring played a prominent role in various economies: it accounted for 13.6% of GDP in Italy, 14.8% of GDP in France, 16.7% in Spain, 11.2% in the UK, and 9.3% in Germany, for instance. In parallel with the growing integration between banks and supply chains along this "intensive" margin (provision of supply chain finance), the banking sector has also become more ramified, expanding its interconnections with firms beyond traditional areas of specialization. Banks previously specialized in financing specific segments of supply chains have diversified their operations, extending their financing to new industries, regions, and hence supply chain segments ("extensive" margin of integration).

In spite of the importance of these structural transformations, little is understood about their macroeconomic consequences. Yet, the continued exposure of production and financial networks to shocks[1] naturally elicits questions on how the multidimensional links between banking sectors and supply chains can influence macroeconomic stability.[2] Does the integration between banks and supply chains enhance or reduce resilience in the face of aggregate shocks? Do the above-mentioned intensive and extensive-margin dimensions of integration between banks and supply chains affect macroeconomic stability in the same manner?

This paper aims at addressing these fundamental questions theoretically and empirically. To this end, we develop a dynamic stochastic general equilibrium model with banks and supply chains and test its key predictions using matched firm-bank data from Italy. The model incorporates a vertical supply chain in which three types of firms (upstream, midstream, and downstream) sell intermediate inputs to each other and borrow both from banks (through bank loans) and suppliers (through trade credit).[3] When

[1] One of the critical disturbances was the 2020-2020 Coronavirus Pandemic which disrupted supply chains, inducing shortages of goods, factory closures, shipping delays, etc. During the 2008-2010 great financial crisis, the aggregate shock originated in the financial sector.

[2] Scholars and practitioners stress that, in the face of recessions and with the increasing complexity of global supply chains, buyers and suppliers are increasingly seeking opportunities to improve the efficiency of working capital by unlocking cash trapped in the financial supply chain (Lodge, 2010; Large and Large, 2010; Richman and Mutter, 2010). This hinges on improving the integration of financial supply chains with the flows of physical goods and information, and so buyers and suppliers are putting their banks under pressure to play a more proactive role in improving physical/financial supply chain (P/FSC) integration (Blount 2008; John Mathis and Cavinato 2010).

[3] According to Levine, Lin, and Xie (2018), 25% of the average firm's total debt liabilities consist of trade credit in their sample of more than 3,500 firms across 34 countries between 1990 and 2011.

borrowing, firms need to pledge collateral. They can use both capital assets and trade credit (accounts receivable) as collateral for bank loans.[4] In addition, firms can sell accounts receivable to banks to obtain immediate liquidity. Thus, in the model economy banks can engage in receivables discounting and in factoring. While factoring entails extra fees charged by banks, it enhances banks' experience with trade credit and intermediate input transactions in the supply chain, making banks' discounting of firms' invoices more efficient. When borrowing from banks, firms choose the shares of capital to pledge to banks specialized in their own supply chain segment and to banks specialized in other supply chain segments ("non-sector" banks).

We calibrate the model to data from Italy and then perturb the economy with banking shocks that reduce the supply of loans to firms. We find that stronger bank-supply chain integration along the extensive margin, in the form of easier ability to borrow from (pledge capital to) banks specialized in other supply chain segments, amplifies the impact of negative banking shocks. In contrast, the quantitative analysis reveals that a stronger integration between banks and supply chains along the intensive margin, in the form of easier use of invoice discounting and factoring, can mitigate the amplification and transmission of banking shocks. The intuition revolves around the influence of the two dimensions of bank-supply chain integration on banks' skills and experience in providing collateralized finance. In both cases, a higher degree of integration between banks and supply chains enhances the pledgeability to banks of a type of collateral by strengthening banks' ability to manage, repossess, and liquidate collateral. Bank-supply chain integration along the extensive margin enhances the pledgeability of capital assets to banks specialized in other supply chain segments. Following a banking shock, this exacerbates the sensitivity of firms' demand for capital as collateral to reductions in firms' appetite for the costlier bank loans. In turn, this aggravates the contraction in firms' capital investments and production. In contrast, integration between banks and supply chains along the intensive margin enhances the pledgeability of trade credit to banks through easier discounting and factoring of invoices. When a banking shock hits downstream firms, this heightens the sensitivity of trade credit supply to the tightening of borrowing constraints, stimulating suppliers' extension of trade credit to the firms hit by the shock. In turn, this improves the resilience of investments and production in the supply chain both directly and by encouraging the extension of bank loans to firms (due to a complementarity between trade credit and bank loans). However, the analysis also reveals that when banks charge sizeable fees for their factoring activities, the stabilizing effects of bank-supply chain integration through factoring are diminished and can even be reversed.

[4] In the model trade credit is backed by intermediate inputs purchased from suppliers.

In further analysis, we next investigate how commercial linkages (that is, a more intense use of trade credit along the supply chain) interacts with bank-supply chain integration in shaping macroeconomic resilience. We find that the beneficial effects of stronger bank-supply chain integration along the intensive margin are more pronounced when there are stronger commercial links among firms. Intuitively, a larger use of trade credit expands the base of inter-firm transactions and collateral pledges (invoices) to which bank-supply chain integration adds experience and value.

We test the key predictions of the model using matched firm-bank data from Italy. Our primary source of information is a large-scale survey of Italian firms, the MET survey, which covers about 25,000 firms in eight waves between 2009 and 2021. The survey provides details on firms' participation in supply chains and use of trade credit, and on the lending banks of the firms. This allows us to match the firm-level information with information on lending banks, including their involvement in supply chain financing (factoring). Italy provides a compelling context for investigating the integration between banks and supply chains. Since the 1990s, the Italian banking sector has undergone significant deregulation and consolidation, leading to enhanced geographic and sectoral integration. This transformation has led banks to expand their financing to new supply chain segments. Concurrently, bank-mediated trade credit and supply chain finance, particularly factoring, has gained prominence. These twin developments—the integration between banks and supply chains along the extensive margin and the institutionalization of factoring—make Italy an ideal context to study how the integration between the financial sector and the production structure influences the transmission of shocks across layers of the production network. We estimate the impact of an exogenous banking shock driven by the crisis of the major Monte dei Paschi (MPS) bank that occurred around 2013. In line with the predictions of the model, our empirical results point to a destabilizing influence of bank-supply chain integration along the extensive margin but a stabilizing influence of bank-supply chain integration along the intensive margin. Moreover, as implied by the model, the stabilizing effect of the intensive margin unfolds through a more countercyclical supply of trade credit when factoring is more intensely used in the supply chain.

Related literature This paper relates to different strands of literature. The first strand studies the propagation of shocks in production networks. The importance of input-output linkages is at the core of Acemoglu, Akcigit, and Kerr (2016) and Barrot and Sauvagnat (2016) who examine how aggregate (demand- and supply-side) shocks and firm-level idiosyncratic shocks propagate through production networks. Bigio and La'o (2020) and Luo (2020) explore the propagation of financial shocks in production networks through bank credit or trade credit using static models. In our setting, we investigate the role of the integration between banks and production networks in the transmission of financial shocks in a dynamic general equilibrium setting.

The second related strand of literature examines the impact of financial integration on macroeconomic stability. Allen and Gale (2000) and Castiglionesi and Eboli (2018) study how the structure of the banking network can moderate or amplify liquidity shocks. Castiglionesi and Wagner (2013) investigate how interbank insurance through pure transfers can be socially efficient while Castiglionesi, Feriozzi, and Lorenzoni (2019) find that financial integration through interbank borrowing and lending can relieve local liquidity shocks. De Haas and Van Lelyveld (2010) and Cetorelli and Goldberg (2012) show that complex multinational banks can operate internal capital markets and transfer liquidity to withstand financial shocks. This paper aims to expand the analysis of financial integration to the interconnections between banks and supply chains. By doing so, it bridges the gap between banking-focused studies and the broader implications for businesses within the financial ecosystem.

Finally, the paper also speaks to the literature on the interaction between bank credit and trade credit, Numerous studies have explored the relationship between these two financing methods. Meltzer (1960) suggests that firms with liquid balances provide trade credit to smaller and less liquid firms during periods of tight money. Theoretical studies by Biais and Gollier (1997) and Burkart and Ellingsen (2004) argue that trade credit can substitute for bank credit. Empirical research by Petersen and Rajan (1997) and Nilsen (2002) further supports Meltzer's hypothesis by demonstrating the redistribution from bank credit to trade credit between firms. On the other hand, Love, Preve, and Sarria-Allende (2007) and Love and Zaidi (2010) contends that there is no clear substitution effect between bank credit and trade credit during financial crises. Despite this ongoing debate at the micro level, little effort has been made to examine the interaction between these two types of credit in aggregate dynamics contexts. This paper contributes to the literature by focusing on the link between trade credit and bank credit associated with the various forms of supply chain finance, including factoring and invoice financing, and the implications of the discussion of supply chain financing.

The paper unfolds as follows. In Section 2, we describe the empirical setting and the data that inform our calibration and empirical tests. Section 3 lays out the model. Section 4 presents the calibration and the main results. In Section 5, we consider model extensions. Section 6 tests salient predictions of the model in the Italian data. Section 7 concludes. Additional details on the model and on the data and further results are relegated to the Online Appendix.

2 Empirical Setting

2.1 Data sources

Our empirical setting combines several sources of firm-level and bank-level data. The primary source is the MET survey of Italian firms, which also provides detailed information on each firm's lender banks. The survey sample is fully representative along three dimensions: firm size (four size classes), geographical location (20 NUTS-2 regions), and industry.[5] The MET survey includes firms of all size classes, including micro-sized enterprises with less than ten employees.[6] This is important for the Italian context, where small firms represent over 95% of the business population and account for approximately 47% of total value added and 63% of employment (as of 2019). This characteristic is doubly important for our research question because smaller firms are *ex ante* more vulnerable to banking shocks. Limited internal financial resources, higher dependence on relationship lending, and greater exposure to localized credit markets make small and medium-sized firms (SMEs) more susceptible to credit supply disruptions. In addition, as we elaborate below, small and medium-sized Italian firms are strongly integrated in supply chains, generally relying on a relatively small number of customers or suppliers.

We use data from the 2008, 2009, 2011, 2013, 2015, 2017, 2019, 2021, and 2023 waves of the MET survey, each comprising approximately 24,000 firm-level observations and a substantial share of panel respondents. In each wave, firms report their outstanding banking relationships along with the duration of each connection. We use this information to fill in missing years and construct a panel of firm-bank linkages covering the period 2006–2023. In addition, the survey collects rich information on firm characteristics, including indicators of financing constraints and a proxy for firms' supply chain participation.

We match the MET information with the business register FrameSBS (Structural Business Statistics), compiled by the Italian National Institute of Statistics (ISTAT), which contains data on firms' sales, number of employees, age, operating sector, and location (at the NUTS-3 level). This source provides yearly data on the universe of Italian firms operating in the manufacturing and service sectors

[5] The MET survey covers firms in the manufacturing sector (60% of the sample) and the production-service sector (40%), stratified into 12 macro-sectors according to the NACE Rev. 2 classification.

[6] For a detailed comparison between the MET survey and the broader population of Italian firms, see Brancati (2025).

(excluding finance and public administration).[7] We complement the MET survey with firm-level balance sheet data from the AIDA Bureau van Dijk database, which covers the universe of incorporated Italian firms. These data provide information on investment, trade credit (accounts payable and receivable), and firm geolocation, which we will use to construct an instrument for supply chain participation (see Section 6.5). The final sample comprises yearly data on about 37,000 firms between 2008 and 2022, with approximately 320,000 firm-year observations in the most conservative specification.

Finally, we complement the MET information with detailed data from banks' balance sheets on factoring activities and other salient indicators for banks' operations with supply chains.

2.2 Banks, supply chains, and their integration in the Italian context

Table 1 presents descriptive statistics for the sample. The figures confirm that our sample predominantly consists of medium-sized and small enterprises. The median firm employs 15 workers, reports annual sales of approximately 2 million, and is 24 years old.

Supply chain participation Italy provides a particularly valuable empirical setting when considering commercial linkages among firms. A large share of its small and medium-sized enterprises operate as part of vertically integrated supply chains. We construct a direct indicator of supply chain participation using data from the MET survey. This binary variable equals one if the firm reports having long-term and quantitatively relevant commercial relationships with other firms for the purchase or sale of semifinished goods or product components. The goal is to capture a stable and economically meaningful form of engagement in supply chains. This measure is based on a taxonomy of production relationships consistent with international and national standards. For example, World Bank (2016) emphasize the role of long-term, input-specific commercial ties as a defining characteristic of modern supply chains, while Cafaggi and Iamiceli (2007) provide detailed illustrations of such arrangements in the Italian context. Similarly, the Italian National Institute of Statistics applies an analogous definition in its periodic surveys of production linkages. In our sample, 34% of the firms report participating in supply chain relationships. This figure shows a significant degree of commercial integration and is closely aligned with official estimates from ISTAT, which in its periodic analysis of Italian firms reports that approximately 35% of manufacturing firms with more than three employees were engaged in stable supply chain linkages between 2011

[7] For sensitivity reasons, data is accessible only upon formal request for authorization and exclusively within the ISTAT secured laboratories (*Laboratorio ADELE*).

and 2018.[8] Supply chain participation in our sample is more prevalent among firms located in Northern Italy and is particularly common in sectors such as transportation and automotive, plastics, and chemicals. Consistent with the importance of supply chain links, trade credit usage is also sizeable—payables and receivables average 16% and 22% of total assets, respectively, with wide cross-firm dispersion.

Bank-supply chain integration. Extensive and intensive margins Since the 1990s, the Italian banking sector has undergone significant deregulation and consolidation, leading to enhanced geographic and sectoral integration. This has redefined traditional, localized firm-bank relationships, leading banks to expand their financing activity to new supply chain segments. Our data set includes firms borrowing from more than 175 individual banks (see the full list in Table A7).[9] Some lenders are universal banks with extensive national and sectoral coverage, while others have retained a narrower geographic and industry focus, serving specific supply chain segments. Notably, around 15% of the firms in our sample borrow from cooperative banks (BCCs), which are widely recognized for their dual specialization: they are deeply embedded in local communities and often target specific economic sectors and supply chain segments such as agriculture, artisanal manufacturing, and small-scale services. Their sectoral expertise, combined with close borrower proximity, enables them to better assess firm-specific risks and provide financial products tailored to specialized segments of supply chains.

Local banks in Italy provide clear examples of the increasing integration between banks and supply chains along the extensive margin. For instance, small cooperative banks in the Veneto region—such as the former Cassa di Risparmio di Vicenza—initially concentrated over 70% of their loan portfolios in the textile and footwear firms of the Vicenza province, but by the late 2000s they had expanded into Treviso and Verona, where they financed leather and light mechanical industries closely tied to the regional fashion cluster. Similarly, banks rooted in Emilia Romagna, including Banca Popolare dell'Emilia Romagna, moved from a strong specialization in Modena's mechanical district—where in the mid-1990s more than 60% of their credit went to metalworking firms—toward Bologna and Reggio Emilia, extending credit to packaging and agri-food companies that relied on mechanical equipment. In

[8] In line with our taxonomy, ISTAT defines long-term supply chain relationships as stable commercial ties involving the sale or purchase of semifinished products or components.

[9] In terms of borrowing relationships, the majority of firms in our sample maintain a single banking relationship: 65% of firms borrow from only one bank, 21% from two, and 14% from three or more. These relationships tend to be long-lasting, with an average duration of approximately 14 years. These figures are broadly consistent with official statistics from the Bank of Italy's Credit Registry, confirming the representativeness of our data. Bonaccorsi Di Patti et al. (2019), using data on the universe of Italian non-financial firms over the period 2008–2016, report shares of single, double, and multiple relationships that closely mirror our findings (62%, 21%, and 17%, respectively).

the South, Banca Popolare di Bari, once highly concentrated (around 65% of lending) in the agricultural firms of Bari province, progressively increased exposure to enterprises in Foggia and Taranto engaged in food processing and logistics, thus following the downstream stages of the agro-food value chain.

In recent decades, in Italy the degree of integration between banks and supply chains has also grown significantly along the intensive margin (banks' provision of supply chain finance). Bank-mediated trade credit, particularly factoring, has gained prominence. In 2023, the Italian factoring market recorded a turnover of nearly €290 billion (Assifact, 2021), maintaining its position as one of Europe's largest.[10] Notably, 81% of Italian factoring transactions are conducted on a non-recourse basis, meaning that the risk of client default is fully transferred to the factoring institution. This is particularly relevant for small and medium-sized enterprises, which make up 63% of the domestic factoring users. The strategic role of factoring is further underscored by its long-term growth: between 2009 and 2020, factoring volumes in Italy more than doubled. For instance, between 2012 and 2024, the bank UniCredit Group's outstanding factoring volume grew by 11%, to about €12.1 billion, while the MPS bank recorded a sharper 42% increase, reaching €2.5 billion.

3 The Model

We consider an infinite-horizon dynamic stochastic general equilibrium model economy in discrete time. The economy is populated by infinitely-lived households, firms, and banks. Households consume final goods, supply labor to firms, and deposit savings at banks. The production structure consists of a vertical supply chain composed of three types of firms—upstream, midstream, and downstream—each supplying intermediate inputs to the next. Firms use capital, labor and intermediate inputs to produce. A final good producer combines firms' outputs to produce the final good used for consumption and investment.

Firms can rely on external financing to operate, borrowing from both banks and suppliers. Due to credit frictions, both loans from banks and trade credit from suppliers are collateralized by firms' assets, consistent, e.g., with the framework of Kiyotaki and Moore (1997). In particular, firms can pledge intermediate inputs as collateral for trade credit and capital and trade credit invoices (accounts receivable) as collateral for bank loans. The banking sector can grant loans to firms and purchase outstanding accounts receivable from firms (factoring). The banking sector consists of (partially) specialized banks, which do business primarily with specific firm segments (upstream, midstrem, or downstream).

[10] https://www.senato.it/application/xmanager/projects/leg18/attachments/documento_evento_procedura_commissione/files/000/369/501/Audizione_Assifact.pdf.

3.1 Households

Building on the framework of Gertler and Karadi (2011), the representative household comprises two types of agents: a fraction f are bankers and the remaining $1-f$ are workers. Homogeneous workers supply labor to firms in exchange for wage income, while bankers operate financial intermediaries and remit dividends to the household. In each period, individuals may switch roles with some exogenous probability. With probability σ, bankers continue their role in the following period, implying an expected survival time of bankers of $\frac{1}{1-\sigma}$ periods. In turn, a measure $(1-\sigma)f$ of workers is randomly reassigned as bankers each period, implying a stationary composition of the household. This turnover between the two occupations is to prevent banks from accumulating enough wealth, which would eventually make their financial (capital) constraints not binding. A small fraction ι of exiting bankers' net worth is allocated as initial capital to entering bankers.

Households' preferences follow Greenwood, Hercowitz, and Huffman (1988). The household's problem is

$$\max_{\{C_{t+j},L_{t+j},D_{t+j}\}_{j\geq 0}} \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j \frac{1}{1-\omega}\left[\left(C_{t+j}-k_c\frac{L_{t+j}^{1+\eta}}{1+\eta}\right)^{1-\omega}-1\right], \tag{1}$$

where C_t denotes consumption and L_t is the labor supply. β denotes the household's discount factor, while k_c governs the relative utility weight of labor. The household's budget constraint is given by:

$$C_t + D_t = W_t L_t + \Pi_t + R_{t-1}D_{t-1}, \tag{2}$$

where W_t represents the wage rate, D_t denotes households' deposits, and R_{t-1} is the gross deposit interest rate. Π_t captures the net transfer from bankers to households, defined as the difference between the dividends remitted by exiting bankers and the startup capital allocated to entering bankers.[11]

3.2 Banks

The model features three representative financial intermediaries—an upstream bank (u), a midstream bank (m), and a downstream bank (d)—each partially specialized in financing a segment of the production network. The degree to which banks can fund firms not belonging to their corresponding supply chain segment (sector) will be a key measure of the extensive-margin integration between banks and sup-

[11]We present most optimizing conditions of households, banks, and firms in the Appendix. In the main text, we highlight those that are particularly useful to interpret the mechanisms of the model.

ply chains. As noted above, in recent decades banks have increasingly extended their financing beyond traditional areas of specialization to new supply chain segments.

Banks gather household deposits and leverage their own net worth, denoted by N_t, to extend credit to firms. While, as noted, their primary lending relationships are with firms within their respective sectors, they are also capable of lending to firms in other segments of the supply chain. In addition to granting loans, banks also engage in factoring, purchasing securitized trade credit claims originating within their own sector. Thus, we incorporate the notion that banks are specialized in evaluating the intermediate inputs that back trade credit within their sector.

3.2.1 Upstream banks

The representative upstream bank determines the allocation of its funds by choosing how much to lend to upstream firms (X_t^{uu}), midstream firms (X_t^{um}), and downstream firms (X_t^{ud}), as well as the volume of household deposits it gathers (D_t^u). These decisions are made to maximize the bank's expected present value of future net worth.

$$V_t^u \equiv \max_{\{X_{t+j}^{uu}, X_{t+j}^{um}, X_{t+j}^{ud}, D_{t+j}^u\}_{j\geq 0}} \mathbb{E}_t \sum_{j=0}^{\infty} (1-\sigma)\sigma^j \Lambda_{t,t+j+1} N_{t+j+1}^u. \tag{3}$$

The upstream bank evaluates future payoffs using the stochastic discount factor $\Lambda_{t,t+j+1}$, which is derived from the household's marginal utility of consumption. In addition to providing loans to firms across all sectors, the upstream bank can also purchase securitized trade credit assets from upstream firms. We denote by f^u the fraction of trade credit extended by upstream firms to midstream firms, valued at $f^u V_t^m$, which is purchased by upstream banks. In return, the upstream bank receives $p f^u R_t^{vm} V_t^m$ in the following period, where $p-1$ captures the premium charged by the bank on upstream firms for its factoring activity.[12]

The upstream bank's resource constraint equates the total use of funds—comprising loans to all firm types and securitized trade credit holdings—with the sum of its net worth N_t^u and household deposits D_t^u:

$$X_t^{uu} + X_t^{um} + X_t^{ud} + f^u V_t^m + \sum_{j\in\{m,d\}} \frac{k^b}{2}(X_t^{uj} - \overline{X_t^{uj}})^2 = N_t^u + D_t^u \qquad [\lambda_t^u]. \tag{4}$$

[12] It is immaterial whether the premium is specified as an extra discount on the amount of trade credit that upstream firms can securatize.

The budget constraint also accounts for any possible small adjustment costs faced by the upstream bank when changing its loans relative to their steady state levels. The upstream bank incurs a small quadratic adjustment cost when lending to non-sector firms, captured by the parameter k^b.

To ensure financial soundness, the bank faces a capital constraint that limits its liabilities to households to a fraction ξ of its total assets. These assets include loans to upstream, midstream, and downstream firms, at gross loan rates R_t^{uu}, R_t^{um}, and R_t^{ud} respectively, along with the securitized value of trade credit at R_t^{vm} (weighted by a factor h)[13]

$$R_t D_t^u \leq \xi \left(R_t^{uu} X_t^{uu} + R_t^{um} X_t^{um} + R_t^{ud} X_t^{ud} + h f^u R_t^{vm} V_t^m \right) \qquad [\mu_t^u]. \tag{5}$$

The upstream bank's net worth, N_{t+1}^u, is defined as the difference between total receivables from all firms—including securitized trade credit—and the gross deposit repayment obligations to households:

$$N_{t+1}^u = R_t^{uu} X_t^{uu} + R_t^{um} X_t^{um} + R_t^{ud} X_t^{ud} + p f^u R_t^{vm} V_t^m - R_t D_t^u. \tag{6}$$

3.2.2 Midstream and downstream banks

The midstream bank faces a problem analogous to the upstream bank. It takes deposits from households and grants loans to upstream (X_t^{mu}), midstream (X_t^{mm}), and downstream firms (X_t^{md}), while also purchasing securitized trade credit from midstream-to-downstream transactions in the amount $f^m V_t^d$ (with the profit margin $p-1$). The bank maximizes the expected discounted value of future net worth:

$$V_t^m \equiv \max_{\{X_{t+j}^{mu}, X_{t+j}^{mm}, X_{t+j}^{md}, D_{t+j}^m\}_{j\geq 0}} \mathbb{E}_t \sum_{j=0}^{\infty} (1-\sigma)\sigma^j \Lambda_{t,t+j+1} N_{t+j+1}^m \tag{7}$$

$$\text{s.t.} \quad X_t^{mu} + X_t^{mm} + X_t^{md} + f^m V_t^d + \sum_{j\in\{u,d\}} \frac{k^b}{2}(X_t^{mj} - \overline{X_t^{mj}})^2 = N_t^m + D_t^m \qquad [\lambda_t^m], \tag{8}$$

$$R_t D_t^m \leq \xi \left(R_t^{mu} X_t^{mu} + R_t^{mm} X_t^{mm} + R_t^{md} X_t^{md} + h f^m R_t^{vd} V_t^d \right) \qquad [\mu_t^m]. \tag{9}$$

The downstream bank solves an analogous problem, choosing the amount of lending to firms and maximizing the present value of future net worth. Unlike the other banks, however, it does not hold any

[13] The parameter h can capture the regulatory treatment of factored trade credit in regulatory based bank capital requirements as well the perception of outside bank investors about such factored assets in market based capital requirements. Observe that the extra factoring profits of upstream banks are added to the banks' net worth but are not included in their capital constraints, as they are not typically classified as bank assets.

securitized trade credit assets, as downstream firms do not extend trade credit:

$$V_t^d \equiv \max_{\{X_{t+j}^{du}, X_{t+j}^{dm}, X_{t+j}^{dd}, D_{t+j}^d\}_{j\geq 0}} \mathbb{E}_t \sum_{j=0}^{\infty} (1-\sigma)\sigma^j \Lambda_{t,t+j+1} N_{t+j+1}^d, \tag{10}$$

$$\text{s.t.} \quad X_t^{du} + X_t^{dm} + X_t^{dd} + \sum_{j\in\{u,m\}} \frac{k^b}{2}(X_t^{dj} - \overline{X_t^{dj}})^2 = N_t^d + D_t^d \qquad [\lambda_t^d], \tag{11}$$

$$R_t D_t^d \leq \xi \left(R_t^{du} X_t^{du} + R_t^{dm} X_t^{dm} + R_t^{dd} X_t^{dd} \right) \qquad [\mu_t^d]. \tag{12}$$

3.3 Firms

Upstream, midstream and downstream firms are owned and operated by entrepreneurs with utility function

$$\mathbb{E}_t \sum_{j=0}^{\infty} \beta_f^j \frac{(C_{t+j}^r)^{1-\gamma} - 1}{1-\gamma}, \tag{13}$$

with $r \in \{u, m, d\}$. β_f is the discount factor used by all entrepreneurs. Entrepreneurs are assumed to be less patient than households ($\beta_f < \beta$). This is a necessary condition for firms being willing to borrow from banks.

Final good producers aggregate goods produced by firms in the supply chain in order to produce the final good.

3.3.1 Upstream firms

The production flow of the supply chain starts from upstream firms. An upstream firm uses capital K_{t-1}^u and labor L_t^u to produce its output Y_t^u. The production technology of upstream firms is

$$Y_t^u = z(K_{t-1}^u)^{\alpha}(L_t^u)^{1-\alpha}, \tag{14}$$

where z denotes the total factor productivity (TFP), and $0 < \alpha < 1$.

Upstream firms can secure external financing from upstream banks, which specialize in serving their sector, and also from banks specialized in other segments of the supply chain. In turn, upstream firms can extend trade credit to midstream firms. The upstream firm's budget constraint reads:

$$\begin{aligned} &C_t^u + K_t^u + R_{t-1}^{uu} X_{t-1}^{uu} + R_{t-1}^{mu} X_{t-1}^{mu} + R_{t-1}^{du} X_{t-1}^{du} + (1-f^u)V_t^m \\ &\quad = X_t^{uu} + X_t^{mu} + X_t^{du} + (1-\delta)K_{t-1}^u + (1-pf^u)R_{t-1}^{vm} V_{t-1}^m - W_t L_t^u + P_t^u Y_t^u, \end{aligned} \tag{15}$$

where X_t^{uu}, X_t^{mu}, and X_t^{du} are the loans from upstream, midstream, and downstream banks, respectively. P_t^u denotes the price of the upstream good Y_t^u in terms of the final good. Trade credit extended to midstream firms is represented by V_t^m, with associated interest rate R_t^{vm}. By securitizing a fraction f^u of its accounts receivable, the upstream firm obtains immediate liquidity $f^u V_t^m$ in the current period in exchange for transferring the obligation to repay $pf^u R_t^{vm} V_t^m$ in the subsequent period, where $p > 1$ represents the gross factoring premium charged by the upstream bank.

As noted, due to limited contract enforceability, the upstream firm must pledge collateral when borrowing from banks. Specifically, it can pledge physical capital to obtain loans from sector (upstream) banks and non-sector banks. In addition, the firm can borrow from its own sector banks by pledging accounts receivable (that is, by discounting invoices). Formally, the upstream firm faces two collateral constraints:

$$R_t^{mu} X_t^{mu} + R_t^{du} X_t^{du} \leq \kappa^n (1 - S_t^u) K_t^u \qquad [\psi_t^{nu}], \tag{16}$$

$$R_t^{uu} X_t^{uu} \leq \kappa S_t^u K_t^u \left(1 - \frac{c S_t^u K_t^u}{2\overline{K^u}}\right) + (1 - f^u)\Omega(f^u) R_t^{v,m} V_t^m \qquad [\psi_t^{uu}], \tag{17}$$

where $S_t^u \in [0,1]$ is the share of capital pledged to the upstream bank and $(1 - S_t^u)$ is the share of capital pledged to non-sector banks. Given that the uptream bank is specialized in the upstream sector in which the firm operates, pledging capital to the upstream bank is relatively easier ($\kappa > \kappa^n$). However, it encounters diseconomies to scale, so that the upstream firm can choose to partially resort to non-sector banks.[14] We will treat κ^n as a parameter governing the degree of bank-supply chain integration along the "extensive" margin, capturing banks' ability to manage non-specialized collateralized capital in supply chain segments outside their traditional sector of specialization. The term $\Omega(f^u)$, on the other hand, governs the pledgeability of non-factored accounts receivable. This will be key for capturing the degree of integration between banks and supply chains along the "intensive" margin, as determined by banks' ability to manage collateralized accounts receivable and engage in invoice discounting. The term $\Omega(f^u)$ depends on the fraction f^u of trade credit receivables that is factored (i.e., securitized and sold) to the upstream bank, as we will elaborate below.

Upstream firms maximize their utility in (13) by choosing consumption C_t^u, labor demand L_t^u, physical capital K_t^u, bank loans X_t^{uu}, X_t^{mu} and X_t^{du}, trade credit extended to midstream firms V_t^m, and the fraction of capital pledged to sector (upstream) banks S_t^u, subject to the budget constraint (15) and the

[14] The intensity of these diseconomies to scale is governed by the parameter c.

collateral constraints (16) and (17). Their first-order conditions read

$$[\partial L_t^u]: P_t^u(1-\alpha)\frac{Y_t^u}{L_t^u} - W_t = 0 \tag{18}$$

$$[\partial K_t^u]: -(C_t^u)^{-\gamma} + \psi_t^{nu}\kappa^n(1-S_t^u) + \psi_t^{uu}\left[\kappa S_t^u - \frac{\kappa c(S_t^u)^2 K_t^u}{\overline{K^u}}\right] + \beta_f E_t(C_{t+1}^u)^{-\gamma}(P_{t+1}^u\alpha\frac{Y_{t+1}^u}{K_t^u} + 1 - \delta) = 0 \tag{19}$$

$$[\partial X_t^{uu}]: (C_t^u)^{-\gamma} - \psi_t^{uu}R_t^{uu} - \beta_f E_t(C_{t+1}^u)^{-\gamma}R_t^{uu} = 0 \tag{20}$$

$$[\partial X_t^{mu}]: (C_t^u)^{-\gamma} - \psi_t^{nu}R_t^{mu} - \beta_f E_t(C_{t+1}^u)^{-\gamma}R_t^{mu} = 0 \tag{21}$$

$$[\partial X_t^{du}]: (C_t^u)^{-\gamma} - \psi_t^{nu}R_t^{du} - \beta_f E_t(C_{t+1}^u)^{-\gamma}R_t^{du} = 0 \tag{22}$$

$$[\partial V_t^m]: (C_t^u)^{-\gamma}[-(1-f^u)] + \psi_t^{uu}(1-f^u)\Omega(f^u)R_t^{v,m} + \beta_f E_t(C_{t+1}^u)^{-\gamma}(1-pf^u)R_t^{v,m} = 0 \tag{23}$$

$$[\partial S_t^u]: -\psi_t^{nu}\kappa^n K_t^u + \psi_t^{uu}\kappa K_t^u\left(1 - \frac{cS_t^u K_t^u}{\overline{K^u}}\right) = 0 \tag{24}$$

Consider the demand for capital in (19). When investing in capital, upstream firms account not only for the future productivity of capital but also for the marginal value of capital as collateral in relaxing borrowing constraints vis-a-vis sector (upstream) banks and non-sector banks. In a similar fashion, when deciding how much trade credit to supply to midstream firms (see (23)), upstream firms account not only for the expected repayment of gross interests but also for the marginal value of accounts receivable as collateral in relaxing borrowing constraints vis-a-vis sector (upstream) banks. This marginal value is increasing in the Lagrangian multiplier ψ^{uu} and in the term $\Omega(f^u)$ that captures the pledgeability of accounts receivable.

Further, consider the choice of how to allocate collateralized capital between sector and non-sector banks (see (24)). When making this choice, upstream firms equalize the marginal value of capital as collateral between sector and non-sector banks.

3.3.2 Midstream firms

Midstream firms use capital K_t^m, labor L_t^m, and intermediate goods (output of upstream firms) Y_t^{iu} as inputs:[15]

$$Y_t^m = z({K_{t-1}^m}^{\alpha}{L_t^m}^{1-\alpha})^{1-\phi}(Y_t^{iu})^{\phi}. \tag{25}$$

[15] As noted a portion of the output Y_t^u of upstream firms, denoted Y_t^{FU}, is used directly in final good production, while the remainder, Y_t^{iu}, is used as intermediate input by midstream firms.

They can obtain bank loans X_t^{um}, X_t^{mm} and X_t^{dm} from upstream, midstream, and downstream banks, respectively, and receive trade credit V_t^m from upstream firms. They also provide trade credit V_t^d to downstream firms, a portion of which can be factored to midstream banks. Their budget constraint reads

$$
\begin{aligned}
& C_t^m + K_t^m + R_{t-1}^{um} X_{t-1}^{um} + R_{t-1}^{mm} X_{t-1}^{mm} + R_{t-1}^{dm} X_{t-1}^{dm} + R_{t-1}^{v,m} V_{t-1}^m + (1-f^m) V_t^d = \\
& \quad X_t^{um} + X_t^{mm} + X_t^{dm} + V_t^m + (1-pf^m) R_{t-1}^{vd} V_{t-1}^d + (1-\delta) K_{t-1}^m + P_t^m Y_t^m - W_t L_t^m - P_t^u Y_t^{iu}, \quad (26)
\end{aligned}
$$

where P_t^m is the price of the midstream firm's product in terms of the final good. Midstream firms face the following borrowing constraints:

$$R_t^{um} X_t^{um} + R_t^{dm} X_t^{dm} \leq \kappa^n (1-S_t^m) K_t^m \qquad [\psi_t^{nm}], \quad (27)$$

$$R_t^{mm} X_t^{mm} \leq \kappa S_t^m K_t^m \left(1 - \frac{c S_t^m K_t^m}{2\overline{K^m}}\right) + (1-f^m)\Omega(f^m) R_t^{v,d} V_t^d \qquad [\psi_t^{mm}], \quad (28)$$

$$R_t^{v,m} V_t^m \leq \nu P_t^u Y_t^{iu} \qquad [\chi_t^m]. \quad (29)$$

The interpretation of the collateral constraints (27) and (28) is analogous to those incurred by upstream firms. (29) is the borrowing constraint when midstream firms borrow trade credit. Due to limited enforcement problems, they need to pledge a fraction ν of the intermediate inputs purchased from the upstream firm as collateral.

Midstream firms maximize the entrepreneurs' utility (13), subject to the budget constraint (26) and the borrowing constraints (27), (28), and (29). It is useful to report here the first-order conditions for their supply of trade credit to downstream firms and for their demand of trade credit from upstream firms (see the Appendix for the full set of optimizing conditions):

$$[\partial V_t^d] : (C_t^m)^{-\gamma}[-(1-f^m)] + \psi_t^{mm}\Omega(f^m) R_t^{vd} + \beta_f E_t (C_{t+1}^m)^{-\gamma}(1-pf^m) R_t^{vd} = 0, \quad (30)$$

$$[\partial V_t^m] : (C_t^m)^{-\gamma} - \chi_t^m R_t^{v,m} - \beta_f E_t (C_{t+1}^m)^{-\gamma} R_t^{v,m} = 0. \quad (31)$$

The intuition for the supply of trade credit in (30) is analogous to that seen for the trade credit supply of upstream firms. As for the trade credit demand in (31), when choosing such demand, midstream firms weigh the benefit of obtaining liquidity from suppliers against the cost of repaying trade credit in the following period, inclusive of interests, as well as the cost of tightening their trade credit borrowing constraint (governed by the Lagrangian multiplier χ.) Combining (30) and (31), it is possible to prove that in our setting midstream firms act as intermediaries of liquidity (simultaneously demanding and supplying trade credit) even when trade credit rates are equal along the supply chain (see the Appendix for a formal proof).

3.3.3 Downstream firms

Downstream firms use capital K_t^d, labor L_t^d and midstream firms' output Y_t^{im} as inputs to produce output Y_t^d:[16]

$$Y_t^d = z({K_{t-1}^d}^{\alpha} {L_t^d}^{1-\alpha})^{1-\phi} (Y_t^{im})^{\phi}. \tag{32}$$

In addition to taking loans from downstream banks (X_t^{dd}) and non-sector banks (X_t^{ud}, X_t^{md}), they can also receive trade credit from midstream firms (V_t^d). Their budget constraint is

$$C_t^d + K_t^d + R_{t-1}^{ud} X_{t-1}^{ud} + R_{t-1}^{md} X_{t-1}^{md} + R_{t-1}^{dd} X_{t-1}^{dd} + R_{t-1}^{v,d} V_{t-1}^d = \tag{33}$$

$$X_t^{ud} + X_t^{md} + X_t^{dd} + V_t^d + (1-\delta) K_{t-1}^d + P_t^d Y_t^d - W_t L_t^d - P_t^m Y_t^{im}. \tag{34}$$

P_t^d is the price of the downstream firm's good. The output of downstream firms is entirely sold to produce the final good. Downstream firms face financing constraints when borrowing from banks and midstream firms analogous to those discussed above:

$$R_t^{ud} X_t^{ud} + R_t^{md} X_t^{md} \leq \kappa^n (1 - S_t^d) K_t^d \qquad [\psi_t^{nd}], \tag{35}$$

$$R_t^{dd} X_t^{dd} \leq \kappa S_t^d K_t^d \left(1 - \frac{c S_t^d K_t^d}{2\overline{K^d}}\right) \qquad [\psi_t^{dd}], \tag{36}$$

$$R_t^{v,d} V_t^d \leq \nu P_t^d Y_t^d \qquad [\chi_t^d]. \tag{37}$$

3.3.4 Final good producers

A final good producer aggregates all the products of the firms in the supply chain to produce the final good Y_t. This is the numeraire of the economy and is consumed by households and entrepreneurs. The final good producer uses a CES technology to produce the final good. The problem of the final good

[16] Similar to the output of upstream firms, the output of midstream firms is sold to produce the downstream firms' good and the final good ($Y_t^m = Y_t^{im} + Y_t^{fm}$).

producer reads:

$$\max_{\{Y_t^{fu}, Y_t^{fm}, Y_t^d\}} \quad Y_t - P_t^u Y_t^{fu} - P_t^m Y_t^{fm} - P_t^d Y_t^d \tag{38}$$

$$s.t. \quad Y_t = \left[\alpha_u (Y_t^{fu})^\varepsilon + \alpha_m (Y_t^{fm})^\varepsilon + (1-\alpha_u-\alpha_m)(Y_t^d)^\varepsilon\right]^{\frac{1}{\varepsilon}}, \tag{39}$$

where α_u and α_m are parameters between 0 and 1.

3.4 Equilibrium

In equilibrium, the total supply of household labor (L_t) equals the aggregate of labor employed by the upstream (L_t^u), midstream (L_t^m) and downstream (L_t^d) firms:

$$L_t = L_t^u + L_t^m + L_t^d. \tag{40}$$

The evolution of net worth for each aggregate banking sector is

$$N_{t+1}^u = \sigma\left(\sum_{j\in\{u,m,d\}} R_t^{uj} X_t^{uj} + pf^u R_t^{v,m} V_t^m - R_t D_t^u\right) + \iota\left(\sum_{j\in\{u,m,d\}} R_t^{uj} X_t^{uj} + pf^u R_t^{v,m} V_t^m\right) + \bar{N}^u \upsilon_{t+1}^u, \tag{41}$$

$$N_{t+1}^m = \sigma\left(\sum_{j\in\{u,m,d\}} R_t^{mj} X_t^{mj} + pf^m R_t^{v,d} V_t^d - R_t D_t^m\right) + \iota\left(\sum_{j\in\{u,m,d\}} R_t^{mj} X_t^{mj} + pf^m R_t^{v,d} V_t^d\right) + \bar{N}^m \upsilon_{t+1}^m, \tag{42}$$

$$N_{t+1}^d = \sigma\left(\sum_{j\in\{u,m,d\}} R_t^{dj} X_t^{dj} - R_t D_t^d\right) + \iota\left(\sum_{j\in\{u,m,d\}} R_t^{dj} X_t^{dj}\right) + \bar{N}^d \upsilon_{t+1}^d, \tag{43}$$

where υ_t^j is a shock to the net worth of the banks in a certain sector $j \in \{u,m,d\}$.

The social resource constraint reads

$$C_t + \sum_{j\in\{u,m,d\}} (C_t^j + K_t^j - (1-\delta)K_{t-1}^j) + \sum_{\substack{i,j\in\{u,m,d\}\\ i\neq j}} \frac{k^b}{2}(X_t^j - \overline{X_t^j})^2 = Y_t. \tag{44}$$

The full set of first-order conditions and market clearing conditions are presented in the Appendix.

3.5 Modelling collateral pledgeability and banks' skills

In what follows, we further elaborate on the specification of firms' borrowing constraints.

Factoring and invoice discounting In our specification, the functions $\Omega(f^u)$ and $\Omega(f^m)$ govern the pledgeability of accounts receivable. Following a broad literature in supply chain finance and in accordance with the view of practitioners, we allow a greater factoring intensity to increase banks' efficiency in managing and repossessing pledged invoices. A broad body of studies documents that, through the factoring process, a bank can acquire information and insight into the status, trustworthiness and financial health of suppliers and customers. In particular, though their factoring activity banks build relationships with suppliers and customers, acquire information useful to assess the risk and creditworthiness of firms' customers, collect data on customers' payment history and patterns, and on fraud indicators. Thus, by building such informational relationships and deeper understanding of customers' payment behavior, factoring banks also become more efficient and experienced in discounting invoices involving the same suppliers and customers and, hence, can pledge a greater share of their remaining accounts receivable as collateral. We capture this features by letting

$$\Omega(f^u) = \theta f^u; \quad \Omega(f^m) = \theta f^m. \tag{45}$$

The parameter θ can capture the impact of institutional and legal features and business practices on the diffusion of invoice discounting in the economy. The specification of $\Omega(f)$ effectively implies that the factoring parameter f scales the pledgeable value of non-factored trade credit claims ($R_t^{vm} V_t^m$ for upstream firms).[17] This can capture the impact of experience acquired through factoring on banks' ability to manage invoice discounting. In the Appendix, we further provide a microfoundation of the functions $\Omega(f^u)$ and $\Omega(f^m)$ along these lines.

Clearly, in an opposite direction, as shown by the borrowing constraints (17) and (28), a greater use of factoring f^u or f^m also pushes more accounts receivable off firms' balance sheets. This mechanically reduces the pledgeability of accounts receivable for suppliers.

Capital pledging to specialized and non-specialized banks In our specification, firms can pledge capital assets both to banks specialized in their supply chain segment and to banks specialized in other segments. In particular, capital pledgeability is initially larger for specialized banks. However, due to diseconomies to scale, at some point the marginal pledgeability of capital assets to specialized banks becomes equal to that of non-sector banks. This specification follows a broad literature that studies the

[17] Thus, the effective pledgeability of accounts receivable as collateral is given by the product between θ and f.

allocation of collateral among lenders with different collateral expertise. Intuitively, similar to several studies in this literature, one can think that initially the most specific projects and capital assets are pledged to specialized banks. However, as pledges increase, a borrowing firm will start pledging less specific projects and assets, on which specialized banks have a lower comparative advantage. Moreover, the scarce monitoring, expertise and evaluation tools of specialized banks will become more strained as they have more collateral capital to manage, monitor, and repossess. Together, these forces will imply that the marginal benefit of using specialized banks will progressively decrease, leading to an interior allocation of collateral capital (and borrowing) between sector and non-sector banks.

4 Model Analysis

We study the effects of financial shocks, in the form of bank net worth shocks. We are interested in the mechanisms of transmission of the shocks and, particularly, in understanding how different dimensions of integration between the banking sector and the production structure shape this transmission, enhancing or reducing macroeconomic resilience.

Inspired by the evidence presented above, we focus on two primary dimensions of bank-supply chain integration. The first is bank-supply chain integration along the extensive margin, meant as the ability of firms in the supply chain to borrow from banks specialized in other segments of the supply chain (non-sector banks). The second is bank-supply chain integration along the intensive margin, meant as the intensity in the usage of bank supply chain financing (invoice discounting and factoring).

4.1 Calibration

Table 2 reports the calibrated values of the model parameters, while Table 3 displays the calibration targets. There are 23 parameters in the model, four pertaining to the household sector, 14 to the firm sector, and five to the banking sector. Of the 23 parameters, 15 adopt standard values commonly used in the literature. On the household side, we set the household discount factor $\beta = 0.99$, which implies a steady-state annual deposit rate of approximately 4%, and impose log utility by fixing the parameter governing risk aversion $\omega = 1$. The labor-disutility weight $k_c = 5.584$ follows Gertler and Kiyotaki (2010), and the inverse Frisch elasticity $\eta = 0.75$ is consistent with Chetty et al. (2011). On the banks' side, following, e.g., Gertler and Kiyotaki (2010) we set a survival rate $\sigma = 0.975$, which implies an expected banker tenure of roughly ten years, and we choose a small entry transfer $\iota = 0.0001$ so that inflows to new bankers remain negligible. On the firms' side, we set the firm discount factor to $\beta_f = 0.98$, making firms slightly more impatient than households, and adopt a quarterly capital depreciation rate $\delta = 0.025$, as in a broad strand of studies in macroeconomics. We choose $\gamma = 0$ to model all firms as risk neutral. The intermediate input share is set to $\phi = 0.5$ so to reflect the sizable role of intermediates in total costs (Leibovici 2021; Nakamura and Steinsson 2010; Atolia and Chahrour 2020). We choose a value of α such that the share of gross revenues accruing to capital is in line with previous studies incorporating intermediate inputs in production. Leibovici (2021) sets a value of α such that capital accounts for one fourth of gross revenues, while Atolia and Chahrour (2020) target a share of capital of about 13% (with intermediate inputs accounting for 60% of gross revenues). [...] estimate a share of capital of 22% using Italian data. We target a share of capital in the middle of these values, equal to 20%. For the final good producer, we set $\varepsilon = 0.75$, which implies an elasticity of substitution in final good production (ε) equal to 4. This value is commonly used in the literature to reflect moderate monopolistic competition among differentiated inputs. The CES weights for upstream and midstream goods in final good production, $\alpha_u = 0.2$ and $\alpha_m = 0.35$, are motivated by input-output data from WIOD and OECD, which show that downstream sectors—being closer to final consumption—contribute more to final output production (Antràs and Fally 2012).

The remaining nine parameters (ξ, κ, κ^n, θ, c, f^u, f^m, ν, and p) are specific to our model and are chosen to match empirical targets. The collateral parameters, κ, κ^n, and c, govern the pledgeability of capital assets and, hence, influence the tightness of firms' borrowing constraints vis-a-vis banks. ξ determines the weight on assets in the capital constraints of banks and, hence, the tightness of banks' capital constraints. ν affects the tightness of firms' borrowing constraints vis-a-vis suppliers. The parameter p governs banks' profit margin in factoring. The parameters f^u and f^m denote the fraction of trade credit receivables that is factored (i.e., securitized and sold) to upstream banks and midstream banks, respectively. Since we do not intend to finely distinguish the factoring intensity across supply chain segments, we let the factoring intensity to be the same for the two bank types and denote it by f.

The internally calibrated parameters are chosen to match the following targets: banks' leverage ratio, firms' leverage ratio, firms' ratio of accounts receivable to bank borrowing, firms' ratio of net trade credit to bank borrowing, banks' ratio of factored assets to loans, the spread between loan rates and deposit rates, the spread between trade credit rates and loan rates, and the profit margin generally observed in the Italian factoring market. We target a leverage ratio of banks of 5, which is approximately the mean leverage ratio observed in our sample of Italian banks. This implies that bank liabilities do not exceed 80% of assets, consistent also with Gertler and Kiyotaki (2010). We target a leverage ratio of firms of 0.58. In the data, firms' ratio of accounts receivable to bank borrowing is 26%, while firms' ratio of net trade credit to bank borrowing is 5%. We target a ratio of banks' factored assets to bank loans of 5%. In the data, the annual loan-deposit spread and trade credit-loan spread equal 1.3% and 2%, respectively. Finally, the parameter p for banks' profit margin in factoring is set to a very small value to approximate the highly competitive factoring market observed in Italy.

Given these targets, we set $\kappa = 0.6$ and $\kappa^n = 0.5$. Further, we set $\theta = 1.2$ so that with f, the effective pledgeability $\Omega(f)$ equals 0.36. Finally, we set a very low value of $p = 1.001$.[18] The calibrated value of $\nu = 1.5$ implies that two-thirds of accounts payable need to be backed by intermediate inputs.[19]

4.2 The response to banking shocks

The mechanisms that shape the transmission of a banking shock reflect the nature of supply chain linkages and the influence of financial integration on such linkages. In our setting, as noted, we distinguish between the extensive margin of bank-supply chain integration, meant as the ability of banks to supply credit to firms outside their traditional sector (supply chain segment) of specialization, and the intensive margin of bank-supply chain integration, meant as the provision of bank loans backed by accounts receivable (invoice discounting) and banks' purchase of accounts receivable (factoring).

4.2.1 Baseline results

We perturb the economy with a banking shock that directly reduces the net worth of banks. We focus on a 10% shock to midstream banks' net worth, and then verify that the conclusions hold for shocks to other segments of banks. Bank net worth shocks can reflect drops in the capitalization of banks due to crises in asset markets in which banks have relevant involvement, such as markets for sovereign debt and for real estate related securities. They can also capture drops in banks' capitalization due to misbehavior of bank managers, ineffective bank investment and acquisition activities, or siphoning of resources from banks induced by political interference. Our focus on midstream banks is primarily motivated by the

[18] Graham, Leary, and Roberts (2015)report that the debt-to-asset ratio is 28-32% for US public firms. Fan, Titman, and Twite (2012) find that Western European firms typically have a 30–45% debt-to-asset ratio. Ulbert, Takács, and Csapi (2022) report a debt-to-equity ratio of 1.38 based on 4,550 firm-year observations.

[19] Levine, Lin, and Xie (2018) find that trade credit accounts for about 25% of firms' total debt liabilities across a broad cross-country sample covering over 3,500 firms from 34 countries.

empirical evidence: as we will see, our banking shock measure is constructed from the crisis of a major Italian bank with has traditionally focused on lending to mid-stream industries.

Figure 2 presents the baseline impulse responses for key variables—banks' net worth (N), bank lending (X), interest rates (R), trade credit (V), total bank borrowing by firm ($U, M, Dloans$), capital (K), the Lagrangian multipliers on bank-borrowing constraints (ψ), the share of capital pledged to the sectoral bank (S), and output (Y). The baseline impulse responses reveal heterogeneous sectoral adjustments. The contraction in midstream banks' net worth leads to a decline in their loan supply to midstream firms (X^{mm}), inducing an increase in the associated loan rate R^{mm}. Midstream firms tilt toward borrowing from non-sector banks: they attempt to replace midstream banks' loans with other loans by reshuffling the capital pledged as collateral from midstream banks to upstream and downstream banks (observe the reduction in S^m). However, the increase in loans from non-sector banks (X^{um} and X^{dm}) is modest and insufficient to compensate for the loan contraction of midstream banks: the total bank lending to midstream firms ($MLoan$) declines. Intuitively, the non-sector banks focus on providing credit to their sector firms, mitigating the loan shortfall induced by the shock to midstream banks. The trade credit extended by upstream firms to midstream firms (V^m) drops too, aggravating the financial shortage suffered by midstream firms. As a result, both their purchase of intermediate inputs and capital and their production drop.

Upstream and downstream firms increasingly rely on in-sector finance to buffer the disturbance. In the case of upstream and downstream firms, in fact, there is some increase in credit, facilitated by the increase in the net worth of their sector banks, which benefit from the higher loan rate they can charge to midstream firms as well as from the increase in loans they can extend to upstream and downstream firms.[20] However, the resulting increase in the production of upstream firms is not enough to compensate for the output contraction of midstream firms, leading to an overall output loss.[21] As we are going to see next, bank-supply chain integration along the extensive and intensive margins can significantly affect these baseline effects of a banking shock.

[20] This substitution between trade credit and bank loans is consistent with empirical findings from Petersen and Rajan (1997) and Nilsen (2002), which document such financing trade-offs. In our model, this substitution emerges in a sector that is not directly affected by the shock, reflecting firms' adaptive reallocation of funding sources when financial stress arises in adjacent sectors.

[21] The output of downstream firms drops too.

4.2.2 Bank-supply chain integration

As we shall see in the following, the two dimensions of bank-supply chain integration (extensive and intensive margin) have sharply asymmetric consequences for the amplification of banking shocks. This asymmetric influence can be reconducted to the same logic: the influence of bank-supply chain integration on banks' skills and experience in providing collateralized finance. In both cases, a higher degree of financial integration improves the pledgeability of a type of collateral, as it entails a stronger ability of banks to manage, repossess and liquidate collateral, and hence extend financing. Bank-supply chain integration along the extensive margin improves the pledgeability of physical capital assets to banks traditionally specialized in other segments of the supply chain. Following supply-side banking shocks, this exacerbates the sensitivity of the demand for capital as collateral to reductions in firms' appetite for the now costlier bank loans, further depressing firms' capital investment and production. Bank-supply chain integration along the intensive margin, on the other hand, enhances the pledgeability of trade credit to banks. This increases the sensitivity of collateralized trade credit supply to tightenings of borrowing constraints for suppliers (which, as we will see, occur following loan supply shocks to downstream supply chain segments). In turn, this stimulates trade credit extension by suppliers, also driving up bank credit (due to the complementarity between intermediate inputs and other production inputs).

4.2.3 Extensive margin of bank-supply chain integration

The integration between banks and supply chains along the extensive margin can be represented as a higher value of the parameter κ^n, which captures the efficiency of non-sector banks at managing capital as collateral. A higher κ^n implies that non-sector banks get closer to the efficiency of banks specialized in the segment of the supply chain.[22] Figure 3 compares impulse responses across alternative levels of κ^n following a midstream banking shock. Overall, we observe that in our setting stronger bank-supply chain integration along the extensive margin does not lead to greater resilience to a banking shock, and a higher κ^n can actually amplify the effects of a shock. On the one hand, the midstream firms hit by the shock reduce by more their pledging of collateral and their capital investment. They also tend to reshuffle more their capital pledging from sector to non-sector banks (S^m drops by nearly 20%). However, non-sector banks do not compensate for the drop in credit from sector banks. They indeed

[22] In the model, all firms borrow both from sector banks and non-sector banks. An extreme form of segmentation of the credit market would occur if firms only borrowed from sector banks, that is, κ^n was so low that firms choose to get loans only from sector banks.

tend to serve more the firms operating in their own supply chain segments, while curtailing credit to midstream firms: under a higher κ^n, the initial expansion in X^{um} and X^{dm} is reduced from about 10% to roughly 2%. Taken together, these adjustments depress collateral demand more, as evidenced by the sharper contraction in midstream firms' capital investment (K^m).

On the bank side, following the shock, the reduction in the net worth N^m of midstream banks is larger under stronger extensive-margin integration than with lower integration, while upstream and downstream banks experience larger increases in net worth. As noted, non-sector banks reallocate credit toward their own sectoral clients—$X^{uu}$and X^{dd} rise— offsetting the shortfall in lending from midstream banks. As a result, the loan rate charged to midstream borrowers increases by roughly 4 percentage points.

Digging deeper into the mechanisms, a higher κ^n tends to raise firms' demand for capital as collateral, and increase the sensitivity of such demand to changes in the multipliers on borrowing constraints. This can be seen by combining midstream firms' first-order condition for capital demand with their first-order condition for the allocation of capital as collateral to sector and non-sector banks (that is, the counterparts of upstream firms' first-order conditions in (19) and (24), respectively. See the Appendix). Recalling our assumption $\gamma = 0$, after some algebra:

$$E_t P_{t+1}^m (1-\phi)\alpha \frac{Y_{t+1}^m}{K_t^m} = \frac{1-\psi_t^{nm}\kappa^n}{\beta_f} - 1 + \delta. \tag{46}$$

Consider then the effect of a negative banking shock hitting the net worth of midstream banks. As expected, the Lagrangian multiplier (ψ^{mm}) on firms' borrowing constraint drops: midstream banks' loan supply shrinks, raising their loan rate (R^{mm}) and, hence, reducing midstream firms' appetite for their loans. The Lagrangian multipliers ψ^{nm} and ψ^{mm} are naturally tied to each other through the first-order conditions for firms' borrowing, implying that ψ^{nm} also drops. The effect of this drop in the borrowing constraint multiplier ψ^{nm} of midstream firms is amplified by a larger κ_n, leading to a larger reduction in midstream firms' incentive to demand capital as collateral and, hence, an overall larger drop in their capital investment (see equation (46)).

A larger κ_n also leads to a bigger reshuffling of the pledging of capital towards non-sector banks, further worsening midstream banks' net worth status. Intuitively, this happens because the reduction in the tightness of the borrowing constraint reduces more the gap in capital pledgeability between sector and non-sector banks. This can be understood by rearranging midstream firms' first-order condition for the share of capital pledged to midstream banks (S^m):

$$\frac{cS_t^m K_t^m}{\overline{K^m}} = 1 - \frac{\psi_t^{nm}\kappa^n}{\psi_t^{mm}\kappa} \tag{47}$$

However, the reshuflling does not result into a larger extension of loans by non-sector banks, and overall stronger bank-supply chain integration along the extensive margin leads to a sharper contraction of total output Y.

Interestingly, for an empirical researcher, when κ^n is higher, the responses to the banking shock of the investment and loan flows of the various types of firms would suggest a stronger segmentation across both credit markets and supply chains. This contrasts with the view that bank–supply chain integration along the extensive margin could improve risk sharing in the face of shocks.

4.2.4 Intensive margin of bank-supply chain integration

In what follows, we investigate the influence of the intensive margin of bank-supply chain integration on the transmission of banking shocks. A first form of such integration between banks and supply chains can be captured by the parameter θ, which governs the ability of firms to pledge trade credit (accounts receivable) as collateral for bank loans. A second form of such dimension of bank-supply chain integration can be reflected in the parameter f, which measures the intensity of factoring. Regulations and industry practices lead to significant cross-sectional (cross-country and cross-industry) variation in the use of invoice discounting and factoring.

Invoice discounting and the pledgeability of accounts receivable Figure 4 contrasts impulse responses under high versus low trade credit pledgability (θ). A higher pledgeability of accounts receivable (higher θ) tends to raise the demand for trade credit as collateral, stimulating the extension of trade credit to customers along the supply chain.[23] In fact, if invoice discounting is used, trade credit is not only extended to earn returns but also to facilitate borrowing from banks. We observe that a higher θ can moderate the effects of banking shocks. In particular, following a negative shock to midstream banks' net worth, a higher θ implies that the amount of trade credit extended by upstream firms to midstream firms (V^m) drops less, and the associated trade credit rate (R^{vm}) drops more. Indeed, the lower trade credit rate results in a smaller contraction of the trade credit taken by midstream firms and in a stronger

[23]To continue to match data targets, when changing θ we accordingly adjust the parameter h.

resilience in their demand for intermediate inputs (Y^{iu}). We also observe that when θ is higher, there is an increased reliance of midstream firms on their own sector bank loans. These effects contrast with what was observed under a stronger bank-supply chain integration along the extensive margin (larger κ^n). Recall that in that case, in fact, while it was still the case that the trade credit rate dropped more, the amount of trade credit extended by upstream firms to midstream firms dropped by a larger amount.

To gain intuition on these effects, observe that the Lagrangian multiplier ψ^{uu} on the borrowing constraint of upstream firms rises following the midstream banks' net worth shock (see again Figure 4).[24] A higher pledgeability of accounts receivable increases the sensitivity of trade credit extension to changes in the tightness (Lagrangian multiplier) of borrowing constraints, as induced, e.g., by changes in the supply of credit by banks. This can be understood by recalling upstream firms' first-order condition for the supply of trade credit to midstream firms ((23)). After some algebraic manipulations:

$$R_t^{vm} = \frac{1-f}{\beta_f(1-pf) + \psi_t^{uu}\theta f(1-f)} \tag{48}$$

An increase in the multiplier ψ^{uu} exerts a greater downward pressure on the trade credit rate demanded by upstream firms when θ is higher. Intuitively, any increase in the Lagrangian multiplier on upstream banks' borrowing constraint gets amplified by a larger θ as upstream firms have a stronger incentive to extend trade credit in order to pledge it as collateral. This results in a larger trade credit extension to midstream firms.[25] In Figure 4, we can see this in the higher amount (smaller reduction) of trade credit offered by upstream firms to the shock-hit midstream firms. The smaller contraction in the trade credit received also acts as a buffer against contractions in bank credit. In particular, while there is no support in terms of loans offered by non-sector banks, due to the complementarity between intermediate inputs and other production inputs, the increased trade credit offered by upstream firms enhances midstream firms' ability to borrow from their own sector banks, partially insulating them from the loan crunch.

The role of factoring A second form of bank-supply chain integration along the intensive margin consists of factoring, whose intensity is captured by the parameter f. The influence of factoring is ambiguous a priori. Higher factoring usage may reduce or increase the role of trade credit as collateral.

[24] For example, from the above, recall that upstream banks experience an increase in net worth, thanks to the reduction in the cost of deposits and to the higher loan rates they can charge on midstream firms (which starve for credit following the midstream banks' shock). This increase in net worth allows them to expand their supply credit, leading to a drop in the loan rates charged to upstream firms and, hence, to an increase in the Lagrangian multiplier ψ^{uu}.

[25] By a similar, but opposite in sign, mechanism midstream firms reduce their trade credit supply to downstream firms by more when θ is larger.

In particular, there is a boost in the pledgeability of accounts receivable due to the experience associated with factoring activities (recall that $\Omega(f)$ is increasing in f). However, by construction, factoring pushes accounts receivable off firms' balance sheets, reducing their use as collateral. Moreover, factoring enters the capital constraint of banks, since factored trade credit constitutes an asset for regulatory purposes. These opposite forces shape the response to a banking shock.

The top two rows of Figure 5 display the net effect of these opposing forces by comparing the impulse responses of key variables for alternative levels of factoring intensity. Importantly, we observe that in our baseline calibration a higher intensity of factoring tends to enhance resilience in the same way as a higher pledgeability of accounts receivable. Indeed, a higher f leads to higher experience in managing invoice discounting, effectively enhancing the pledgeability of trade credit as collateral. This, in turn, promotes the extension of trade credit from upstream to midstream firms. The collateral share pledged by midstream firms to their sector banks (S^m) increases by more, too, and overall the decline in total bank financing to midstream firms ($MLoan$) is also mitigated, supporting midstream firms' production and the aggregate output Y. However, in quantitative terms these effects are smaller than in the case of a higher θ.

Profit margins in factoring In the baseline calibration, we approximated the highly competitive factoring market of Italy by setting a very small value of p. Figure 5. last row, replicates the experiments on the effects of a negative shock to midstream banks' net worth when banks obtain larger profits from their factoring activity. On the one hand, such larger profits tend to boost the net worth of banks. This can mitigate the negative impact of a bank net worth shock. On the other hand, the higher cost associated with factoring tends to dilute suppliers' incentive to extend trade credit. This implies that higher bank profit margins on factoring activities can weaken a key form of resilience. We observe that the latter force appears to dominate. In fact, a higher profit wedge appears to exacerbate the impact of the negative bank net worth shock. In particular, in the bottom row of Figure 5, trade credit to midstream firms (V^m), total bank borrowing by midstream firms ($MLoan$), and aggregate output (Y) move in the opposite direction relative to the baseline (low p) scenario.[26]

[26] A more nuanced aspect regards the influence of profit margins (p) on the effects of factoring intensity f. In Figure A4, we display the differenced impulse response with respect to f for two different values of p. We find that higher profit margins dilute the stabilizing influence of more intense factoring.

4.3 Relative Volatility of Aggregate Variables

We assess how stronger bank–supply chain integration along both extensive and intensive margins shapes aggregate volatility by comparing a baseline model with an alternative specification that features greater cross sector lending and broader factoring of trade credit receivables. To discipline the shock process, we estimate an AR(1) for banks' net worth disturbances using Bank of Italy data from 2011Q1–2025Q2 (log-transformed and HP-filtered), obtaining a persistence of 0.557 and an innovation standard deviation of 0.027. Given this shock process, we compute the theoretical variances of four aggregate variables—final good output, total investment, total bank loans, and total credit (bank plus trade credit)—under both models. As reported in Table 6, the alternative model yields lower or comparable variances for all aggregates relative to the benchmark. This pattern suggests that deeper integration between banks and supply chains enhances risk sharing and reallocative smoothing—by broadening funding channels and monetizing receivables—thereby attenuating the transmission of bank net worth shock to the real economy and reducing the amplitude of aggregate fluctuations.

5 Additional Analysis and Extensions

We extend the baseline model in various dimensions. First, we study how the tightness of commercial links along the supply chain interacts with bank-supply chain integration (Section 6.1). We then extend the model to account for alternative regulatory treatments of factoring and alternative specifications of the factoring process (6.2).

5.1 Commercial linkages and bank-supply chain integration

In our model economy, the strength of commercial and trade credit links along the supply chain is governed by the parameter ν. The parameter ν, in particular, captures the extent to which intermediate inputs can be pledged as collateral and, hence, governs the use of trade credit along the supply chain. [27].

In Figure 6, we display the first-differenced impulse response functions relative to θ and f for different values of ν. In the first row, we observe that a more intense use of trade credit (higher ν) tends to enhance the stabilizing effects of the intensive margin of bank-supply chain integration. For example, the lower contraction of trade credit from upstream firms to midstream firms observed when θ is higher

[27] The parameter ϕ, on the other hand, determines the degree of reliance of firms on intermediate inputs offered by suppliers. We focus our attention on ν which more directly determines the use of trade credit

is more evident when ν is larger.[28] And the attenuation of the total output drop is also reinforced by a larger ν. Intuitively, the mechanisms discussed above, in Section 4.2.4, tend to be accentuated when trade credit is used more intensely along the supply chain. For example, the incentive to extend more trade credit associated with a higher bank-supply chain integration along the intensive margin is stronger when trade credit is used more intensely.[29] In the bottom row of Figure 6, we reach similar conclusions when inspecting the influence of ν on the stabilizing effect of factoring intensity (f).

5.2 Alternative specifications

Bank capital regulation and bank-supply chain integration In recent years, as part of the revision of bank capital regulation, a debate has emerged on the treatment of income on factored assets in banks' capital requirements. In particular, policy makers debate whether profits realized by banks on factoring activities should be treated as assets pledgeable by banks in complying with capital adequacy requirements. In this robustness analysis, we aim to understand whether such a treatment can have a material impact on the role of bank-supply chain integration in macroeconomic stability.

In Appendix Figure A5, we consider an alternative scenario in which profits on factoring are incorporated in the assets pledgeable by banks in their capital constraints. The impulse responses show that all the results are robust to this alternative specification. Further. the quantitative difference in the results appears to be small, pointing to a limited relevance of this regulatory treatment for aggregate stability.

Factoring costs In the baseline model, we assumed that the additional fees associated with banks' factoring activities $(p-1)$ are completely borne by suppliers. We considered an alternative model specification in which the payment of these fees is shared between suppliers and customers (this implies, for example, that downstream firms will also share part of the cost of factoring activities). Appendix Figure A6 displays the impulse responses and reveals that the results remain fully robust to this alternative specification.

[28] The mitigation of the loan contraction to mid-stream firms is also more evident.

[29] On the other hand, there are also direct effects of commercial linkages. The pledging of trade credit (accounts playable) as collateral for bank loans creates a direct transmission mechanism along the supply chain: a contraction in trade credit downstream driven, e.g., by a banking shock will trigger a contraction in the value of collateralizable accounts payable upstream, shrinking the value of bank loans that can be obtained by upstream segments of the supply chain (suppliers). This deleveraging, amplifying channel tends to be more pronounced when trade credit is more intensely used.

6 From Model to Data

We test the key mechanisms of the model in the Italian data. To this end, we exploit the financial distress of the major Italian bank Monte dei Paschi di Siena (MPS) as a source of plausibly exogenous banking shock. Monte dei Paschi di Siena has historically exhibited a marked concentration in midstream industries within the Tuscan and Central Italian production system. Its lending is anchored in the productive fabric of central Italy, where firms are typically positioned in intermediate stages of supply chains. Unlike cooperative banks that often serve farmers or raw-material producers, MPS is closely tied to manufacturing and processing companies—textiles in Prato, leather in Tuscany, machinery and equipment in Emilia and Marche—that transform inputs into higher-value goods. In particular, a substantial share of its lending is directed towards agribusiness processing (wine, olive oil, and food transformation), leather and tanning, and intermediate manufacturing such as machinery for textiles and ceramics—sectors that are neither purely upstream suppliers nor final consumer industries, but critical nodes in regional value chains. Data from the late 2000s confirm that MPS was one of the most active lenders to agriculture and agro-industry in Italy,[30] and its dedicated arm MPS Banca Verde—originating from the Federated Institute of Agricultural Credit for Tuscany—underscores the long-standing sectoral orientation of its portfolio. In sum, MPS became the reference bank for "middle-layer" firms, financing the bulk of operations that stood between upstream resource extraction and downstream retail. Accordingly, while the bank's distress constitutes a major systemic shock, it disproportionately affected those mid-chain industries structurally dependent on its credit.

6.1 Identifying a banking shock

The MPS crisis constitutes a major episode in the Italian banking sector, triggered by the overvalued acquisition of Banca Antonveneta and compounded by a series of governance failures and accounting irregularities. These events precipitated a sharp deterioration in the MPS bank's balance sheet, leading to mounting losses and, ultimately, regulatory intervention. In response, MPS undertook a substantial retrenchment in its lending activity aimed at meeting capital adequacy requirements. Crucially, this adjustment was driven by *internal* financial constraints rather than changes in borrower creditworthiness or macroeconomic fundamentals. We argue that the resulting contraction in credit supply represents a

[30] See Financial needs in the agriculture and agri-food sectors in Italy, fi-compass/EIB, 2010. Available at: https://www.fi-compass.eu/sites/default/files/publications/financial_needs_agriculture_agrifood_sectors_Italy.pdf

large and yet idiosyncratic, bank-specific event that allows for credible identification of the real effects of a banking shock. The shock propagated beyond firms directly borrowing from MPS, affecting broader segments of the corporate sector through supply chain linkages. We use this setting to examine how bank disruptions translate into firm-level outcomes—focusing on sales and employment—and to explore the role of bank-supply chain linkages in amplifying or moderating banking shocks.

The origins of the crisis trace back to late 2007, when MPS acquired Banca Antonveneta for 9 billion, a price well above its market value. The acquisition was largely financed through debt, significantly weakening the bank's capital position. Between 2008 and 2011, mounting losses from the acquisition, combined with the emergence of complex and opaque derivative transactions (the "Alexandria" and "Santorini" deals), further impaired the bank's balance sheet. In 2012, Italian regulators launched investigations into these transactions, leading to heightened scrutiny. The crisis escalated in early 2013 with the disclosure of previously hidden losses and the initiation of criminal proceedings against former executives. Over the subsequent years, MPS implemented a restrictive credit policy and offloaded non-performing loans, resulting in a substantial contraction of credit supply. Table A1 provides a detailed chronology of the MPS crisis.

6.2 Bank-supply chain integration and commercial linkages

We exploit various measures of bank-supply chain integration and commercial links: measures of extensive-margin bank-supply chain integration based on the distribution of MPS branch penetration across provinces and industries; measures of intensive-margin bank-supply chain integration based on the incidence of supply chain finance (factoring) in bank financing; and a measure of commercial links based on sectoral input–output linkages to MPS-dependent industries. We implement a difference-in-differences framework that compares pre- and post-shock outcomes across firms with different levels of integration and exposure. We define 2012 as the final pre-treatment year, as it marks the period before the public disclosure of hidden losses, which formalized the bank's restructuring process and triggered the lending retrenchment (Table A1).

The variable *ExtInteg* captures the degree of extensive-margin bank-supply chain integration. It is defined as the share of MPS bank branches in the firm's province in 2012, based on administrative data from the Bank of Italy on branch penetration. Using pre-crisis data helps mitigate concerns about the endogenous adjustment of MPS's branch network in response to the shock. In alternative to this geographical measure of integration, we also use a sectorial measure of extensive margin integration, based on the share of businesses in the firm's industry that are financed by MPS. At the provincial level, MPS branches accounted for an average of 7% of all bank branches, with substantial variation across the country—from 0% to over 45%.[31] Appendix Figure A9 illustrates the geographical distribution of MPS branches as of 2012.[32] Although MPS's historical base in Central Italy—particularly in regions such as Tuscany and Umbria—is clearly visible, the maps also reveal a broader territorial footprint. Many provinces across the South and parts of the North exhibit non-negligible levels of MPS presence. This combination of strong regional concentration and wide dispersion results in substantial cross-sectional heterogeneity.

To capture bank–supply chain integration along the intensive margin, we construct measures of bank factoring intensity. Exploiting bank-level data from firm–bank relationships in the MET survey, we compute the ratio between factored accounts receivable and total bank loans ($Int(Factor)Integ$), collecting 2010 factoring activity of the lender bank rescaled by total credits.[33] Factoring variables are fixed pre-crisis to allay concerns about endogeneity. We complement this indicator with a sectoral measure of factoring intensity, defined as a dummy for firms in the top ten industries by factoring usage (Assifact, 2024).[34] These industries represent 33% of our sample.

To capture commercial (supply chain) links we construct the variable $Comm-Link$. For each 2-digit NACE Rev. 2 sector, we first calculate the share of firms borrowing from MPS prior to the shock (based on MET data). We then use the 2012 ISTAT input–output matrix to compute the degree to which each sector relies on other sectors for intermediate input purchases and output sales. These inter-sectoral weights allow us to build, for each firm, measures of both upstream linkages (through input purchases) and downstream linkages (through output sales) to sectors more affected by the MPS shock. Note that using 2012 data ensures that the structure of commercial linkages reflects pre-crisis conditions, reducing concerns about endogenous commercial network reconfigurations following the shock. Untabulated descriptive statistics reveal marked sectoral heterogeneity in upstream and downstream commercial linkages. Upstream commercial exposure is relatively high in sectors such as Printing and Publishing, Basic Metals, and Chemicals, Plastics, and Rubber, while lower levels are observed in sectors like Transport Equipment and Apparel. Downstream commercial exposure is highest in the Transport and Commu-

[31] About 18% of companies in our sample reported having an active credit relationship with the MPS bank in 2012.

[32] The left panel reports the total number of MPS branches by province, while the right panel presents the spatial distribution of our variable $\%\text{MPS}_{p(i)}$, which measures the share of MPS branches relative to all branches in the local banking market.

[33] The amount of factoring was hand-collected from banks' balance sheet statements available online.

[34] www.assifact.it/wp-content/uploads/2025/06/Rapporto-sul-mercato-del-factoring-2024.pdf

nications sector, followed by Basic Metals, Machinery, and Printing and Publishing. Sectors such as Electrical Machinery and Furniture and Wood exhibit comparatively lower downstream linkages. Differences in input dependencies and market destinations generate meaningful cross-sectional variation in supply chain linkages. This heterogeneity is valuable for identification, as it allows us to compare firms located in the same geographical areas but facing different levels of commercial exposure due to their distinct positions within sectoral production networks.

6.3 Direct exposure to MPS and credit rationing

Before introducing our empirical strategy, we begin by assessing whether firms directly exposed to Monte dei Paschi di Siena actually experienced a worsening of credit conditions following the onset of the bank's crisis. This preliminary analysis serves to validate the relevance of the MPS case as a meaningful source of variation in credit supply within our sample. We discuss here key elements of this analysis, relegating details to the Appendix.

We identify a firm as directly connected to MPS if it reported borrowing from the bank in the MET survey prior to the crisis, i.e., before 2013. To estimate the impact of this connection, we implement a difference-in-differences specification where we interact a pre-crisis MPS exposure indicator with a post-2012 dummy. The model includes controls for time-varying firm characteristics—namely, sales, employment, and firm age—and absorbs firm, year, and lender bank fixed effects. In a more saturated specification, we additionally include Region $\times$ Sector $\times$ Year fixed effects to account for differential trends across local credit markets and industries.

Appendix Table A2 presents the results. The dependent variables capture different dimensions of credit availability. In Columns 1 and 4, we use a survey-based binary indicator that equals one if the firm reports having forgone potentially profitable investment opportunities (i.e., with positive net present value) due to a lack of external financial resources. This serves as a broad measure of credit rationing. In Columns 2 and 5, we use an alternative proxy, also based on survey responses, which equals one if the firm reports that access to bank credit was restricted by the lack of sufficient collateral or guarantees. Finally, in Columns 3 and 6, we consider the logarithm of total bank debt, drawn from AIDA balance sheet data, which provides a continuous measure of actual credit received.

The estimated coefficients on the interaction term $\text{MPS}_i \times \text{Post}_{i,t}$ are positive and statistically significant in Columns 1, 2, 4, and 5, indicating that firms directly connected to MPS were more likely to experience financial constraints after 2012. Columns 3 and 6 show a significant negative association between MPS exposure and bank debt, suggesting a contraction in credit volume for exposed firms.

6.4 The empirical model

Our baseline empirical model reads:

$$\begin{aligned} Y_{i,t} = \alpha &+ \beta_1 \left(\text{Commercial-Link}_{s(i)} \times \text{Post}_t\right) + \beta_2 \left(\text{Commercial-Link}_{s(i)} \times \text{Post}_t \times SC_i\right) \\ &+ \beta_3 \left(SC_i \times \text{Post}_t\right) + \gamma_1 \left(\text{Ext-Integ}_{p(i)} \times \text{Post}_t\right) + \gamma_2 \left(\text{Ext-Integ}_{p(i)} \times \text{Post}_t \times SC_i\right) \\ &+ \delta_1 \left(\text{Int(Factor)-Integ}_{b(i)} \times \text{Post}_t\right) + \delta_2 \left(\text{Int(Factor)-Integ}_{b(i)} \times \text{Post}_t \times SC_i\right) \\ &+ \zeta^\top X_{i,t-1} + \mu_i + \theta_{B(i)} + \eta_{p(i),s(i)} + \lambda_t + \varepsilon_{i,t}. \end{aligned} \tag{49}$$

where $Y_{i,t}$ is the logarithm of sales or employment for firm i in year t. Commercial-Link$_{s(i)}$ reflects firm i's exposure to MPS-dependent sectors through input-output linkages, capturing the extent of commercial (supply chain) links. Ext-Integ$_{p(i)}$ captures the measure of extensive-margin integration, as detailed above. Int(Factor)-Integ$_{b(i)}$ proxies for the degree of intensive-margin bank-supply chain integration, namely the intensity of factoring activities pre crisis (in 2010), normalized by the loan credit extension activity. We define the supply chain participation of a firm with a pre-crisis indicator, SC_i, measured before the onset of the MPS shock (i.e., prior to 2013). This helps reduce concerns about reverse causality or contemporaneous adjustments in supply chain participation driven by the banking shock itself.[35]

Each measure of bank-supply chain integration and commercial links is interacted with a post-2012 dummy to capture the differential effect of the shock across firms, and further interacted with the supply chain indicator $SC_{i,t-1}$ to test whether supply chain participation affects the shock transmission. The vector of controls $X_{i,t-1}$ includes lagged values of log sales and firm age, which serve as proxies for firm size and maturity. These variables help account for pre-determined firm characteristics that may be correlated with subsequent performance outcomes. We include a rich set of fixed effects to further address potential confounding factors. Firm fixed effects μ_i absorb time-invariant unobserved heterogeneity across firms, such as managerial ability, long-run productivity, or persistent access to external finance. Because the vast majority of firms in our sample (more than 95%) do not change either their sector or location over the period of analysis, these firm fixed effects already capture most of the baseline

[35]Thus, the interaction terms including SC_i will be identified, while the main effect of SC_i will be absorbed by firm fixed effects.

variation in Ext-Integ$_{p(i)}$, which is fixed at the province level, and Commercial-Link$_{s(i)}$, which is fixed at the sector level. We further include $\eta_{p(i),s(i)}$, a set of province-sector fixed effects, to fully absorb any remaining variation in the baseline integration measures. As such, identification relies exclusively on the interaction terms with the post-shock period and with supply chain participation.

We also insert year fixed effects λ_t to control for aggregate macroeconomic trends and common policy shocks, and lender fixed effects $\theta_{B(i)}$ to account for time-invariant characteristics of firms' main banks, including their business model. These lender fixed effects also absorb the average effect of borrowing from MPS across all periods. To capture time-varying credit disruptions specifically linked to direct exposure to MPS as a lender, we additionally control for the interaction term $MPS_i \times \text{Post}_t$ in the vector $X_{i,t-1}$. This ensures that our estimates isolate the additional effects of bank-supply chain and commercial integration beyond the direct lending channel. This flexible structure ensures that identification comes from within-firm variation over time in exposure to the MPS shock, net of both firm-specific trajectories and broader credit market dynamics.

6.5 Endogeneity of supply-chain participation

A potential concern in our empirical setup is the endogeneity of supply chain participation, SC_i. Although we use lagged values to mitigate simultaneity bias—ensuring that supply chain status is determined prior to the outcomes we study—firms may still self-select into supply chains based on unobserved characteristics, which could also influence their exposure to banking shocks and subsequent performance trajectories. To address this concern, we implement an instrumental variables strategy that exploits variation in firms' access to digital infrastructure. Specifically, we construct an instrument for supply chain participation, SC_i, based on the geographical distance between each firm and the nearest Strategic Geographical Unit (SGU) offering advanced IT services. Our approach relies on precise geolocation data for both firms and SGUs, allowing us to compute exact distances at the firm level.

The identifying assumption is that proximity to digital infrastructure facilitates integration into supply chains by lowering coordination and transaction costs, without directly affecting firm outcomes such as sales or employment. This assumption is supported by prior research showing that access to IT infrastructure reduces barriers to inter-firm coordination and promotes the formation of production networks (Brynjolfsson and Hitt 2000; Freund and Weinhold 2004; Cusolito, Safadi, and Taglioni 2016). The Italian context is especially well-suited to this strategy, as the rollout of digital infrastructure varies substantially across provinces. Crucially, this variation is largely driven by differences in local bureaucratic capacity and historical patterns of administrative responsiveness, rather than by firm-level strategic location choices. As documented by Perri and Vaciago (2023) and Ghezzi (2023), many Italian municipalities display persistent gaps in digital readiness, often due to cultural conservatism and uneven investment in digital transformation. Moreover, given that most firms in our sample are small, family-owned businesses that tend to remain rooted in their place of origin, it is unlikely that firms systematically sort into locations based on digital infrastructure quality. This reduces concerns that our instrument might capture unobserved firm-level characteristics rather than exogenous variation in supply chain participation.

A remaining concern is that proximity to digital infrastructure may influence firm outcomes not solely through supply chain integration, but rather by facilitating direct online sales channels, such as the use of e-commerce platforms or firm-operated digital storefronts. While the rich set of controls and fixed effects in equation (50)—including firm, year, and lender fixed effects, as well as lagged firm characteristics—help mitigate this risk, we take an additional step to allay concerns. Specifically, we control for a firm-specific measure of e-commerce usage, constructed as a binary indicator equal to one if the firm reports using either general-purpose or industry-specific e-commerce platforms to sell its products, or if it operates its own website, which may capture direct online sales. This measure, derived from responses to the MET survey, captures variation in firms' direct digital commercial channels that could otherwise confound the effect of digital infrastructure on supply chain participation.[36] By accounting for this additional source of heterogeneity, we further reduce concerns that the instrument affects firm performance through channels unrelated to inter-firm production linkages.

6.6 Estimation results

Main estimates In Figure A10 we display a parallel trend analysis. The figure shows that there was no systematic increase or decrease in the sales of MPS-financed firms before the MPS shock.

Table 4 presents the main estimation results. The first stage estimates confirm that our instrument has strong explanatory power for supply chain participation; see Table A3. In the second stage, in line with the predictions of the model, we detect a negative impact of the shock for firms participating in supply chains and with commercial links to industries hit by the shock. Most interestingly for our purposes,

[36]The variables used to construct our measure of e-commerce usage are available only in the last three waves of the MET survey. For earlier waves, we impute this measure backward by exploiting additional information on firms' investments in ICT, which we use as an indirect proxy. When both variables are available, the correlation between ICT investment and our e-commerce indicator is 0.44, suggesting that ICT investment provides a meaningful, albeit imperfect, proxy for e-commerce adoption.

we estimate an amplifying effect of (the degree of) extensive margin bank-supply chain integration: the interaction term $Ext - Integ_{p(i)} \times \text{Post}_t \times SC_i$ is significantly negative across specifications. On the other hand, again in line with the model predictions, we detect an attenuating effect of the degree of intensive margin bank-supply chain integration, as captured by the interaction term $\text{Int(Factor)-Integ}_{p(i)} \times \text{Post}_t \times SC_i$. In column 2, for example, the estimated coefficient on the interaction term between the degree of factoring intensity, the *post*-shock dummy, and the supply chain participation indicator is consistently positive. And if we interact the factoring measure with the sectorial indicator for factoring intensity, rather than with the supply chain indicator, we again find that the attenuating effect is more pronounced in industries in which factoring is typically used more intensely. In column 4, we further refine our measurement of bank-supply chain intensive-margin integration by interacting our integration measure with the value of accounts receivable remaining on the firm's balance sheet (normalized by the firm's assets). Plausibly, the firms with more accounts receivable still recorded on their balance sheets use factoring less intensely, and in line with this, we estimate a negative coefficient on the interaction term $\text{Int(Factor)-Integ}_{p(i)} \times \text{Post}_t \times Receivables_i$.

The results are robust to the use of an alternative instrument, constructed as before, but interacting the distance from GSU with a measure of IT usage at the sectorial level (see Appendix Table A4). Specifically, we use data from the EU-EFIGE/Bruegel-UniCredit survey, which reports the share of firms in each sector that regularly use IT for commercial transactions.[37] When constructing the alternative instrument, we interact this sector-level IT usage measure with our proxy for local IT infrastructure, defined as the firm's distance from the nearest SGU.[38]

More on the transmission mechanisms In the model, a key mechanism through which the intensive margin of bank-supply chain integration enhances resilience is by incentivizing the extension of trade credit by suppliers to firms hit by a banking shock. We investigate the presence of this mechanism more directly by testing the following empirical model:

$$\begin{aligned} Receiv_{i,t} = \alpha + \gamma_1 \left(\text{Int(Factor)-Integ}_{b(i)} \times \text{Post}_t\right) + \gamma_2 \left(\text{Int(Factor)-Integ}_{b(i)} \times \text{Post}_t \times SC_i\right) \\ + \rho_1 \left(SC_i \times \text{Post}_t\right) + \zeta^\top X_{i,t-1} + \mu_i + \theta_{B(i)} + \eta_{p(i),s(i)} + \lambda_t + \varepsilon_{i,t}. \end{aligned} \tag{50}$$

[37]The EFIGE survey, conducted in 2010, covers a representative sample of approximately 15,000 firms across seven European countries (Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom). The sample is stratified by sector, region, and firm size to ensure national representativeness.

[38]In Appendix Tables A4 and A5) we also show robustness to using a time-varying measure of supply chain participation and to considering the effects on firms' employment.

The dependent variable is now the value of accounts receivable of firm i in year t (scaled by the firm's assets). All the other variables in the estimating regression (50) are defined as above.

The estimation results, displayed in Table 5), show that following the MPS banking shock firms that participated in supply chains and whose banks were more intensely involved in factoring activities received more trade credit from their suppliers. In line with the predictions of the model, this points to a shock-attenuating influence of the intensive margin of integration working through trade credit extension.[39]

7 Conclusion

In this paper, we have investigated the transmission of business cycles in an economy where banks finance supply chains and salient forms of financial integration are present. In the model economy, both banking integration and bank-supply chain integration can be analyzed. The results reveal possibly strikingly different consequences of financial integration for macroeconomic stability. On the one hand, larger banking integration across the supply chain (i.e. banks' ability to serve different segments of a supply chain) leads to stronger amplification of banking shocks. Greater intregration between banks and supply chains instead enhances macroeconomic resilience in the face of banking shocks, both when it takes the form of a larger use of invoice discounting and of factoring activities. Empirical evidence from matched bank-firm data from Italy confirms the implications of the model.

The analysis leaves open questions for future research. One such question regards the possible mechanisms through which the integration between banks and global value chains could influence the transmission of trade shocks, e.g., in the form of higher tariffs imposed on the purchase of intermediate inputs from international suppliers. This could provide new insights into the impact of the international financial integration on the integration or fragmentation of trade flows. We leave this and other relevant issues to future research,

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[39] The results carry through if we use the average factoring intensity of the banks serving the suppliers of the firm, rather than the factoring intensity of the bank serving the firm itself. See column 2 of the table.

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Table 1: Descriptive statistics

	Mean	Median	Stdev	Min	Max	N
Sales	14.28	14.55	2.92	0.00	24.35	480,575
Employment	2.85	2.77	1.40	0.00	10.87	336,977
Supply Chain	0.34	0.00	0.47	0.00	1.00	480,575
Commercial-Link$_{s(i)}$	0.08	0.08	0.06	0.00	0.44	480,575
Ext-Integ (Provincial)	0.07	0.06	0.06	0.00	0.45	480,575
Ext-Integ (Sectorial)	0.11	0.11	0.02	0.09	0.13	480,575
Int(Factor)-Integ$_{b(i)}$	0.02	0.01	0.01	0.00	0.08	451,511
Payables	0.11	0.01	0.15	0.00	0.72	370,622
Receivables	0.15	0.00	0.21	0.00	0.84	400,585
High factoring sector	0.33	0.00	0.47	0.00	1.00	480,575
MPS$_i$	0.17	0.00	0.38	0.00	1.00	480,575
Age	3.06	3.18	0.67	0.00	5.08	480,575
E-commerce	0.31	0.00	0.46	0.00	1.00	480,575

Notes: Descriptive statistics for the main variables employed in the analysis.

Table 2: Model Parameters. Baseline Calibration

		Households
β	0.99	Household discount factor
ω	1	Household CRRA
k_c	5.584	Relative utility weight of labor
η	0.75	Inverse Frisch elasticity of labor supply
		Banks
σ	0.975	Survival rate of the bankers
ξ	0.8	Weight of bank assets in capital constraint
ι	0.0001	Proportional transfer to entering bankers
ρ	0.85	Persistence of banking shock
p	1.00001	Gross profit margin of banks for factoring trade credit
		Firms
β_f	0.98	Firm discount factor
δ	0.025	Depreciation rate
α	0.4	Capital share before intermediate input
α_u	0.2	Share of Y^u for production of Y
α_m	0.35	Share of Y^m for production of Y
γ	0	Firm CRRA
ϕ	0.5	Share of input Y^{iu}, Y^{im} for production of Y^m, Y^d
κ	0.6	% of capital liquidated by sector bank
κ^n	0.5	% of capital liquidated by non-sector bank
c	0.3	Cost of sector bank liquidation
θ	1.2	% of trade credit profit liquidated by bank
f	0.3	% of trade credit factored to bank
ν	1.5	% of input inventory liquidated for trade credit default
ε	0.75	Substitution parameter

Table 3: Model Targets and Data Comparison

Target	Baseline Model	Data
*Bank Leverage Ratio (R*X+f*Rv*V)/N*		
Bank Average (weighted by assets)	4.747	4.9
*Firm Leverage Ratio (R*X+Rv*V)/(K+(1-f)*Rv*V+P*Y)*		
Firm Average (weighted by assets)	0.579	0.58
*Firm TC Borrowing / Bank Loan (Rv*V/R*X)*		
Firm Average (weighted by assets)	0.286	0.28
*Firm Net TC / Bank Loan (Rvm*Vm - Rvd*Vd)/R*X*		
Midstream	0.064	0.07
*Factored TC / Bank Loan (f*Rv*V/R*X)*		
Average (weighted by assets)	0.086	0.07
Loan–Deposit Spread	0.012	0.013
Trade Credit–Loan Spread	0.0188	0.020

Table 4: Main Estimation Results

	Sales					
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial-Link$_{s(i)}$ × Supply chain × Post$_t$	-4.362***	-4.611***	-4.582***	-7.449***	-0.451***	-0.490***
	[0.919]	[0.965]	[0.962]	[2.157]	[0.0844]	[0.0862]
Supply chain × Post$_t$	11.28***	11.51***	11.81***	18.83***	13.00***	13.77***
	[2.355]	[2.409]	[2.460]	[5.421]	[2.254]	[2.322]
Commercial-Link$_{s(i)}$ × Post$_t$	1.647***	1.746***	1.698***	2.753***	0.231***	0.228***
	[0.348]	[0.367]	[0.362]	[0.801]	[0.0428]	[0.0445]
Ext-Integ × Post$_t$	0.590***	0.621***	0.616***	0.973***	1.342***	1.417***
	[0.128]	[0.134]	[0.133]	[0.290]	[0.234]	[0.243]
Ext-Integ × Supply chain × Post$_t$	-1.742***	-1.826***	-1.807***	-2.886***	-5.780***	-6.114***
	[0.366]	[0.381]	[0.379]	[0.834]	[1.006]	[1.038]
Int(Factor)-Integ $_{B(i)}$ × Post$_t$		-5.657*	-0.168	2.416**		-0.532
		[2.940]	[0.486]	[1.178]		[0.383]
Int(Factor)-Integ $_{B(i)}$ × Supply chain × Post$_t$		21.99**				
		[10.22]				
Int(Factor)-Integ$_{B(i)}$ × High factoring sector × Post$_t$			2.815***			2.036***
			[0.557]			[0.434]
Int(Factor)-Integ$_{B(i)}$ × Receivables × Post$_t$				-7.443**		
				[3.530]		
Payables × Post$_t$				-0.968***		
				[0.241]		
Receivables × Post$_t$				0.326***		
				[0.0907]		
High factoring sector × Post$_t$			0.379***			0.159***
			[0.0516]			[0.0222]
Bank integration	Provincial	Provincial	Provincial	Provincial	Sectorial	Sectorial
Supply chain and Trade credit	Fixed (pre-crisis)					
Firm FE	Y	Y	Y	Y	Y	Y
Region × Sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Observations	480,769	451,678	451,678	333,702	485,412	456,144
Underidentification p-value	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald F	23.174	16.313	21.867	7.419	197.775	187.132
Cragg-Donald Wald F statistic	25.693	18.017	24.101	7.754	229.031	215.725

Notes: This table reports estimates for the effects of the MPS banking shock and the extensive and intensive margin of banks-supply chain integration on firms' sales. In the regressions Supply chain is instrumented as detailed in Section 6.5. See Section 6.2 for details on measurement and Section 6.4 for details on the empirical model. Robust standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 5: Accounts receivable and factoring

	Receivables	
	(1)	(2)
Factoring × Supply chain × Post$_t$	1.529**	16.75**
	[0.750]	[8.376]
Supply chain × Post$_t$	-0.0480**	0.464***
	[0.0205]	[0.133]
Factoring × Post$_t$	-0.981***	-0.0500
	[0.231]	[2.540]
Supply chain	Fixed (pre-crisis)	Fixed (pre-crisis)
Factoring definition	Int(Factor)-Integ$_{b(i)}$	Factoring (Suppliers)
Firm FE	Y	Y
Region × Sector FE	Y	Y
Year FE	Y	Y
Bank FE	Y	Y
Observations	321,938	340,465
Underidentification p-value	0.000	0.000
Kleibergen-Paap rk Wald F	607.104	23.167
Cragg-Donald Wald F statistic	925.883	32.108

Notes: Column 1 reports the 2010 factoring intensity of firm *i*'s lender bank. Column 2 uses the average factoring intensity of the lenders of firm *i*'s suppliers. This measure is obtained by weighting the lender banks' factoring intensity at the 2-digit sector level with the 2010 input–output matrix corresponding to firm i's sector. Robust standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 6: Variances of the aggregate variables

Variable	Benchmark	Alternative
Final good	0.124	0.114
Investment	11.539	9.279
Bank Loan	0.292	0.253
Total Credit	0.271	0.275

Note: Numbers are multiplied by 1e3.

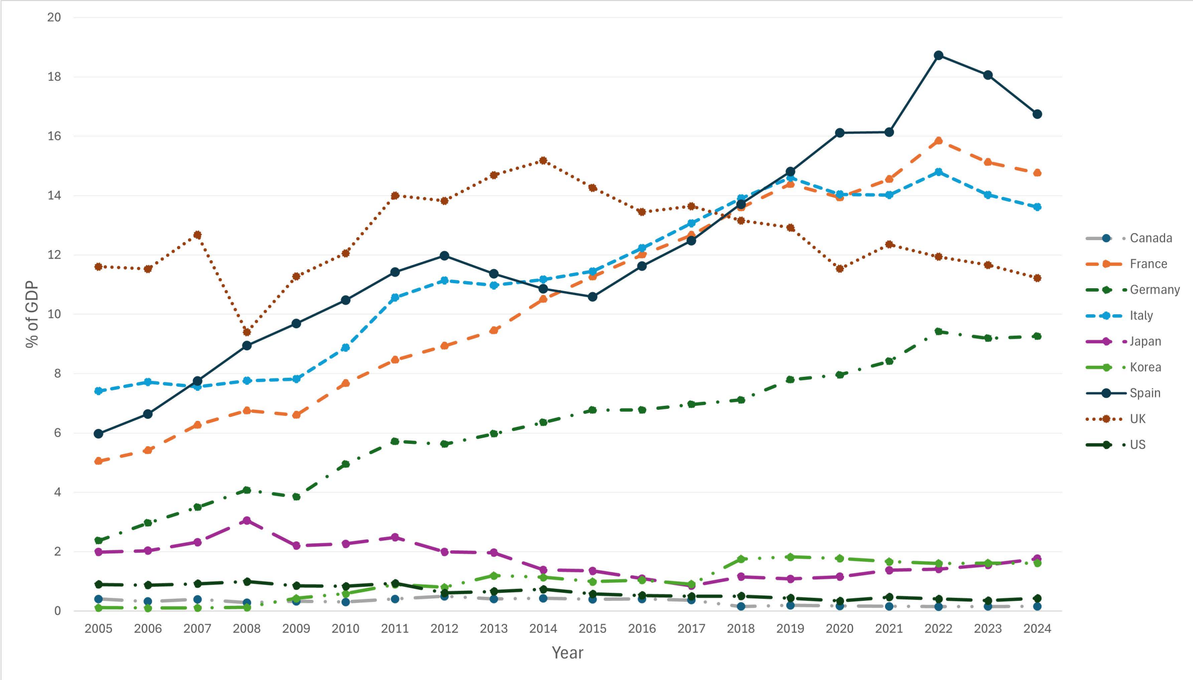

Figure 1: **Trends in Factoring & Commercial Finance (in Percent of GDP)**

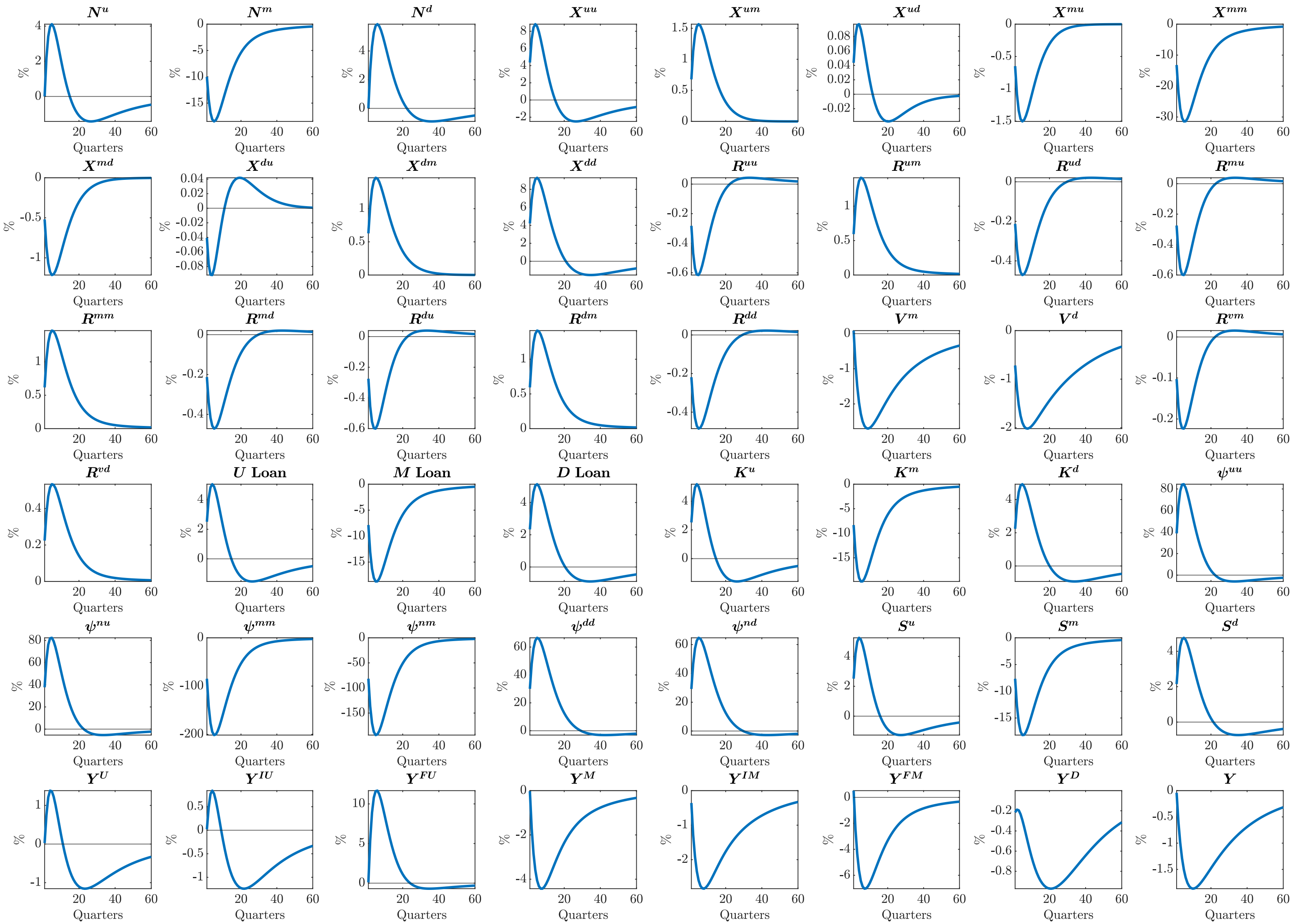

Figure 2: **Baseline Results**

Note: Interest rates R_t^{uu} to R_t^{vd} show the response in percentage points.

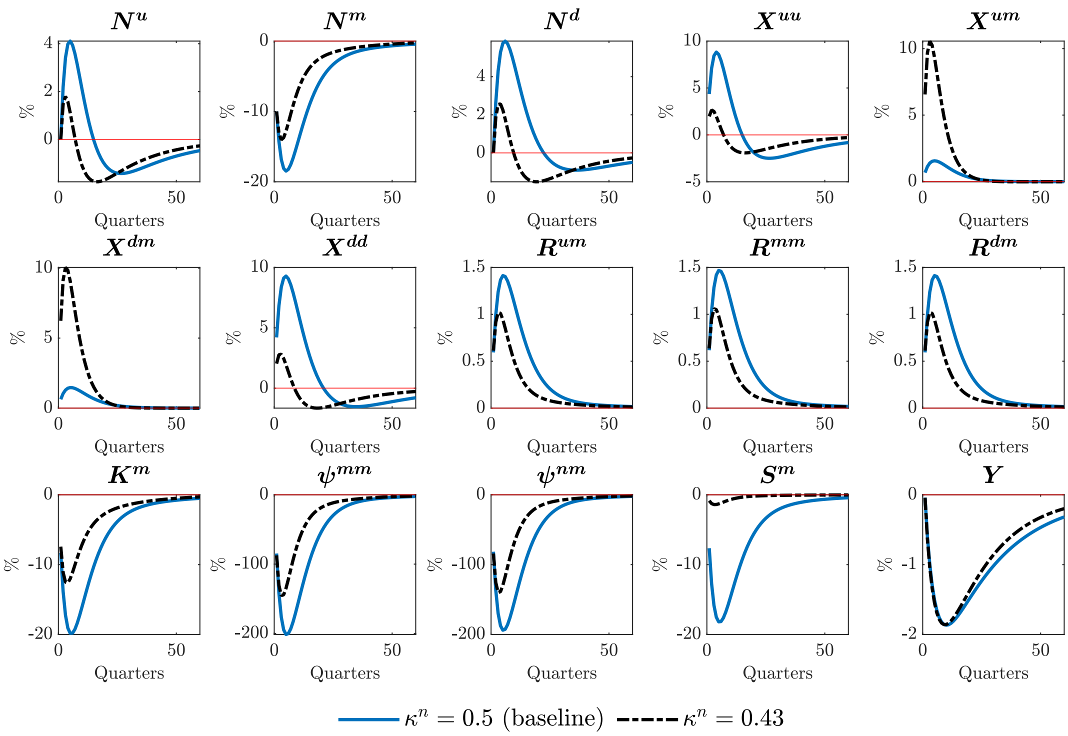

Figure 3: **Extensive Margin Result**

Note: Changes in the interest rates R_t^{um}, R_t^{mm}, R_t^{dm} are measured in percentage points.

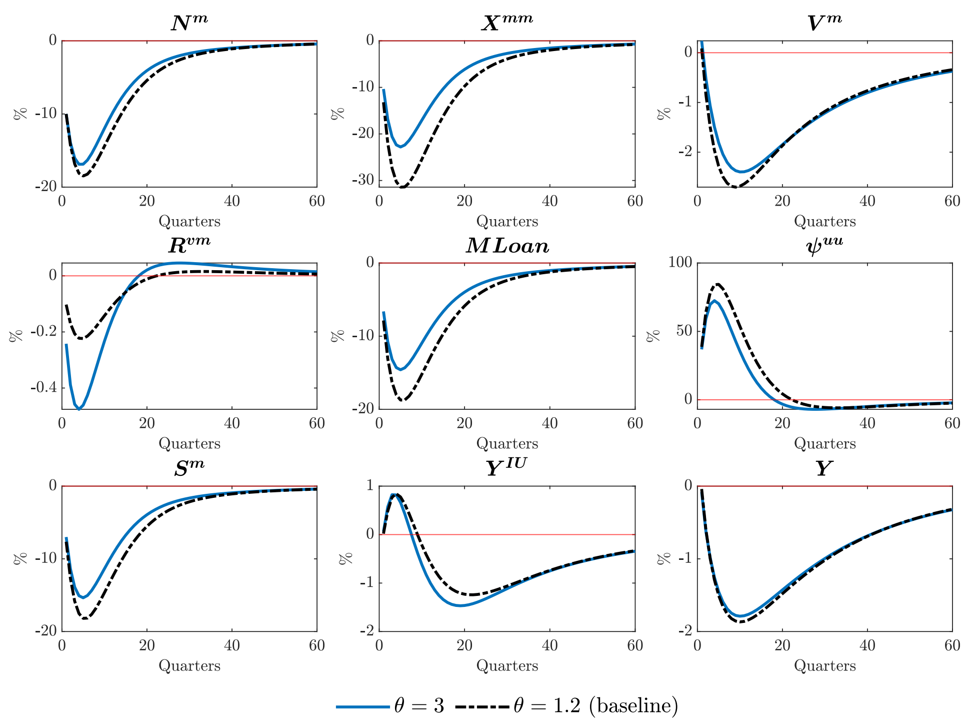

Figure 4: **Intensive Margin Result**

Note: Changes in the trade credit rate $R_t^{vm}$are measured in percentage points.

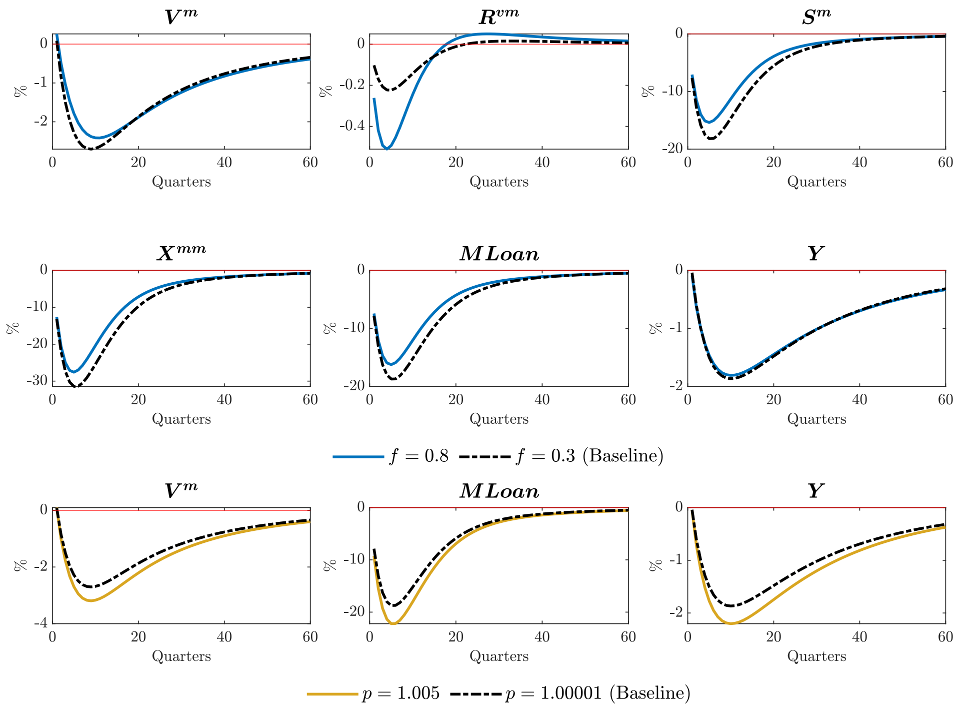

Figure 5: **Intensive Margin**

Note: Changes in the trade credit rate R_t^{vm} are measured in percentage points.

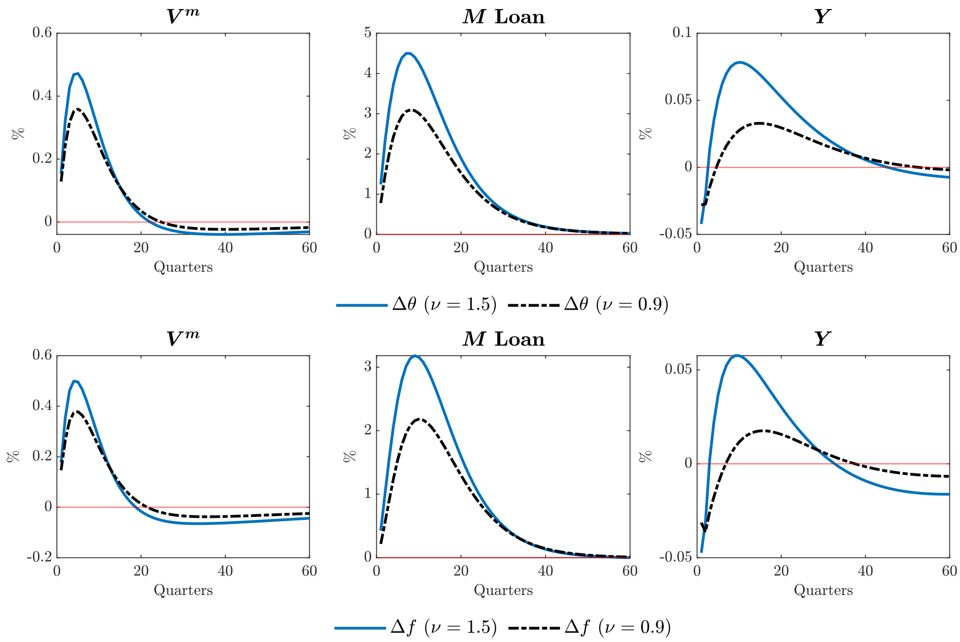

Figure 6: **Commercial Linkage**

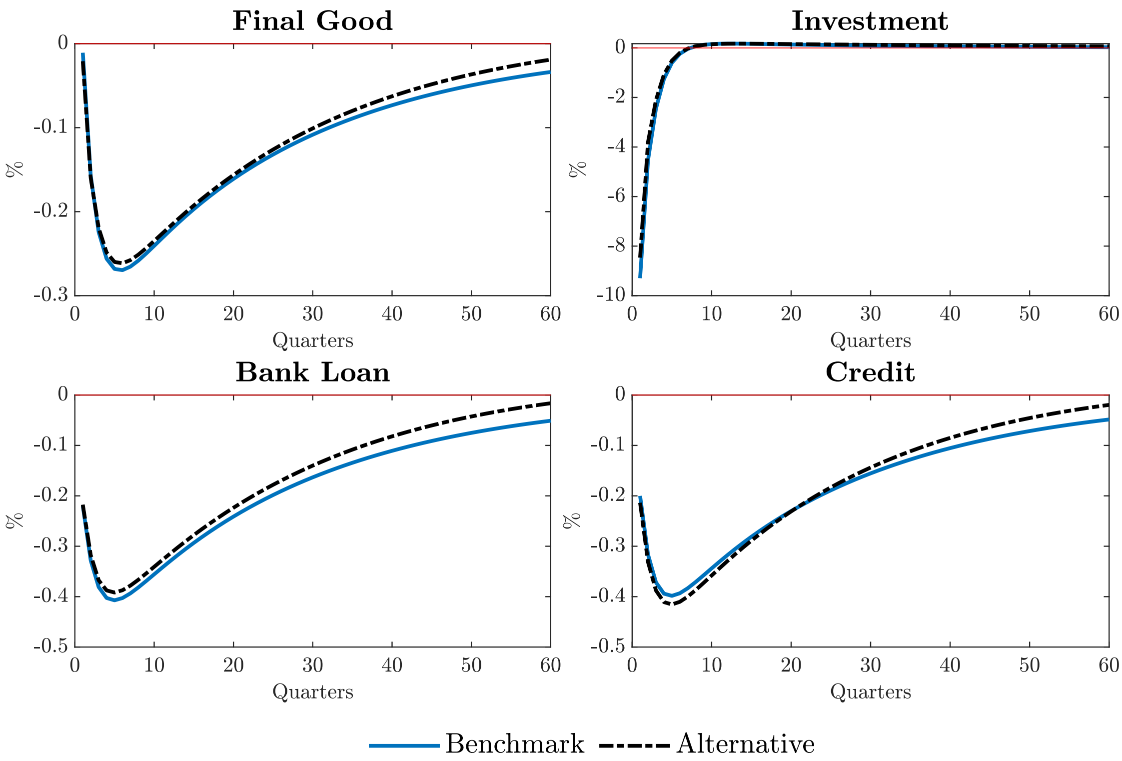

Figure 7: **Aggregate variables**

Online Appendix

This Online Appendix presents further details on the model solution (Appendix A1) and additional details on data and empirical results (Appendix A2).

A1 Further Details on Model Solution and Results

Details on full set of model equations

The equilibrium consists of 70 variables and 70 equations as shown in the following.

- **Variables:**

  Quantities:

$$
\begin{aligned}
&C_t, C_t^u, C_t^m, C_t^d, \quad L_t, L_t^u, L_t^m, L_t^d, \quad K_t^u, K_t^m, K_t^d,\\
&X_t^{uu}, X_t^{um}, X_t^{ud}, X_t^{mu}, X_t^{mm}, X_t^{md}, X_t^{du}, X_t^{dm}, X_t^{dd},\\
&V_t^m, V_t^d, \quad Y_t^U, Y_t^{IU}, Y_t^{FU}, Y_t^M, Y_t^{IM}, Y_t^{FM}, Y_t^D, Y_t,\\
&D_t, D_t^u, D_t^m, D_t^d, \quad N_t^u, N_t^m, N_t^d, \quad S_t^u, S_t^m, S_t^d
\end{aligned}
$$

  Prices:

$$
\begin{aligned}
&R_t, R_t^{uu}, R_t^{um}, R_t^{ud}, R_t^{mu}, R_t^{mm}, R_t^{md}, R_t^{du}, R_t^{dm}, R_t^{dd},\\
&R_t^{v,m}, R_t^{v,d}, \quad W_t, \quad P_t^U, P_t^M, P_t^D,\\
&\psi_t^{uu}, \psi_t^{nu}, \psi_t^{mm}, \psi_t^{nm}, \psi_t^{dd}, \psi_t^{nd},\\
&\chi_t^m, \chi_t^d, \quad \lambda_t^u, \lambda_t^m, \lambda_t^d, \quad \mu_t^u, \mu_t^m, \mu_t^d
\end{aligned}
$$

- **Households.** Budget constraint and labor aggregation:

$$
\begin{aligned}
&C_t + D_t = W_t L_t + \Pi_t + R_{t-1} D_{t-1},\\
&L_t = L_t^u + L_t^m + L_t^d,\\
&D_t = D_t^u + D_t^m + D_t^d.
\end{aligned}
$$

  Π_t is the difference between net worth of exiting bankers and transfers to new bankers:

$$
\begin{aligned}
\Pi_{t+1} = (1-\sigma)\left(\sum_{j\in\{uu,um,ud,mu,mm,md,du,dm,dd\}} R_t^j X_t^j + pf^u R_t^{v,m} V_t^m + pf^m R_t^{v,d} V_t^d - R_t D_t\right)\\
-\iota\left(\sum_{j\in\{uu,um,ud,mu,mm,md,du,dm,dd\}} R_t^j X_t^j + pf^u R_t^{v,m} V_t^m + pf^m R_t^{v,d} V_t^d\right).
\end{aligned}
$$

First-order conditions:

$$[\partial L_t]: \quad U^H_{C,t}\left(W_t - k_c L_t^{\eta}\right) = 0,$$

$$[\partial D_t]: \quad E_t[\Lambda_{t,t+1}]R_t = 1,$$

with

$$U^H_{C,t} = \left[C_t - k_c \frac{L_t^{1+\eta}}{1+\eta}\right]^{-\omega}, \qquad \Lambda_{t,t+1} = \frac{\beta\, U^H_{C,t+1}}{U^H_{C,t}}.$$

- **Banks.** First-order conditions:

Upstream bank

$$[\partial X_t^{uu}]: \; E_t[\Lambda_{t,t+1}]R_t^{uu}(1-\sigma+\sigma\lambda_{t+1}^u) - \lambda_t^u + \mu_t^u \xi R_t^{uu} = 0,$$

$$[\partial X_t^{um}]: \; E_t[\Lambda_{t,t+1}]R_t^{um}(1-\sigma+\sigma\lambda_{t+1}^u) - \lambda_t^u + \mu_t^u \xi R_t^{um} - k_b\lambda_t^u(X_t^{um} - \overline{X_t^{um}}) = 0,$$

$$[\partial X_t^{ud}]: \; E_t[\Lambda_{t,t+1}]R_t^{ud}(1-\sigma+\sigma\lambda_{t+1}^u) - \lambda_t^u + \mu_t^u \xi R_t^{ud} - k_b\lambda_t^u(X_t^{ud} - \overline{X_t^{ud}}) = 0,$$

$$[\partial D_t^u]: \; -R_t E_t[\Lambda_{t,t+1}](1-\sigma+\sigma\lambda_{t+1}^u) + \lambda_t^u - \mu_t^u R_t = 0.$$

Midstream bank

$$[\partial X_t^{mu}]: \; E_t[\Lambda_{t,t+1}]R_t^{mu}(1-\sigma+\sigma\lambda_{t+1}^m) - \lambda_t^m + \mu_t^m \xi R_t^{mu} - k_b\lambda_t^m(X_t^{mu} - \overline{X_t^{mu}}) = 0,$$

$$[\partial X_t^{mm}]: \; E_t[\Lambda_{t,t+1}]R_t^{mm}(1-\sigma+\sigma\lambda_{t+1}^m) - \lambda_t^m + \mu_t^m \xi R_t^{mm} = 0,$$

$$[\partial X_t^{md}]: \; E_t[\Lambda_{t,t+1}]R_t^{md}(1-\sigma+\sigma\lambda_{t+1}^m) - \lambda_t^m + \mu_t^m \xi R_t^{md} - k_b\lambda_t^m(X_t^{md} - \overline{X_t^{md}}) = 0,$$

$$[\partial D_t^m]: \; -R_t E_t[\Lambda_{t,t+1}](1-\sigma+\sigma\lambda_{t+1}^m) + \lambda_t^m - \mu_t^m R_t = 0.$$

Downstream bank

$$[\partial X_t^{du}]: \; E_t[\Lambda_{t,t+1}]R_t^{du}(1-\sigma+\sigma\lambda_{t+1}^d) - \lambda_t^d + \mu_t^d \xi R_t^{du} - k_b\lambda_t^d(X_t^{du} - \overline{X_t^{du}}) = 0,$$

$$[\partial X_t^{dm}]: \; E_t[\Lambda_{t,t+1}]R_t^{dm}(1-\sigma+\sigma\lambda_{t+1}^d) - \lambda_t^d + \mu_t^d \xi R_t^{dm} - k_b\lambda_t^d(X_t^{dm} - \overline{X_t^{dm}}) = 0,$$

$$[\partial X_t^{dd}]: \; E_t[\Lambda_{t,t+1}]R_t^{dd}(1-\sigma+\sigma\lambda_{t+1}^d) - \lambda_t^d + \mu_t^d \xi R_t^{dd} = 0,$$

$$[\partial D_t^d]: \; -R_t E_t[\Lambda_{t,t+1}](1-\sigma+\sigma\lambda_{t+1}^d) + \lambda_t^d - \mu_t^d R_t = 0.$$

Aggregate net worth dynamics (survivors + transfers):

$$N_{t+1}^{u}=\sigma\left(\sum_{j\in\{uu,um,ud\}}R_t^jX_t^j+pf^uR_t^{v,m}V_t^m-R_tD_t^u\right)+\iota\left(\sum_{j\in\{uu,um,ud\}}R_t^jX_t^j+pf^uR_t^{v,m}V_t^m\right),$$

$$N_{t+1}^{m}=\sigma\left(\sum_{j\in\{mu,mm,md\}}R_t^jX_t^j+pf^mR_t^{v,d}V_t^d-R_tD_t^m\right)+\iota\left(\sum_{j\in\{mu,mm,md\}}R_t^jX_t^j+pf^mR_t^{v,d}V_t^d\right),$$

$$N_{t+1}^{d}=\sigma\left(\sum_{j\in\{du,dm,dd\}}R_t^jX_t^j-R_tD_t^d\right)+\iota\left(\sum_{j\in\{du,dm,dd\}}R_t^jX_t^j\right).$$

- **Upstream firms.** First-order conditions:

$$[\partial L_t^u]:\ P_t^u(1-\alpha)\frac{Y_t^u}{L_t^u}-W_t=0,$$

$$[\partial K_t^u]:\ -(C_t^u)^{-\gamma}+\psi_t^{nu}\kappa^n(1-S_t^u)+\psi_t^{uu}\left[\kappa S_t^u-\frac{\kappa c(S_t^u)^2K_t^u}{\overline{K^u}}\right]$$
$$+\beta_fE_t\left[(C_{t+1}^u)^{-\gamma}\right]\left(P_{t+1}^u\alpha\frac{Y_{t+1}^u}{K_t^u}+1-\delta\right)=0,$$

$$[\partial X_t^{uu}]:\ (C_t^u)^{-\gamma}-\psi_t^{uu}R_t^{uu}-\beta_fE_t\left[(C_{t+1}^u)^{-\gamma}\right]R_t^{uu}=0,$$

$$[\partial X_t^{mu}]:\ (C_t^u)^{-\gamma}-\psi_t^{nu}R_t^{mu}-\beta_fE_t\left[(C_{t+1}^u)^{-\gamma}\right]R_t^{mu}=0,$$

$$[\partial X_t^{du}]:\ (C_t^u)^{-\gamma}-\psi_t^{nu}R_t^{du}-\beta_fE_t\left[(C_{t+1}^u)^{-\gamma}\right]R_t^{du}=0,$$

$$[\partial V_t^m]:\ (C_t^u)^{-\gamma}(-1+f^u)+\psi_t^{uu}\theta f^u(1-f^u)R_t^{v,m}+\beta_fE_t\left[(C_{t+1}^u)^{-\gamma}\right](1-pf^u)R_t^{v,m}=0,$$

$$[\partial S_t^u]:\ -\psi_t^{nu}\kappa^nK_t^u+\psi_t^{uu}\left[\kappa K_t^u-\frac{\kappa cS_t^u(K_t^u)^2}{\overline{K^u}}\right]=0.$$

- **Midstream firms.** First-order conditions:

$$[\partial L_t^m]:\ P_t^m(1-\phi)(1-\alpha)\frac{Y_t^m}{L_t^m}-W_t=0,$$

$$[\partial K_t^m]:\ -(C_t^m)^{-\gamma}+\psi_t^{nm}\kappa^n(1-S_t^m)+\psi_t^{mm}\left[\kappa S_t^m-\frac{\kappa c(S_t^m)^2K_t^m}{\overline{K^m}}\right]$$
$$+\beta_fE_t\left[(C_{t+1}^m)^{-\gamma}\right]\left[1-\delta+P_{t+1}^m(1-\phi)\alpha\frac{Y_{t+1}^m}{K_t^m}\right]=0,$$

$$[\partial X_t^{um}]:\ (C_t^m)^{-\gamma}-\psi_t^{nm}R_t^{um}-\beta_fE_t\left[(C_{t+1}^m)^{-\gamma}\right]R_t^{um}=0,$$

$$[\partial X_t^{mm}]:\ (C_t^m)^{-\gamma}-\psi_t^{mm}R_t^{mm}-\beta_fE_t\left[(C_{t+1}^m)^{-\gamma}\right]R_t^{mm}=0,$$

$$[\partial X_t^{dm}]:\ (C_t^m)^{-\gamma}-\psi_t^{nm}R_t^{dm}-\beta_fE_t\left[(C_{t+1}^m)^{-\gamma}\right]R_t^{dm}=0,$$

$$[\partial V_t^m]:\ (C_t^m)^{-\gamma}-\chi_t^mR_t^{v,m}-\beta_fE_t\left[(C_{t+1}^m)^{-\gamma}\right]R_t^{v,m}=0,$$

$$[\partial V_t^d]:\ (C_t^m)^{-\gamma}(-1+f^m)+\psi_t^{mm}\theta f^m(1-f^m)R_t^{v,d}+\beta_fE_t\left[(C_{t+1}^m)^{-\gamma}\right](1-pf^m)R_t^{v,d}=0,$$

$$[\partial Y_t^{iu}]:\ (C_t^m)^{-\gamma}\left(P_t^m\phi\frac{Y_t^m}{Y_t^{iu}}-P_t^u\right)+\chi_t^m\nu P_t^u=0.$$

- **Downstream firms.** First-order conditions:

$$[\partial L_t^d]:\ P_t^d(1-\phi)(1-\alpha)\frac{Y_t^d}{L_t^d}-W_t=0,$$

$$[\partial K_t^d]:\ -(C_t^d)^{-\gamma}+\psi_t^{nd}\kappa^n(1-S_t^d)+\psi_t^{dd}\left[\kappa S_t^d-\frac{\kappa c(S_t^d)^2K_t^d}{\overline{K^d}}\right]$$
$$+\beta_f E_t\left[(C_{t+1}^d)^{-\gamma}\right]\left[1-\delta+P_{t+1}^d(1-\phi)\alpha\frac{Y_{t+1}^d}{K_t^d}\right]=0,$$

$$[\partial X_t^{ud}]:\ (C_t^d)^{-\gamma}-\psi_t^{nd}R_t^{ud}-\beta_f E_t\left[(C_{t+1}^d)^{-\gamma}\right]R_t^{ud}=0,$$

$$[\partial X_t^{md}]:\ (C_t^d)^{-\gamma}-\psi_t^{nd}R_t^{md}-\beta_f E_t\left[(C_{t+1}^d)^{-\gamma}\right]R_t^{md}=0,$$

$$[\partial X_t^{dd}]:\ (C_t^d)^{-\gamma}-\psi_t^{dd}R_t^{dd}-\beta_f E_t\left[(C_{t+1}^d)^{-\gamma}\right]R_t^{dd}=0,$$

$$[\partial V_t^d]:\ (C_t^d)^{-\gamma}-\chi_t^d R_t^{v,d}-\beta_f E_t\left[(C_{t+1}^d)^{-\gamma}\right]R_t^{v,d}=0,$$

$$[\partial Y_t^{im}]:\ (C_t^d)^{-\gamma}\left(P_t^d\phi\frac{Y_t^d}{Y_t^{im}}-P_t^m\right)+\chi_t^d\nu P_t^M=0.$$

- **Final good producer.** First-order conditions:

$$[\partial Y_t^{fu}]:\ \frac{1}{\varepsilon}Y_t^{1-\varepsilon}\,\alpha_u\varepsilon(Y_t^{fu})^{\varepsilon-1}-P_t^u=0,$$
$$[\partial Y_t^{fm}]:\ \frac{1}{\varepsilon}Y_t^{1-\varepsilon}\,\alpha_m\varepsilon(Y_t^{fm})^{\varepsilon-1}-P_t^m=0,$$
$$[\partial Y_t^{d}]:\ \frac{1}{\varepsilon}Y_t^{1-\varepsilon}\,(1-\alpha_u-\alpha_m)\varepsilon(Y_t^{d})^{\varepsilon-1}-P_t^d=0.$$

A1.1 More details on model properties and on microfoundations

Loan rates and trade credit rates

In the model, each of the three banks sets three firm-specific loan rates, for a total of nine. Banks' first-order conditions imply within-bank equalization in steady state: a given bank charges the same loan rate to all firms it lends to. For example, the upstream bank's steady-state first-order condition for lending to the upstream firm yields

$$R^{uu}=\frac{\lambda^u}{\beta\left[(1-\sigma+\sigma\lambda^u)(1-\xi)+\xi\lambda^u\right]},$$

and the same expression applies to R^{um} and R^{ud}. Analogous conditions hold for the midstream and downstream banks.

Firms' first-order conditions then imply cross-bank equalization. Combining equations 23 and 24 shows that the upstream firm faces the same loan rate from the midstream and downstream banks in steady state. Applying the same argument to the remaining firms implies that all nine loan rates coincide in steady state. It follows that the six firm-side Lagrange multipliers on borrowing constraints, ψ, also equalize.

There are two trade-credit rates, R^{vm} and R^{vd}. The steady-state first-order conditions with respect to V^m and V^d imply

$$R^{vm} = \frac{(C^u)^{-\gamma}(1-f^u)}{\psi^{uu}\,\theta f^u(1-f^u)+\beta_f(C^u)^{-\gamma}(1-pf^u)},$$
$$R^{vd} = \frac{(C^m)^{-\gamma}(1-f^m)}{\psi^{mm}\,\theta f^m(1-f^m)+\beta_f(C^m)^{-\gamma}(1-pf^m)}.$$

From the firms' first-order conditions, the multipliers equalize in steady state, $\psi^{uu} = \psi^{mm}$. Therefore, under our parameterization, the two right-hand sides coincide, so $R^{vm} = R^{vd}$. This means there is a single steady-state price of inter-firm credit, and upstream and midstream face the same marginal cost of extending or factoring trade credit.

The equalization of loan rates is driven by the integration at the extensive margin between banks and the supply chain. If credit markets are fragmented and firms borrow only from their sector bank, with $\kappa^n = 0$, then cross-bank arbitrage cannot operate and loan rates across banks need not coincide. A similar logic applies to trade-credit rates. When credit markets are segmented, the firm-side multipliers ψ need not equalize. Consequently, the two trade-credit rates need not coincide.

Midstream firms' trade credit demand and supply

In the steady state of the model, midstream firms simultaneously borrow from upstream firms and extend trade credit to downstream firms, even though the interest rates are identical ($R^{vm} = R^{vd}$). This arises primarily from the assumption that trade credit extended to downstream firms can be pledged as collateral when borrowing from sector banks (invoice discounting).

To better illustrate this point, we show that without invoice discounting ($\Omega(.) = 0$), midstream firms would not simultaneously borrow and extend trade credit. Specifically, under the assumption that no profits are generated from factoring ($p = 1$), the steady-state first-order conditions (**??**) and (**??**) reduce to

$$(C^m)^{-\gamma} + \beta_f (C^m)^{-\gamma} R^{vd} + \zeta = 0,$$
$$(C^m)^{-\gamma} - \chi^m R^{v,m} - \beta_f (C^m)^{-\gamma} R^{v,m} = 0,$$

where ζ_t is the multiplier on the non-negativity constraint $V_{d \geq 0}$ introduced into the midstream bank's problem for this illustration. Using the result $R^{v,m} = R^{v,d}$, these first-order conditions imply that $\zeta = \chi^m R^{v,m} > 0$ if and only if $\chi^m > 0$. In other words, whenever the borrowing constraint to borrow from upstream firms is binding ($\chi^m > 0$), the midstream firms will not extend trade credit to downstream firms ($\zeta > 0$ and $V^d = 0$).

More details on microfoundations

We sketch here a microfoundation for the specification of firms' borrowing constraint in (18) and (30). We can think that whenever a bank purchases accounts receivable from a firm (supplier), it gains knowledge and information about the customer to whom the trade credit was extended. This knowledge can then be reused by the bank to improve its ability to engage in invoice discounting. In particular, similar to Kiyotaki and Moore (1997), in our setting a supplier can "run away" with loans collateralized by invoices. If this happens, the bank will be able to repossess the trade credit (invoices) pledged as collateral. However, the bank's ability to step in the collection of trade credit depends on its knowledge and familiarity with the customer. The larger this knowledge, the lower the value lost in the collection process. Thus, the larger the amount of factoring carried out, the more the bank will be able to step in and extract value from pledged invoices.

Formally, denote by θ the degree of knowledge acquired by the bank on the customer per unit of factored trade credit. We can think that the share of pledged invoices recoverable in the event of strategic default of the supplier will be θf. We can also think that the activity of factoring is costly, precisely because it entails the acquisition of information on customers. Denote by $p-1$ the information acquisition effort that the bank needs to carry out per unit of factored trade credit. It is immediate that the bank will ask to be compensated with a factoring fee of $p-1$ per unit of trade credit.

Additional model results

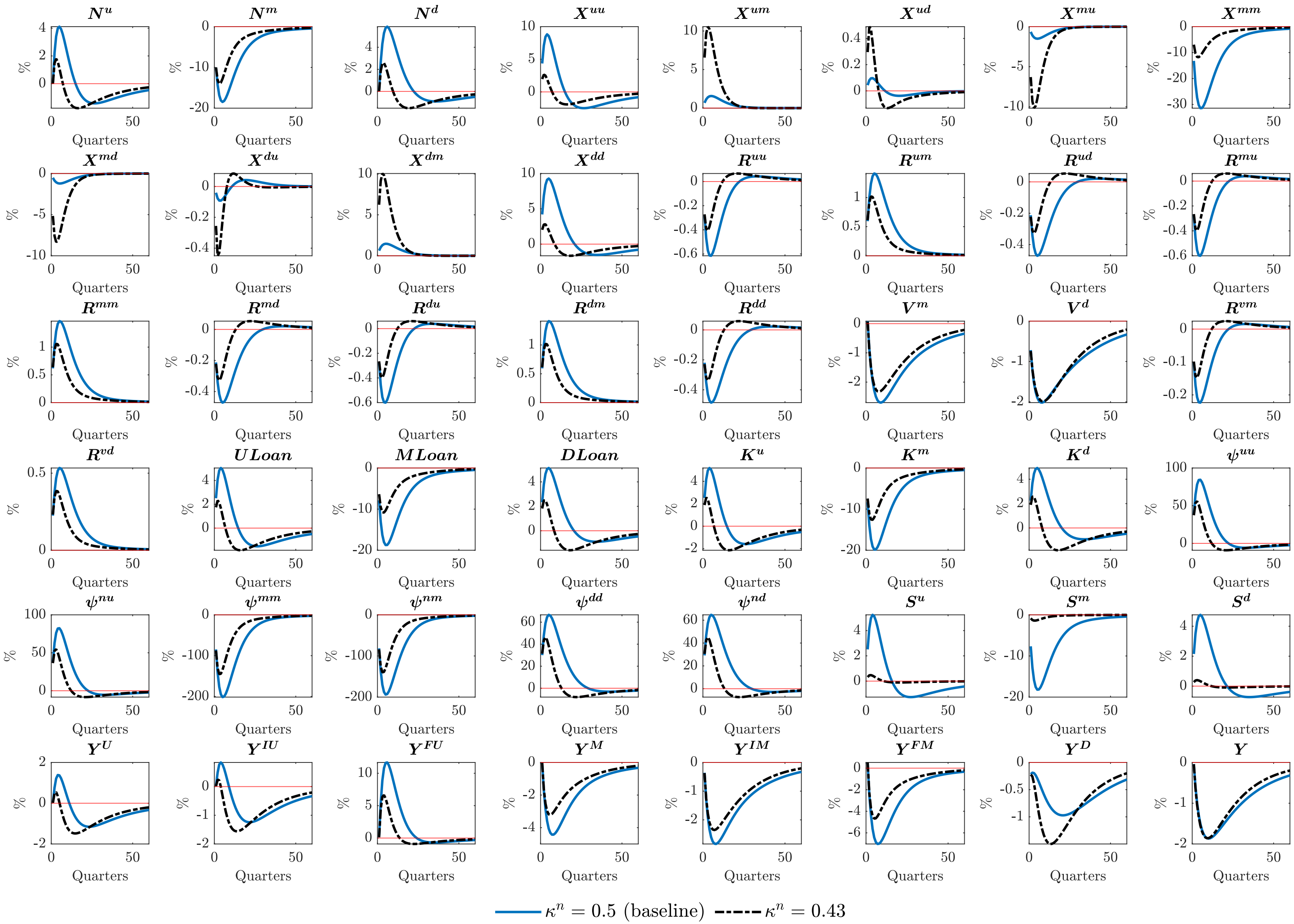

Figure A1: **Extensive margin experiments with major variables**

Note: Interest rates R_t^{uu} to R_t^{vd} show the response in percentage points.

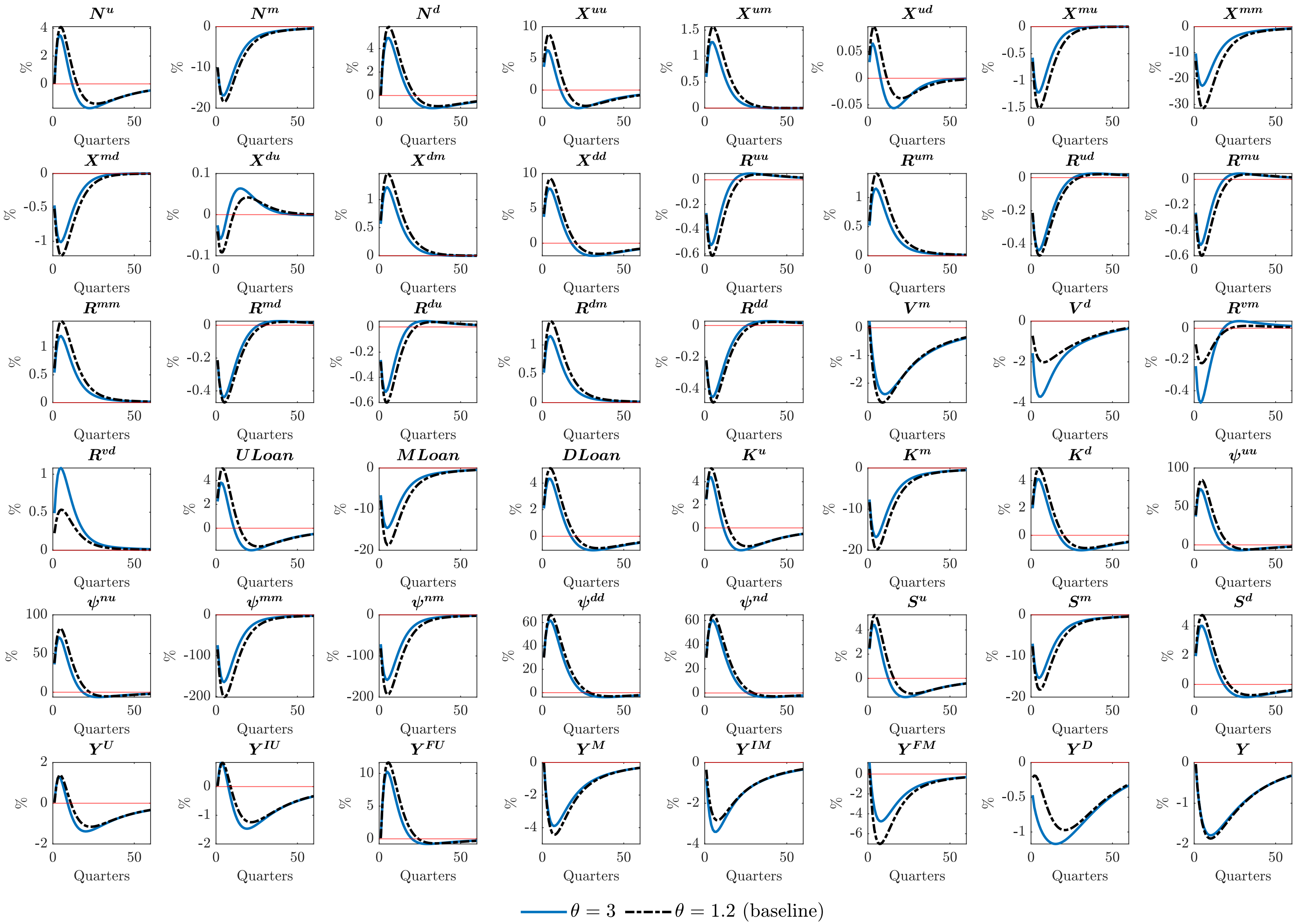

Figure A2: **Intensive margin experiments (θ) with major variables**

Note: Interest rates R_t^{uu} to R_t^{vd} show the response in percentage points.

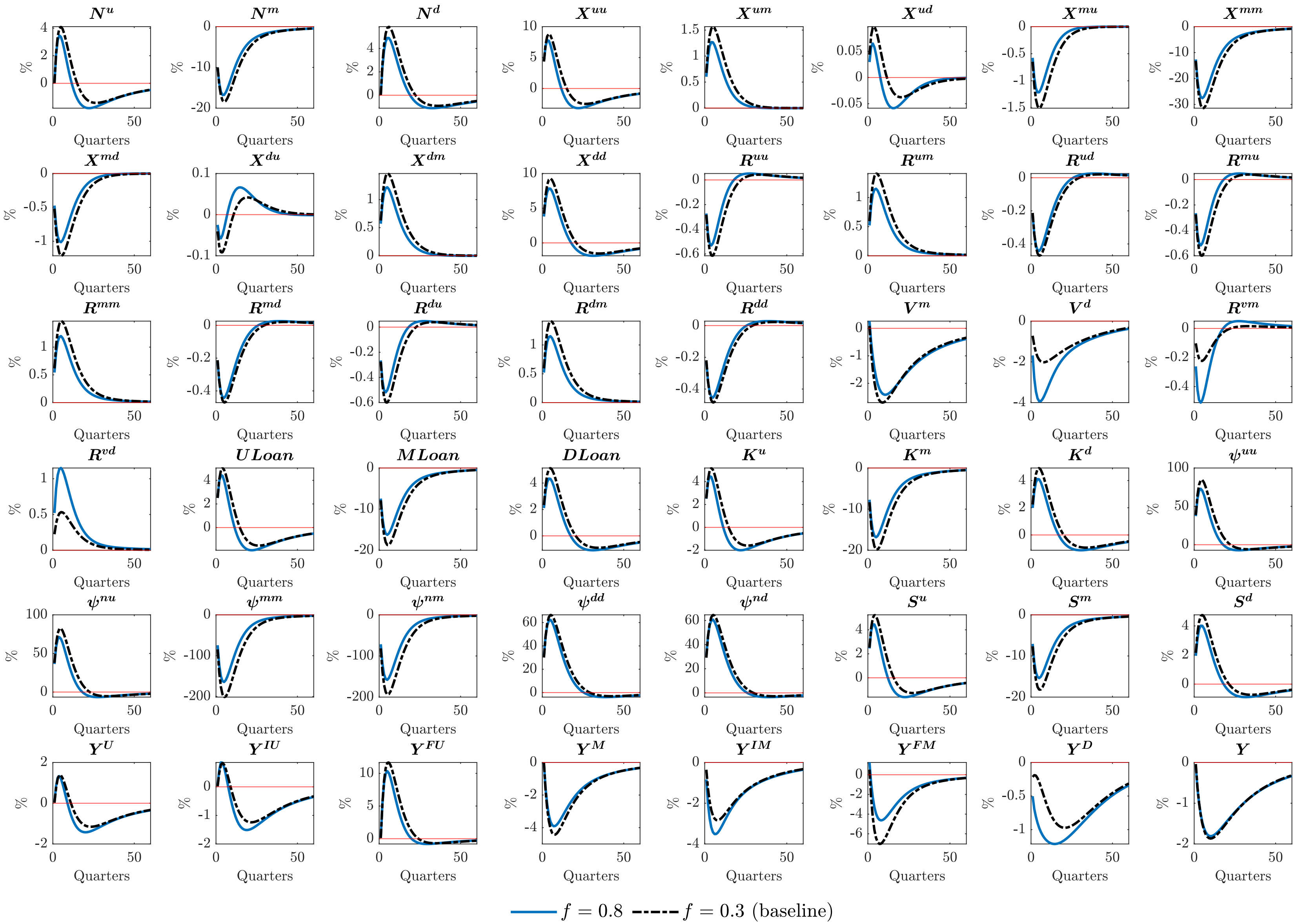

Figure A3: **Intensive margin experiments (f) with major variables**

Note: Interest rates R_t^{uu} to R_t^{vd} show the response in percentage points.

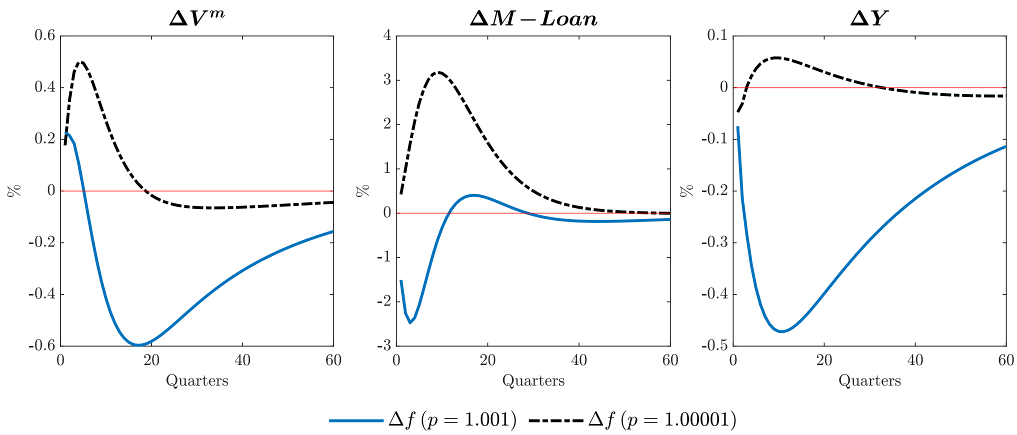

Figure A4: **Double-Difference IRFs: Factoring Level f Across Profit Margin Changes p**

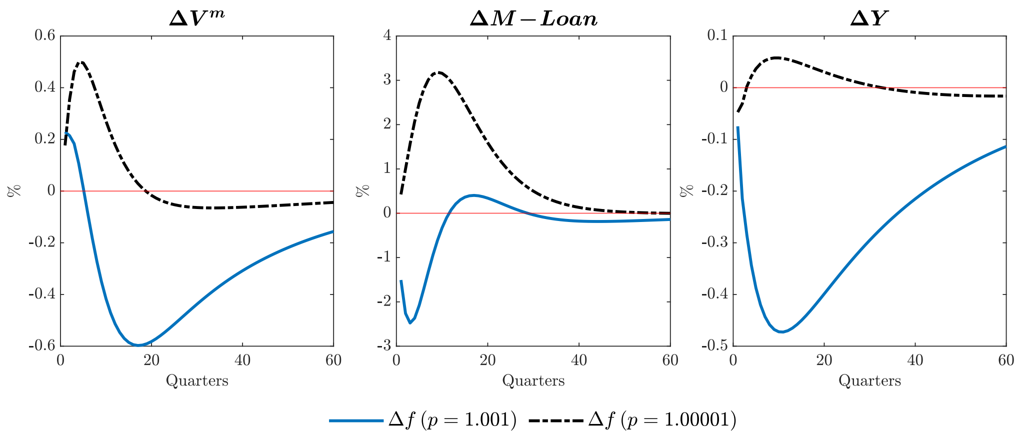

Figure A5: **Double-Difference IRFs: Factoring Level f Across Profit-Margin Changes p (with p treated as a bank asset)**

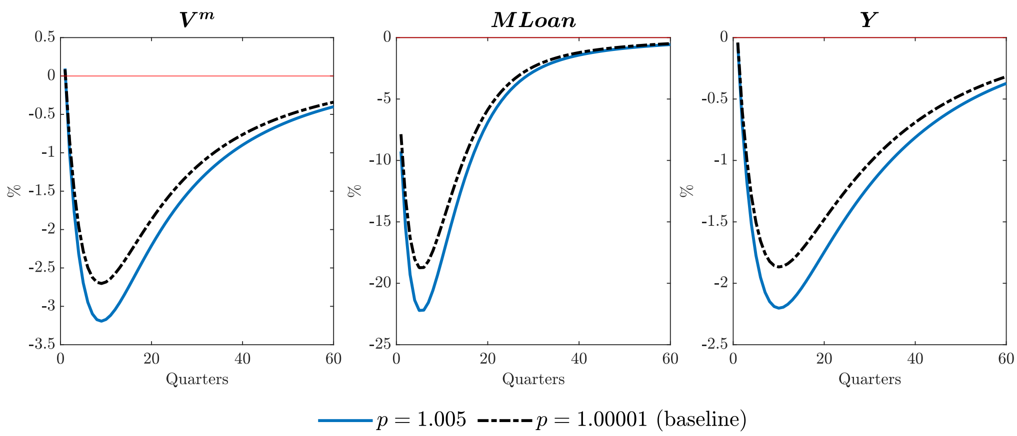

Figure A6: **IRF responses of Factoring Profit p changes (with p paid by buyer and customer firm of trade credit)**

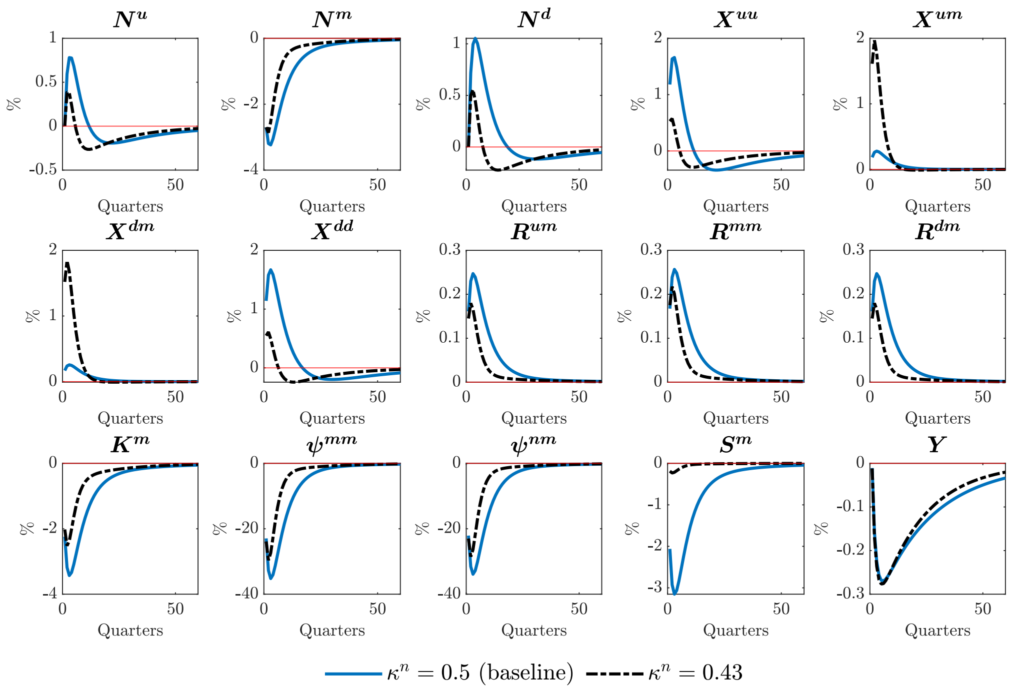

Figure A7: **Extensive Margin Result with Estimated Persistence**

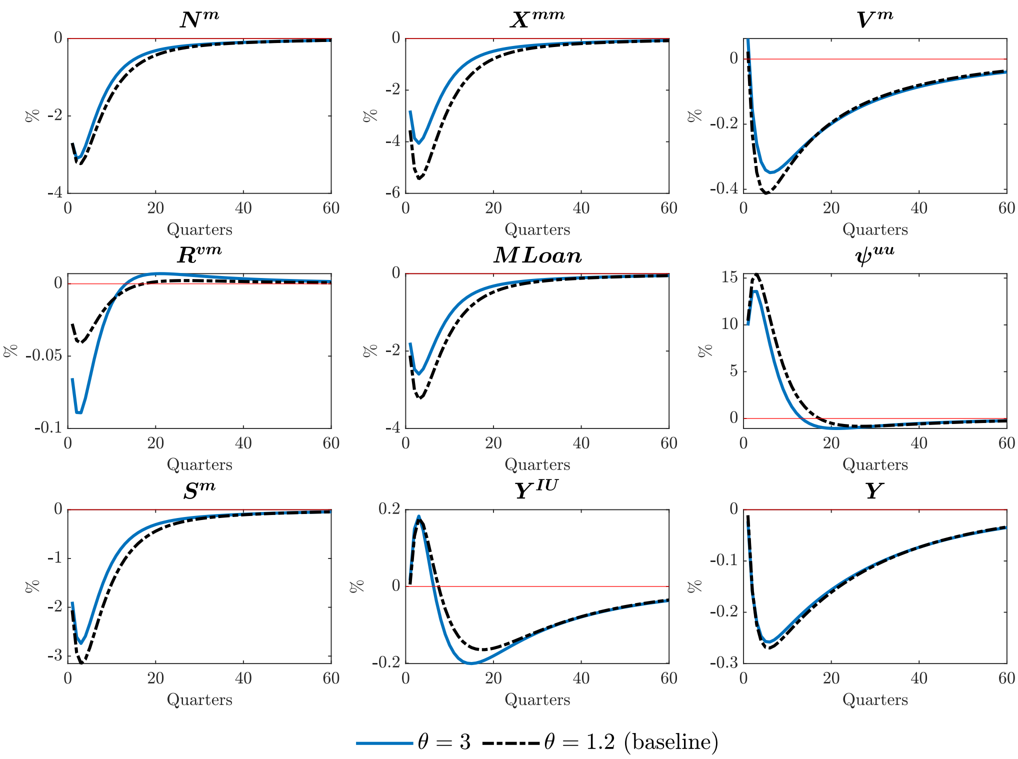

Figure A8: **Intensive Margin Result with Estimated Persistence**

A2 Further Details on Data and Empirical Results

Further details on shock and MPS

Table A1: Timeline of the MPS crisis

Year	Event	Implications
2007	MPS acquires Banca Antonveneta from Banco Santander for 9 billion, significantly higher than Santander's purchase price. The acquisition was debt-financed, relying heavily on complex derivatives, raising concerns about financial stability.	Increased financial strain due to high acquisition costs and reliance on derivatives.
2008-11	The global financial crisis exacerbates liquidity pressures. MPS uses opaque derivative contracts (Alexandria, Santorini, Nota Italia) with Deutsche Bank and Nomura to conceal losses, artificially inflating capital.	delayed recognition of financial distress and systemic risk exposure.
2012	New leadership acknowledges accounting irregularities and launches recapitalization efforts. The Italian government provides a 4 billion bailout via Monti Bonds, highlighting systemic vulnerabilities.	Demonstrates reliance on state support and systemic risks within the banking sector.
2013	Investigations reveal fraudulent reporting and supervisory violations. Former executives face charges of false accounting and market manipulation. Record losses prompt restructuring efforts, including branch closures and asset sales.	Exposes deep financial vulnerabilities and governance failures.
2014-16	Despite two capital increases (5 billion in 2014, 3 billion in 2015), MPS remains financially fragile. The ECB requires significant reduction in non-performing loans, further straining the balance sheet.	Continued financial fragility and regulatory pressures.
2017	The Italian government acquires a 68% stake in MPS, injecting 5.4 billion in public funds. This includes a large-scale disposal of 26 billion in NPLs and a restructuring plan with 8,000 job cuts and 600 branch closures.	Highlights the need for state intervention and significant restructuring.
2018-21	Efforts to privatize MPS, including negotiations with UniCredit, fail due to disagreements over financial conditions. However, the bank shows signs of recovery, reducing NPL exposure and returning to profitability in 2021.	Gradual recovery but ongoing challenges in privatization efforts.
2021-24	In 2022, MPS completes another 2.5 billion capital increase with significant state participation. Discussions explore potential mergers or acquisitions to facilitate the bank's exit from government ownership.	Ongoing efforts to restore market confidence and exit state ownership.

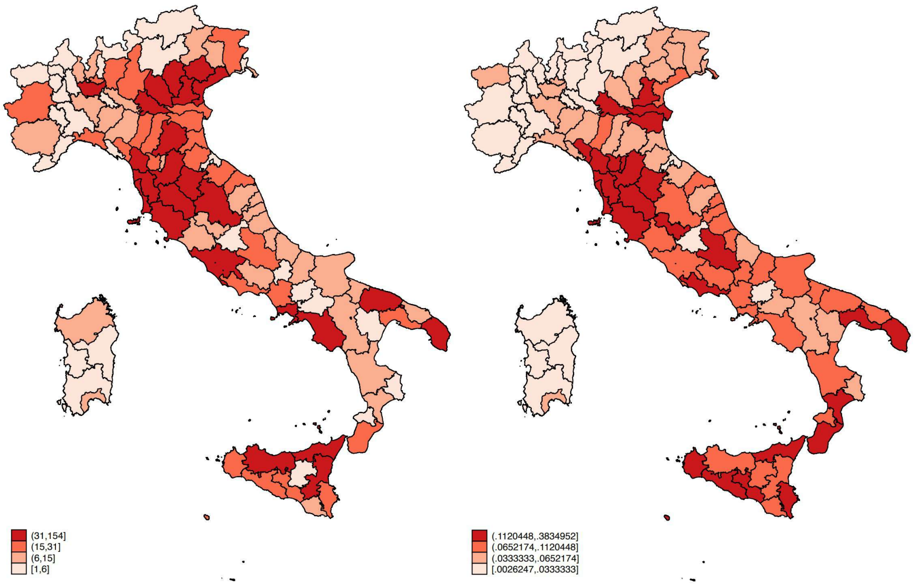

Figure A9: Diffusion of MPS branches.

Notes: The left plot reports the total number of MPS branches by Italian province (as of 2012). The right plot, reports the MPS branch share of the province's overall branches.

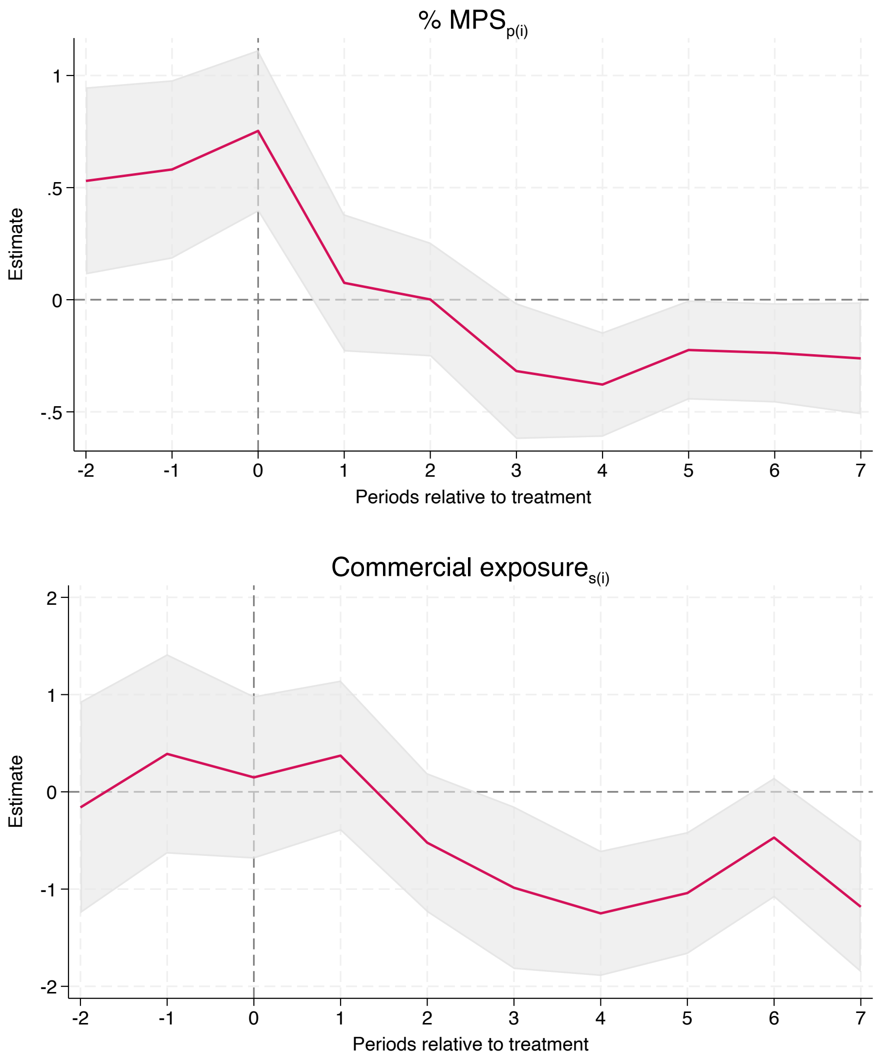

Figure A10: Pre-trends.

Notes: The top and bottom panels display, respectively, the point estimates of % MPS$p(i)$ and Upstream exposure$_{s(i)}$ across periods relative to treatment, while the shaded regions indicate the 95% confidence intervals.

Further details on preliminary analysis on effect of MPS shock

We identify a firm as directly connected to MPS if it reported borrowing from the bank in the MET survey prior to the crisis, i.e., before 2013. In that year, MPS was the third-largest banking group in Italy in terms of total assets, and approximately 18% of firms in our sample reported having an active credit relationship with the bank. We rely on pre-crisis information to define this exposure as a precautionary measure to mitigate concerns about endogenous bank selection—since more creditworthy firms may have had the ability to drop MPS as a lender after the shock and switch to better-capitalized banks. Reassuringly, the risk of selection through switching is limited in our context: as documented by D'Auria, Foglia, and Reedtz (1999), Italian firms tend to maintain stable banking relationships over time and typically add, rather than replace, banking partners. Consistent with this evidence, actual switching is negligible in our data, with fewer than 0.05% of firms reporting a change in their main bank over the sample period. To estimate the impact of this connection, we implement a difference-in-differences specification where we interact a pre-crisis MPS exposure indicator with a post-2012 dummy. The model includes controls for time-varying firm characteristics—namely, sales, employment, and firm age—and absorbs firm, year, and lender bank fixed effects. In a more saturated specification, we additionally include Region $\times$ Sector $\times$ Year fixed effects to account for differential trends across local credit markets and industries.

The dependent variables capture different dimensions of financing constraints and credit availability. In Columns 1 and 4, we use a survey-based binary indicator that equals one if the firm reports having forgone potentially profitable investment opportunities (i.e., with positive net present value) due to a lack of external financial resources. This serves as a broad measure of credit rationing. In Columns 2 and 5, we use an alternative proxy, also based on survey responses, which equals one if the firm reports that access to bank credit was restricted by the lack of sufficient collateral or guarantees. Finally, in Columns 3 and 6, we consider the logarithm of total bank debt, drawn from AIDA balance sheet data, which provides a continuous measure of actual credit received. Taken together, these measures capture both firms' perceived financial constraints and their realized borrowing outcomes, offering a complementary view of credit conditions before and after the MPS shock.

Table A2 presents the results of this exercise. The estimated coefficients on the interaction term $\text{MPS}_i \times \text{Post}_{i,t}$ are positive and statistically significant in Columns 1, 2, 4, and 5, indicating that firms directly connected to MPS were more likely to report experiencing financial constraints after 2012. This holds for both the broad investment-based proxy and the collateral-based proxy, across both baseline and saturated specifications. In parallel, Columns 3 and 6 show a significant and negative association between MPS exposure and the log of bank debt, suggesting a contraction in credit volume for exposed firms.

While the reduction in bank debt could, in principle, reflect weaker credit demand rather than supply-side tightening, this interpretation appears inconsistent with the survey-based evidence on financing constraints. Specifically, firms report having to forgo profitable investments and facing collateral-related barriers to accessing credit—patterns that are difficult to reconcile with a purely demand-driven contraction. Taken together, these results are consistent with a decline in credit availability for firms reliant on MPS following the onset of the bank's distress. These findings motivate our subsequent analysis, which examines how the MPS-induced banking shock—and the associated shock transmitted through commercial linkages—propagates across firms depending on their degree of supply chain participation.

Table A2: MPS direct link, credit constraints, and bank credit

	FC (investment) (1)	FC (collateral) (2)	Bank debt (3)	FC (investment) (4)	FC (collateral) (5)	Bank debt (6)
$\text{MPS}_{i,t} \times \text{Post}_t$	0.0322***	0.0197*	-0.171**	0.0270***	0.0249**	-0.232***
	(0.0103)	(0.0103)	(0.0740)	(0.0102)	(0.00991)	(0.0720)
$\text{Sales}_{i,t-1}$	-0.00298**	-0.00582***	0.0867***	-0.00361***	-0.00576***	0.0865***
	(0.00128)	(0.00188)	(0.00861)	(0.00132)	(0.00172)	(0.0102)
$\text{Employment}_{i,t-1}$	0.000599	-0.00307	0.826***	0.000210	-0.00224	0.835***
	(0.00281)	(0.00384)	(0.0324)	(0.00293)	(0.00404)	(0.0385)
$\text{Age}_{i,t-1}$	-0.0198	-0.0472**	1.979***	-0.0139	-0.0454*	1.832***
	(0.0166)	(0.0213)	(0.100)	(0.0182)	(0.0251)	(0.129)
Firm FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	–	–	–
Region × Sector × Year FE	N	N	N	Y	Y	Y
Adj R-squared	0.324	0.228	0.759	0.329	0.234	0.761
Observations	103,780	75,781	319,784	103,648	75,649	319,349

Notes: OLS estimates. In columns 1 and 4, the dependent variable is a broad indicator of financial constraints. It is a dummy that equals 1 if the firm reports having potentially profitable investment opportunities (i.e., positive net present value) that were not pursued due to a lack of financial resources (MET survey). In columns 2 and 5, the dependent variable is an alternative proxy for financial constraints, a dummy that equals 1 if the firm's access to bank credit was restricted by the availability of collateral or equivalent guarantees, and 0 otherwise (MET survey). In columns 3 and 6, the dependent variable is the logarithm of bank debt (balance sheet data). Robust standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Further empirical results

Table A3: First stage regressions

	Ext-Integ $\times$ Supply chain $\times$ Post$_t$	Commercial-Link$_{s(i)}$ $\times$ Supply chain $\times$ Post$_t$	Supply chain $\times$ Post$_t$
Distance from SGU$_i$ $\times$ Post	0.0311***	0.0338***	0.0176***
	[0.000436]	[0.000242]	[0.000150]
Ext-Integ $\times$ Distance from SGU$_i$ $\times$ Post	-0.0493***	0.000920**	-0.00729***
	[0.000718]	[0.000374]	[0.000242]
Commercial-Link$_{s(i)}$ $\times$ Distance from SGU$_i$ $\times$ Post	-0.0135***	-0.0693***	-0.0291***
	[0.000848]	[0.00131]	[0.000661]
Ext-Integ $\times$ Post$_t$	0.172***	-0.00815***	-0.0310***
	[0.00306]	[0.00139]	[0.000902]
Commercial-Link$_{s(i)}$ $\times$ Post$_t$	-0.0867***	0.119***	-0.114***
	[0.00194]	[0.00241]	[0.00122]
Sales$_{t-1}$	0.00237***	0.00241***	0.00250***
	[0.000252]	[0.000274]	[0.000161]
Age$_{t-1}$	-0.00520*	-0.0262***	-0.00762***
	[0.00295]	[0.00310]	[0.00187]
E-commerce$_{t-1}$	-0.00482***	0.000889	-0.00377***
	[0.00187]	[0.00200]	[0.00124]
Definition of Supply chain		Fixed (pre-crisis)	
Firm FE		Y	
Year FE		Y	
Bank FE		Y	
Observations		480,769	
Underidentification p-value		0.000	
Kleibergen-Paap rk Wald F		23.174	
Cragg-Donald Wald F statistic		25.693	

Notes: Robust standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A4: Robustness: Alternative instrument and time-varying measures

	Sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commercial-Link$_{s(i)}$ × Supply chain × Post$_t$	-3.131***	-4.652***	-0.318***		-2.230***	-0.716***		-1.919***
	[0.622]	[1.130]	[0.0608]		[0.444]	[0.157]		[0.409]
Supply chain × Post$_t$	8.378***	12.15***	10.52***	2.847***	6.388***	7.596***	2.699***	5.662***
	[1.643]	[2.923]	[1.802]	[0.584]	[1.245]	[1.561]	[0.726]	[1.164]
Commercial-Link$_{s(i)}$ × Post$_t$	1.189***	1.727***	0.170***	0.0729***	0.905***	0.348***	0.00382	0.778***
	[0.237]	[0.422]	[0.0319]	[0.0186]	[0.185]	[0.0791]	[0.0206]	[0.168]
Ext-Integ × Post$_t$	0.452***	0.642***	1.092***	0.349***	0.268***	0.895***	0.402***	0.241***
	[0.0931]	[0.163]	[0.189]	[0.0795]	[0.0587]	[0.173]	[0.119]	[0.0555]
Ext-Integ × Supply chain × Post$_t$	-1.344***	-1.933***	-4.710***	-1.139***	-0.771***	-2.732***	-1.073***	-0.697***
	[0.266]	[0.467]	[0.811]	[0.242]	[0.157]	[0.571]	[0.303]	[0.148]
Int(Factor)-Integ $_{B(i)}$ × Post$_t$		1.395*						
		[0.809]						
Int(Factor)-Integ$_{B(i)}$ Receivables × × Post$_t$		-4.240*						
		[2.355]						
Ext-Integ × Payables × Post$_t$				0.380***			0.118	
				[0.0892]			[0.0867]	
Ext-Integ × Receivables × Post$_t$				-0.123***			-0.0866**	
				[0.0368]			[0.0425]	
Payables × Post$_t$		-0.722***		-1.068***			-0.378*	
		[0.146]		[0.190]			[0.213]	
Receivables × Post$_t$		0.258***		0.371***			0.307***	
		[0.0632]		[0.0620]			[0.0936]	
Sales$_{t-1}$	0.635***	0.633***	0.644***	0.643***	0.463***	0.469***	0.458***	0.464***
	[0.00478]	[0.00633]	[0.00424]	[0.00491]	[0.00884]	[0.00864]	[0.0115]	[0.00881]
Age$_{t-1}$	-0.773***	-0.839***	-0.741***	-0.794***	-0.674***	-0.695***	-0.761***	-0.675***
	[0.0218]	[0.0307]	[0.0202]	[0.0243]	[0.0337]	[0.0321]	[0.0499]	[0.0333]
E-commerce$_{t-1}$	0.101***	0.123***	0.0778***		0.0784***	0.0907***		0.0803***
	[0.0101]	[0.0175]	[0.00684]		[0.00931]	[0.00765]		[0.00888]
Supply chain and Trade credit	Fixed (pre-crisis)				Time-varying (pre-determined)			
Bank integration	Provincial	Provincial	Sectorial	Provincial	Provincial	Sectorial	Provincial	Provincial
Instrument	Alternative	Alternative	Alternative	Alternative	Baseline	Baseline	Baseline	Alternative
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Region × Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	480,769	333,702	485,412	355,250	311,466	314,214	202,932	311,466
Underidentification p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald F	35.991	16.017	274.836	154.864	23.102	36.640	37.209	24.140
Cragg-Donald Wald F statistic	44.758	18.114	339.361	185.027	38.251	58.509	64.580	43.186

Notes: Robust standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A5: Robustness: Effects on firm employment

	Employment				
	(1)	(2)	(3)	(4)	(5)
Commercial-Link$_{s(i)}$ × Supply chain × Post$_t$	-0.630**	-0.127***	-0.163*		
	[0.249]	[0.0301]	[0.0832]		
Supply chain × Post$_t$	1.659**	2.861***	0.482*	0.381**	0.600**
	[0.653]	[0.823]	[0.254]	[0.193]	[0.235]
Commercial-Link$_{s(i)}$ × Post$_t$	0.261***	0.0791***	0.0865**	0.0313***	0.0264***
	[0.0954]	[0.0153]	[0.0366]	[0.00605]	[0.00715]
Ext-Integ × Post$_t$	0.0836**	0.260***	0.0108	0.0371	0.0821**
	[0.0371]	[0.0869]	[0.0115]	[0.0264]	[0.0373]
Ext-Integ × Supply chain × Post$_t$	-0.257**	-1.243***	-0.0526*	-0.147*	-0.244**
	[0.105]	[0.368]	[0.0312]	[0.0794]	[0.0980]
Ext-Integ × Payables × Post$_t$				0.0842***	0.0317
				[0.0322]	[0.0278]
Ext-Integ × Receivables × Post$_t$				-0.0238	-0.0260*
				[0.0145]	[0.0138]
Payables × Post$_t$				-0.207***	-0.0848
				[0.0680]	[0.0733]
Receivables × Post$_t$				0.0861***	0.119***
				[0.0254]	[0.0322]
Sales$_{t-1}$	0.135***	0.137***	0.102***	0.140***	0.0980***
	[0.00159]	[0.00141]	[0.00224]	[0.00169]	[0.00302]
Age$_{t-1}$	-0.0432***	-0.0365***	-0.00532	-0.0428***	-0.0165
	[0.0110]	[0.00968]	[0.0127]	[0.0116]	[0.0187]
E-commerce$_{t-1}$	0.0396***	0.0356***	0.0350***		
	[0.00380]	[0.00287]	[0.00258]		
Supply chain and	Fixed	Fixed	Time-varying	Fixed	Time-varying
Trade credit	pre-crisis	pre-crisis	(predetermined)	pre-crisis	(predetermined)
Bank integration	Provincial	Sectorial	Provincial	Provincial	Provincial
Firm FE	Y	Y	Y	Y	Y
Region × Sector FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Observations	337,007	340,031	247,482	245,745	169,618
Underidentification p-value	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald F	15.044	89.270	44.678	81.106	31.230
Cragg-Donald Wald F statistic	24.713	168.038	81.273	168.690	50.727

Notes: Robust standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A6: Variable description

Variable name	Definition
$\text{Sales}_{i,t}$	logarithm of firm i's total annual sales in year t. Source: Frame SBS (ISTAT).
$\text{Employment}_{i,t}$	logarithm of the number of employees of firm i in year t. Source: Frame SBS (ISTAT).
Post_t	indicator equal to one for years after 2012, and zero otherwise. It identifies the post–MPS shock period following the disclosure of hidden losses and the initiation of the bank's restructuring process.
Supply Chain	indicator equal to one if firm i participates in a supply chain, and zero otherwise. A firm is classified as belonging to a supply chain if it declares having long-term, quantitatively significant relationships with other firms for commercial purposes involving the sale or purchase of semifinished products or components. In the main analysis, supply chain participation is fixed at the pre-crisis level (2012). In robustness checks, we also employ a time-varying measure based on the year prior to the outcome. Source: MET survey.
$\text{Commercial-Link}_{s(i)}$	sector-level measure of exposure to the MPS shock. For each 2-digit NACE Rev. 2 sector, we calculate the share of firms borrowing from MPS in 2012 (MET survey) and weight it by inter-sectoral input–output linkages in 2012 (ISTAT), capturing reliance on other sectors for intermediate input purchases (upstream) and output sales (downstream). This reflects pre-crisis commercial network conditions. Sources: MET survey; ISTAT.
Ext-Integ (Provincial)	share of Monte dei Paschi di Siena (MPS) branches in the province of firm i in 2012. Source: Bank of Italy.
Ext-Integ (Sectorial)	share of firms in the operating (ATECO 2-digit) industry of firm i financed by MPS in 2012. Source: MET survey.
$\text{Int(Factor)-Integ}_{b(i)}$	intensive-margin bank–supply chain integration. Computed as the ratio of factored accounts receivables to total bank loans of firm i's lender bank, based on 2010 factoring activity. In the case of multiple lending relationships, values are averaged across the firm's lenders. Factoring data are hand-collected from banks' online balance sheet statements and rescaled by total credits. Sources: MET survey; banks' balance sheets.
Factoring (Suppliers)	average factoring intensity of the lenders of firm i's suppliers, obtained by weighting banks' 2010 factoring intensity at the 2-digit sector level with the 2010 input–output matrix corresponding to firm i's sector. Sources: banks' balance sheets; ISTAT input–output tables.
Payables	ratio of firm i's trade payables to total assets. In the main analysis, this variable is fixed at the pre-crisis level (2012). In robustness checks, we also employ a time-varying measure based on the year prior to the outcome. Source: Aida (Bureau van Dijk).
Receivables	ratio of firm i's trade receivables to total assets. In the main analysis, this variable is fixed at the pre-crisis level (2012). In robustness checks, we also employ a time-varying measure based on the year prior to the outcome. Source: Aida (Bureau van Dijk).
High factoring sector	dummy equal to one if firm i operates in one of the top ten industries by factoring usage, and zero otherwise. Source: Assifact.
MPS_i	indicator equal to one if firm i had an active credit relationship with MPS in 2012, zero otherwise. Source: MET survey.
Distance from SGU_i	distance between firm i and the nearest Strategic Geographical Unit (SGU) offering advanced IT services. It is used to instrument for Supply chain participation. Source: geolocation data on firms (Aida, Bureau van Dijk).
Alternative instrument	constructed by interacting firm i's distance from the nearest Strategic Geographical Unit (SGU) with a sector-level measure of IT usage. The latter is based on the share of firms in each sector that regularly use IT for commercial transactions, as reported in the EU-EFIGE/Bruegel-UniCredit survey (2010). Source: geolocation data; EU-EFIGE/Bruegel-UniCredit survey (2010).
Age	logarithm of (1+) age of firm i, measured as the difference between the current year and the firm's year of establishment. Source: Frame SBS (ISTAT).
E-commerce	dummy equal to one if firm i declares using general-purpose or industry-specific e-commerce platforms, or operates its own website for online sales; zero otherwise. Source: MET survey.
FC (investment)	dummy equal to one if firm i reports having potentially profitable investment opportunities (positive net present value) that were not pursued due to a lack of financial resources, and zero otherwise. Source: MET survey.
FC (collateral)	dummy equal to one if firm i reports that access to bank credit was restricted by the availability of collateral or equivalent guarantees, and zero otherwise. Source: MET survey.
Bank debt	logarithm of firm i's outstanding bank debt. Source: Aida (Bureau van Dijk).

Table A7: Main banks in the sample

Ambrosiano Veneto	Bca Pop Italiana	CR di Alessandria
Banco Desio	Bca Pop Pugliese	CR di Asti
Bca Adriatico	Bca Pop Valconica	CR di Bologna
Bca Antonveneta	Bca Pop Vesuviana	CR di Bra
Bca Apulia	Bca Popolare del Trentino	CR di Carrara
Bca Bipielle	Bca Prossima	CR di Cesena
Bca Carime	Bca Reale	CR di Chieti
Bca Caripe	Bca Regionale Europea	CR di Civitavecchia
Bca Cattolica	Bca Sella	CR di Fabriano e Cupramontana
Bca Centropadana	Bca Tercas	CR di Fano
Bca CIS	Bca Valsabbina	CR di Ferrara
Bca Commerciale Italiana	BCC Agrobresciano	CR di Firenze
Bca del Fucino	BCC Bca di Udine	CR di Foligno
Bca del Piemonte	BCC Brianza e Laghi	CR di Forlì e della Romagna
Bca dell'Etruria e del Lazio	BCC Carate Brianza	CR di Imola
Bca della Campania	BCC Caravaggio e Cremasco	CR di Loreto
Bca della Ciociaria	BCC Credifriuli	CR di Lucca Pisa e Livorno
Bca di Asti	BCC della Valsabbina	CR di Orvieto
Bca di Imola	BCC di Bergamo e Valli	CR di Parma e Piacenza
Bca di Legnano	BCC di Brescia	CR di Pistoia e della Lucchesia
Bca di Trento e Bolzano	BCC di Busto Garolfo e Buguggiate	CR di Ravenna
Bca di Valle Camonica	BCC di Cantù	CR di Rieti
Bca Etica	BCC di Credicoop Emil Bca	CR di Rimini
Bca Federico del Vecchio	BCC di Padova e Rovigo	CR di Saluzzo
Bca Generali	BCC di Ravennate, Forlivese e Imolese	CR di San Miniato
Bca ITB (Bca 5)	BCC Emil Bca	CR di Savona
Bca Mediolanum	BCC Milano	CR di Terni e Narni
Bca Monte di Lucca	BCC Pordenonese e Monsile	CR di Venezia
Bca Monte Parma	BCC Roma	CR di Viterbo
BNL	BCC Romagnolo	Credem
BNP Paribas	BCC (others)	Credit Agricole
Bca Nuova	Bco 3 Venezie	Credito Bergamasco
Bca Piacenza	Bco di Brescia	Credito Valtellinese
Bca Pop Commercio e Industria	Bco di Lucca e del Tirreno	Deutsche Bank
Bca Pop del Cassinate	Bco di Napoli	Fideuram
Bca Pop del Mezzogiorno	Bco di Salerno	Fineco Bank
Bca Pop dell'Emilia Romagna	Bco di Sardegna	Hypo Alpe Adria
Bca Pop delle Prov Molisane	Bco di Sassari	IFIS
Bca Pop di Ancona	Bco Passadore	ING Bank
Bca Pop di Aprilia	Bco Popolare	Intesa Sanpaolo
Bca Pop di Bari	Bco San Giorgio	La Cassa
Bca Pop di Bari Group	Bco Sanfelice	Mediobanca
Bca Pop di Bergamo	Biver Bca	Monte Dei Paschi di Siena
Bca Pop di Cortona	BNP Paribas	Nuova Bca delle Marche
Bca Pop di Fondi	BNP Paribas Group	Poste Italiane
Bca Pop di Lajatico	BPER	Sella
Bca Pop di Lanciano e Sulmona	BPM	Serfina Bca
Bca Pop di Mantova	C Rurale Bolzano Raiffeisen	UBI
Bca Pop di Ravenna	Carige	UBI Banca
Bca Pop di Sondrio	CR Città di Castello	Unicredit
Bca Pop di Spoleto	CR dell'Umbria (CR di Spoleto)	Unipol Banca
Bca Pop di Verona e Novara	CR della Provincia dell'Aquila	Veneto Banca
Bca Pop di Vicenza	CR della Spezia	Volksbank
Bca Pop Friuladria	CR delle Provincia Lombarde	