BIS Working Papers

No 1350

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Monetary and Economic Department

May 2026

JEL classification: E23, E32, E41, E44, E51, F65

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This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Elasticity of money in production networks, working capital, credit lines and financial conditions*

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This version: April 29, 2026
First version: August 15, 2025

Abstract

The elastic supply of money through overdrafts and credit lines overcomes cash-in-advance constraints, enabling large-value payments without waiting for incoming cash. This elasticity is crucial in long supply chains, where cash-in-advance constraints could otherwise cause gridlock. In essence, money elasticity and the supply of working capital are two sides of the same coin, with undrawn credit lines serving as the operative link. This paper examines how shifts in financial conditions influence money elasticity and, in turn, impact firm activity within production networks. Using granular firm-level data, we demonstrate that production-network-driven working capital needs introduce a cyclical element that dances to the tune of financial conditions. Tighter conditions, such as rising credit spreads or a stronger US dollar, significantly reduce output, with spillovers through production networks amplifying the effects. These findings underscore the importance of money elasticity in supporting economic stability.

Keywords: Money elasticity, Working capital, Credit lines, Financial conditions, Input-output linkages.
JEL Codes: E23, E32, E41, E44, E51, F65.

*We thank Muhammed Yildirim for useful discussions on modelling working capital in production networks. We are grateful for comments from seminar participants at the Bank for International Settlements. The views expressed in this paper are those of the authors and do not necessarily represent those of the Bank for International Settlements.
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1. Introduction

Today's monetary system built around trusted intermediaries supports payment activity through account updates. If the payer and payee both have accounts at the same intermediary – say, a commercial bank, then the bank executes the payment by debiting the account of the payer and crediting the account of the payee. If the payer and payee hold accounts at different banks, then settlement on the central bank's balance sheet between the payer's bank and payee's bank implements the payment. International payments involve more complex account updates through correspondent banks, but the principles remain the same – payments are executed through a sequence of account updates performed by trusted intermediaries.

A key difference between commodity-based money (say, gold coins or stablecoins) and the intermediary-based monetary system is the ability of the latter to provide money *elastically* to allow an account holder to make a payment by drawing on a credit line or an overdraft facility. By using these facilities, the account holder can create money (deposits) in a discretionary way to settle obligations in a timely way. Such provision of liquidity on demand allows financial obligations to be settled efficiently, preventing gridlock and mitigating the disruptive effects of shocks on the broader economy.

The elasticity of money is particularly vital for firms operating in long production chains. For these firms, the need for liquidity on demand is often substantial due to the prolonged time lag between incurring production costs and receiving cash flow from sales (Kim and Shin (2023)). Additionally, they may need liquidity to prepay suppliers to secure essential inputs for production (Antràs and Foley (2015), Schmidt-Eisenlohr (2013)). When this elasticity is impaired, the resulting disruptions are likely to have a disproportionately large impact on these firms.

In this paper, we explore how changes in the elasticity of money, as reflected in shifts in financial conditions, influence firm activity. Our analysis exploits cross-sectional variations in firms' undrawn credit lines–representing readily accessible liquidity–needed to meet their working capital requirements in production networks.

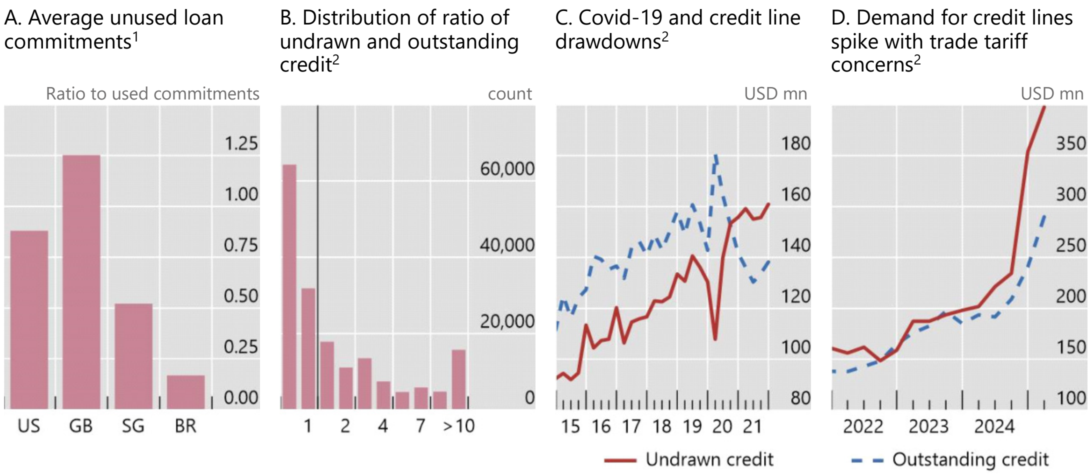
The demand for liquidity, or "potential money"– the capacity to draw down committed credit lines that can be monetised at the borrower's discretion, subject to bank terms – is substantial among non-financial firms. Panel A of Figure 1 shows that, across selected countries, the aggregate share of unused loan commitments from banks ranges from 20% to over 100% of utilised credit commitments. At the firm level, data from a global cross-section of firms shows that approximately 50% of them have undrawn credit lines that exceed their outstanding debt (Panel B).

Recent shocks have highlighted the critical role of money elasticity. During the early stages of the Covid-19 pandemic, firms drew down, on average, 20% of their initial outstanding debt through credit lines (Figure 1, Panel C). More recently, potentially in anticipation of trade tariffs following the 2024 US presidential election, firms have sought to secure larger credit lines (Panel D). These credit lines, among other purposes, provide working capital to finance production, enabling firms to bring shipments forward to avoid tariffs, and helping to avoid gridlock by covering tariff payments to clear goods from customs.

Despite its critical role in the economy, the demand-driven nature of money elasticity is often inadequately addressed in many theories of money supply. For example, the loanable funds view portrays banks as passive intermediaries that must wait for deposits to arrive before issuing new loans. Under this framework, banks cannot provide liquidity on demand – such as through credit lines – unless these facilities are pre-funded.

While the 'loans create deposits' theory offers a more accurate depiction of banks' role in money creation, it still falls short of capturing the borrower-driven nature of money elasticity. This theory, as described by McLeay et al. (2014) and Jakab and Kumhof (2018), highlights that banks simultaneously write up both sides of their balance sheet when granting loans. However, the essence of money elasticity lies in its demand-driven dynamics, where borrowers actively expand the money supply by taking out new loans or drawing down on credit lines (Goodhart (2017)).

As highlighted by Goodhart (2017), the elasticity of money is shaped by both borrowers and



[1] Average since 2015 except for Singapore from 2021. Commercial and industrial loans for US and loans to manufacturing sector for GB, SG and BR. [2] Seasonally adjusted medians. Outstanding credit includes commercial paper, revolving credit and term loans.

Sources: Central Bank of Brazil; Bank of England; Monetary Authority of Singapore; Board of Governors of the Federal Reserve System; S&P Global Market Intelligence; BIS.

Figure 1: **The large economic demand for liquidity.** Undrawn and outstanding credit of non-financial corporates. Panel A is based on aggregate country-level data. Panels B, C and D on a global panel of non-financial firms.

banks. Borrowers decide when to create the money by drawing on credit lines, while banks set the terms and conditions under which credit is extended to the private sector.

The elasticity of credit lines is dictated by broader financial conditions, which encompass factors such as credit spreads on new lending and borrowing limits. Such borrowing limits represent the potential money that banks are prepared to provide.

Our paper investigates the relationship between money elasticity and real activity in a supply chain setting. In long supply chains, the elasticity of money is likely to play a pivotal role because of the significant liquidity required to ensure their seamless functioning. Upstream firms in long production chains need more working capital to cover payment delays (Kim and Shin (2023)), while downstream firms in long chains potentially need more working capital to finance prepayments to secure intermediate inputs (Schmidt-Eisenlohr (2013)). This suggests a strong and direct relationship between money elasticity and real activity, with its influence likely to be more critical the longer and more complex the production networks.

To establish causality between money elasticity and firm activity, our identification strategy relies on structural variations in firms' working capital demands, which are inherently influenced by their position within the production network.

We begin by presenting a conceptual framework that illustrates how a firm's position within production networks shapes its working capital requirements. Specifically, the framework demonstrates that working capital needs to bridge payment delays are closely linked to Antràs and Chor (2013)'s measure of production network upstreamness. Similarly, it shows that working capital requirements for partially prepaying intermediate goods are strongly associated with Miller and Temurshoev (2017)'s measure of downstreamness.

Next, we empirically examine the relationship between firms' credit lines – the supply of working capital most closely linked to money elasticity – and their position within the production network. To this end, we construct a cross-country panel dataset of firms with information on undrawn credit lines spanning the period from 2005 to 2024. This dataset is then merged with World Input-Output Tables (WIOTs), which we use to derive measures of upstreamness and downstreamness.

Our analysis reveals a robust positive correlation between firms' undrawn credit lines and their upstreamness and downstreamness within production networks. This relationship holds even after accounting for other determinants of credit line size identified in the literature, although the influence of upstreamness overall appears to be most robust. These findings align with our conceptual framework, showing that the size of firms' undrawn credit lines reflects their implied working capital needs based on their position in the production network.

We then investigate how shifts in money elasticity – proxied by changes in financial conditions – differentially affect firm activity based on the size of their undrawn credit lines. To quantify this impact, we employ an instrumental variables local projection (IVLP) model. Our primary variable of interest is the interaction between changes in financial conditions and the size of a firm's undrawn credit lines. The former captures the terms on which credit lines are provided, such as credit spreads, while the latter captures firms' exposure to these conditions.

Since factors beyond a firm's production network position likely influence the size of its credit lines, we instrument undrawn credit lines using measures of upstreamness and downstreamness within production networks. Our conceptual framework, along with the strong observed correlation between these measures and undrawn credit lines, supports their relevance as instruments. Furthermore, we take several steps to ensure that our instruments satisfy the exclusion restriction.

Our findings reveal that firms with greater exposure to money elasticity through their credit lines experience more pronounced output declines when financial conditions tighten. These effects peak approximately four quarters after the shock and take around nine quarters for output to return to its initial level. Economically, the impact is significant: our estimates suggest that for a one standard deviation tightening of financial conditions, increasing a firm's undrawn credit ratio from the 25th to the 75th percentile of the distribution leads to a 10 percentage point decline in sales after four quarters – a substantial effect compared to the median annual sales growth of approximately 5% in our sample. The responses of other variables, such as a decline in accounts receivable (trade credit) and an increase in cash holdings, are consistent with a reduction in money elasticity. These results show that money elasticity and the supply of working capital are two sides of the same coin, with undrawn credit lines serving as the operative link.

Among the various dimensions of financial conditions, we find that tighter corporate bond spreads and declining equity valuations are particularly associated with significant output effects. Furthermore, a strengthening of the broad US dollar exchange rate is linked to sharper output declines for firms with greater exposure to production-network-driven working capital demands. This effect is especially pronounced for non-US firms with short-term US dollar debt, compared to their US-based counterparts. These findings align with recent studies highlighting the unique role of the US dollar exchange rate in shaping bank lending conditions and credit supply to the corporate sector (e.g., Niepmann and Schmidt-Eisenlohr (2023), Hardy et al. (2023)). They also reinforce the view that the US dollar acts as a barometer of global liquidity in financial intermediation (Bruno and Shin (2015)).

Finally, our analysis uncovers significant spillovers within production networks that amplify the impact of shifts in money elasticity on output. Overall, spillovers from upstream firms to their downstream customers appear to play a more prominent role in shock propagation compared to spillovers originating from shocks to downstream customers. Our findings suggest that these network spillovers account for approximately two-thirds of the total effect of changes in money elasticity on a firm's output. This magnitude is comparable to the international network spillovers of US monetary policy on global stock markets, as documented by Di Giovanni and Hale (2022).

Endogeneity poses a significant challenge to clean identification. We address these concerns through several strategies. First, our instrumental variable specification mitigates reverse causality by using measures of upstreamness and downstreamness that are fixed to their 1995-2005 averages. This approach captures structural sectoral characteristics determined by technological factors, such as the extent to which a firm's production technology integrates inputs from multiple sectors or its output is utilised across various sectors. Additionally, by measuring upstreamness and downstreamness at the sector level, our instrument is insulated from firm-specific demand fluctuations.

A related concern is the potential endogeneity of financial conditions and final demand. To address this, we provide additional estimates based on orthogonalised shocks to financial conditions, following the methodology of Gilchrist and Zakrajšek (2012). This ensures that our analysis isolates the causal impact of financial conditions on firm activity.

Our paper contributes to the fast-growing literature examining how production networks propagate shocks. Acemoglu et al. (2012) highlights how in the presence of intersectoral input-output linkages, microeconomic idiosyncratic shocks may lead to aggregate fluctuations. Ozdagli and Weber (2026) and Di Giovanni and Hale (2022) examine how monetary shocks which impact final consumer demand are then transmitted through domestic and global production networks. Differently from these papers, we analyse spillovers from shocks to the supply of working capital that firms need to operate in long production chains.

We also contribute to the literature on the transmission of financial shocks to the economy through input-output linkages. Recent studies highlight the critical role of trade credit as a transmission channel for financial shocks across production networks. Luo (2020) investigates how interconnected production and financial linkages propagate financial shocks, emphasising the importance of trade credit in this process. Reischer (2026) examines the dual role of trade credit in a multisector economy, showing how it can both smooth and amplify the propagation of shocks, with firms extending trade credit generating significant spillovers in a calibrated model consistent with the dynamics of the 2008 financial crisis. Gofman and Wu (2022) examines how providing trade credit depends on a firm's connections in production networks, finding that upstream firms tend to borrow more from suppliers and lend more to customers, which in turn influences firm profitability. Bocola and Bornstein (2023) examines the macroeconomic implications of trade credit as a long-term contractual arrangement, emphasising that the larger output declines of financially constrained firms during the Great Recession can be attributed to reputational losses arising from their inability to extend trade credit to customers. Kim and Shin (2023) explain how the cost of working capital shapes the length of supply chains, resulting in a duality between real economic activity and financial conditions.

Relative to these studies, our study contributes by causally linking shifts in money elasticity to firm activity based on firms' structural working capital needs within a supply chain. By using undrawn credit lines to capture exposure to money elasticity and instrumenting them with network position metrics, we show that tightening financial conditions disproportionately reduce output for firms that rely heavily on on-demand liquidity from credit lines to sustain their activity in complex production networks.

Our paper is also connected to Bartolucci et al. (2025), who analyse the informational value of the upstreamness and downstreamness measures developed by Antràs and Chor (2013) and Miller and Temurshoev (2017). Relative to their work, our conceptual framework underscores the strong relationship between working capital requirements within production networks and these measures of upstreamness and downstreamness.

Finally, our paper contributes to the literature on the heterogeneous effects of financial conditions on firm activity. Several studies explore how variations in financial factors shape the transmission of monetary policy to firms. For example, Ottonello and Winberry (2020) analyse the role of firm leverage and default risk, Cloyne et al. (2023) focus on credit constraints proxied by firm age, Jungherr et al. (2024) investigate the impact of debt maturity, and Jeenas (2023) examine the role of cash holdings. Building on this literature, we contribute by investigating how differences in firms' reliance on credit lines to support production across networks influence the transmission of financial conditions to firm activity.

The paper is organised as follows: section 2 provides a conceptual framework that illustrates how a firm's position within production networks shapes its working capital requirements; section 3 describes our data set; section 4 examines the relationship between a firm's undrawn credit ratio and its position in production chains; section 5 presents our main results on the influence of money elasticity on firm activity; section 6 examines the robustness of our results; section 7 examines extensions to our baseline results; section 8 assesses amplification through production networks; finally, section 9 concludes.

2. Conceptual Framework

To guide our empirical strategy, we present a conceptual framework that illustrates how a firm's position within production networks influences its dependence on working capital. First, we derive conditions linking working capital needs to the time lag between incurring production costs and receiving cash flow from sales, similar to Kim and Shin (2023), but applied to production networks rather than production chains. We show that this relationship is closely connected to Antràs and Chor (2013)'s upstreamness measure. Next, we derive conditions that tie a firm's working capital requirements to the need to prepay for a fraction of the value added embedded in intermediate inputs, demonstrating a strong connection to the downstreamness measure of Miller and Temurshoev (2017). Finally, we combine these perspectives to derive working capital needs based on both the time lag between production and final sales and prepayment requirements for intermediate inputs.

These results highlight how variations in working capital are intricately linked to a firm's position within production networks, which subsequently empirically assess in section 4.

2.1 Working capital to bridge the gap between production and final sales

To assess how the delay between production and final sales influences working capital needs, consider an economy with N firms. For each firm $i \in 1, 2, ..., N$, the value of gross output, Y_i, equals the sum of its final demand, F_i, plus its intermediate output to all other firms $\sum_j z_{ij}$, where Z_{ij} is the value of sales of intermediate goods from firm i to firm j. Denoting the dollar amount of firm i's output needed per dollar's worth of firm j's output by $a_{ij} \equiv Z_{ij}/Y_j$ (referred to as the direct requirement coefficient), the above output identity can be written as

$$Y_i = F_i + \sum_j a_{ij} Y_j \tag{1}$$

By consecutively substituting Equation 1 for Y_j in the right-hand side, total output Y_i can be alternatively written as

$$Y_i = F_i + \sum_j a_{ij} F_j + \sum_{j,k} a_{ik} a_{kj} F_j + \sum_{j,k,l} a_{il} a_{lk} a_{kj} F_j + \cdots \tag{2}$$

Using the value-added share $\gamma_i = V_i/Y_i$ and the input-output coefficients a_{ij}, total value added of the firm, V_i can be expressed as follows

$$V_i = \gamma_i F_i + \sum_j \gamma_i a_{ij} F_j + \sum_{j,k} \gamma_i a_{ik} a_{kj} F_j + \sum_{j,k,l} \gamma_i a_{il} a_{lk} a_{kj} F_j + \cdots \tag{3}$$

Now consider the total working capital needs of the firm WC_i. Following Kim and Shin (2023), assume that value added, such as paying for labour, must be financed with working capital and that payments are received with delays depending on the production round. Then, total working capital per unit of output can be expressed as

$$WC_i = \gamma_i F_i + 2\sum_j \gamma_i a_{ij} F_j + 3\sum_{j,k} \gamma_i a_{ik} a_{kj} F_j + 4\sum_{j,k,l} \gamma_i a_{il} a_{lk} a_{kj} F_j + \cdots \tag{4}$$

Total working capital needs are ultimately determined by the accumulated delays before payments are received in each successive round of production. For instance, the first term on the right-hand side of Equation 4 corresponds to the working capital required to finance value added for the firm's sales to final consumers, which is received in the first period. The second term accounts for the working capital required to finance value-added in first-round intermediate sales that are converted to final sales within one round, with payment received in the second period. The third term captures the working capital required for value-added in second-round intermediate sales, which is received in the third period, and so on. The coefficients $2, 3, 4, \ldots$ represent the time delays (in periods) before payments are received for the respective rounds of production.

The working capital requirements of all firms WC can be expressed in matrix form as

$$WC \;=\; \Gamma F \;+\; 2\Gamma A F \;+\; 3\Gamma A^2 F \;+\; 4\Gamma A^3 F \;+\; \cdots$$

where $WC = [WC_i]$, $F = [F_i]$, $A = [a_{ij}]$ and $\Gamma = \mathrm{diag}(\gamma_1, \ldots, \gamma_n)$. Using the identity $\sum_{r=0}^{\infty}(r+1)A^r = (I-A)^{-2}$ (for $\rho(A) < 1$), we obtain the compact form

$$WC \;=\; \Gamma(I-A)^{-2}F \tag{5}$$

As can be seen, total working capital needs of firm i has a very close relationship with Antràs and Chor (2013)'s upstreamness measure U_i

$$U_i = 1\cdot\frac{F_i}{Y_i} + 2\sum_j \frac{a_{ij}F_j}{Y_i} + 3\sum_{j,k}\frac{a_{ik}a_{kj}F_j}{Y_i} + 4\sum_{j,k,l}\frac{a_{il}a_{lk}a_{kj}F_j}{Y_i} + \cdots \;=\; \frac{1}{Y_i}\Big[(I-A)^{-2}F\Big]_i \tag{6}$$

2.2 Working capital for partial prepayment of upstream value added

Firms may also need working capital to make prepayments for intermediate inputs (Antràs and Foley (2015), Schmidt-Eisenlohr (2013)). To assess working capital needs for prepayment for intermediate inputs, we start with the input-side accounting identity which states that firm i's total input, which should be equal to total output, Y_i, is equal to the value of its primary inputs (value added) V_i plus its intermediate input purchases from all industries $\sum_j Z_{ji}$.

If we denote the share of industry j's output that is used in industry i's production by $b_{ji} \equiv Z_{ji}/Y_j$, referred to as the allocation coefficient, then the above input identity can be written as

$$Y_i = V_i + \sum_j Y_j b_{ji} \tag{7}$$

By consecutively substituting Equation 7 for or Y_j in the right-hand side, total input Y_i can also be written as

$$Y_i = V_i + \sum_j V_j b_{ji} + \sum_{j,k} V_j b_{jk} b_{ki} + \sum_{j,k,l} V_j b_{jk} b_{kl} b_{li} + \cdots \tag{8}$$

We now consider the working capital a firm must hold to prepay a fraction θ_i of the value added embodied in intermediate inputs. Similar to subsection 2.1, we assume that delivery time increases with network distance, and that firm i only prepays its immediate suppliers (who in turn, prepay their own suppliers). Under these assumptions, the working capital of firm i needed to prepay upstream value added is

$$WC_i = \theta_i \left[1 \cdot \sum_j V_j \, b_{ji} \; + \; 2 \cdot \sum_{j,k} V_k \, b_{kj} \, b_{ji} \; + \; 3 \cdot \sum_{j,k,\ell} V_\ell \, b_{\ell k} \, b_{kj} \, b_{ji} \; + \; \cdots \right] \tag{9}$$

where the factor $s = 1, 2, 3, \cdots$ multiplies the value added located s stages upstream because funds advanced today are tied up for s periods until delivery. Noting that $\sum_j V_j \, b_{ji} = \big(B^\top V\big)_i$, $\sum_{j,k} V_k \, b_{kj} b_{ji} = \big((B^\top)^2 V\big)_i$, …, this can be expressed in matrix form as

$$WC \;=\; \Theta\Big(B^\top V + 2(B^\top)^2 V + \cdots\Big) \;=\; \Theta B^\top (I - B^\top)^{-2} V \tag{10}$$

where $\Theta = \mathrm{diag}(\theta_1, \ldots, \theta_n)$. As can be seen, total working capital needs for prepayment has a very close relationship with Miller and Temurshoev (2017)'s downstreamness measure D_i

$$\begin{aligned} D_i \;&=\; \frac{V_i}{Y_i} \;+\; 2\,\frac{\sum_j V_j b_{ji}}{Y_i} \;+\; 3\,\frac{\sum_{j,k} V_k b_{kj} b_{ji}}{Y_i} \;+\; 4\,\frac{\sum_{j,k,\ell} V_\ell b_{\ell k} b_{kj} b_{ji}}{Y_i} \;+\; \cdots\,, \\ &=\; \frac{1}{Y_i}\Big[(I - B^\top)^{-2} V\Big]_i \end{aligned} \tag{11}$$

2.3 Total working capital with payment delays and partial prepayment

Given the coexistence of both payment delays and partial prepayment (Schmidt-Eisenlohr (2013)), total working capital needs of a firm can be expressed as the sum of working capital to bridge payment delays adjusted for funds received from prepayments (i.e. $(1-\theta_x)$ terms)

$$WC_i^{\text{delay}} = \gamma_i \Bigg[1 \cdot F_i \;+\; 2 \cdot \sum_j (1-\theta_j)\, a_{ij} F_j \;+\; 3 \cdot \sum_{j,k} (1-\theta_k)(1-\theta_j)\, a_{ik} a_{kj} F_j + \;\cdots \Bigg]. \tag{12}$$

and working capital needed to prepay for a fraction of value added in intermediate inputs

$$WC_i^{\text{prepay}} = \theta_i \Bigg[1 \cdot \sum_j V_j b_{ji} \;+\; 2 \cdot \sum_{j,k} V_k b_{kj} b_{ji} \;+\; 3 \cdot \sum_{j,k,\ell} V_\ell b_{\ell k} b_{kj} b_{ji} \;+\; \cdots \Bigg], \tag{13}$$

which can be expressed in matrix form as

$$WC^{\text{total}} \;=\; \Gamma\big(I - AT\big)^{-2} F \;+\; \Theta B^\top (I - B^\top)^{-2} V, \qquad T = I - \Theta \tag{14}$$

Comparing the elements of Equation 14 with the measures of upstreamness (Equation 6) and downstreamness (Equation 11) highlights how the total working capital needs of firms are strongly influenced by both their upstreamness and downstreamness. We use this insight in our empirical strategy to isolate how shifts in money elasticity impact the output of firms, depending on their production network-driven working capital needs.

3. Data

Our main dataset consists of firm-level, industry-level and financial conditions data from 2005 to 2024. Our firm-level dataset consists of quarterly balance sheet, income and cashflow statement data from Capital IQ. We further supplement this with Capital IQ data on undrawn credit lines defined as the remaining availability a company has on its lines of credit and revolving credit facilities. This results in a sample of 6,834 non-financial non-utility firms from 47 countries. For our baseline analysis, we focus on firms in the manufacturing sector, where we have data for 3,243 firms from 46 countries.

To measure a firm's production network position, we use the world input-output tables from the OECD's inter-country input-output dataset. From these world input-output tables, we compute measures of upstreamness and downstreamness at the country-sector level. We merge this to our firm-level data by creating a crosswalk between NAICS 2022 and ISIC Revision 4 industry classifications. In our analysis, to capture the deep and stable technological characteristic of supply chains and avoid concerns that these measures may shift with changes in money elasticity during our sample period of our firm-level data, we freeze these measures to their 1995-2005 average.

To capture financial conditions, we use a variety of different measures. For our main results we use the Goldman Sachs Financial Conditions Index for the United States (Hatzius et al. (2017)). This index has been shown to capture global financial conditions well, not least because of the dominant role of US monetary policy (see for example, Di Giovanni and Hale (2022)). Importantly, this index also classifies US dollar appreciation as tightening of financial conditions, which has been shown to be a key measure of financial conditions globally (see Hofmann and Park (2020), Erik et al. (2020) and references therein). We also confirm our results using the Federal Reserve Bank of Chicago financial conditions index and use subcomponents of the Goldman Sachs index to assess the specific dimensions of financial conditions which particularly impact trade credit through production networks.

Table 1 presents summary statistics of key variables in our dataset. The undrawn credit of firms in our sample is large. They have access to liquidity through credit lines and revolving facilities of around 13% of firm total assets on average. This amount of liquidity is around 3 times larger than their short-term debt for the median firm, and comparable to total long-term debt. The distribution of firms' cash and short-term liquid assets on hand is very similar to that for undrawn credit.

Beyond undrawn credit, trade credit represents a highly significant portion of firms' working capital. Firms' accounts receivable are around 16% of firm total assets, similar in magnitude to undrawn credit. There is a gap between accounts receivable and payable in our sample, potentially due to our sample being composed of larger firms which tend to extend trade credit to smaller firms. Total inventories are similar in size to accounts receivable highlighting the interplay between intermediate inputs and trade credit. Total assets of firms in our sample range from around 30 million US dollars at the 25th percentile to over 750 million at the 75th percentile. Total firm sales in a quarter are on average around two times the size of undrawn credit lines and grow by around 1.1% per quarter.

On average the measure of firm downstreamness tends to be slightly higher than upstreamness in our sample. Additionally, Figure 2 shows that upstreamness and downstreamness are positively correlated in our sample, consistent with the findings of Miller and Temurshoev (2017) and Antràs and Chor (2018).

Variable	Mean	Std Dev	p25	p50	p75
Undrawn credit	12.9	10.1	5.3	10.2	17.7
Short-term debt	7.1	9.0	0.4	3.3	10.2
Long-term debt	15.6	14.0	2.6	13.1	24.9
Cash	12.7	11.8	3.9	9.2	17.9
Accounts receivable	16.0	8.8	9.5	14.7	21.0
Accounts payable	10.7	7.8	5.3	8.9	14.0
Inventories	16.6	9.6	9.5	14.7	22.0
log(Total assets)	5.0	2.2	3.5	5.1	6.6
Sales	25.1	11.7	16.7	23.2	31.8
Sales growth	1.6	17.7	-6.0	1.1	9.2
Profits	0.8	2.5	0.1	1.1	2.1
Upstreamness	2.1	0.6	1.7	1.9	2.5
Downstreamness	2.3	0.3	2.2	2.3	2.5

Table 1: **Summary statistics.** This table reports summary statistics for firms in the manufacturing sector. Undrawn credit, short-term debt, long-term debt, accounts receivable, accounts payable, inventories, cash, sales and profits are all expressed as a ratio of total assets in percent. Total assets are expressed in millions of US dollars.

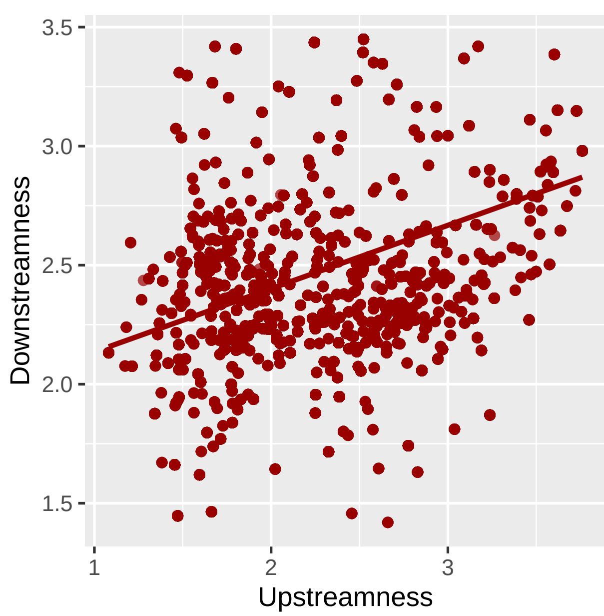


Figure 2: **Manufacturing firms's positioning in production networks.** This figure shows measures of Upstreamness and Downstreamness defined in Equation 6 and Equation 11 for firms in the manufacturing sector and the OLS fitted line.

4. Production networks and demand for credit lines

In this section, we empirically show that firms in sectors further upstream or downstream in production networks hold larger undrawn credit lines, leaving them more exposed to shifts in the elasticity of money. This finding emphasises that the elasticity of money and the supply of working capital are two sides of the same coin, with undrawn credit lines providing the operative link between them.

As demonstrated in section 2, there is likely to be a close connection between a firm's working capital needs and its position in the production network. To investigate this, we estimate the following regression to examine how a firm's upstreamness and downstreamness – and, by extension, its working capital requirements – relate to the amount of undrawn credit.

$$\begin{aligned}\text{UndrawnCredit}_{isct} =& \lambda_U Upstreamness_{sct} + \lambda_D Downstreamness_{sct} \\ &+ \mathbf{Q_{isct}}\boldsymbol{\Omega} + \varphi_s + \text{Fixed effects}_{sct}\end{aligned} \tag{15}$$

where $UndrawnCredit_{isct}$ is the ratio of undrawn credit to total assets of firm i in sector s and country c in a given quarter t. $Upstreamness_{sct}$ is the upstreamness of the firm, defined by Equation 6 and $Downstreamness_{sct}$ defined by Equation 11. We include a vector of control variables $\mathbf{Q_{isct}}$ to control for other determinants of credit line size found in the literature (see e.g. Chodorow-Reich et al. (2022)). We include controls for the size of the firm as larger firms tend to benefit from lower spreads. Relatedly, credit lines may be large for more profitable firms as they may be granted at more favourable rates or looser terms and conditions. We control for firm sales relative to assets, credit lines and sales growth, which firms may extend when growth is slower. We include controls for short-term and long-term debt ratios of the firm to control for the presence of financial constraints. We further control for accounts receivable as credit lines may also be larger if firms grant more trade credit and additionally control for accounts payable, inventories and cash holdings. We then include a battery of different fixed effects to absorb any unobserved sector, country or quarter invariant effects. We cluster standard errors by firm and sector×time, where the former accounts for firm-level correlation in the outcome variables, and the latter captures within-industry correlation at any given point in time.

The results in Table 2 suggest that both greater upstreamness and downstreamness are associated with firms having higher amounts of undrawn credit lines. This is consistent with the influence of both factors on working capital implied by the conceptual framework in section 2. Column (1) shows that this relationship holds for both upstreamness and downstreamness with a pooled OLS specification. The following columns assess the robustness of these findings to a battery of fixed effects. Columns (2) and (3) show that the introduction of sector-fixed and sector×time effects does not qualitatively change the results, although their inclusion tends to raise the point estimates on downstreamness and reduce the significance on upstreamness, which drops to the 10% level.

Controlling for country-specific effects reveals that the correlation between undrawn credit and upstreamness is particularly robust. Specifically, the introduction of country effects shifts the results towards a stronger relationship between undrawn credit and upstreamness. Columns (4) and (5) introduce country and country×time-fixed effects. Once these fixed effects are introduced, the coefficient on upstreamness is significant at the 5% level, while the coefficient on downstreamness becomes statistically insignificant. Finally, columns (6), (7) and (8) introduce respectively combinations of: sector and time; country×time and sector×country; and sector×time and country×time. With these combinations, the point estimates on upstreamness are somewhat higher, while the coefficients on downstreamness are statistically insignificant.

Among the other control variables, only a few display a consistent significant relationship with undrawn credit across the specifications. Firms with a higher ratio of sales to assets tend to have larger credit lines, while firms with strong sales growth tend to have a lower undrawn credit ratio. Firms with larger accounts receivable to assets tend to have larger credit lines, highlighting the possible need for greater liquidity on tap if a firm provides trade credit to its customers. By

Dependent Variable:	Undrawn Credit / Total assets							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Upstreamness	2.113**	2.916*	3.131*	1.890**	1.781**	4.428**	5.245***	4.561**
	(0.9136)	(1.751)	(1.793)	(0.8536)	(0.8600)	(1.839)	(1.911)	(1.870)
Downstreamness	3.595**	3.610**	3.656**	-1.992	-1.912	-3.925	-3.725	-3.409
	(1.798)	(1.834)	(1.779)	(2.301)	(2.307)	(2.586)	(3.821)	(2.536)
log(Assets)	-0.9545***	-0.7585***	-0.7347***	-0.2282	-0.2191	-0.1442	-0.1580	-0.1710
	(0.1883)	(0.1868)	(0.1891)	(0.1718)	(0.1836)	(0.1878)	(0.2082)	(0.1872)
Profits	0.5028***	0.3915***	0.3939***	0.1680	0.1824	0.1381	0.1123	0.1633
	(0.1452)	(0.1315)	(0.1337)	(0.1211)	(0.1291)	(0.1238)	(0.1223)	(0.1259)
Sales	0.1418***	0.1452***	0.1612***	0.1524***	0.1672***	0.1692***	0.1812***	0.1711***
	(0.0440)	(0.0470)	(0.0487)	(0.0432)	(0.0457)	(0.0504)	(0.0532)	(0.0512)
Sales growth	-0.0665***	-0.0621***	-0.0701***	-0.0585***	-0.0732***	-0.0712***	-0.0744***	-0.0724***
	(0.0116)	(0.0115)	(0.0119)	(0.0107)	(0.0118)	(0.0119)	(0.0121)	(0.0122)
Short-term debt	0.2401***	0.2113***	0.2193***	0.0798	0.0898*	0.0857	0.0751	0.0850
	(0.0530)	(0.0534)	(0.0538)	(0.0515)	(0.0533)	(0.0525)	(0.0525)	(0.0529)
Long-term debt	-0.0566**	-0.0580**	-0.0589***	-0.0061	-0.0126	-0.0219	-0.0245	-0.0148
	(0.0237)	(0.0227)	(0.0228)	(0.0227)	(0.0239)	(0.0236)	(0.0263)	(0.0234)
Accounts receivable	0.0397	0.0733	0.0799	0.1837***	0.1810***	0.1910***	0.1879***	0.1908***
	(0.0548)	(0.0600)	(0.0607)	(0.0566)	(0.0588)	(0.0634)	(0.0646)	(0.0640)
Accounts payable	-0.1772***	-0.1820***	-0.1900***	-0.1372**	-0.1351*	-0.1284*	-0.1526*	-0.1348*
	(0.0669)	(0.0684)	(0.0700)	(0.0668)	(0.0694)	(0.0706)	(0.0784)	(0.0718)
Inventories	0.1172***	0.1430***	0.1346***	0.1186***	0.1144**	0.1196**	0.1105**	0.1164**
	(0.0449)	(0.0480)	(0.0484)	(0.0432)	(0.0460)	(0.0482)	(0.0481)	(0.0481)
Cash	-0.0659*	-0.0323	-0.0378	-0.0124	-0.0166	-0.0055	-0.0294	-0.0048
	(0.0363)	(0.0363)	(0.0372)	(0.0361)	(0.0384)	(0.0383)	(0.0294)	(0.0390)
Fixed-effects								
Sector		Yes				Yes		
Sector-Time			Yes					Yes
Country				Yes				
Country-Time					Yes	Yes	Yes	Yes
Sector-Country							Yes	
Fit statistics								
Observations	69,008	69,008	69,008	69,008	69,008	69,008	69,008	69,008
R^2	0.01491	0.01765	0.05181	0.03239	0.05635	0.05792	0.07471	0.08965

Table 2: **Undrawn credit and production network position.** This table reports estimates from Equation 15. The dependent variable is undrawn credit to total assets of the firm. Upstreamness and downstreamness are defined by Equation 6 and Equation 11 and computed as the average of the measures between 1995 and 2005. The following control variables are normalised by total assets: profits, sales, short-term debt, long-term debt, inventories, cash, accounts receivable and accounts payable. Standard errors clustered at the firm and sector×time level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

contrast, greater accounts payable tends to be associated with lower levels of undrawn credit, highlighting a possible substitution between bank and firm sources of working capital. Finally, firms with a greater inventory ratio tend to have a higher undrawn credit ratio.

Taken together, the results in Table 2 suggest that both a firm's upstreamness and downstreamness tend to positively correlate with its undrawn credit ratio, although the relationship with upstreamness appears to be more robust to the inclusion of a battery of fixed effects. This relationship suggests that the influence of network position in determining the size of credit lines potentially influences how shifts in money elasticity impact firm activity in the cross-section.

5. Financial conditions, credit lines and firm activity

To empirically examine how shifts in the elasticity of money influence firm activity, we leverage cross-sectional differences in firms' exposure to undrawn credit, driven by their positions within production networks.[1] Specifically, we employ an instrumental variable local projection model to test whether firms with greater exposure to undrawn credit are more sensitive to changes in the elasticity of money. A firm's exposure is captured by interacting its undrawn credit lines with variations in financial conditions. Since factors beyond network position likely affect the size of a firm's undrawn credit, we instrument this exposure using network position metrics, namely upstreamness and downstreamness, which are structural factors determined by technology.

5.1 Network position as instruments

For network position variables, as captured by upstreamness and downstreamness, to be valid instruments, they must be relevant and satisfy the exclusion restriction assumption. As shown in section 2 and section 4, they are relevant both from theoretical and empirical perspective.

Several factors support the validity of these measures in satisfying the exclusion restriction. A

[1] In this respect, this element of our identification shares similarities to Rajan and Zingales (1998) in terms of dependence on external finance and Fisman and Love (2003), in terms of dependence on trade credit. Our study, by contrast examines dependence on undrawn credit lines.

sector's network position is shaped by structural, technology-driven factors, such as the extent to which its production technology relies on inputs from other sectors and the extent to which its output serves as inputs for others. Since technology evolves slowly and is fixed to a pre-period in our analysis, the sector's position within production networks is unlikely to be influenced by short-term fluctuations in output, which is the focus of this paper. However, firms' sensitivity to financial conditions may vary by country and sector, potentially correlating with network position due to factors such as trade exposure, import content, or dollar invoicing. To address this, we include firm fixed effects to account for unobserved, time-invariant heterogeneity at the country-sector level, as well as country-time effects to control for unobserved, time-varying heterogeneity at the country level.

Another concern regarding the exclusion restriction is that a tightening of financial conditions may create cascades through the production network via the undrawn credit exposure of linked firms. If these links are correlated with a firm's own production network position, this could result in overstating the direct effects of the firm's own undrawn credit exposure. Given this possibility, we investigate the sensitivity of our direct effect to network spillovers in section 8. Anticipating our results, we find that while network spillover effects are important, they do not significantly change our quantitative estimates of the direct effects supporting that our instrument satisfies the exclusion restriction assumption.

Upstreamness and downstreamness appear to be strong instruments. The first column of Table 3 shows the first stage regression results using upstreamness alone as an instrument. It shows that there is a strong positive correlation between $\Delta FCI_t \times UndrawnCredit_t$ and $\Delta FCI_t \times Upstreamness$ even after controlling for the change in financial conditions, with the F-statistic being well over 10 which is often seen as a cut off for weak instruments (Andrews et al. (2019)). Column (2) further indicates a strong positive correlation between $\Delta FCI_t \times UndrawnCredit_t$ and $\Delta FCI_t \times Downstreamness$ and an F-statistic of 21. Finally, column (3) assess whether both upstreamness and downstreamness could be jointly used as instruments. $\Delta FCI_t \times UndrawnCredit_t$

continues to be positively and significantly correlated with $\Delta FCI_t \times Upstreamness$, but the correlation with the downstream counterpart is no longer statistically significant. Nevertheless, the F-statistic remains above 10, and the Sargan overidentification test indicates that the instruments are exogenous, so for the remainder of the paper we use both as separate instruments.

5.2 Instrumental variable local projections

With these instruments in hand, we estimate the following IVLP to trace out the impact of money elasticity on firm activity

$$\begin{aligned} y_{isct+h} - y_{isct-1} =& \beta_{1h}\Delta FCI_t + \beta_{2h}UndrawnCredit_{isct} + \beta_{3h}\Delta FCI_t \times UndrawnCredit_{isct} \\ &+ \mathbf{Q_{isct-1}}\mathbf{\Theta_h} + \mu_{ih} + \gamma_{cth} + \epsilon_{isct} \end{aligned} \tag{16}$$

where $h \in \{0, 1, 2, \cdots, H\}$ denotes the horizon of the estimated effect, y_{isct} is the natural logarithm of sales of firm i in sector s in country c and quarter t, ΔFCI_t is the change in the financial conditions index between period $t-1$ and t.[2] We instrument the exposure of a firm to shifts in the elasticity of money using the undrawn credit to assets ratio interacted with changes in financial conditions, $\Delta FCI_t \times UndrawnCredit_{isct}$, with the upstreamness and downstreamness measures interacted with changes in financial conditions. We also include a vector of control variables $\mathbf{Q_{isct-1}}$ dated in period t-1, which include log total assets, sales growth as well as the ratios of profitability, sales, short-term debt, long-term debt, inventories, cash, accounts receivable and accounts payable to total assets. Finally, the baseline regression also includes firm fixed effects μ_{ih} and country×time fixed effects γ_{cth} to control for unobserved time-invariant firm characteristics and unobserved country specific common factors in any given period. The key variable of interest is β_{3h} capturing whether output of firms with more exposure to undrawn credit tends to be more sensitive to changes in financial conditions. We again cluster standard errors by firm and sector×time, where the former

[2] ΔFCI_t is calculated as the three-month change in financial conditions leading up to the month of the firm's reporting period end date. As a result, it may differ from the firm's calendar quarter.

Dependent Variable:	$\Delta FCI_t \times UndrawnCredit_t$		
Model:	(1)	(2)	(3)
Variables			
ΔFCI_t × Upstreamness	1.758***		1.549***
	(0.3905)		(0.4267)
ΔFCI_t × Downstreamness		3.187**	2.469
		(1.448)	(1.522)
ΔFCI_t	9.112***	5.437	3.951
	(0.9835)	(3.319)	(3.197)
Profits_{t-1}	0.0728	0.0700	0.0711
	(0.1273)	(0.1273)	(0.1275)
Sales_{t-1}	0.0375	0.0399	0.0372
	(0.0471)	(0.0470)	(0.0470)
Short-term debt_{t-1}	-0.0264	-0.0266	-0.0271
	(0.0533)	(0.0533)	(0.0533)
Long-term debt_{t-1}	0.0506*	0.0502*	0.0506*
	(0.0259)	(0.0259)	(0.0259)
Inventories_{t-1}	0.0322	0.0329	0.0295
	(0.0536)	(0.0534)	(0.0535)
Cash_{t-1}	-0.0540**	-0.0517**	-0.0534**
	(0.0262)	(0.0260)	(0.0262)
$\log(\text{Assets}_{t-1})$	-1.638*	-1.595	-1.635*
	(0.9831)	(0.9807)	(0.9811)
Sales growth_{t-1}	0.0012	0.0009	0.0014
	(0.0098)	(0.0098)	(0.0098)
Accounts receivable_{t-1}	-0.1652**	-0.1648**	-0.1650**
	(0.0791)	(0.0792)	(0.0791)
Accounts payable_{t-1}	-0.0432	-0.0411	-0.0424
	(0.0480)	(0.0479)	(0.0480)
Fixed-effects			
Firm	Yes	Yes	Yes
Time-Country	Yes	Yes	Yes
Fit statistics			
F-stat	35.27	21.14	23.73
Sargan overidentification stat			1.46

Table 3: **Undrawn credit and network position.** This table reports estimates from first stage estimates of Equation 16. ΔFCI_t is the change in financial conditions over quarter. Upstreamness and downstreamness are defined by Equation 6 and Equation 11 and computed as the average of the measures between 1995 and 2005. The following variables are normalised by total assets: undrawncredit, profits, sales, short-term debt, long-term debt, inventories, cash, accounts payable and accounts receivable. Standard errors clustered by firm and sector×time are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

accounts for firm-level correlation in the outcome variables, and the latter captures within-industry correlation at any given point in time.

Shifts in money elasticity have a strong impact on firms' output. Figure 3 plots the instrumental local projection impulse response of output based on the β_{3h} coefficients. The instrumental variable local projection shows that firms with higher instrumented exposure to undrawn credit, hence higher exposure to shifts in the elasticity of money, see a larger drop in their output when financial conditions tighten. The impact peaks at around four quarters after the shock. The estimates further suggest that it takes around nine quarters for output to return to its initial level. The economic effects are large. The coefficient estimates indicate that shifting a firm's undrawn credit ratio from the 25th percentile to the 75th percentile will result in a 10 percentage point larger fall in sales in response to one standard deviation tightening of financial conditions. This is sizeable given that median sales growth in our sample is around 5%.

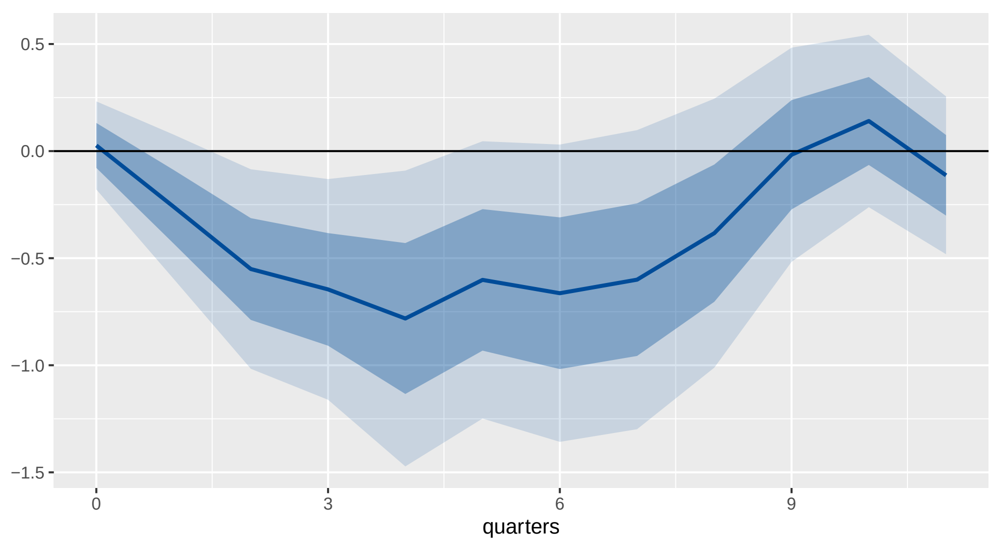


Figure 3: **Output response to tighter financial conditions conditional on undrawn credit.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between $\Delta FCI_t \times UndrawnCredit_t$ based on the instrumental variable local projections (Equation 16). The dependent variable is the log change in sales between $t-1$ and $t+h$. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

Money elasticity also influences other firm-level variables. To explore this, we further use the IVLP specification to examine its influence on other variables. For firms with high production network driven undrawn credit lines, a tightening of financial conditions has pronounced effects on other variables (Figure 4). The impulse responses show that accounts receivable decline roughly one-to-one with the fall in output (Panel A), as do accounts payable (Panel B). This decline in trade credit is consistent with Reischer (2026). Firms additionally run down their inventories (Panel C), thus, as the elasticity of money tightens, firms make adjustments to reduce their net working capital needs (Panel D). Panel E shows that the impact on short-term debt is statistically insignificant. As money becomes less elastic, firms with high production network driven demand for working capital tend to increase their cash buffers (Panel F). Our estimates do not point to conclusive impact on capital expenditures, though they tend to fall on average (Panel G), however, firms do reduce their markups (Panel H).

Figure 4: **Response to tighter financial conditions conditional on undrawn credit.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between $\Delta FCI_t \times UndrawnCredit_t$ based on the instrumental variable local projections (Equation 16). The dependent variables are the change between $t-1$ and $t+h$ for log accounts receivable (panel A), log accounts payable (panel B), log inventories (panel C) networking capital needs less short-term debt - defined as accounts receivable plus inventories less accounts payable and short-term debt (panel D), log short-term debt (panel E), ratio of cash to assets (panel F), the logarithm of capital expenditures (panel F) and markups as measured by the log sales less cost of goods sold as a ratio of costs of goods sold (Panel H). Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

6. Robustness

We conduct a number of additional analyses to examine the robustness of our results. First, we run placebo tests to check for pre-trends. Second, given concerns about the endogeneity of financial conditions, we assess the robustness of our results to using an orthogonalised shock following Gilchrist and Zakrajšek (2012). Finally, we assess whether our results are robust to including non-financial firms outside of the manufacturing sector.

6.1 Pre-trends

To assess the exogeneity of our shock, we first assess if there are any trends in the pre-shock window by running the following regressions to assess if our main variable of interest $\Delta FCI_t \times UndrawnCredit_{isct}$ is correlated with output growth

$$\begin{aligned} y_{isct+h} - y_{isct+h-1} =& \beta_{1h} \Delta FCI_t + \beta_{2h} UndrawnCredit_{isct} + \beta_{3h} \Delta FCI_t \times UndrawnCredit_{isct} \\ & + \mu_{ih} + \gamma_{cth} + \epsilon_{isct}, \quad h \in \{-1, -2, \cdots, -7\} \end{aligned} \tag{17}$$

where $y_{isct+h} - y_{isct+h-1}$ is output growth of the firm in the $h \in \{-1, -2, \cdots, -7\}$ quarter before the change in financial conditions ΔFCI_t in period t. Figure 5 shows that the estimated β_{3h} coefficients are statistically insignificant suggesting little evidence of any pre-trends. Nevertheless, the point estimates are all positive indicating that these firms may have been growing somewhat more strongly on average over the preceding two years before the shock, which may reflect the overall positive correlation between longer supply chains and productivity growth (Kim and Shin (2012)).

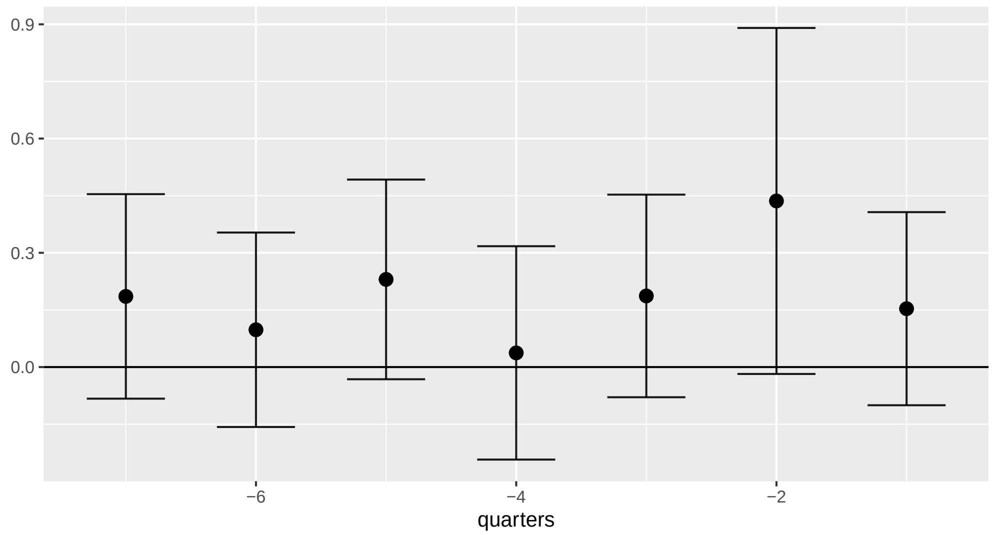


Figure 5: **Output response to tighter financial conditions conditional on undrawn credit.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between $\Delta FCI_t \times UndrawnCredit_t$ based on the instrumental variable local projections (Equation 16), where undrawn credit is a ratio to total assets. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

6.2 Endogeneity of financial conditions

One concern is the endogeneity of financial conditions. Financial conditions themselves respond to the macroeconomic environment, thus changes in financial conditions may respond to aggregate output. In Equation 15, we include country×time fixed effects to absorb common unobserved factors such as changes in aggregate output at the country level. However, it is still possible that output of sectors and firms with higher exposure to undrawn credit are more sensitive to the business cycle. Thus, our results could be confounded by the influence of output fluctuations on financial conditions. To address this concern, we construct an orthogonalised financial conditions shock from a three variable VAR consisting of log changes in global industrial production, log changes in aggregated accounts receivable and changes in financial conditions. Following Gilchrist and Zakrajšek (2012), we identify orthogonalised financial conditions shocks using a Choleski ordering.

Appendix Figure A.1 shows that when estimating Equation 16 with the orthogonalised financial conditions shocks, this results in very similar dynamics of output. Similarly, Appendix Figure A.2

shows that the impact on other variables is broadly similar to our baseline results.

6.3 Firm exposure to US dollar debt

Another concern is that our results are driven by economic dynamics of the US economy rather than a specific channel through exposure to undrawn credit lines. To address this concern, we run the following triple interaction regression to test if a tightening of US financial conditions has a stronger effect on output of firms for whom US dollar exposure, through their credit lines, is higher

$$\begin{aligned} y_{isct+h} - y_{isct-1} = & \beta_{1h}\Delta FCI_t + \beta_{2h}UndrawnCredit_{isct} + \phi_{1h}ST\,dollar\,Debt_{isct} \\ & + \beta_{3h}\Delta FCI_t \times UndrawnCredit_{isct} + \phi_{2h}\Delta FCI_t \times ST\,dollar\,Debt_{isct} \\ & + \phi_{3h}UndrawnCredit_{isct} \times dollar\,Debt_{isct} \\ & + \phi_{4h}\Delta FCI_t UndrawnCredit_{isct} \times dollar\,Debt_{isct} \\ & + \mathbf{Q_{isct-1}}\mathbf{\Theta_h} + \mu_{ih} + \gamma_{cth} + \epsilon_{isct} \end{aligned} \tag{18}$$

where $ST\,dollar\,Debt_{isct}$ is the short-term US dollar denominated debt relative to total assets of firm i in period t.[3]. The triple interaction term itself is instrumented with both upstreamness and downstreamness interacted with the change in financial conditions and short-term US dollar debt to assets. The double interaction term continues to be instrumented using the baseline instruments. If the coefficient ϕ_{4h} is negative and significantly different from zero, this would be a powerful falsification of the hypothesis that our results are driven by dynamics of the US economy and strong result in favour of our money elasticity hypothesis.

As the results in Figure 6 show, the negative ϕ_{4h} coefficients on the triple interaction term is consistent with our results running through the influence of tighter US financial conditions reducing the elasticity of money. Conditional on undrawn credit, firms with higher short-term US dollar

[3]As we do not have information on the currency composition of the undrawn credit lines, we proxy this with the currency of its outstanding short-term US dollar denominated debt.

denominated debt do experience a larger fall in output, consistent with a specific tightening in US dollar liquidity.

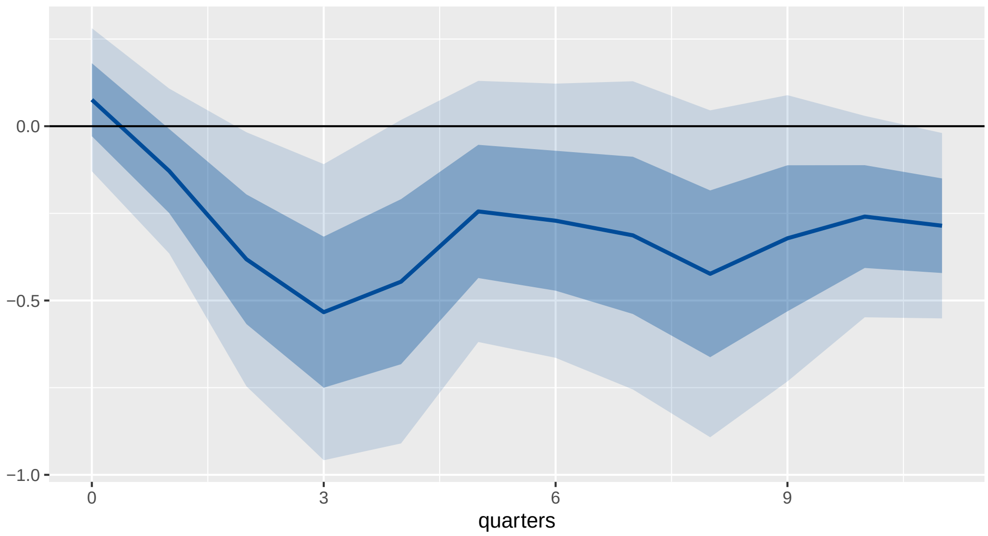


Figure 6: **Tighter US financial conditions have a larger impact on output of firms with higher short-term US dollar debt exposure conditional on undrawn credit.** The Figure shows estimates of ϕ_{4h}, the coefficient on the triple interaction between a one standard deviation tightening of financial conditions, the firm's undrawn credit to assets ratio and the firm's short-term US dollar debt to assets ratio from the IVLP Equation 18. The dependent variable is the log change in sales between $t-1$ and $t+h$. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector$\times$ time.

6.4 Effects beyond the manufacturing sector

Our results presented thus far have been restricted to firms in the manufacturing sector. Focusing on the manufacturing sector helps to ensure that our analysis focuses on differences in a firms' position in production networks, while keeping other factors, such as the type of production processes more homogeneous. However, it does raise questions about the generality of our results, not least as our measures of network position are computed over all sectors in the input-output tables. To address this concern, we re-estimate out main IVLP regression but using data of firms from all non-financial sectors, excluding utilities. The impulse response shown in Appendix Figure A.3 shows that our main results hold, namely that firms with more exposure to undrawn credit arising from it network position tend to experience larger falls in output when financial conditions tighten. Moreover, the results shown in Appendix Figure A.4 further show that the results are also similar for firm-level variables.

7. Extensions

In this section we investigate which specific dimensions of financial conditions are driving our results. Financial conditions indices aim to summarise overall financing conditions by summarising information from different financial instruments, and some of these subcomponents may be more closely linked to factors driving the elasticity of money compared with others. Underlying the Goldman Sachs financial conditions index that we use are five sub-components: an index of corporate spreads, the ratio of equity prices to the 10-year average earnings per share, the trade-weighted US dollar exchange rate index, short-term interest rates and long-term interest rates.

Overall, financial conditions related to credit conditions drive the relationship between financial conditions and firm output via production network driven demand for undrawn credit. Figure 7 plots the impulse responses of output based on Equation 16, separately using individually one of the five components of the financial conditions index in turn. Panel A, shows the impact of changes in the corporate bond spread index. The impact on output closely follows the impulse responses based on the aggregate financial conditions index (Figure 3). Panel B shows that fluctuations in the equity-based component of financial conditions also results in similar output dynamics. The similarity between the two is perhaps unsurprising because of the tight link between corporate bond spreads and equities (e.g. Philippon (2009)).

Similarly, an appreciation of the US dollar is strongly associated with output declines for firms demanding high working capital, reinforcing its role as a global liquidity barometer. In fact, Panel C of Figure 7 shows that an appreciation of the US dollar against a basket of currencies is also associated with a larger fall in output among firms with greater production network driven working capital demand. There are a number of channels that could explain the relevance of the US dollar exchange rate (Hofmann and Park (2020)). Given the dominance of the US dollar in financial

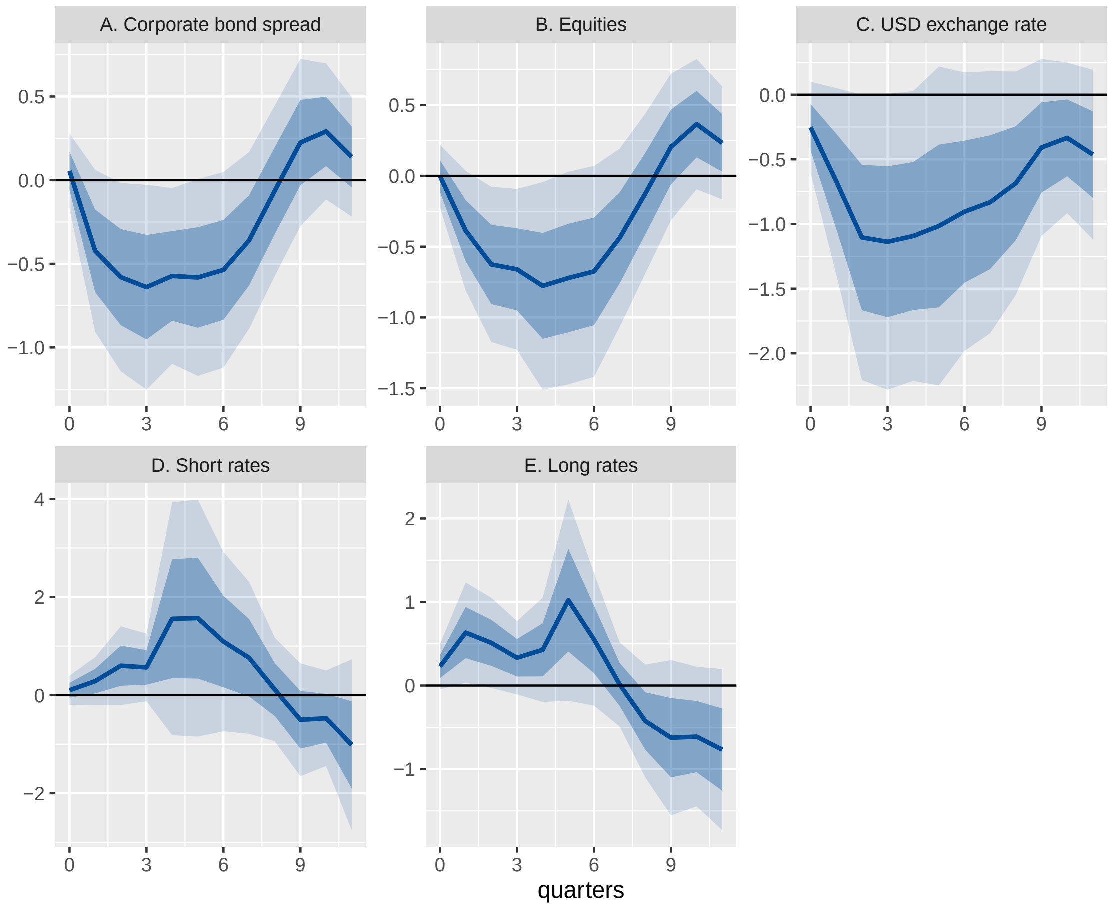


Figure 7: **Which dimensions of financial conditions? Output response conditional on undrawn credit for different components of the financial conditions index.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between a one standard deviation increase in the specific component of financial condition index and the undrawn credit ratio using the instrumental variable local projections Equation 16. The dependent variable is the log change in sales between $t-1$ and $t+h$. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

markets, recent papers have also highlighted how the broad US dollar exchange rate is an important determinant of money elasticity through its impact on bank lending conditions and a barometer for conditions in global credit intermediation (Bruno and Shin (2015), Niepmann and Schmidt-Eisenlohr (2023), Hardy et al. (2023)). In addition, the global corporate sector raises a significant portion of credit that is denominated in US dollars. As Hardy et al. (2023) shows, US dollar appreciation is associated with tightening in the terms and conditions on dollar liquidity for non-US firms which form a significant part of our dataset.

The US dollar appreciation should additionally mean that non-US firms with US dollar short-term liabilities would experience higher costs relative to US firms with similar US dollar exposures, which should further weigh on output. In order to assess this, we re-estimate Equation 18 in the sub-samples of non-US firms and US firms. Appendix Figure A.5 shows that indeed, that the impact of US dollar appreciation, conditional on the short-term US dollar debt exposure and undrawn credit has a more immediate and larger effect on output of non-US firms compared with US firms.

The influence of interest rates, however, is less clear. Panels D examines the influence of short-term interest rates, suggesting a somewhat different relationship. Although there is a lot of volatility, it appears that higher short-term rates have only a muted and if anything a delayed influence on firm output. The limited influence of short-term interest rates could be due to the fact that policy rates were at the effective lower bound during much of our sample period. But it also could reflect that the spread on borrowing rates rather than the level may better capture credit supply conditions (Lombardi et al. (2025)). Panel E even shows that higher long-term interest rates have been associated with somewhat stronger output in firms with more undrawn credit. But it may also reflect distortions in the relationship between long-term interest rates and financial conditions due to unconventional monetary policies enacted over a large part of our sample period.

8. Money elasticity spillovers through production networks

While production networks can help to identify exposure to money elasticity through demand for working capital, they can also amplify shocks to the elasticity of money. Firms who themselves have little need for working capital might themselves be little affected by shifts in money elasticity. Nevertheless, they may be adversely impacted by a tightening of financial conditions affecting connected firms that depend on working capital. Such spillovers through production networks may well amplify the initial shock. Moreover, as discussed in subsection 5.1, our estimates above of the direct impact may potentially capture additional network spillovers if its undrawn credit and its upstreamness and downstreamness are correlated with those of linked firms.

To assess the influence of production network spillovers from shifts in the elasticity of money, we estimate the following regression

$$\begin{aligned}\Delta y_{isct,t+h,t-1} = \beta\, x_{isct} \;+\; \theta_D\, WX^{Up}_{isct} \;+\; \theta_U\, WX^{Down}_{isct} \\ +\; \mathbf{Q_{isct-1}\Theta_h} \;+\; \mu_i \;+\; \tau_{ct} \;+\; \varepsilon_{isct},\end{aligned} \tag{19}$$

where $\Delta y_{it,t+h,t-1}$ is the log change in output outcome for firm i between $t-1$ and $t+h$, x_{isct} is the instrumented firm-level shock to money elasticity, constructed similar to construct the instrumented firm-level shock similar to the first stage of Equation 16, $x_{it} \equiv \widehat{\mathbb{E}}[x^{\text{raw}}_{it} \,|\, \alpha_i, \tau_{ct}, \Delta FCI_t \times Upstream_i, \Delta FCI_t \times Downstream_i]$, where $x_{it} \equiv \Delta FCI_t \times UndrawnCredit_{it}$. $\mathbf{Q}_{isct-1}$ is a vector of lagged controls as in Equation 16, μ_i are firm fixed effects, and τ_{ct} are country×time fixed effects.

WX^m_{it} are network-weighted averages of the money elasticity shocks, x_{ft}, for all firms f in the network linked to firm i. These links are categorised as either upstream (Up), representing shocks to suppliers or downstream ($Down$), representing shocks to customers. To compute WX^m_{it}, we first calculate the sector-level average shock $\bar{x}_{st} = \frac{1}{N_{st}} \sum_{f \in s} x_{ft}$ for each sector s at time t. We then construct the spillover by premultiplying the vector of sector averages by the weighting matrix

W^m.[4]

In our empirical analysis, we use different network weights W^m to capture either immediate links or propagation along the entire production chain. For upstream (supplier) shocks, we capture exposure to immediate suppliers using the transpose of the direct requirement matrix, $A^\top$, where $A_{ji} = Z_{ji}/Y_i$ represents the share of firm i's total inputs sourced from sector j. For the entire upstream chain, we use the transpose of the Leontief inverse, $L^\top = [(I - A)^{-1}]^\top$. Analogously, for downstream (customer) shocks, we capture exposure to immediate customers using the allocation coefficient matrix B, where $B_{ij} = Z_{ij}/Y_i$ represents the share of firm i's total sales going to sector j. To capture links along the entire customer chain, we use the Ghosh inverse $G = [I - B]^{-1}$. Due to the two-stage estimation procedure, we compute standard errors with a two-way block bootstrap to be consistent with the two-way clustering by firm and by sector×time used in our baseline IVLPs.

Even when accounting for these network spillovers, the estimated direct effects of a firm's exposure to undrawn credit remain highly stable and robust. The estimations in Table 4 reveal that when financial conditions shift, the direct effects related to a firm's exposure to undrawn credit are close to our baseline results excluding network spillovers. The coefficients on the instrumented direct effect, $\Delta FCI_t \times UndrawnCredit_{it}$, are negative and statistically significant across all specifications. Quantitatively, the point estimates are stable across all specifications and are very close to our baseline impact reported in Figure 3, providing additions support that our instruments satisfy the exclusion restriction assumption.

Disaggregating the sources of spillovers reveals that shocks primarily propagate from upstream firms down to their customers, rather than in the reverse direction. As an initial breakdown, column (1) examines the impact of spillovers from the immediate suppliers of firm i, represented by $WX_{it}^{Up,A^\top}$. The point estimate is negative and significant, indicating that shocks to suppliers spill over into the output of their customers. Column (2) extends this analysis to include the entire upstream chain of supplier exposure to the shock, $WX_{it}^{Up,L^\top}$, which is also associated with

[4]See the Appendix for details on the normalisation and the leave-self-out adjustment used for own-sector spillovers.

Dependent Variable:	$\Delta log(sales)_{t+2,t-1}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\Delta FCI_t \times UndrawnCredit_{it}$	-0.0786**	-0.0714**	-0.0799**	-0.0755**	-0.0789**	-0.0719**
	(0.0321)	(0.0307)	(0.0327)	(0.0317)	(0.0321)	(0.0307)
$WX_{it}^{Up,A^\top}$	-0.1706**				-0.1804**	
	(0.0678)				(0.0860)	
$WX_{it}^{Up,L^\top}$		-0.1520***				-0.3733**
		(0.0577)				(0.1564)
$WX_{it}^{Down,B}$			-0.0985		0.0139	
			(0.0636)		(0.0804)	
$WX_{it}^{Down,G}$				-0.1100*		0.2389
				(0.0564)		(0.1535)
Fit statistics						
Observations	60,849	60,849	60,849	60,849	60,849	60,849
R^2	0.47360	0.47364	0.47352	0.47356	0.47360	0.47370
Direct effect	-0.079**	-0.071**	-0.080**	-0.076**	-0.079**	-0.072**
	(0.032)	(0.031)	(0.033)	(0.032)	(0.032)	(0.031)
Indirect effect	-0.171**	-0.152***	-0.098	-0.110*	-0.166**	-0.134**
	(0.068)	(0.058)	(0.064)	(0.056)	(0.073)	(0.058)
Total effect	-0.249***	-0.223***	-0.178**	-0.185***	-0.245***	-0.206***
	(0.072)	(0.063)	(0.069)	(0.062)	(0.077)	(0.062)

Table 4: **Network spillovers from shifts in money elasticity.** This table reports estimates from Equation 19. The dependent variable is the log change in sales between $t-1$ and $t+2$. The regressors, WX_{it}^m, $m \in \{Up, A^\top; Up, L^\top; Down, B; Down, G\}$ are respectively the network weighted averages of the money elasticty shock (instrumented $\Delta FCI_t \times UndrawnCredit_{jt}$) over the j network linked firms where weights are respectively computed from the transpose of the direct requirements matrix ($A^\top$), transpose of the Leontief inverse ($L^\top$), allocation matrix (B) or the Ghosh inverse (G). All regressions include the following control variables: log assets, sales growth and the ratios of profits, sales, short-term debt, long-term debt, inventories, cash, accounts receivable and accounts payable to total assets. Two-way block bootstrapped standard errors by firm and by sector×time are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

significant spillovers on customer output.

Column (3) shifts focus to spillovers from immediate customers, represented by $WX_{it}^{Down,B}$. In contrast to the significant spillovers from immediate suppliers, the exposure of immediate customers to the shock is negative but statistically insignificant. Column (4) considers the entire downstream chain of customers of firm i, represented by $WX_{it}^{Down,G}$. When this is included, the point estimate becomes statistically significant at the 10% level.

Columns (5) and (6) incorporate spillovers from shocks to both upstream and downstream firms. These results suggest that, overall, shocks to the elasticity of money tend to propagate from upstream firms to downstream firms within the manufacturing sector. This finding differs somewhat from Luo (2020), who observed that, across US industries, spillovers from shocks to the loan supply of a firm's customers were associated with larger output declines following the Lehman Brothers' 2008 default. One potential source of this difference is that we measure exposure to shocks based on a firm's working capital needs. Another contributing factor is our inclusion of international upstream and downstream production network linkages, where upstream manufacturing exports have been found to be particularly sensitive to credit supply shocks (Amiti and Weinstein (2011)).

Our estimates indicate significant network amplification effects. On average across the specifications in Table 4 the direct effects account for roughly one third of the total impact on firm output, with network spillovers accounting for around two thirds of the impact. This degree of network amplification is consistent with other studies, for example, Di Giovanni and Hale (2022) find that network effects account for around 60 to 70% of the amplification of US monetary policy shocks on global stock market prices.

9. Conclusion

This paper demonstrates that the elasticity of money plays a visible and pivotal role in shaping real economic outcomes within supply chains. We provide a conceptual framework which shows that when there are payment delays and prepayments in production networks, then the firms' position in production networks determines its working capital needs. We then leverage granular firm-level data to analyse how shifts in financial conditions – the terms and conditions of money – impact firm activity depending on the production network driven demand for working capital, revealed by their undrawn credit lines. Our findings show that the elasticity of money and the supply of working capital are two sides of the same coin. Undrawn credit lines are key to linking the two.

Our findings underscore the particular importance of the elasticity of money for firms with large production network driven working capital needs. These firms experience larger declines in output when tightening financial conditions reduce the elasticity of money and hence the supply of working capital. Moreover, spillovers through production networks significantly amplify the shock, accounting for around two thirds of the total impact on output.

The results also reveal the nuanced role of different dimensions of financial conditions. Corporate bond spreads and the US dollar exchange rate emerge as key drivers of the observed dynamics, with interest rates playing a more muted role. These findings align with the view that credit spreads and liquidity conditions are more relevant than nominal interest rates in capturing the elasticity of money.

Our study contributes to the growing literature on production networks, credit, and the heterogeneous effects of financial conditions on firm outcomes. It shows that when financial conditions are loose, money elasticity helps firms in complex production networks to smooth through shocks – such as the significant 2025 increases in US trade tariffs.

Future research could extend this analysis by further examining the role of credit lines. For instance, how the specific terms and conditions on credit lines influence firm decisions to access them. This would in turn help to provide a more complete picture of the influence of money elasticity within production networks. Future research could also extend our analysis to study the implications for monetary policy and financial regulation. As the longer production chains require more working capital which amplifies the effects of shifts in money elasticity, it raises questions about the extent to which monetary policy or financial sector regulation should aim to dampen the procyclicality of financial conditions. It also raises questions about tools to support production in long production chains during periods of financial stress.

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A. Appendix

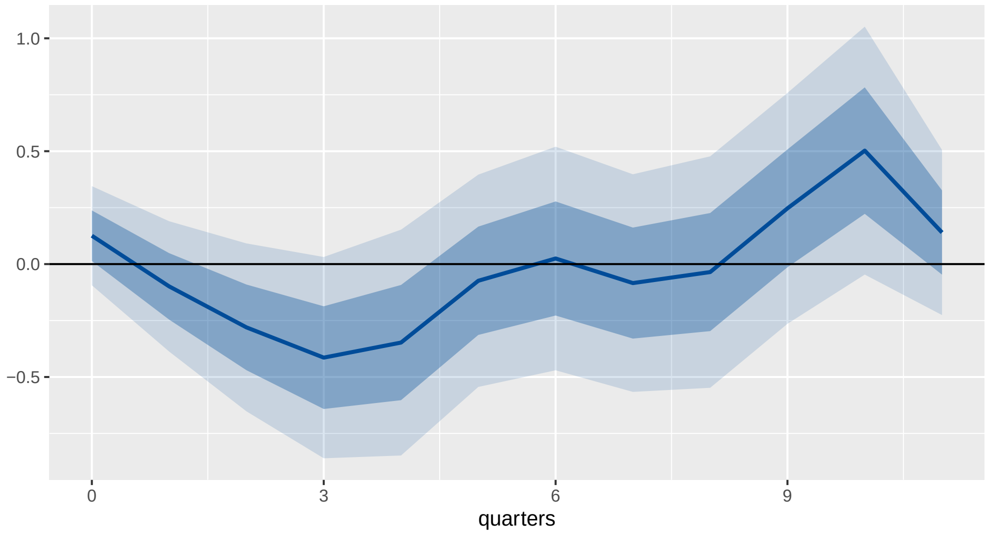

Figure A.1: **Output response to orthogonalised financial condition shocks conditional on undrawn credit.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between an orthogonalised financial conditions shock derived from a three variable VAR with global industrial production, accounts receivable and the Goldman Sachs financial conditions index, interacted with undrawn credit on firm output using instrumental variable local projections Equation 16. The dependent variable is the log change in sales between $t-1$ and $t+h$. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

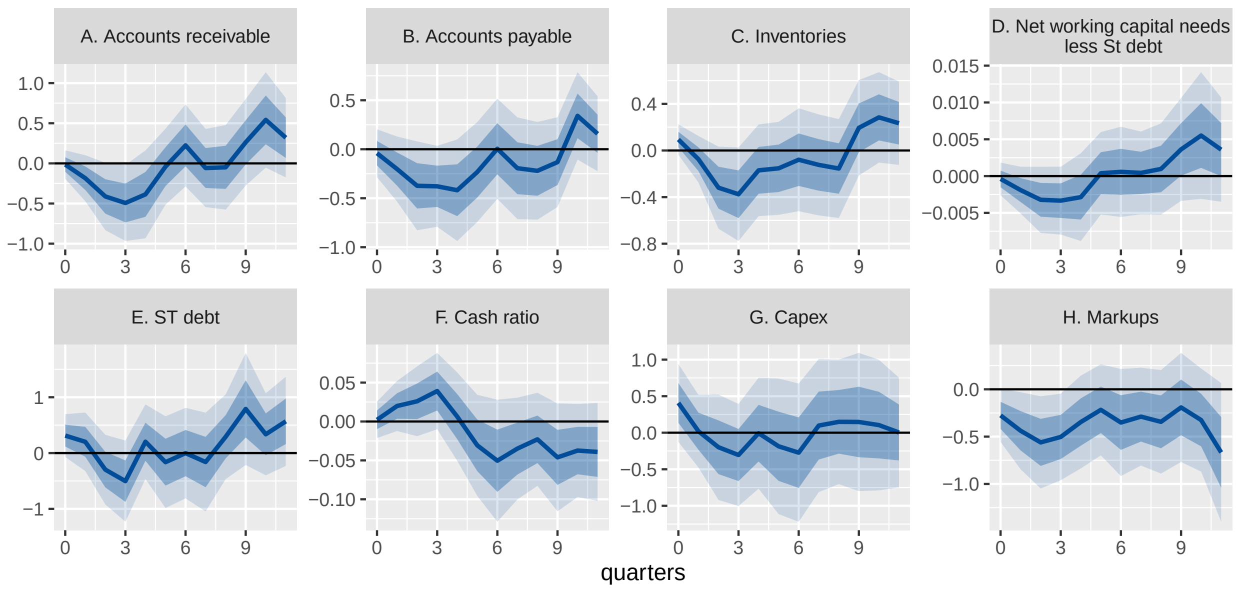

Figure A.2: **Response to orthogonalised financial conditions shocks conditional on undrawn credit.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between orthogonalised financial conditions shocks and undrawn credit to total assets using the instrumental variable local projections Equation 16. The financial conditions shock is derived from a three variable VAR with global industrial production, accounts receivable and the Goldman Sachs financial conditions index. The dependent variables are the change between $t-1$ and $t+h$ for log accounts receivable (panel A), log accounts payable (panel B), log inventories (panel C) networking capital needs less short-term debt - defined as accounts receivable plus inventories less accounts payable and short-term debt (panelD), log short-term debt (panel E), ratio of cash to assets (panel F), the logarithm of capital expenditures (panel G) and markups as measured by the log sales less cost of goods sold as a ratio of costs of goods sold (Panel H). Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

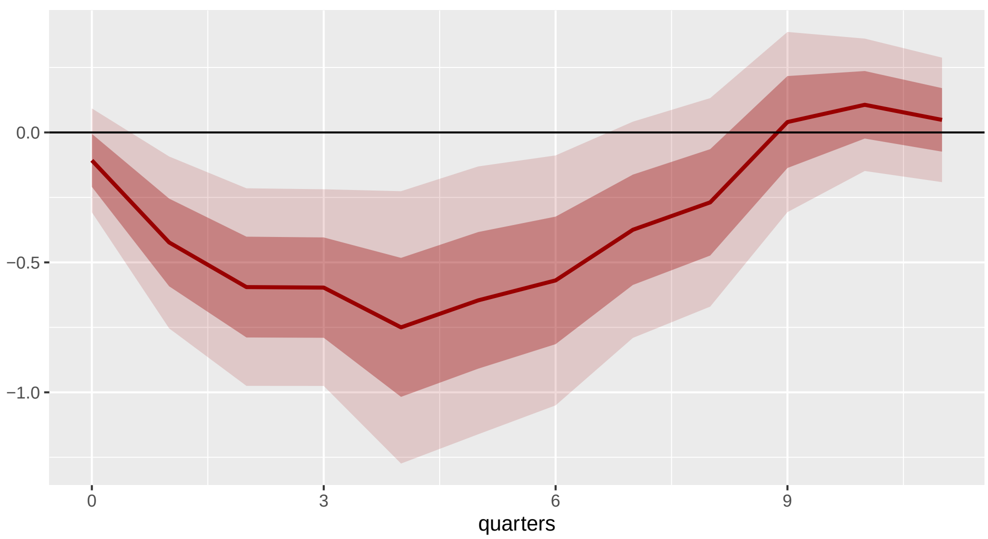

Figure A.3: **Output response to tighter financial conditions conditional on undrawn credit - all non-financial sectors.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between $\Delta FCI_t \times UndrawnCredit_t$ based on the instrumental variable local projections Equation 16. The dependent variable is the log change in sales between $t-1$ and $t+h$. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

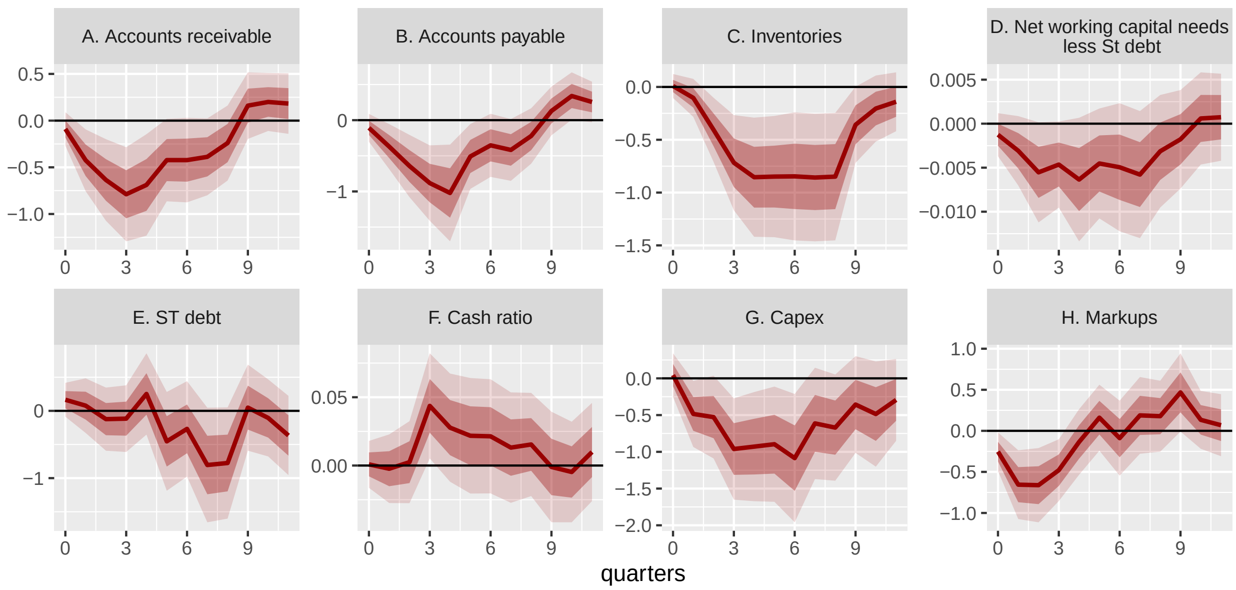

Figure A.4: **Output response to tighter financial conditions conditional on undrawn credit - all non-financial sectors.** The Figure shows estimates of β_{3h}, the coefficient on the interaction between financial conditions shocks and undrawn credit to total assets using the instrumental variable local projections Equation 16. The dependent variables are the change between $t-1$ and $t+h$ for log accounts receivable (panel A), log accounts payable (panel B), log inventories (panel C) networking capital needs less short-term debt - defined as accounts receivable plus inventories less accounts payable and short-term debt (panel D), log short-term debt (panel E), ratio of cash to assets (panel F), the logarithm of capital expenditures (panel G) and markups as measured by the log sales less cost of goods sold as a ratio of costs of goods sold (Panel H). Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector×time.

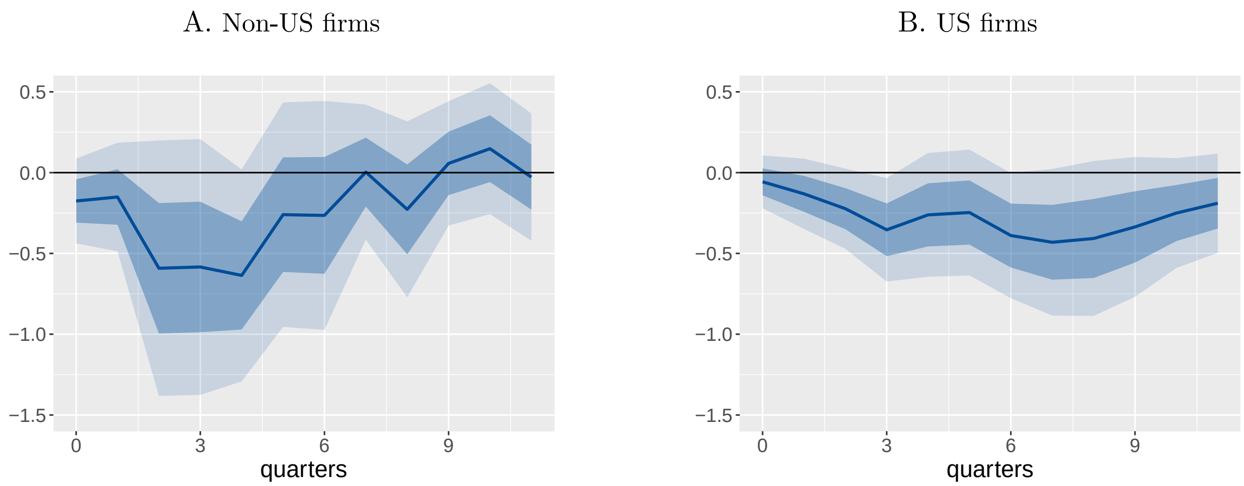

Figure A.5: **Output response to a US dollar appreciation conditional on undrawn credit and short-term US dollar debt.** The Figure shows estimates of ϕ_{4h}, the coefficient on the triple interaction between a one standard deviation US dollar appreciation, the firm's undrawn credit to assets ratio and the firm's short-term US dollar debt to assets ratio from the IVLP Equation 18. The dependent variable is the log change in sales between $t-1$ and $t+h$. Shaded areas show 95% and 68% confidence intervals based on standard errors clustered by firm and sector$\times$time. Panel A shows estimates in the subset of non-US firms, while Panel B shows estimates in the subset of US firms.

Constructing the network-weighted regressors WX_{it}^m. Let $k(i)$ denote the sector of firm i, and let $N_{t\ell}$ be the number of sample firms observed in sector ℓ at time t. We denote the sector-level average shock as $\bar{x}_{\ell t} = \frac{1}{N_{t\ell}} \sum_{j:k(j)=\ell} x_{jt}$. For a given industry-by-industry matrix $W^m = \{w_{k\ell}^m\}$, where $m \in \{B, G, A^\top, L^\top\}$, the weights $w_{k\ell}^m$ capture the economic exposure of sector k to sector ℓ. Specifically, $m = B$ and $m = G$ represent downstream exposure to customers (immediate and total, respectively), while $m = A^\top$ and $m = L^\top$ represent upstream exposure to suppliers. We define the firm-level network exposure as a row-normalised average that incorporates a leave-self-out (LSO) adjustment for the firm's own sector:

$$WX_{it}^m \equiv \frac{\sum_{\ell \neq k(i)} w_{k(i)\ell}^m \bar{x}_{\ell t} + w_{k(i)k(i)}^m \bar{x}_{it}^{LSO}}{\sum_{\ell \neq k(i)} w_{k(i)\ell}^m \mathbb{I}(N_{t\ell} > 0) + w_{k(i)k(i)}^m \mathbb{I}(N_{tk(i)} > 1)}$$

where $\bar{x}_{it}^{LSO} = \frac{1}{N_{tk(i)}-1} \sum_{j:k(j)=k(i), j \neq i} x_{jt}$ is the average shock among firm i's sectoral peers. The regressor is set to 0 if the denominator is ≤ 0 or if the sector of firm i is unknown.

Direct and indirect effects (uniform-shock experiment). We compute spillovers by first taking the partial derivative of Equation 19 matrix with respect to x

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}'} = \beta \, \mathbf{I}_N + \sum_{m \in \{A^\top, L^\top, B, G\}} \theta_m \, \mathbf{W}^m,$$

where $\mathbf{W}^m$ is the firm-level row-normalized neighbor matrix corresponding to WX^m. We then compute a uniform one-unit increase in x across all firms, the average effects

$$\text{Direct effect} = \beta, \qquad \text{Indirect effect} = \sum_m \theta_m \, \bar{c}_m, \qquad \text{Total effect} = \text{Direct effect} + \text{Indirect effect},$$

where $\bar{c}_m$ is the sample average row sum of $\mathbf{W}^m$.