# Financial frictions across the production network and the transmission of monetary policy

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**Abstract**

We examine how sector-specific financial frictions and production network linkages shape monetary policy transmission. Using granular country-sector data for the euro area we construct novel measures of upstream and downstream financial frictions. Panel local projections show that financial frictions among upstream suppliers and downstream customers substantially amplify the effects of monetary policy on prices and output. Importantly, this amplification is not driven solely by a sector's own financial position: indirect financial frictions transmitted through production networks account for a significant share of the response. We further document that downstream financial frictions reinforce the contractionary effects of monetary policy through a demand channel, while upstream financial frictions generate a countervailing cost channel by raising sectoral prices. A multi-sector model with heterogeneous financial frictions rationalizes these findings and highlights the importance of network-based financial channels for monetary policy transmission.

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# Non-technical summary

Financial positions and production network linkages have been identified as key determinants of the transmission of macroeconomic shocks. In this paper, we bring together these two dimensions and study how the transmission of monetary policy is affected by their interaction. To this end, we develop a novel set of empirical measures for a sector's exposure to up- and downstream financial frictions, i.e. to the leverage of its suppliers and customers. Equipped with these measures, we investigate the effects of monetary policy in the euro area when explicitly accounting for sector-specific financial conditions and production networks linkages.

Our results show that both direct and indirect financial frictions significantly amplify the effect of a monetary policy shock, with indirect financial frictions accounting for a large share of the overall effect on prices and output. In addition, we find that while downstream financial frictions seem to reinforce the decline in prices and output following a monetary policy tightening shock, upstream frictions tend to partly mitigate these effects. While a tightening shock lowers downstream customers' demand for intermediate goods, we document a novel network-induced cost channel of monetary policy: a monetary policy tightening pushes upstream suppliers to raise prices, possibly to mitigate negative revenue effects stemming from a tightening of financing conditions.

From a policy perspective, these findings underscore the importance of considering both financial frictions and production networks in combination when assessing the potential impacts of monetary policy. For instance, ignoring the possible amplification of dampening demand effects of a monetary policy tightening that can be attributed to downstream customers' financial frictions may result in underestimating its full impact. While a "traditional" balance-sheet channel accounts for a sector's own degree of financial constraints only, we document that "indirect" balance-sheet channels stemming from such downstream exposures need to be adequately accounted for as well. At the same time, the upward effect on sectoral prices stemming from a sector-specific cost channel may dampen the overall efficacy of monetary policy. By understanding these dynamics, central banks can better anticipate the effects of their actions on different sectors and the broader economy.

# 1 Introduction

Understanding how monetary policy affects the economy remains a central question in macroeconomics. A key difficulty lies in the complex and multilayered transmission process through which policy decisions by central banks influence economic dynamics. As a result, monetary policy is generally thought to operate with "long and variable lags"[1] stemming from the interaction of multiple agents and channels, as well as from the prevailing economic and financial conditions. Disentangling the mechanism that governs this transmission, and the sources of its timing and strength, therefore requires moving beyond purely aggregate analysis and adopting a more granular perspective.

In this paper, we take a step in this direction by focusing on two factors that the current macroeconomic debate has identified as central to the transmission of monetary policy. The first is the role of financial frictions in amplifying the effects of monetary policy, as formalized in Bernanke and Gertler (1995) and Bernanke et al. (1999) and empirically documented, for example, in Gilchrist and Zakrajšek (2012), Ottonello and Winberry (2020), and Anderson and Cesa-Bianchi (2024). The second is the role of production networks in shaping the transmission of shocks across the economy (Acemoglu et al., 2012, 2016), an issue that has featured prominently, for instance, in the debate on the supply- versus demand-side origins of the inflation surge following the Covid-19 pandemic.[2]

Specifically, we investigate the extent to which the transmission of monetary policy depends on financial frictions across the production network, by looking at both sectors' own financial positions and those of their trading partners. In doing so, we assess the importance of both direct and indirect channels through which financial frictions may amplify or dampen the transmission of monetary policy. Financial frictions directly affecting firms in a specific sector may amplify the transmission through the traditional balance-sheet channel (Bernanke and Gertler, 1995). More recently, a growing literature has emphasized that firms with higher leverage are more exposed to policy-induced changes in financing conditions (Anderson and Cesa-Bianchi, 2024). This interpretation provides a direct link between leverage-based empirical measures of financial vulnerability and the working-capital-type financial frictions commonly used in theoretical models.

[1] See Friedman (1961). See also the remarks by Federal Reserve Chair Jerome Powell on 21 September 2022 referring to this argument.

[2] See for instance Bernanke and Blanchard (2025, 2024); Giannone and Primiceri (2024).

In our theoretical framework, leverage proxies for firms' exposure to changes in external finance premia, which we model as distortions in the cost of financing variable production inputs. Monetary policy tightening increases these premia, thereby effectively tightening working-capital constraints and forcing firms to adjust prices and quantities. Importantly, we show that the balance-sheet channel can also be indirectly amplified through the production network, depending on both the degree of interconnectedness across sectors and the financial positions of upstream and downstream trading partners. For instance, when financially vulnerable downstream firms face tighter financing conditions, their demand for intermediate inputs declines, exerting downward pressure on output and prices of upstream suppliers (a downstream demand channel). At the same time, upstream firms facing tighter financial conditions may raise prices to preserve cash flow and alleviate financing pressures, propagating cost increases downstream (Gilchrist et al., 2017). Failing to account for these indirect financial spillovers may therefore lead to a systematic understatement of the aggregate effects of monetary policy. In addition, explicitly accounting for the role of upstream and downstream financial frictions sheds light on the timing of transmission and on the relative importance of upstream "cost" and a downstream "demand" channels across the production network.

The empirical analysis is conducted using a monthly euro area country–sector panel dataset comprising information on prices, real activity, intersectoral linkages as captured by euro area input–output (IO) tables, and sector-specific indicators of financial frictions. Financial frictions are proxied by sector-level corporate leverage, in line with standard practice in the literature.[3] Specifically, sectoral measures of financial frictions are constructed by aggregating firm-level data from Orbis and subsequently combined with IO tables to derive proxies for the financial frictions faced by each sector's suppliers ("upstream") and customers ("downstream") within the production network. These measures are then embedded in a panel local projections framework (Jordà and Taylor, 2016; Jordà, 2005) to analyse their interaction with monetary policy shocks. While an unconditional increase in leverage may, in principle, reflect a sector's growth potential rather than a source of financial vulnerability, we control for time-invariant cross-sectoral differences in the "neutral" level

[3]Several empirical studies documented the negative impact high debt holdings may have on firms' investment activity and broader economic developments, see e.g.Vermeulen (2002), Jäger (2003), Benito and Hernando (2007), Martinez-Carrascal and Ferrando (2008), Pal and Ferrando (2010), Goretti and Souto (2013), Ferrando et al. (2017), Kalemli-Özcan et al. (2018), Gebauer et al. (2018), or Barbiero et al. (2020).

of leverage and for its key macroeconomic confounders. This allows us to isolate the *conditional*, marginal tightening or easing of financial frictions – in line with a broad literature that has documented a "financial accelerator" mechanism originating from firms' external financing positions.[4]

The results of the empirical analysis can be summarized as follows. First, both direct and indirect financial frictions significantly amplify the contractionary effects of a monetary policy tightening on output and prices, with indirect financial frictions accounting for a significant share of this amplification effect. Second, further decomposing the indirect channel, we find that downstream financial frictions reinforce the monetary policy effect, especially on prices, consistent with a tightening of financial constraints that reduces downstream customers' demand for intermediate goods produced by other sectors ("demand channel"). By contrast, tighter upstream financial frictions offset this effect by strengthening suppliers' incentives to raise prices ("cost channel"). The downstream demand channel dominates, however, thus giving rise to the overall amplifying effect of indirect financial frictions in the transmission of monetary policy.

Finally, we rationalize our empirical findings in a multi-sector model with input–output linkages and sector-specific financing frictions. While the model features working-capital constraints rather than explicit leverage, these constraints capture the same underlying mechanism highlighted in the empirical analysis: monetary policy affects firms by altering the cost of externally financed production inputs, with the strength of this effect depending on firms' exposure to external finance premia. By mapping empirically observed leverage heterogeneity into sector-specific financial frictions, the model provides a coherent interpretation of how these frictions propagate through production networks and shape the transmission of monetary policy.

[4]See, inter alia, Bernanke and Gertler (1989), Bernanke and Gertler (1995), Bernanke et al. (1999), or Kiyotaki and Moore (1997) for early theoretical contributions, and Ottonello and Winberry (2020), Auer et al. (2021) Bahaj et al. (2022), Jeenas (2023), Cloyne et al. (2023), or Anderson and Cesa-Bianchi (2024) for recent empirical evidence on (the heterogeneous effects of) a monetary-policy related financial accelerator. We also point out that the terms "constraints" and "frictions" may bear different connotations, depending on the research question and design at hand. In this paper we use these terms interchangeably to refer to situation of relatively tight sectoral financial positions, and only refer to the possible nature of the underlying frictions explicitly in the theoretical discussions of section 7.

The remainder of the paper is organized as follows: section 2 reviews the relevant literature, section 3 describes the data, section 4 shows how we construct the sector-specific measures of financial frictions, section 5 outlines the econometric strategy, and section 6 presents the empirical results. We rationalize our empirical financial constraints measures by reporting both analytic derivations and comparative statics analyses based on a theoretical multi-sector economy model in section 7. Section 8 concludes.

## 2 Literature

Our work intersects with multiple strands of existing theoretical and empirical literature. First, we contribute to the empirical literature on monetary policy transmission across production networks by providing new evidence for the euro area. Indeed, despite the growing body of studies on the transmission of shocks in production network, empirical evidence remains relatively scarce and has mainly been obtained for the United States.[5] For example, Ozdagli and Weber (2017) analyze the impact of monetary policy shocks measured via high-frequency changes in financial market data occurring around Federal Reserve press releases. Using stock return data, they find that between 50 and 85 percent of the overall monetary policy effect is attributable to indirect network effects. More recently, Ghassibe (2021) employs monthly data on US sectoral consumption and finds that at least 30 percent of the effect of monetary shocks on aggregate consumption stems from amplification through input-output linkages. At the sectoral level, he finds that the network effect increases with the degree of price stickiness and intermediate input intensity. We expand on this area of research by incorporating the interaction of financial frictions and sectoral linkages in our empirical analysis. From a methodological perspective, our study relates to recent work using disaggregated price data to examine monetary policy transmission to consumer prices (Borağan Aruoba and Drechsel, 2024; Allayioti et al., 2024). In contrast to those studies, we analyze the production side of the economy, and highlight the role of financial frictions within production networks. By accounting for financial variables in the empirical framework, we document a novel cost channel of monetary policy running through the propagation of sectoral financial frictions across the production network, extending earlier findings

[5] A notable exception is the early contribution by Peersman and Smets (2005), which, although it does not account for intersectoral linkages, adopts a sectoral perspective by examining monetary policy transmission across European industries.

by BarthIII and Ramey (2002). This cost channel operates both directly through firms' financial frictions, and indirectly through the frictions faced by a firm's suppliers and customers. Moreover, our study complements Demir et al. (2024), who examine the transmission of supply shocks through a production network, and find that the transmission of such shocks is amplified by low liquidity holdings of some firms. We document similar amplification effects for monetary policy shocks, and we show that these shocks propagate both from suppliers to customers via a cost channel, and from customers to suppliers via a demand channel.

Second, our work relates to the broader literature on financial frictions in the transmission of monetary policy shocks. The importance of financial frictions has been widely acknowledged since Bernanke and Gertler (1995) and Bernanke et al. (1999) and remains a central theme in macro-financial research. However, the role of micro-level financial frictions in transmitting shocks to the macroeconomy has only recently been explored. Ottonello and Winberry (2020) show that financially constrained firms invest significantly less following a monetary policy shock compared to non-constrained firms, rationalizing this finding within a heterogeneous firm New Keynesian DSGE model. Similarly, Jeenas (2023) finds that firms with low liquid asset holdings invest less after unexpected policy rate increases, independent of their leverage or size, highlighting the role of corporate liquidity management in monetary policy transmission. Our study builds on this literature by demonstrating that sectoral financial frictions not only affect individual firms but also propagate through supplier-customer relationships. In this regard, our findings connect with Adelino et al. (2023), who examine the role of trade credit in the transmission of unconventional monetary policy. We broaden this perspective by considering the transmission of interest rate policy through the production network and by disentangling a demand and a cost channel that works through sectoral linkages.

Third, we contribute to the theoretical literature on production networks and shock propagation. Following the seminal work of Acemoglu et al. (2012), research has extensively examined how different types of shocks, including productivity, government spending, financial distortions and monetary policy, travel through supply chains and affect aggregate outcomes. For example, La'O and Tahbaz-Salehi (2022) examine the influence of production networks on optimal monetary policy, finding that optimal stabilization requires a price index that places greater weight on industries that are larger, have higher price stickiness, and are positioned further upstream. Similarly, Rubbo (2023) show that in a multi-sector economy with input-output linkages, the "divine coincidence" – i.e., the simultaneous stabilization of

both output and prices via monetary policy – no longer holds. Our theoretical model is an extension of the framework developed in Bigio and La'O (2020), who show that the US input-output structure amplified financial distortions roughly by a factor of two during the Great Financial Crisis. More recently, Su (2024) highlights how input-output linkages amplify sectoral financial distortions, influencing aggregate total factor productivity (TFP) shocks. Our analysis builds on this work by demonstrating that sectoral financial frictions significantly impact monetary policy transmission through firms, with network effects amplifying or mitigating their impact, depending on the financial conditions of upstream and downstream firms.

# 3 Data

We construct a monthly country–sector panel covering the period from January 1999 to December 2024 for 20 euro area countries and 64 sectors, broadly corresponding to the NACE-2 two-digit classification.[6] Our dataset consists of four main components:

1. country-level macroeconomic indicators, including aggregate monetary policy shocks;
2. sector-level data on producer prices and activity, reported at the NACE-2 level;
3. input–output data for 64 sectors, capturing bilateral cross-sector flows across all euro area countries;
4. firm-level balance sheet data from Orbis, aggregated at the country–sector–year level to provide measures of sector-specific financial frictions.

In the following, we describe each component in greater detail. Summary statistics for each category are reported in Table 6.

**Country-level data and monetary policy shocks**

We collect a set of standard country-level macroeconomic control variables, including data on prices, real economic activity, interest rates and macro-financial variables obtained from Eurostat and the International Monetary Fund (IMF). We identify common euro area monetary policy shocks via high-frequency movements in the

[6]The NACE-2 digits classification comprises 88 sectors; we aggregate these into 64 sectors to match the lower granularity of the input–output tables. See Eurostat (2008) for further details on the NACE classification.

**Table 1:** Summary statistics of used variables

| | Observations | Mean | Standard deviation | Median |
|---|---|---|---|---|
| *Euro area level* | | | | |
| CISS | 312 | 0.18 | 0.15 | 0.12 |
| EUR/USD exchange rate | 312 | 1.18 | 0.16 | 1.17 |
| Composite 10y sov. bond yield (%) | 312 | 3.03 | 1.60 | 3.41 |
| IMF commodity index | 256 | 134.08 | 38.25 | 126.39 |
| 3-month OIS (%) | 305 | 1.47 | 1.75 | 0.78 |
| Monetary policy shock (bps) | 312 | 0.16 | 2.67 | 0.00 |
| *Country level* | | | | |
| Real GDP (€bn) | 2,380 | 475.15 | 894.54 | 54.49 |
| GDP Deflator | 2,266 | 88.53 | 15.68 | 89.25 |
| Unemployment (%) | 7,115 | 8.79 | 4.14 | 7.98 |
| Hours worked (bn) | 2,338 | 10.61 | 19.76 | 1.67 |
| Employed persons (mil) | 1,971 | 29.97 | 53.73 | 2.54 |
| HICP | 6,409 | 95.51 | 15.81 | 97.96 |
| QE holdings (€bn) | 3,424 | 100.23 | 208.25 | 12.58 |
| 10y sov. bond yield (%) | 2,974 | 2.60 | 1.83 | 2.85 |
| *Sector level* | | | | |
| Producer price index (PPI) | 145,986 | 52.81 | 48.01 | 74.04 |
| Industrial production (IP) | 197,951 | 84.83 | 88.09 | 92.59 |
| Turnover | 220,521 | 101.23 | 2533.46 | 83.60 |
| Employment index | 98,710 | 42.77 | 53.98 | 0.00 |
| Hours worked index | 87,323 | 33.06 | 53.37 | 0.00 |
| Job Vacancy rate | 3,768 | 1.96 | 4.12 | 1.20 |
| Gross wages | 96,507 | 34.09 | 45.79 | 0.00 |

Sources: Eurostat, ECB, Altavilla et al. (2019), IMF.

3-month OIS rate over a narrow window (ca. 135 minutes) around the publication of the press release and the press conference following ECB Governing Council meetings. We draw these movements from the euro area monetary policy-event database constructed by Altavilla et al. (2019). In order to isolate monetary policy shocks from information shocks, we use the so-called "poor-man's sign restriction" approach developed in Jarociński and Karadi (2020). We thus identify monetary policy shocks as high-frequency changes in the 3-months OIS rate over the event window coinciding with stock prices movements in the opposite direction.[7]

**Country-sector data**

We collect data on prices, industrial production, turnover, employment, hours worked, and wages from the Short-term Business Statistics (STS) dataset of Eurostat.[8] As no information on price indices for the trade sector (NACE codes G00, G45, G46, G47) are reported in the STS, we compute them by dividing nominal turnover by real turnover, consistent with the methodology employed by Eurostat.[9] In addition, we proxy the producer price index (PPI) for the construction sector (NACE code F00) with the PPI for residential buildings construction.[10] Moreover, as STS do not cover the agriculture sector (A01), we complement PPI data for this sector with quarterly information from another Eurostat dataset, which we linearly interpolate to obtain monthly observations.[11] We also add industrial production (IP) indices for agriculture from the "Economic accounts for agriculture (aact_eaa)" dataset provided by Eurostat, even if reported data is only available at annual frequency.[12]

In STS, data on employment, hours worked, and wages are mainly available at quarterly frequency, and only partly provided at monthly frequency on voluntary basis by national statistical offices.[13] Data on prices, industrial production,

[7] Our empirical results in section 6.1 are robust to identifying monetary policy shocks based on the first principal component of high-frequency changes in 1-, 3-, 6-, and 12-month OIS rates, instead of relying on 3-month OIS changes only (Jarociński and Karadi, 2020).

[8] More details on STS data can be found here.

[9] More precisely, we divide turnover values by the volume of sales (deflated turnover).

[10] This refers to the statistical classification of products by activity (CPA) code F411X, the main component of sector F41 which covers "new buildings" only.

[11] The "Price indices of agricultural products (apri_pi)" data which can be found here.

[12] Given the low frequency, we do not interpolate annual agricultural data into monthly observations. The "Economic accounts for agriculture (aact_eaa)" data which can be found here.

[13] See STS regulations here.

and turnover are available both at monthly and quarterly frequency, depending on the respective country, sector and time period.[14] To maximize the number of observations while preserving the consistency of the dataset, we linearly interpolate quarterly series to monthly and we either take the original monthly series or the quarterly interpolation, depending on which of the two has more observations.

For all available indices, we use seasonally adjusted series and perform a three-step cleaning procedure:[15]

1. We exclude all observations of a specific index variable reported with a value of zero.
2. We drop all observations of a series with exactly identical data entries for more than six subsequent months (if the series is monthly) or more than four quarters (if the series is quarterly).
3. We drop entirely data series exhibiting an implausibly high level of volatility or poor data quality, i.e. due to implausibly large discrete jumps at random intervals.

**Input-output data**

We obtain information on the EU inter-country and industry-by-industry input-output relations from the Eurostat's "Full international and global accounts for research in input-output Analysis (FIGARO)" database.[16] These tables are available at annual frequency from 2010 to 2022, and we extrapolate the 2010 figures to preceding years and the 2022 table for the subsequent years. This way, we cover the entire period of interest, and we take comfort in doing so from the fact that IO linkages are changing only very gradually over time. Table 7 provides a schematic example of a multi-country IO matrix with just two countries, $A$ and $B$, and two industries, 1 and 2, to illustrate the key metrics we derive from IO tables.

In this table, $x_{ij}^{A,B}$ is the flow of goods produced by sector $i$ in country $A$ and sold to sector $j$ in country $B$,[17] $c_1^A$ indicates the amount of output produced by sector 1 in

[14] This implies that for a given country-sector pair we may be able to retrieve only monthly or only quarterly observations, or both. Moreover, monthly and quarterly observations, if both available, are not perfectly consistent at all times in STS.

[15] We derive seasonally adjusted series in cases for which the seasonal adjustment is not directly carried out by Eurostat by performing a LOESS transformation.

[16] Further information on FIGARO data can be found here.

[17] Note that part of the sector's output could be used by the same sector for production, so one can have $x_{ii}^{X,X} \geq 0$.

**Table 2:** Simplified Multi-Country Input-Output Table

| | $A_1$ | $A_2$ | $B_1$ | $B_2$ | *Final consumption* | *Total* |
|---|---|---|---|---|---|---|
| $A_1$ | $x_{11}^{A,A}$ | $x_{12}^{A,A}$ | $x_{11}^{A,B}$ | $x_{12}^{A,B}$ | $c_1^A$ | $y_1^A = \sum_{s,c} x_{1s}^{A,c} + c_1^A$ |
| $A_2$ | $x_{21}^{A,A}$ | $x_{22}^{A,A}$ | $x_{21}^{A,B}$ | $x_{22}^{A,B}$ | $c_2^A$ | $y_2^A = \sum_{s,c} x_{2s}^{A,c} + c_2^A$ |
| $B_1$ | $x_{11}^{B,A}$ | $x_{12}^{B,A}$ | $x_{11}^{B,B}$ | $x_{12}^{B,B}$ | $c_1^B$ | $y_1^B = \sum_{s,c} x_{1s}^{B,c} + c_1^B$ |
| $B_2$ | $x_{21}^{B,A}$ | $x_{22}^{B,A}$ | $x_{21}^{B,B}$ | $x_{22}^{B,B}$ | $c_2^B$ | $y_2^B = \sum_{s,c} x_{2s}^{B,c} + c_2^B$ |
| *Labor* | $l_1^A$ | $l_2^A$ | $l_1^B$ | $l_2^B$ | | $l = \sum_{s,c} l_s^c$ |
| *Value added* | $v_1^A$ | $v_2^A$ | $v_1^B$ | $v_2^B$ | | $v = \sum_{s,c} v_s^c$ |
| *Taxes* | $t_1^A$ | $t_2^A$ | $t_1^B$ | $t_2^B$ | | $t = \sum_{s,c} t_s^c$ |

country $A$ going into final consumption (e.g. government and households), $l_1^A$ is the amount of labor used, $v_1^A$ stands for value added and $t_1^A$ for net taxes. The sum of the elements in a given row $i$ is equal to the total output produced (for intermediate and final consumption) by sector $i$. The sum of the elements in a given column $j$ gives the total cost of inputs (including labor, taxes, and value added) used in the production of sector $j$.

First, we calculate the share of each sector's labor expenses, taxes and value added in total input expenses. In our simplified table, this is given by

$$\alpha_{1A} = \frac{l_1^A + v_1^A + t_1^A}{x_{11}^{A,A} + x_{21}^{A,A} + x_{11}^{B,A} + x_{21}^{B,A} + l_1^A + v_1^A + t_1^A} \tag{1}$$

for industry 1 in country $A$.[18] This represents the share of a sector's inputs other than intermediate input goods acquired from the production network.

[18]In the FIGARO tables from Eurostat, for each sector, we compute the share of input sourced outside the production network as the sum of labor, value added and taxes (i.e. rows *"W2_D21X31 - Taxes less subsidies on products"*, *"W2_OP_NRES - Purchases of non-residents in the domestic territory"*, *"W2_OP_RES - Direct purchase abroad by residents"*, *"W2_D1 - Compensation of employees"*, *"W2_D29X39 - Other net taxes on production"*, *"W2_B2A3G - Gross operating surplus"*) divided by the total input cost of production.

Second, we compute the share of output used for final consumption, i.e. the share of a sector's output that is not used as an intermediate input in production by any sector. For sector 1 in country $A$, this would be given by[19]

$$\tilde{\alpha}_{1A} = \frac{c_1^A}{x_{11}^{A,A} + x_{12}^{A,A} + x_{11}^{A,B} + x_{12}^{A,B} + c_1^A} \tag{2}$$

Matrix $\mathbf{X}$ is the square input-output matrix and reports only the flows of goods and services between sectors:

$$\mathbf{X} = \begin{bmatrix} x_{11}^{A,A} & x_{12}^{A,A} & x_{11}^{A,B} & x_{12}^{A,B} \\ x_{21}^{A,A} & x_{22}^{A,A} & x_{21}^{A,B} & x_{22}^{A,B} \\ x_{11}^{B,A} & x_{12}^{B,A} & x_{11}^{B,B} & x_{12}^{B,B} \\ x_{21}^{B,A} & x_{22}^{B,A} & x_{21}^{B,B} & x_{22}^{B,B} \end{bmatrix} \tag{3}$$

Following Baqaee and Farhi (2020)[20], we calculate the matrix of cost shares $\mathbf{\Omega}$ by dividing each element of $\mathbf{X}$ by the total operating costs of the sector (intermediate inputs and labor)[21]:

$$\mathbf{\Omega} = \begin{bmatrix} \omega_{11}^{A,A} & \omega_{12}^{A,A} & \omega_{11}^{A,B} & \omega_{12}^{A,B} \\ \omega_{21}^{A,A} & \omega_{22}^{A,A} & \omega_{21}^{A,B} & \omega_{22}^{A,B} \\ \omega_{11}^{B,A} & \omega_{12}^{B,A} & \omega_{11}^{B,B} & \omega_{12}^{B,B} \\ \omega_{21}^{B,A} & \omega_{22}^{B,A} & \omega_{21}^{B,B} & \omega_{22}^{B,B} \end{bmatrix} \tag{4}$$

In this matrix, the element $\omega_{ij}^{A,B}$ represents the relative importance of sector $i$ in country $A$ as a supplier of sector $j$ in country $B$. In a similar vein, the matrix of

[19] In the FIGARO tables from Eurostat, for each sector, we compute the share of output going to final consumption as the sum of government and household consumption, capital formation and inventories (i.e. columns *"P3_S13 - Final consumption expenditure of general government", "P3_S14 - Final consumption expenditure of households", "P3_S15 - Final consumption expenditure of non-profit institutions serving households", "P51G - Gross fixed capital formation", "P5M - Changes in inventories and acquisition less disposals of valuables"*) divided by total output.

[20] In our empirical setting, we do not observe the cost-based input–output matrix defined by the elasticity of sector $i$'s marginal cost with respect to the price of sector $j$. We therefore approximate it using observed input cost shares. The distinction between cost- and revenue-based input–output matrices is relevant in the presence of distortions, as in Baqaee and Farhi (2020), where the two generally differ. Under perfect competition and no distortions, as in Acemoglu et al. (2012), cost and revenue shares coincide, so the two matrices collapse into one.

[21] For example: $\omega_{11}^{A,A} = \dfrac{x_{11}^{A,A}}{\sum_{i,J} x_{i1}^{J,A} + l_1^A}$.

sales shares $\tilde{\mathbf{\Omega}}$ is obtained by dividing each element of matrix $\mathbf{X}$ by the total of the respective column where the element is located[22]:

$$\tilde{\mathbf{\Omega}} = \begin{bmatrix} \tilde{\omega}_{11}^{A,A} & \tilde{\omega}_{12}^{A,A} & \tilde{\omega}_{11}^{A,B} & \tilde{\omega}_{12}^{A,B} \\ \tilde{\omega}_{21}^{A,A} & \tilde{\omega}_{22}^{A,A} & \tilde{\omega}_{21}^{A,B} & \tilde{\omega}_{22}^{A,B} \\ \tilde{\omega}_{11}^{B,A} & \tilde{\omega}_{12}^{B,A} & \tilde{\omega}_{11}^{B,B} & \tilde{\omega}_{12}^{B,B} \\ \tilde{\omega}_{21}^{B,A} & \tilde{\omega}_{22}^{B,A} & \tilde{\omega}_{21}^{B,B} & \tilde{\omega}_{22}^{B,B} \end{bmatrix} \tag{5}$$

In this matrix, the element $\tilde{\omega}_{ij}^{A,B}$ indicates how much of the output of sector $j$ in country $B$ goes to buy goods from sector $i$ in country $A$.

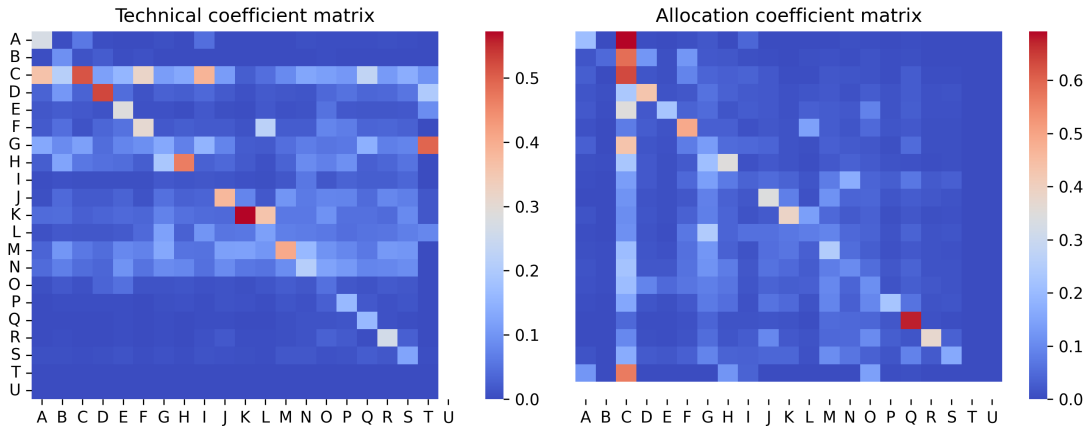
Figure 7 presents heatmaps illustrating the technical and allocation coefficients for NACE 1-digit sectors in the euro area. These coefficients quantify inter-sectoral dependencies by mapping the flow of goods and services across sectors. The left heatmap corresponds to the data counterpart to the technical coefficients matrix $\mathbf{\Omega}$, given by equation 17, such that any given element measures the share of inputs that the sector in a respective column provides to the buying sector in the respective row. The right heatmap, correspondingly, shows the data counterpart to the allocation coefficient matrix $\tilde{\mathbf{\Omega}}$, given by equation 18. Red-shaded cells indicate that the two respective sectors in the corresponding row and column have strong bilateral exposures in the input-output structure. They show that the euro area production network can be broadly characterized as "diagonal", with internal (roundabout) exchange of inputs and outputs in a respective sector being relatively important. However, some sectors such as manufacturing (C) or wholesale/retail trade (G) are important suppliers to and/or customers of other sectors, as indicated by the lighter-blue/red shades of respective cells.

Both the matrix of cost shares $\mathbf{\Omega}$ and the matrix of revenue shares $\tilde{\mathbf{\Omega}}$ take only the first-order flows of goods and services between sectors into account. However, multi-layered production chains imply that the impact of a shock transmitting trough the production network will be amplified at each step of the production chain. Following Acemoglu et al. (2016), we account for such higher-order effects by deriving the cost-based and the revenue-based Leontief inverses, given by $\mathbf{Z} \equiv (\mathbf{I} - \mathbf{\Omega}^T)^{-1}$ and $\tilde{\mathbf{Z}} \equiv (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}$, where $\mathbf{I}$ is the identity matrix.

To summarize, throughout the paper we will make use of the objects and definitions summarized in table 8.

[22] For example: $\tilde{\omega}_{11}^{A,A} = \dfrac{x_{11}^{A,A}}{\sum_{i,J} x_{i1}^{J,A} + l_1^A + v_1^A + t_1^A}$.

**Figure 1:** Heatmaps of technical and allocation coefficients for NACE 1-digit at euro area level




**Notes:** The heatmaps show input-output tables for 2015 as given by 17 and 18 for the euro area (fixed composition), obtained by aggregating across countries and sectors. Sector definitions follow the applied at NACE-1 level categorization: *A: Agriculture, B: Mining, C: Manufacturing, D: Electricity/Gas, E: Water/Waste, F: Construction, G: Wholesale/Retail, H: Transport/Storage, I: Accommodation/Food, J: IT/Communication, K: Financial/Insurance, L: Real Estate, M: Professional/Scientific, N: Admin/Support, O: Public Admin, P: Education, Q: Health/Social Work, R: Arts/Entertainment, S: Other Services, T: Household Activities, U: Intl. Organizations.*

### Firm-level data and financial frictions measures

We use firm-level data from Orbis to derive sector-specific financial frictions measures. We clean Orbis data following Gopinath et al. (2017) and Kalemli-Özcan et al. (2024). Table 9 lists the set of financial frictions measures we derive from firm-level data and incorporate in our empirical setup in section 5, and table 10 shows summary statistics for these sector-level measures. We use total sectoral leverage as the default variable for financial frictions, but also assess the working capital share in our empirical setup given its conceptual proximity to the financial frictions approach developed in the theoretical model presented in section 7.

To match the level of aggregation of the rest of the data, we compute the financial frictions measures for each of the 64 sectors in our dataset using the sector-specific weighted average of the ratios, with weights derived from firm sales. As a robustness check, we recompute the financial frictions measures by using the sectoral median level of the financial frictions measure in the computations.

**Table 3:** Summary of notation and formulas

| Object | Formula | Definition |
|---|---|---|
| Upstream effect | From supplier to customer $x_{i\to j}$ | Transmission from upstream supplier $i$ to downstream customer $j$, reflecting cost channel propagation. |
| Downstream effect | From customer to supplier $x_{i\leftarrow j}$ | Transmission from downstream customer $j$ to upstream supplier $i$, reflecting demand channel propagation. |
| Input-output matrix | $\mathbf{X} = [x_{ij}^{c,d}]$ | Intermediate sales from sector $i$ in country $c$ to sector $j$ in country $d$. |
| Total output value | $y_j = \sum_{i,c} x_{ij}^{c,d} + c_j$ | Total production of sector $j$ (intermediate sales + final demand). |
| Total input cost | $\sum_{i,c} x_{ij}^{c,d} + l_j + v_j + t_j$ | Total production cost of sector $j$ (including value added and taxes). |
| Cost-share matrix | $\mathbf{\Omega} = \left[\frac{x_{ij}^{c,d}}{\sum_{k,e} x_{kj}^{e,d} + l_j}\right]$ | Expenditures of $j$ on inputs from $i$ as a share of $j$'s total costs. |
| Revenue-share matrix | $\tilde{\mathbf{\Omega}} = \left[\frac{x_{ij}^{c,d}}{y_j}\right]$ | Expenditures of $j$ on inputs from $i$ as a share of $j$'s total revenues. |
| Cost-based Leontief | $\mathbf{Z} = (\mathbf{I} - \mathbf{\Omega}^T)^{-1}$ | Total upstream exposure (direct and indirect production linkages). Captures the (forward) propagation of costs. |
| Revenue-based Leontief | $\tilde{\mathbf{Z}} = (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}$ | Total downstream exposure (direct and indirect sales linkages). Captures the (backward) propagation of demand. |

# 4 Up- and downstream financial friction measures

To quantify the exposure of customers and suppliers in sector $i$ are exposed to financial frictions, we combine the financial frictions measures described in section 3 with the input-output data. In particular, we define:

$$\begin{aligned}\Phi_{ic,t_{12}} &= (1 - \alpha_{ic,t_{12}}) \sum_{\substack{j\neq i \\ d\neq c}} \omega_{jd,ic,t_{12}} \times \varphi_{jd,t_{12}} \\ \tilde{\Phi}_{ic,t_{12}} &= (1 - \tilde{\alpha}_{ic,t_{12}}) \sum_{\substack{j\neq i \\ d\neq c}} \tilde{\omega}_{ic,jd,t_{12}} \times \varphi_{jd,t_{12}}\end{aligned} \tag{6}$$

**Table 4:** Definitions of the financial frictions measures

| Measure | Definition |
|---|---|
| Total leverage | Ratio of total liabilities excluding shareholders funds to total assets. |
| Working capital share | Ratio of working capital to total assets, with working capital position computed as the sum of stocks plus trade debit minus trade credit. |

**Table 5:** Financial friction measures: sector level descriptive statistics

| | Observations | Mean | Standard Deviation | Median |
|---|---|---|---|---|
| Total leverage | 249,144 | 0.59 | 0.16 | 0.60 |
| Working capital share | 249,144 | 0.15 | 0.15 | 0.14 |

Source: Orbis data after the cleaning procedure described in the paper.

$$\Phi'_{ic,t_{12}} = (1 - \alpha_{ic,t_{12}}) \sum_{j,d} (z_{jd,ic,t_{12}} - 1_{j=i,d=c}) \times \varphi_{jd,t_{12}}$$
$$\tilde{\Phi}'_{ic,t_{12}} = (1 - \tilde{\alpha}_{ic,t_{12}}) \sum_{j,d} (\tilde{z}_{ic,jd,t_{12}} - 1_{j=i,d=c}) \times \varphi_{jd,t_{12}} \quad (7)$$

where variables $\Phi_{ic,t_{12}}$ and $\tilde{\Phi}_{ic,t_{12}}$ are annual measures for up- and downstream financial frictions, respectively.[23] They are obtained by summing the products of sector $i$'s exposure to each supplier (customer) sector $j \in J$ in country $d \in D$ as measured by the respective bilateral objects from the input-output tables – the technical and allocation matrices 17 and 18 (equation 6, the baseline case used for results presented in section 6) or the cost- and revenue-based Leontief matrices (equation 7) – and the degree of financial frictions in sector $j$ in country $d$, $\varphi_{jd,t_{12}}$, given by the respective measure in table 9.

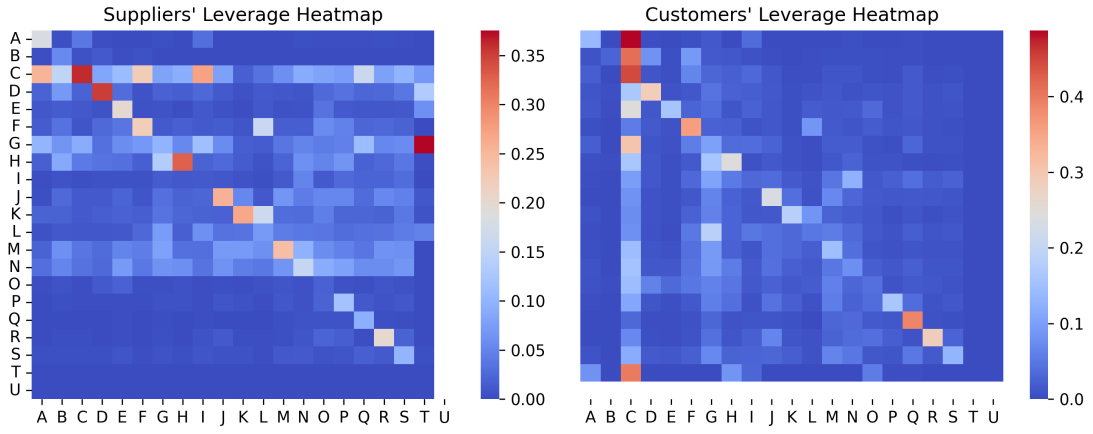
Following Acemoglu et al. (2016), we account for indirect effects stemming from a sector's exposure to its own level of financial frictions by either taking it out (equation 6) or subtracting a value of one from the diagonal elements of cost- and revenue-based Leontief matrices (equation 7) when $j = i$ and $d = c$. This procedure

[23] To highlight the difference in frequency, we label all variables at annual frequency with the subscript 12.

yields a weighted measure of a sector $i$'s exposure to financial frictions accruing to sectors it is interacting with, net of the impact of financial conditions in $i$ itself.

As discussed in the previous section, we take sectoral weighted averages of the financial frictions measure $\varphi_{jd,t_{12}}$ in each sector in the interaction with IO table information. Figure 2 illustrates intersectoral financial dependencies among NACE-1 sectors at the euro area level. Following the specification in equation 6, the respective heatmaps are generated by multiplying the two heatmaps in figure 7 (reflecting $\omega_{jd,ic,t_{12}}$ and $\tilde{\omega}_{ic,jd,t_{12}}$, respectively) with the vector of total leverage, as defined in table 9 (reflecting $\varphi_{jd,t_{12}}$), resulting in the set of bilateral exposures to financial frictions across the 20 NACE-1 sectors in the euro area. Concretely, in the left panel of figure 2, cell values are computed as $\omega^{EA}_{j,i,t_{12}} \times \varphi^{EA}_{j,t_{12}}$. Summing across rows within a given column yields $\sum_{j,d} \omega^{EA}_{j,i,t_{12}} \times \varphi^{EA}_{j,t_{12}}$. Similarly, the right panel shows $\tilde{\omega}^{EA}_{i,j,t_{12}} \times \varphi^{EA}_{j,t_{12}}$, where summing the columns in a specific row results in $\sum_{j,d} \tilde{\omega}^{EA}_{i,j,t_{12}} \times \varphi^{EA}_{j,t_{12}}$.

**Figure 2:** Heatmaps of bilateral leverage exposures for NACE 1-digit sectors at euro area level

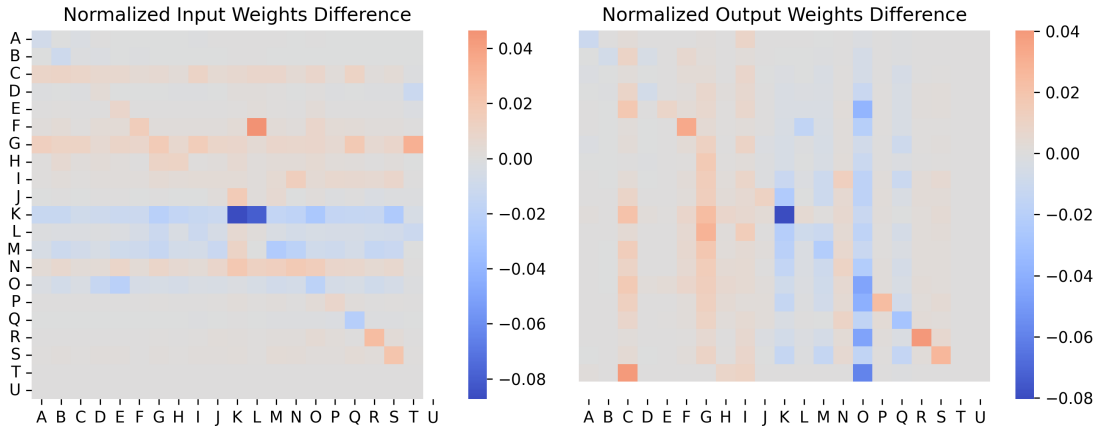



**Notes:** Heatmaps for 2015 showing the interaction of technical (left) and allocation (right) coefficients with the vector of leverages at sectoral level for the euro area. Sector definitions follow the applied at NACE-1 digit level categorization: *A: Agriculture, B: Mining, C: Manufacturing, D: Electricity/Gas, E: Water/Waste, F: Construction, G: Wholesale/Retail, H: Transport/Storage, I: Accommodation/Food, J: IT/Communication, K: Financial/Insurance, L: Real Estate, M: Professional/Scientific, N: Admin/Support, O: Public Admin, P: Education, Q: Health/Social Work, R: Arts/Entertainment, S: Other Services, T: Household Activities, U: Intl. Organizations.*

Figure 3 illustrates how the relative significance of upstream (supplier) and downstream (customer) financial frictions across NACE-1 sectors in the euro area changes once IO entries are interacted with total leverage. In the left panel, a blue cell indicates that the corresponding row sector has a lower relative importance as a supplier

compared to when only the flow of goods and services is considered. In the right panel, a red cell signifies that the corresponding column sector's relative importance as a buyer of the row sector increases when leverage is taken into account. As the figure illustrates, the relative importance of certain sectors can vary considerably, with some sectors gaining up to 4% in importance as leverage transmitters, while others experience a decline of up to 8% when compared to an analysis based solely on intersectoral flows of goods and services.

**Figure 3:** Leverage-induced change in relative importance of upstream and downstream exposures for NACE 1-digit sectors at euro area level




**Notes:** Changes in the relative importance of upstream (suppliers) and downstream (customers) financial frictions across NACE 1-digit sectors in the euro area when leverage is considered. Data refer to 2015. Left panel: change in sectoral exposure to suppliers with leverage relative to standard input-output exposures (figure 7). Right panel: change in sectoral exposure to customers with leverage relative to standard input-output exposures (figure 7). Sector definitions follow the applied at NACE-1 level categorization: *A: Agriculture, B: Mining, C: Manufacturing, D: Electricity/Gas, E: Water/Waste, F: Construction, G: Wholesale/Retail, H: Transport/Storage, I: Accommodation/Food, J: IT/Communication, K: Financial/Insurance, L: Real Estate, M: Professional/Scientific, N: Admin/Support, O: Public Admin, P: Education, Q: Health/Social Work, R: Arts/Entertainment, S: Other Services, T: Household Activities, U: Intl. Organizations.*

# 5 Econometric Strategy

In the following, we employ a panel local projection setup similar to that used in Jordà and Taylor (2016)[24] to study monetary policy transmission while explicitly taking into account the role of production networks and financial frictions.

We estimate the following model:

$$
\begin{aligned}
y_{ic,t+h} - y_{ic,t-1} = & \underbrace{\beta_1^h \varphi_{ic,t_{12}-1} \times s_t}_{\substack{\text{Direct financial frictions} \\ \text{effect}}} + \overbrace{\underbrace{\beta_2^h \Phi'_{ic,t_{12}-1} \times s_t}_{\text{Upstream effect}} + \underbrace{\beta_3^h \tilde{\Phi}'_{ic,t_{12}-1} \times s_t}_{\text{Downstream effect}}}^{\substack{\text{Indirect financial frictions} \\ \text{effect}}} + \\
& \underbrace{\beta_4^h \alpha_{ic,t_{12}-1} \times s_t + \beta_5^h \tilde{\alpha}_{ic,t_{12}-1} \times s_t + \beta_6^h s_t}_{\text{Non-network effect}} \\
& + \sum_{l=0}^{L} \gamma^{\mathbf{h}} \mathbf{H_{t-l}} + \sum_{l=1}^{L} \delta^{\mathbf{h}} \mathbf{K_{t-l}} + \sum_{l=0}^{L} \eta^{\mathbf{h}} \mathbf{\Delta X_{t-l}} + \theta_m + \kappa_{t+h} + \epsilon_{ic,t+h}
\end{aligned} \tag{8}
$$

$$
\text{with} \qquad h = 1, 2, ..., H
$$

$$
\mathbf{H_t} = \begin{bmatrix} \alpha_{ic,t_{12}-1} \\ \tilde{\alpha}_{ic,t_{12}-1} \\ \varphi_{ic,t_{12}-1} \\ \Phi'_{ic,t_{12}-1} \\ \tilde{\Phi}'_{ic,t_{12}-1} \end{bmatrix}, \mathbf{K_t} = \begin{bmatrix} \Delta y_{ic,t} \\ \varphi_{ic,t_{12}-1} \times s_t \\ \alpha_{ic,t_{12}-1} \times s_t \\ \tilde{\alpha}_{ic,t_{12}-1} \times s_t \\ \Phi'_{ic,t_{12}-1} \times s_t \\ \tilde{\Phi}'_{ic,t_{12}-1} \times s_t \\ s_t \end{bmatrix}
$$

We follow Jordà and Taylor (2024) and estimate the model in long-differences, with $\Delta x_t = x_t - x_{t-1}$.[25] We estimate model 8 to study the importance of nonlinear interactions between production networks and financial frictions for the overall transmission of monetary policy shocks $s_t$. In our model, the full impact of the shock is determined by the sum of three separate transmission channels: a direct, an indirect and a non-network channel. First, we account for a "direct financial frictions" channel captured by the coefficient $\beta_1^h$ on the interaction of the monetary policy shock $s_t$ with the respective sector's level of financial frictions as measured

[24] This framework is particularly suited for studying the transmission of exogenously identified shocks and requires only few assumptions regarding the data generating process.

[25] As shown in appendix section C.2, our main results reported in section 6 are robust to estimating the model in levels.

by $\varphi_{ic,t}$.[26] This channel can be interpreted as a sector-level representation of the traditional balance sheet channel (Bernanke and Gertler, 1995) affecting a sectors' own borrowing capacities.

We then identify an additional "indirect financial frictions" channel taking into account how a monetary policy tightening may be amplified via balance sheet channel dynamics in other parts of the production network sector $i$ interacts with. To this end, we interact the up- and downstream financial frictions measures $\Phi'_{ic,t_{12}}$ and $\tilde{\Phi}'_{ic,t_{12}}$ given by equation 7 with the monetary policy shock $s_t$, and we account for endogeneity by interacting the shock in period $t$ with the one-year lag of the financial frictions measure. This approach also allows us to disentangle the overall "indirect financial frictions channel" explicitly into downstream ($\beta_2^h$) and upstream ($\beta_3^h$) financial frictions effects. We also control for the degree to which the transmission of the monetary policy shock to aggregate output and prices depends on a sector $i$'s activity taking place outside the production network. To account for the importance of non-network customers of sector $i$, we interact the policy shock $s_t$ with $\tilde{\alpha}_{ic,t}$, the share of production sold to final customers outside the network as given by equation 15 ($\beta_4^h$). Likewise, we account for the importance of obtaining inputs from outside the network in the transmission of the monetary policy shock by interacting $s_t$ with $\alpha_{ic,t}$, the share of production inputs purchased by sector $i$ from outside the network, as given by equation 14 ($\beta_5^h$). Finally, coefficient $\beta_6$ account for all other possible channels through which monetary policy shocks may transmit to the real economy, i.e. independent of up- and downstream financial frictions and the broader production network.[27] In the main results presented in section 6, we refer to coefficients $\beta_4^h$ to $\beta_6^h$ jointly as "non-network effects".

Finally, matrix $\mathbf{H_t}$ contains the remaining single elements in our interaction terms unrelated to the monetary policy shock $s_t$ which are not of first-order interest in our analysis. Matrix $\mathbf{K_t}$ collects lags of first-differences of the dependent variable $\Delta y_{ic,t}$ and the shock variables. Matrix $\mathbf{X_t}$ contains a set of macro-financial control variables including the euro area OIS3m rate, a GDP-weighted 10y composite euro area sovereign bond yield, the euro-dollar exchange rate, and log-levels of the euro area Composite Indicator of Systemic Stress (CISS), the IMF Commodities Price

[26] Similarly to the annual notation introduced in section 4, the notation $t_{12} - 1$ refers to the one-year lag of a variable at annual frequency reported for the previous year.

[27] Such channels may include the interest rate channel, the exchange rate channel, asset price channels, risk-taking and expectation channels. See for instance Beyer et al. (2017) for an overview of traditional transmission channels of monetary policy.

Index, the euro area harmonized index of consumer prices (HICP) and the euro area unemployment rate, as well as sectoral employment which we add as an additional sector-specific macroeconomic control. $\theta_m$ depict month fixed-effects,[28] and we control for the Covid-19 pandemic by adding a forward dummy $\kappa_{t+h}$ entering the model at the same horizon as the dependent variable.[29]

# 6 Results

## 6.1 Main results

In this section, we report our main findings on the role of production networks and financial frictions obtained with the model presented in section 5. We show results using total leverage as our financial friction measure of interest, $\varphi_{ic,t_{12}-1}$, and we ensure consistency in units between $\varphi_{ic,t_{12}-1}$, $\Phi_{ic,t_{12}-1}$, $\tilde{\Phi}_{ic,t_{12}-1}$, $\alpha_{ic,t_{12}-1}$ and $\tilde{\alpha}_{ic,t_{12}-1}$ by scaling the beta coefficients of the interaction terms such that a one-unit change refers to a z-score change in leverage, i.e. a one-standard deviation of leverage from the mean.[30] All impulse responses are scaled to the impact of a monetary policy shock that leads to a 25 basis point peak increase of the 3m OIS rate within the first year after the shock.[31] We use cluster-robust standard errors in all specifications by clustering at the country-sector and time level.[32]

**Finding 1.** *Prices and production fall in response to a monetary policy tightening shock, with financial friction amplifying the contractionary effect over the medium term.*

[28] We only account for month fixed-effects as long-differencing eliminates entity (i.e. country-sector) fixed effects. As shown in appendix section C.2, we obtain identical results when estimating the model in levels including both month and country-sector fixed-effects.

[29] The forward dummy takes a value of one for the pandemic period being defined as lasting from March 2020 to April 2023, in line with the World Health Organization' declaring the end of Covid-19 as a global health emergency in May 2023.

[30] Formally, the z-score is defined as $z_{ic,t} = \frac{x_{ic,t}-\mu}{\sigma}$, with $x_{ic,t}$ being the country-sector-time observation, and $\mu$ and $\sigma$ indicating the population mean and standard deviation, respectively.

[31] See appendix section B for details on the scaling routine.

[32] Following Jordà and Taylor (2024), we use cluster-robust standard errors as the default, as using for instance Driscoll and Kraay (1998) standard errors to account for heteroscedasticity and autocorrelation would require a large time-series dimension $T$ compared to the cross-sectional dimension $N$, which is not the case in our setup.

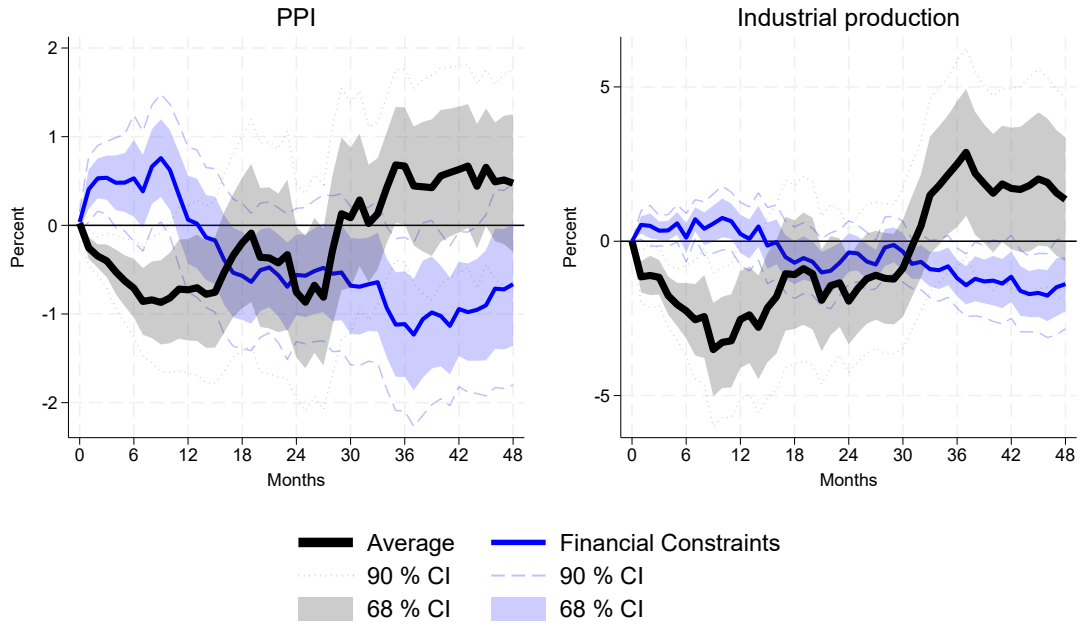
As shown in figure 4, both producer prices and industrial production fall significantly in response to a monetary policy tightening shock. For producer prices, the average effect of a monetary policy shock ($\beta_6^h$ in equation 8), i.e. with all financial frictions measures at the mean (black line in the LHS panel of figure 4), amounts to a trough decline of 0.8 percent between 6 to 12 months after the shock. In addition, the blue line in figure 4 reports the *additional* overall effect of an one standard deviation increase in network-wide financial frictions above the mean, as measured by the linear combination of coefficients $\beta_1^h$, $\beta_2^h$, and $\beta_3^h$. Initially, an increase in network-wide financial frictions partly counteracts the decline in prices and output in the first year, before it starts adding to the downward economic effects induced by a monetary policy tightening. As we discuss below, the difference in short-to medium financial frictions effects can be attributed to additional indirect downstream demand effects materializing – and overcompensating short-term cost-channel effects – over the medium term. At the trough, the additional disinflationary effect of a monetary policy shock due to a one standard deviation increase of network-wide leverage amounts to approximately one percent. The average decline in production stands at approximately 3 percent 9 months after the shock (black line in the RHS panel of figure 4), with an additional contractionary effect of the monetary policy shock due to financial frictions materializing after approximately 3 years (blue line in the RHS panel of figure 4).

**Finding 2.** *Effects stemming from network-related financial frictions are statistically significant and economically sizable.*

Figure 5 decomposes the overall financial frictions effect reported in blue in figure 4 into the direct financial frictions effect related to the interaction of the monetary policy shock with the respective sector's own leverage (as measured by $\beta_1^h$ in equation 8), and the indirect effect of financial frictions in the transmission of monetary policy shocks (as measured by the linear combination of $\beta_2^h$ and $\beta_3^h$ in equation 8). Figure 5 shows that direct financial frictions significantly induce upward pressure on prices and dampen activity, whereas indirect financial frictions decrease producer prices particularly over the medium term. While the upward effect from direct financial frictions on prices proves persistent throughout the horizon, the trough impacts for indirect financial frictions effects are reached approximately 3 years after the shock (green and brown lines in LHS panel).[33] The direct effect explains a large

[33] As for the cross-sectoral exposures discussed in more detail in the following paragraph and figure 6, potentially counterbalancing cost and demand channels stemming from within-sector firm

**Figure 4:** Impulse responses to monetary policy tightening shock




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

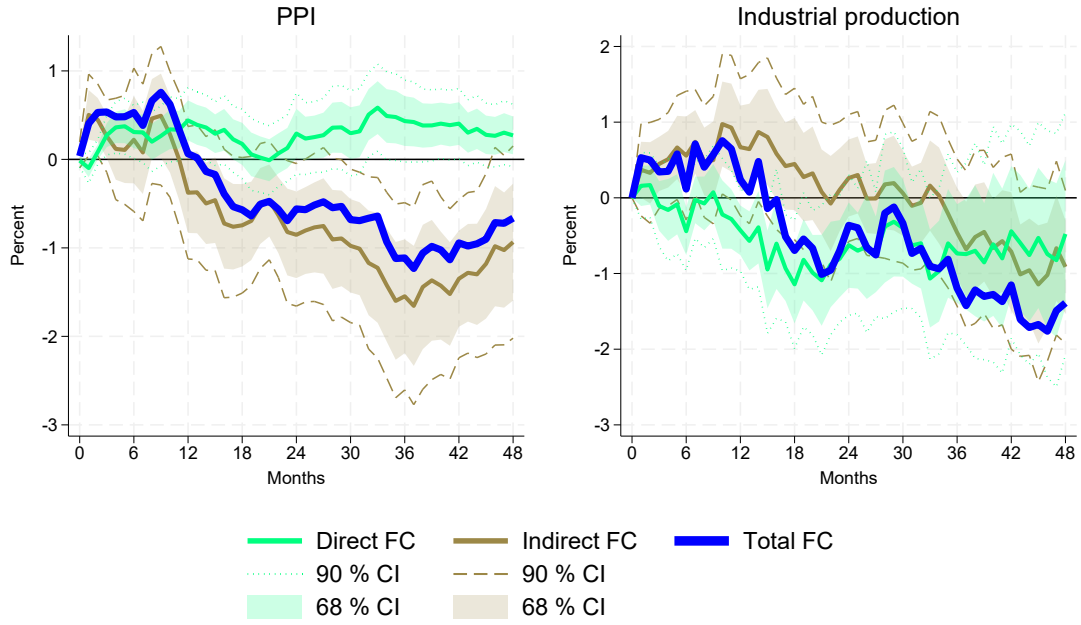
share of the inflationary impact of overall network-induced financial frictions in the short term, while price-dampening indirect effects dominate in the total financial constraints effect over the medium-term horizon. As for industrial production (RHS panel in figure 5), the trough impact of direct financial frictions is reached after around 1.5 years and only after 46 months in the case of indirect financial frictions. Regarding respective shares in total financial constraints effects (blue line), indirect effects turn out as the dominating factor in the short term, while indirect effects play a relatively stronger role in total financial frictions impacts over the medium term.

**Finding 3.** *Downstream (upstream) frictions reinforce (dampen) the drop in prices, consistent with upstream cost and downstream demand channels.*

Finally, figure 6 provides a breakdown of the indirect financial frictions effects reported by the brown lines in figure 5 into up- and downstream financial frictions

exposures determine the overall shape and sign of the direct effect. In particular, the fact that some firms may act primarily as buyers from or sellers to firms *within the same sector* may induce the same channels as described in the following, with downstream demand effects appearing to dominate across specifications.

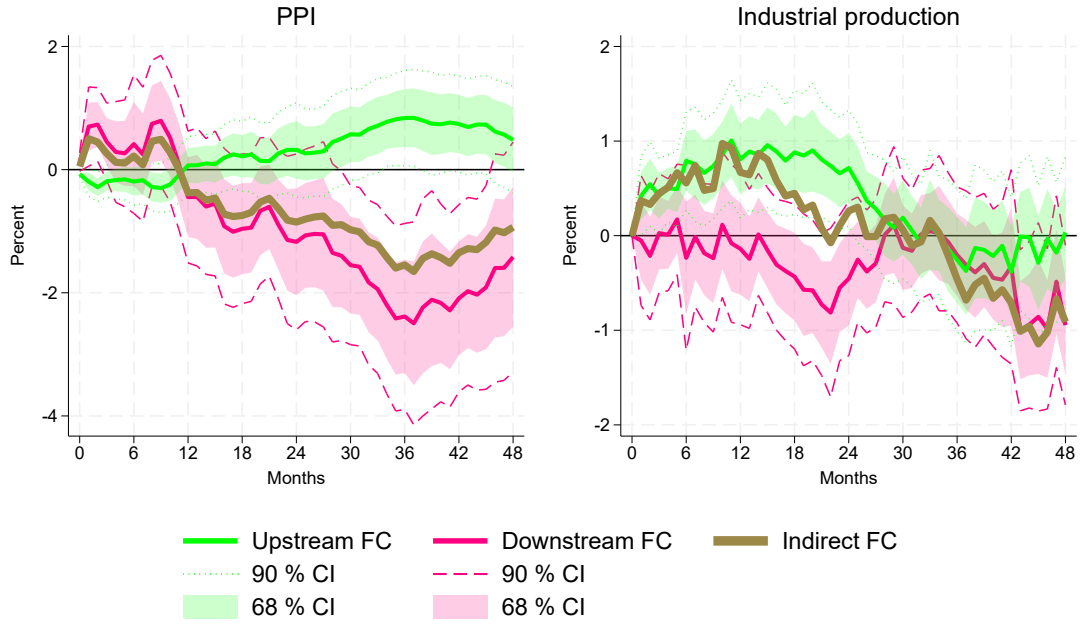
**Figure 5:** Impulse responses to monetary policy tightening shock - direct vs. indirect financial frictions effects




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

(as measured by $\beta_2^h$ and $\beta_3^h$ in equation 8, respectively). While downstream financial frictions seem to reinforce the decline in prices and output following a monetary policy tightening shock (pink lines in figure 6), upstream frictions tend to partly mitigate these effects (green lines in figure 6). In particular, the overall medium-term drop in prices associated to the interaction of the monetary policy shock and indirect financial frictions (brown line LHS panel of figure 6) can be largely attributed to downstream financial frictions, while the impulse response function associated to the upstream financial frictions interaction term remains positive for most of the horizon. Similarly, upstream financial frictions seem to mitigate the drop in industrial production over the first two years after the shock (green line RHS panel of figure 6), while downstream financial frictions seem to aggravate the additional drop to some extent over the same horizon (pink line RHS panel of figure 6). Taken together, results thus indicate that a tightening of financial conditions seems to lower downstream customers' demand for intermediate goods produced by sector $i$ (in line with a sector-specific "demand channel"), while fostering incentives for upstream suppliers to raise prices to alleviate financial frictions (in line with a sector-specific "cost channel").

**Figure 6:** Impulse responses to monetary policy tightening shock - upstream vs. downstream financial frictions effects




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

## 6.2 Robustness

We report a detailed set of robustness checks in appendix section C, and only provide a brief summary of these checks here. Our main interest relates to the robustness of our findings to changing elements specific to our setup. First, we assess robustness when using the working capital share as reported in table 9 as an alternative candidate for the financial frictions measure $\varphi_{t_{12}}$, in addition to using total leverage as in the baseline results in figures 4 to 6. Second, we assess how differences in aggregating firm-level data on financial frictions measures to the sectoral level affect the result. Third, we discuss robustness to an alternative specification of our financial frictions measures when accounting for distortions as in Baqaee and Farhi (2020). While main results in figures 4 to 6 where derived using sales-based weighted averages of firm level data to generate sectoral measures, we re-estimate the model with sectoral levels of total leverage being given by the median firm's leverage holdings.

Overall, results presented in appendix section C show that our main findings remain robust when carrying out these tests. In all specifications, prices and output fall in response to a monetary policy tightening shock, with financial frictions adding

to the dampening impact. Also, we report robustness regarding the significance of both direct and indirect financial frictions effects, and importantly, the opposing directions in which upstream and downstream financial frictions affect the price impact of a monetary policy tightening.

# 7 Transmission Mechanism: A Production-Network Model with Financial Frictions

This section lays out a tractable model that clarifies the transmission of monetary policy to sectoral prices through three channels: direct cost, upstream supplier costs, and downstream customer demand. The model's key insight is that financing constraints ($\varphi_j$) amplify or dampen each transmission channel depending on where a sector sits in the production network. Section 6 will show that the empirical implications of this mechanism are borne out in the data.

## 7.1 Setup: Network, Frictions, and Pricing

The economy has $n$ sectors linked via an input-output network. Sector $j$ produces using Cobb-Douglas technology:

$$y_j = a_j l_j^{\alpha_j} \prod_{k=1}^{n} x_{kj}^{\omega_{kj}}, \qquad \alpha_j + \sum_{k=1}^{n} \omega_{kj} = 1, \tag{9}$$

where $\omega_{kj}$ is seller $k$'s cost share in buyer $j$ (row=seller, column=buyer). Firms pre-finance variable production costs. A sector-specific parameter $\varphi_j \geq 0$ measures this financial friction: it scales the policy-rate pass-through into effective production costs.

Under perfect competition, price equals marginal cost times the financing wedge:

$$p_j = (1 + i\varphi_j)\, \tilde{mc}_j, \qquad \tilde{mc}_j = \frac{1}{a_j} w_j^{\alpha_j} \prod_{k=1}^{n} p_k^{\omega_{kj}}. \tag{10}$$

Equation (10) encodes the mechanism: when the policy rate $i$ rises, the term $(1 + i\varphi_j)$ increases directly proportional to $\varphi_j$, raising marginal cost and thus price $p_j$. The network propagates this cost impulse through suppliers and customers.

Let $f_j = \frac{\varphi_j}{1+i\varphi_j}$ denote the semi-elasticity of the financing wedge (used in all subsequent derivatives). The system of prices is determined jointly by network exposures

and friction parameters. At $\sigma = 1$ (Cobb-Douglas demand, which is our focus), the system is block-triangular and admits an exact closed-form decomposition. This tractability is valuable for deriving sign predictions and sufficient statistics that can be matched to data.

## 7.2 Five-Channel Decomposition of Price Response

Define the Leontief inverses $\mathbf{H} = (\mathbf{I} - \mathbf{\Omega}^\top)^{-1}$ (upstream cost propagation) and $\mathbf{Z} = (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}$ (downstream demand propagation), where $\tilde{\omega}_{kj} = \omega_{kj}/(1 + i\varphi_j)$. At $\sigma = 1$, the semi-elasticity of sector $k$'s price is exactly:

$$\frac{d \log p_k}{di} = \underbrace{(1-\alpha_k) f_k}_{\text{Direct}} + \underbrace{\sum_j (h_{kj} - \mathbf{1}_{j=k})(1-\alpha_j) f_j}_{\text{Supplier}} - \underbrace{\alpha_k \beta_k}_{\text{Own-cust.}} - \underbrace{\sum_j (h_{kj} - \mathbf{1}_{j=k}) \alpha_j \beta_j}_{\text{Supp.-cust.}} + \underbrace{[\mathbf{H}\boldsymbol{\alpha}]_k \hat{e}}_{\text{Income}}, \tag{11}$$

where $\beta_j = \frac{[\mathbf{Z}\tilde{\mathbf{\Omega}}\text{diag}(\mathbf{f})\rho]_j}{\rho_j}$ is customer-friction exposure and $\hat{e}$ is the income semi-elasticity (derived from numeraire condition; details in Appendix D).

**7.2.0.1 Economic interpretation.** Channels 1–2 (direct and supplier) push prices up: a rate hike raises a sector's own financing cost and the financing costs of its upstream suppliers. Channels 3–4 (own and suppliers' customers) push prices down: a rate hike raises financing costs for customers, contracting their demand for the sector's output. Channel 5 (income) is ambiguous but absorbed by time fixed effects in empirical work.

**7.2.0.2 Sign structure.** The model delivers sign predictions:

direct $> 0$, supplier $> 0$, own-customers $< 0$, supp.-customers $< 0$, income: ambiguous.

## 7.3 Mapping to Empirical Proxies

The empirical specification (equation 8 in Section 5) uses interactions of the monetary shock $s_t$ with three sector characteristics: own leverage $\varphi_j$, upstream exposure $[(\mathbf{H} - \mathbf{I})\boldsymbol{\varphi}]_j$, and downstream exposure $[(\mathbf{Z} - \mathbf{I})\boldsymbol{\varphi}]_j$.

At $i \to 0$ and $\sigma = 1$, the decomposition in equation (11) implies

$$\Delta \log p_k \approx \underbrace{(1-\alpha_k)\varphi_k}_{\text{direct}} s_t + \underbrace{\sum_j (h_{kj} - \mathbf{1}_{j=k})(1-\alpha_j)\varphi_j}_{\text{upstream}} s_t - \underbrace{[\mathbf{H}(\boldsymbol{\alpha} \circ (\mathbf{Z}-\mathbf{I})\boldsymbol{\varphi})]_k}_{\text{downstream}} s_t + O(i). \tag{12}$$

Hence the empirical proxies $\varphi_k$, $[\mathbf{H}\boldsymbol{\varphi}]_k$, and $[(\mathbf{Z}-\mathbf{I})\boldsymbol{\varphi}]_k$ are exact reduced-form sufficient statistics for the model's cross-sectional comparative statics.

The proposition yields testable sign restrictions:

$$\beta_1^h > 0 \quad \text{(direct)}, \quad \beta_2^h > 0 \quad \text{(upstream)}, \quad \beta_3^h < 0 \quad \text{(downstream)}.$$

In plain terms: after a monetary tightening, sectors with high own leverage see prices rise (cost channel dominates). Sectors with high upstream leverage experience less price decline (suppliers are financially constrained, demand stays up). Sectors with high downstream leverage experience sharper price decline (customer constraint dominates demand destruction). Section 6 confirms all three signs empirically; their consistency is what makes the empirical specification credible.

## 7.4 Why Leverage is the Empirical Proxy for $\varphi_j$

The model parameter $\varphi_j$ measures how much financing frictions amplify the policy rate's impact on sector $j$'s effective production costs. We use sectoral leverage as the empirical proxy for three complementary reasons.

1. **Balance-sheet mechanics.** When firms finance working capital externally, higher debt-to-assets mechanically raises sensitivity to policy-rate changes. A 100bp rate increase costs a 50% leveraged sector twice as much as a 25% leveraged sector. This is the literal content of $\varphi_j$.

2. **Credit-pricing amplification.** Anderson and Cesa-Bianchi (2024) show that when monetary policy tightens and intermediary constraints bind, highly leveraged firms face large increases in their financing spreads. This amplifies the mechanical effect captured by $\varphi_j$: a tightening raises both the level of interest rates and the premium that leveraged firms pay. This combined mechanism ensures that leverage is not merely a mechanical scaling of the policy rate but an economically substantive proxy for financial vulnerability.

3. **Aggregation and stability.** Sectoral leverage aggregates firm-level heterogeneity into a stable sector-year measure. Using lagged leverage in interactions with monetary shocks avoids reverse causality while preserving the model's identifying variation (cross-sector differences in financial vulnerability).

Thus, the empirical strategy is not a generic reduced-form exercise: each interaction term in equation (8) corresponds to a specific model channel in equation (11).

## 7.5 Validation: Simulations Support the Empirical Design

A natural question is whether the first-order proxy mapping in Proposition **??** remains informative when the CES elasticity $\sigma$ deviates from unity and the linear approximation is no longer exact. We validate the empirical design using simulations.

We simulate $R = 500$ heterogeneous CES economies (each with $n = 70$ sectors) and estimate two regressions in simulated data:

**Regression 1 (Channel decomposition):** Regress CES prices on the five exact channels from the model at $\sigma = 1$. This measures how well the Cobb-Douglas decomposition captures price responses.

**Regression 2 (Empirical proxies):** Estimate the same proxy regression as in the data (equation 8 reduced to interaction terms only):

$$\Delta \log p_k = \gamma_1(s_t \varphi_k) + \gamma_2(s_t[\mathbf{H}\boldsymbol{\varphi}]_k) + \gamma_3(s_t[(\mathbf{Z} - \mathbf{I})\boldsymbol{\varphi}]_k) + \varepsilon_k. \tag{13}$$

The simulation yields three concrete checks:

1. **Decomposition coherence.** CD channels explain 99.97% of CES price variation ($R^2 = 0.9997$), with coefficients nearly one (direct: 1.016, supplier: 1.008, own-cust: 0.997, supp.-cust: 1.011; Table 11). The decomposition is numerically faithful to the model's mechanism.

2. **Proxy regression performance.** The empirical proxies recover the predicted signs ($\hat{\gamma}_1 = 1.610 > 0$, $\hat{\gamma}_2 = 0.912 > 0$, $\hat{\gamma}_3 = -2.163 < 0$) with non-trivial explanatory power ($R^2 = 0.5128$; Figure 21). This is the direct quantitative counterpart of Proposition **??**.

3. **Channel sign recovery.** Sign analysis shows 100% correct sign recovery for the four unambiguous channels (direct cost, supplier cost, own customers, suppliers' customers; Table 12). Only the income channel—which is absorbed by time fixed effects—shows mixed signs.

These results validate that the empirical proxy system is not only directionally plausible but quantitatively faithful to the underlying model in simulated equilibrium. Complete simulation outputs are reported in Appendix E, including the decomposition regression (Table 11), predicted-vs-actual fit (Figure 21), sign diagnostics (Table 12), channel contributions (Figure 22), channel importance (Table 13), and robustness across elasticities (Tables 14 and 15).

### 7.6 Summary

The model delivers a parsimonious mechanism: monetary policy transmits through three financing-mediated channels (direct cost, upstream supplier cost, downstream customer demand) whose cross-sectional strength is determined by leverage. Simulation confirms that the empirical proxy system (leverage interacted with network exposures) faithfully captures this mechanism, as shown by Table 11, Figure 21, and Table 12, with robustness in Tables 14 and 15. Full derivations are in Appendix D; detailed simulation outputs are in Appendix E.

## 8 Conclusion

In this paper, we provide new evidence that financial frictions embedded in production networks play a quantitatively important role in shaping the transmission of monetary policy. By combining firm-level balance-sheet information with sectoral input–output linkages, the analysis moves beyond standard approaches that focus on financial frictions, at aggregate or more granular level, in isolation. Instead, it shows that, when taking into account supply chain linkages, both a sector's own financial position and the financial situation of its suppliers and customers matter, and materially affect the response of prices and real activity to monetary policy shocks.

Empirically, the paper documents that a contractionary monetary policy shock leads to a persistent decline in producer prices and output, with effects that are economically large and heterogeneous across sectors. Importantly, these responses

are significantly amplified in sectors that are more exposed to financial frictions. A key result is that this amplification does not stem solely from a sector's own financial frictions. Exposure to indirect financial frictions – arising from the leverage of upstream suppliers and downstream customers – exerts an independent and sizeable effect on price and output dynamics. These network-based effects account for a substantial share of the overall amplification, and explicitly incorporating them leads to a markedly larger estimated disinflationary impact of monetary policy than specifications that abstract from production-network linkages.

The paper further shows that upstream and downstream financial frictions operate through distinct mechanisms and exert pressures in opposite directions. Financially constrained downstream sectors reduce demand for intermediate inputs after an interest rate increase, transmitting it to their suppliers and reinforcing the decline in prices and activity due to the own leverage. By contrast, financial frictions in upstream sectors lead to higher marginal costs for those sectors, inducing them to raise prices in the short run, for example, to stabilize cash flows. While this upstream cost channel can partially offset disinflationary pressures at the sectoral level, the empirical evidence indicates that the downstream demand channel dominates in the aggregate. As a result, higher network-level leverage leads to a stronger and more persistent fall in prices and output following a monetary policy tightening.

These findings have direct implications for how monetary policy transmission is assessed and interpreted. They imply that aggregate indicators of corporate leverage or financial conditions may be insufficient to gauge the strength of policy transmission if they abstract from supply chain linkages and the distribution of financial frictions across the production network. Two economies with similar average leverage can display markedly different inflation and output responses to the same policy shock, depending on their production network structure and where financial constraints are concentrated along supply chains. In this sense, production networks act as an amplifier for monetary policy, with financially constrained sectors occupying central upstream or downstream positions exerting a disproportionate influence on aggregate outcomes.

The theoretical multi-sector model developed in the paper provides a coherent framework to interpret these empirical results. By mapping the empirically constructed measures of upstream and downstream leverage to explicit borrowing constraints and working-capital requirements, the model reproduces the dynamics empirically estimated. It clarifies what drives the demand-driven downstream effects

and under which conditions, while also explaining the upward pressure on prices generated by upstream cost channels. The model further highlights how the strength of these mechanisms depends on the level of interest rates and on the overall degree of financial tightness, suggesting potentially important non-linearities in policy transmission.

From a policy perspective, the results underscore the value of incorporating network-aware financial indicators into monetary policy analysis. Monitoring leverage and financing conditions at key nodes of the production network can improve assessments of the inflation persistence, the strength of the transmission mechanism and the timing of monetary policy.

Overall, by integrating granular balance-sheet data with production-network structure, this paper shows that indirect financial channels are not a second-order refinement but a core component of monetary policy transmission. Recognizing the network nature of financial frictions enhances the understanding of sectoral heterogeneity, improves the interpretation of inflation dynamics and opens new avenues for policy-relevant research on the design and coordination of stabilization policies in complex production economies.

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# A Data

We construct a monthly country–sector panel covering the period from January 1999 to December 2024 for 20 euro area countries and 64 sectors, broadly corresponding to the NACE-2 two-digit classification.[34] Our dataset consists of four main components:

1. country-level macroeconomic indicators, including aggregate monetary policy shocks;
2. sector-level data on producer prices and activity, reported at the NACE-2 level;
3. input–output data for 64 sectors, capturing bilateral cross-sector flows across all euro area countries;
4. firm-level balance sheet data from Orbis, aggregated at the country–sector–year level to provide measures of sector-specific financial frictions.

In the following, we describe each component in greater detail. Summary statistics for each category are reported in Table 6.

**Country-level data and monetary policy shocks**

We collect a set of standard country-level macroeconomic control variables, including data on prices, real economic activity, interest rates and macro-financial variables obtained from Eurostat and the International Monetary Fund (IMF). We identify common euro area monetary policy shocks via high-frequency movements in the 3-month OIS rate over a narrow window (ca. 135 minutes) around the publication of the press release and the press conference following ECB Governing Council meetings. We draw these movements from the euro area monetary policy-event database constructed by Altavilla et al. (2019). In order to isolate monetary policy shocks from information shocks, we use the so-called "poor-man's sign restriction" approach developed in Jarociński and Karadi (2020). We thus identify monetary policy shocks as high-frequency changes in the 3-months OIS rate over the event window coinciding with stock prices movements in the opposite direction.[35]

[34] The NACE-2 digits classification comprises 88 sectors; we aggregate these into 64 sectors to match the lower granularity of the input–output tables. See Eurostat (2008) for further details on the NACE classification.

[35] Our empirical results in section 6.1 are robust to identifying monetary policy shocks based on the first principal component of high-frequency changes in 1-, 3-, 6-, and 12-month OIS rates, instead of relying on 3-month OIS changes only (Jarociński and Karadi, 2020).

**Table 6:** Summary statistics of used variables

| | Observations | Mean | Standard deviation | Median |
|---|---|---|---|---|
| *Euro area level* | | | | |
| CISS | 312 | 0.18 | 0.15 | 0.12 |
| EUR/USD exchange rate | 312 | 1.18 | 0.16 | 1.17 |
| Composite 10y sov. bond yield (%) | 312 | 3.03 | 1.60 | 3.41 |
| IMF commodity index | 256 | 134.08 | 38.25 | 126.39 |
| 3-month OIS (%) | 305 | 1.47 | 1.75 | 0.78 |
| Monetary policy shock (bps) | 312 | 0.16 | 2.67 | 0.00 |
| *Country level* | | | | |
| Real GDP (€bn) | 2,380 | 475.15 | 894.54 | 54.49 |
| GDP Deflator | 2,266 | 88.53 | 15.68 | 89.25 |
| Unemployment (%) | 7,115 | 8.79 | 4.14 | 7.98 |
| Hours worked (bn) | 2,338 | 10.61 | 19.76 | 1.67 |
| Employed persons (mil) | 1,971 | 29.97 | 53.73 | 2.54 |
| HICP | 6,409 | 95.51 | 15.81 | 97.96 |
| QE holdings (€bn) | 3,424 | 100.23 | 208.25 | 12.58 |
| 10y sov. bond yield (%) | 2,974 | 2.60 | 1.83 | 2.85 |
| *Sector level* | | | | |
| Producer price index (PPI) | 145,986 | 52.81 | 48.01 | 74.04 |
| Industrial production (IP) | 197,951 | 84.83 | 88.09 | 92.59 |
| Turnover | 220,521 | 101.23 | 2533.46 | 83.60 |
| Employment index | 98,710 | 42.77 | 53.98 | 0.00 |
| Hours worked index | 87,323 | 33.06 | 53.37 | 0.00 |
| Job Vacancy rate | 3,768 | 1.96 | 4.12 | 1.20 |
| Gross wages | 96,507 | 34.09 | 45.79 | 0.00 |

Sources: Eurostat, ECB, Altavilla et al. (2019), IMF.

**Country-sector data**

We collect data on prices, industrial production, turnover, employment, hours worked, and wages from the Short-term Business Statistics (STS) dataset of Eurostat.[36] As no information on price indices for the trade sector (NACE codes G00, G45, G46, G47) are reported in the STS, we compute them by dividing nominal turnover by real turnover, consistent with the methodology employed by Eurostat.[37] In addition, we proxy the producer price index (PPI) for the construction sector (NACE code F00) with the PPI for residential buildings construction.[38] Moreover, as STS do not cover the agriculture sector (A01), we complement PPI data for this sector with quarterly information from another Eurostat dataset, which we linearly interpolate to obtain monthly observations.[39] We also add industrial production (IP) indices for agriculture from the "Economic accounts for agriculture (aact_eaa)" dataset provided by Eurostat, even if reported data is only available at annual frequency.[40]

In STS, data on employment, hours worked, and wages are mainly available at quarterly frequency, and only partly provided at monthly frequency on voluntary basis by national statistical offices.[41] Data on prices, industrial production, and turnover are available both at monthly and quarterly frequency, depending on the respective country, sector and time period.[42] To maximize the number of observations while preserving the consistency of the dataset, we linearly interpolate quarterly series to monthly and we either take the original monthly series or the quarterly interpolation, depending on which of the two has more observations.

For all available indices, we use seasonally adjusted series and perform a three-step cleaning procedure:[43]

[36] More details on STS data can be found here.

[37] More precisely, we divide turnover values by the volume of sales (deflated turnover).

[38] This refers to the statistical classification of products by activity (CPA) code F411X, the main component of sector F41 which covers "new buildings" only.

[39] The "Price indices of agricultural products (apri_pi)" data which can be found here.

[40] Given the low frequency, we do not interpolate annual agricultural data into monthly observations. The "Economic accounts for agriculture (aact_eaa)" data which can be found here.

[41] See STS regulations here.

[42] This implies that for a given country-sector pair we may be able to retrieve only monthly or only quarterly observations, or both. Moreover, monthly and quarterly observations, if both available, are not perfectly consistent at all times in STS.

[43] We derive seasonally adjusted series in cases for which the seasonal adjustment is not directly carried out by Eurostat by performing a LOESS transformation.

1. We exclude all observations of a specific index variable reported with a value of zero.
2. We drop all observations of a series with exactly identical data entries for more than six subsequent months (if the series is monthly) or more than four quarters (if the series is quarterly).
3. We drop entirely data series exhibiting an implausibly high level of volatility or poor data quality, i.e. due to implausibly large discrete jumps at random intervals.

**Input-output data**

We obtain information on the EU inter-country and industry-by-industry input-output relations from the Eurostat's "Full international and global accounts for research in input-output Analysis (FIGARO)" database.[44] These tables are available at annual frequency from 2010 to 2022, and we extrapolate the 2010 figures to preceding years and the 2022 table for the subsequent years. This way, we cover the entire period of interest, and we take comfort in doing so from the fact that IO linkages are changing only very gradually over time. Table 7 provides a schematic example of a multi-country IO matrix with just two countries, $A$ and $B$, and two industries, 1 and 2, to illustrate the key metrics we derive from IO tables.

**Table 7:** Simplified Multi-Country Input-Output Table

| | $A_1$ | $A_2$ | $B_1$ | $B_2$ | *Final consumption* | *Total* |
|---|---|---|---|---|---|---|
| $A_1$ | $x_{11}^{A,A}$ | $x_{12}^{A,A}$ | $x_{11}^{A,B}$ | $x_{12}^{A,B}$ | $c_1^A$ | $y_1^A = \sum_{s,c} x_{1s}^{A,c} + c_1^A$ |
| $A_2$ | $x_{21}^{A,A}$ | $x_{22}^{A,A}$ | $x_{21}^{A,B}$ | $x_{22}^{A,B}$ | $c_2^A$ | $y_2^A = \sum_{s,c} x_{2s}^{A,c} + c_2^A$ |
| $B_1$ | $x_{11}^{B,A}$ | $x_{12}^{B,A}$ | $x_{11}^{B,B}$ | $x_{12}^{B,B}$ | $c_1^B$ | $y_1^B = \sum_{s,c} x_{1s}^{B,c} + c_1^B$ |
| $B_2$ | $x_{21}^{B,A}$ | $x_{22}^{B,A}$ | $x_{21}^{B,B}$ | $x_{22}^{B,B}$ | $c_2^B$ | $y_2^B = \sum_{s,c} x_{2s}^{B,c} + c_2^B$ |
| *Labor* | $l_1^A$ | $l_2^A$ | $l_1^B$ | $l_2^B$ | | $l = \sum_{s,c} l_s^c$ |
| *Value added* | $v_1^A$ | $v_2^A$ | $v_1^B$ | $v_2^B$ | | $v = \sum_{s,c} v_s^c$ |
| *Taxes* | $t_1^A$ | $t_2^A$ | $t_1^B$ | $t_2^B$ | | $t = \sum_{s,c} t_s^c$ |

In this table, $x_{ij}^{A,B}$ is the flow of goods produced by sector $i$ in country $A$ and sold to sector $j$ in country $B$,[45] $c_1^A$ indicates the amount of output produced by sector 1 in

[44] Further information on FIGARO data can be found here.

[45] Note that part of the sector's output could be used by the same sector for production, so one can have $x_{ii}^{X,X} \geq 0$.

country $A$ going into final consumption (e.g. government and households), $l_1^A$ is the amount of labor used, $v_1^A$ stands for value added and $t_1^A$ for net taxes. The sum of the elements in a given row $i$ is equal to the total output produced (for intermediate and final consumption) by sector $i$. The sum of the elements in a given column $j$ gives the total cost of inputs (including labor, taxes, and value added) used in the production of sector $j$.

First, we calculate the share of each sector's labor expenses, taxes and value added in total input expenses. In our simplified table, this is given by

$$\alpha_{1A} = \frac{l_1^A + v_1^A + t_1^A}{x_{11}^{A,A} + x_{21}^{A,A} + x_{11}^{B,A} + x_{21}^{B,A} + l_1^A + v_1^A + t_1^A} \tag{14}$$

for industry 1 in country $A$.[46] This represents the share of a sector's inputs other than intermediate input goods acquired from the production network.

Second, we compute the share of output used for final consumption, i.e. the share of a sector's output that is not used as an intermediate input in production by any sector. For sector 1 in country $A$, this would be given by[47]

$$\tilde{\alpha}_{1A} = \frac{c_1^A}{x_{11}^{A,A} + x_{12}^{A,A} + x_{11}^{A,B} + x_{12}^{A,B} + c_1^A} \tag{15}$$

Matrix $\mathbf{X}$ is the square input-output matrix and reports only the flows of goods and services between sectors:

$$\mathbf{X} = \begin{bmatrix} x_{11}^{A,A} & x_{12}^{A,A} & x_{11}^{A,B} & x_{12}^{A,B} \\ x_{21}^{A,A} & x_{22}^{A,A} & x_{21}^{A,B} & x_{22}^{A,B} \\ x_{11}^{B,A} & x_{12}^{B,A} & x_{11}^{B,B} & x_{12}^{B,B} \\ x_{21}^{B,A} & x_{22}^{B,A} & x_{21}^{B,B} & x_{22}^{B,B} \end{bmatrix} \tag{16}$$

[46] In the FIGARO tables from Eurostat, for each sector, we compute the share of input sourced outside the production network as the sum of labor, value added and taxes (i.e. rows *"W2_D21X31 - Taxes less subsidies on products"*, *"W2_OP_NRES - Purchases of non-residents in the domestic territory"*, *"W2_OP_RES - Direct purchase abroad by residents"*, *"W2_D1 - Compensation of employees"*, *"W2_D29X39 - Other net taxes on production"*, *"W2_B2A3G - Gross operating surplus"*) divided by the total input cost of production.

[47] In the FIGARO tables from Eurostat, for each sector, we compute the share of output going to final consumption as the sum of government and household consumption, capital formation and inventories (i.e. columns *"P3_S13 - Final consumption expenditure of general government"*, *"P3_S14 - Final consumption expenditure of households"*, *"P3_S15 - Final consumption expenditure of non-profit institutions serving households"*, *"P51G - Gross fixed capital formation"*, *"P5M - Changes in inventories and acquisition less disposals of valuables"*) divided by total output.

Following Baqaee and Farhi (2020)[48], we calculate the matrix of cost shares $\mathbf{\Omega}$ by dividing each element of $\mathbf{X}$ by the total operating costs of the sector (intermediate inputs and labor)[49]:

$$\mathbf{\Omega} = \begin{bmatrix} \omega_{11}^{A,A} & \omega_{12}^{A,A} & \omega_{11}^{A,B} & \omega_{12}^{A,B} \\ \omega_{21}^{A,A} & \omega_{22}^{A,A} & \omega_{21}^{A,B} & \omega_{22}^{A,B} \\ \omega_{11}^{B,A} & \omega_{12}^{B,A} & \omega_{11}^{B,B} & \omega_{12}^{B,B} \\ \omega_{21}^{B,A} & \omega_{22}^{B,A} & \omega_{21}^{B,B} & \omega_{22}^{B,B} \end{bmatrix} \tag{17}$$

In this matrix, the element $\omega_{ij}^{A,B}$ represents the relative importance of sector $i$ in country $A$ as a supplier of sector $j$ in country $B$. In a similar vein, the matrix of sales shares $\tilde{\mathbf{\Omega}}$ is obtained by dividing each element of matrix $\mathbf{X}$ by the total of the respective column where the element is located[50]:

$$\tilde{\mathbf{\Omega}} = \begin{bmatrix} \tilde{\omega}_{11}^{A,A} & \tilde{\omega}_{12}^{A,A} & \tilde{\omega}_{11}^{A,B} & \tilde{\omega}_{12}^{A,B} \\ \tilde{\omega}_{21}^{A,A} & \tilde{\omega}_{22}^{A,A} & \tilde{\omega}_{21}^{A,B} & \tilde{\omega}_{22}^{A,B} \\ \tilde{\omega}_{11}^{B,A} & \tilde{\omega}_{12}^{B,A} & \tilde{\omega}_{11}^{B,B} & \tilde{\omega}_{12}^{B,B} \\ \tilde{\omega}_{21}^{B,A} & \tilde{\omega}_{22}^{B,A} & \tilde{\omega}_{21}^{B,B} & \tilde{\omega}_{22}^{B,B} \end{bmatrix} \tag{18}$$

In this matrix, the element $\tilde{\omega}_{ij}^{A,B}$ indicates how much of the output of sector $j$ in country $B$ goes to buy goods from sector $i$ in country $A$.

Figure 7 presents heatmaps illustrating the technical and allocation coefficients for NACE 1-digit sectors in the euro area. These coefficients quantify inter-sectoral dependencies by mapping the flow of goods and services across sectors. The left heatmap corresponds to the data counterpart to the technical coefficients matrix $\mathbf{\Omega}$, given by equation 17, such that any given element measures the share of inputs that the sector in a respective column provides to the buying sector in the respective row. The right heatmap, correspondingly, shows the data counterpart

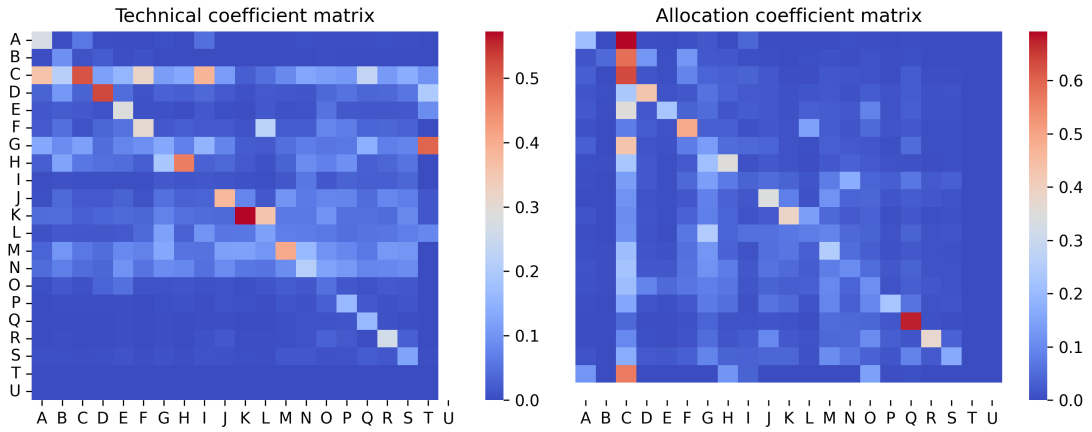
[48] In our empirical setting, we do not observe the cost-based input–output matrix defined by the elasticity of sector $i$'s marginal cost with respect to the price of sector $j$. We therefore approximate it using observed input cost shares. The distinction between cost- and revenue-based input–output matrices is relevant in the presence of distortions, as in Baqaee and Farhi (2020), where the two generally differ. Under perfect competition and no distortions, as in Acemoglu et al. (2012), cost and revenue shares coincide, so the two matrices collapse into one.

[49] For example: $\omega_{11}^{A,A} = \dfrac{x_{11}^{A,A}}{\sum_{i,J} x_{i1}^{J,A} + l_1^A}$.

[50] For example: $\tilde{\omega}_{11}^{A,A} = \dfrac{x_{11}^{A,A}}{\sum_{i,J} x_{i1}^{J,A} + l_1^A + v_1^A + t_1^A}$.

to the allocation coefficient matrix $\tilde{\mathbf{\Omega}}$, given by equation 18. Red-shaded cells indicate that the two respective sectors in the corresponding row and column have strong bilateral exposures in the input-output structure. They show that the euro area production network can be broadly characterized as "diagonal", with internal (roundabout) exchange of inputs and outputs in a respective sector being relatively important. However, some sectors such as manufacturing (C) or wholesale/retail trade (G) are important suppliers to and/or customers of other sectors, as indicated by the lighter-blue/red shades of respective cells.

**Figure 7:** Heatmaps of technical and allocation coefficients for NACE 1-digit at euro area level




**Notes:** The heatmaps show input-output tables for 2015 as given by 17 and 18 for the euro area (fixed composition), obtained by aggregating across countries and sectors. Sector definitions follow the applied at NACE-1 level categorization: *A: Agriculture, B: Mining, C: Manufacturing, D: Electricity/Gas, E: Water/Waste, F: Construction, G: Wholesale/Retail, H: Transport/Storage, I: Accommodation/Food, J: IT/Communication, K: Financial/Insurance, L: Real Estate, M: Professional/Scientific, N: Admin/Support, O: Public Admin, P: Education, Q: Health/Social Work, R: Arts/Entertainment, S: Other Services, T: Household Activities, U: Intl. Organizations.*

Both the matrix of cost shares $\mathbf{\Omega}$ and the matrix of revenue shares $\tilde{\mathbf{\Omega}}$ take only the first-order flows of goods and services between sectors into account. However, multi-layered production chains imply that the impact of a shock transmitting trough the production network will be amplified at each step of the production chain. Following Acemoglu et al. (2016), we account for such higher-order effects by deriving the cost-based and the revenue-based Leontief inverses, given by $\mathbf{Z} \equiv (\mathbf{I} - \mathbf{\Omega}^T)^{-1}$ and $\tilde{\mathbf{Z}} \equiv (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}$, where $\mathbf{I}$ is the identity matrix.

To summarize, throughout the paper we will make use of the objects and definitions summarized in table 8.

**Table 8:** Summary of notation and formulas

| Object | Formula | Definition |
|---|---|---|
| Upstream effect | From supplier to customer $x_{i\to j}$ | Transmission from upstream supplier $i$ to downstream customer $j$, reflecting cost channel propagation. |
| Downstream effect | From customer to supplier $x_{i\leftarrow j}$ | Transmission from downstream customer $j$ to upstream supplier $i$, reflecting demand channel propagation. |
| Input-output matrix | $\mathbf{X} = [x_{ij}^{c,d}]$ | Intermediate sales from sector $i$ in country $c$ to sector $j$ in country $d$. |
| Total output value | $y_j = \sum_{i,c} x_{ij}^{c,d} + c_j$ | Total production of sector $j$ (intermediate sales + final demand). |
| Total input cost | $\sum_{i,c} x_{ij}^{c,d} + l_j + v_j + t_j$ | Total production cost of sector $j$ (including value added and taxes). |
| Cost-share matrix | $\mathbf{\Omega} = \left[\frac{x_{ij}^{c,d}}{\sum_{k,e} x_{kj}^{e,d} + l_j}\right]$ | Expenditures of $j$ on inputs from $i$ as a share of $j$'s total costs. |
| Revenue-share matrix | $\tilde{\mathbf{\Omega}} = \left[\frac{x_{ij}^{c,d}}{y_j}\right]$ | Expenditures of $j$ on inputs from $i$ as a share of $j$'s total revenues. |
| Cost-based Leontief | $\mathbf{Z} = (\mathbf{I} - \mathbf{\Omega}^T)^{-1}$ | Total upstream exposure (direct and indirect production linkages). Captures the (forward) propagation of costs. |
| Revenue-based Leontief | $\tilde{\mathbf{Z}} = (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}$ | Total downstream exposure (direct and indirect sales linkages). Captures the (backward) propagation of demand. |

### Firm-level data and financial frictions measures

We use firm-level data from Orbis to derive sector-specific financial frictions measures. We clean Orbis data following Gopinath et al. (2017) and Kalemli-Özcan et al. (2024). Table 9 lists the set of financial frictions measures we derive from firm-level data and incorporate in our empirical setup in section 5, and table 10 shows summary statistics for these sector-level measures. We use total sectoral leverage as the default variable for financial frictions, but also assess the working capital share in our empirical setup given its conceptual proximity to the financial frictions approach developed in the theoretical model presented in section 7.

To match the level of aggregation of the rest of the data, we compute the financial frictions measures for each of the 64 sectors in our dataset using the sector-specific weighted average of the ratios, with weights derived from firm sales. As a robustness

**Table 9:** Definitions of the financial frictions measures

| Measure | Definition |
|---|---|
| Total leverage | Ratio of total liabilities excluding shareholders funds to total assets. |
| Working capital share | Ratio of working capital to total assets, with working capital position computed as the sum of stocks plus trade debit minus trade credit. |

check, we recompute the financial frictions measures by using the sectoral median level of the financial frictions measure in the computations.

**Table 10:** Financial friction measures: sector level descriptive statistics

| | Observations | Mean | Standard Deviation | Median |
|---|---|---|---|---|
| Total leverage | 249,144 | 0.59 | 0.16 | 0.60 |
| Working capital share | 249,144 | 0.15 | 0.15 | 0.14 |

Source: Orbis data after the cleaning procedure described in the paper.

# B Impulse response scaling

We scale the size of a monetary policy tightening shock $s_t$ in model 8 to imply a peak increase in the 3m OIS rate – the market-based monetary policy rate proxy from which monetary policy shocks are identified – by 25 basis points in the first year after the shock. We then scale the impulse response functions for the macroeconomic variables of interest to be consistent with such a 25bps peak impact monetary policy tightening shock. To do so, we proceed in two steps. First, we estimate a euro area local projection model including broadly the same control variables as in the country-sector panel model 8, but at the aggregate level, to account for the fact that the dependent variable $y_t$ is observed at the euro area level only in this setting. We then derive a scaling parameter $\tau \equiv \frac{0.25}{\psi}$, with $\psi$ referring to the peak of the impulse response of the OIS 3m rate to a monetary policy tightening shock within the first year after the shock, expressed in percentage points. We finally use $\tau$ as a scaling parameter in the impulse response functions of the dependent variable of interest shown in section 6.

The euro area aggregate model is given by:

$$y_{t+h} = \beta_1^h s_t + \sum_{l=1}^{L} \delta^{\mathbf{h}} \mathbf{K_{t-1}} + \sum_{l=0}^{L} \eta^{\mathbf{h}} \mathbf{X_{t-1}} + \epsilon_{t+h} \tag{19}$$

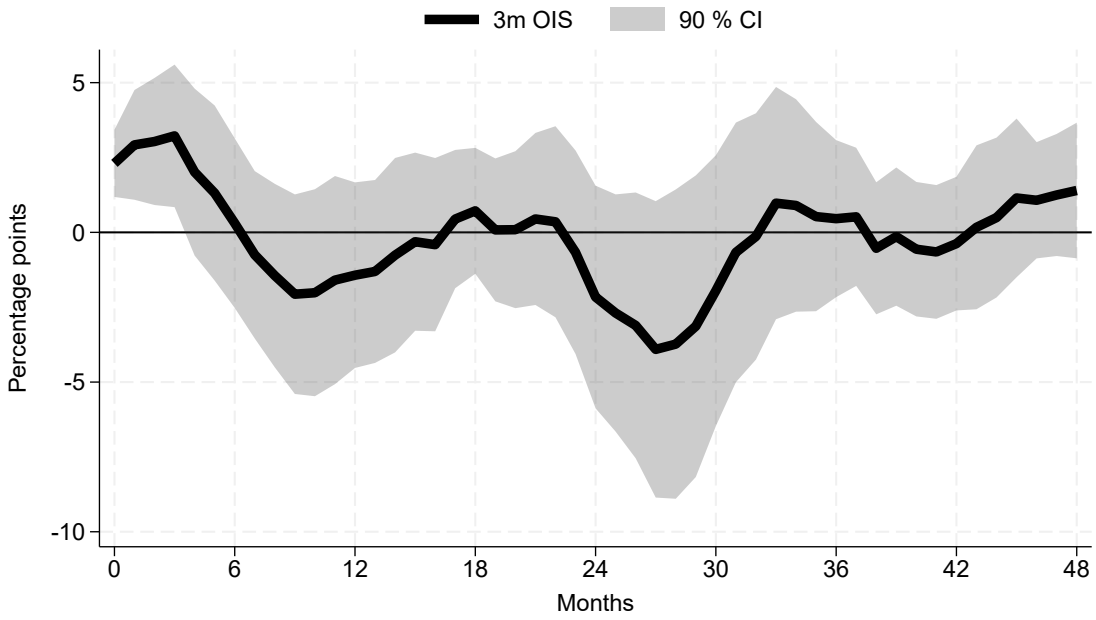
$$\text{with} \qquad h = 1, 2, ..., H, \mathbf{K_t} = \begin{bmatrix} y_t \\ s_t \end{bmatrix}$$

with vector $\mathbf{K_t}$ indeed collecting lags of the dependent variable $y_t$ and of the shock $s_t$. Matrix $\mathbf{X_t}$ contains the contemporaneous values and lags of the same set of macro-financial control variables as included in model 8, i.e. a GDP-weighted 10y composite euro area sovereign bond yield, the euro-dollar exchange rate, and log-levels of the euro area Composite Indicator of Systemic Stress (CISS), the IMF Commodities Price Index, the euro area harmonized index of consumer prices (HICP) and the euro area unemployment rate. It also includes our main variables of interest, industrial production and producer prices, now measured at the euro area aggregate level.

Figure 8 shows the impulse response function to a monetary policy tightening shock as obtained from model 19. Without scaling, the shock refers a one percentage point increase in the shock series from the mean. Given that the mean monetary policy shock in our sample only amounts to 0.2 basis points, the shock impact as

measured by $\beta_1^h$ in equation 19 and shown in figure 8 turns out large.[51] Within the first year, the peak increase in the OIS 3m rate is reached three months after the shock and amounts to 3.2 percentage points. This implies a the scaling parameter $\tau \approx 0.078$.

**Figure 8:** Impulse responses to monetary policy tightening shock - aggregate model




**Notes:** Impulse responses to a monetary policy tightening shock. Estimates for model 19 estimated on aggregate euro area data with Newey and West (1987) standard errors.

[51] As discussed in section 3, we identify monetary policy shocks by applying the Jarociński and Karadi (2020) "poor man's" sign restrictions to the innovations in the 3m OIS rate around policy events as identified by Altavilla et al. (2019).

# C Robustness checks

In the following, we provide robustness checks to the results obtained with empirical model presented in section 6. We particularly assess the robustness of our main empirical results in figures 4 to 6 to using an alternative financial frictions measure, namely firms' working capital as listed in table 9, to using different means of aggregating firm-level leverage data to the sectoral level, and to running different model specifications.

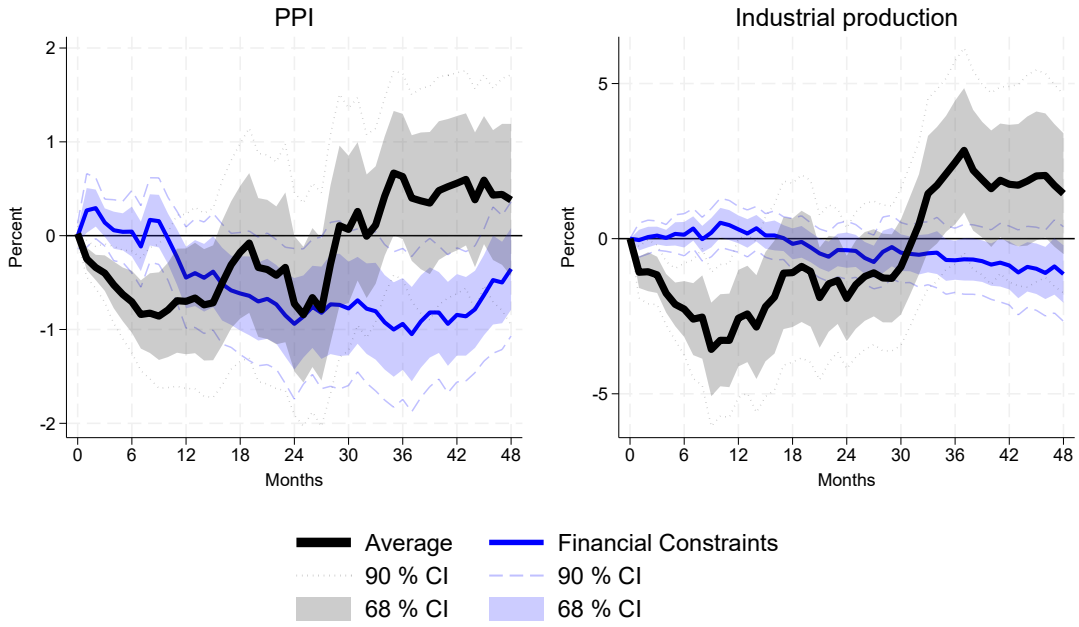
## C.1 Financial frictions measures

In this section, we show that our results remain broadly robust when using an alternative empirical financial frictions measure for $\varphi$ in equations 6, 7, and 8. Figures 9 to 11 show the same set of impulse response as depicted in figures 4 to 6 when sector-aggregates of firm level data on the working capital share, defined as working capital expenses/total assets instead of total leverage is used (table 9). We assess robustness to working capital also in light of its importance in the theoretical analysis we carry out in section 7. Overall, results are robust to using the working capital share, with results still indicating the same diverging effects of up- and downstream financial frictions in the transmission of monetary policy over the medium term as displayed in section 6.1. However, using the working capital share results in a slight tilting of results in the short term, with downstream demand effects potentially dominating direct financial constraints effects in the first year after the shock. As shown in figure 10, the direct financial frictions effect is negative in the first year after the shock, before upstream cost effects become the dominant driver of direct financial constraints effects as in the baseline specification (figure 5). This in turn results in a muting of the inflationary short-term financial constraints effects reported in the baseline results when reyling on working capital shares instead of total leverage (figure 4 vs figure 9).

We also test for differences in aggregating firm-level data on financial frictions measures to the sectoral level. While main results in figures 4 to 6 where derived using sales-based weighted averages of firm level data to generate sectoral measures, figures 12 to 14 show that results are robust to changing aggregation such that sectoral levels of total leverage reflect the median firm's leverage holdings.

Finally, we adjust our baseline financial frictions measure in equation 7 to proxy for additional possible distortions requiring a differentiation between cost-

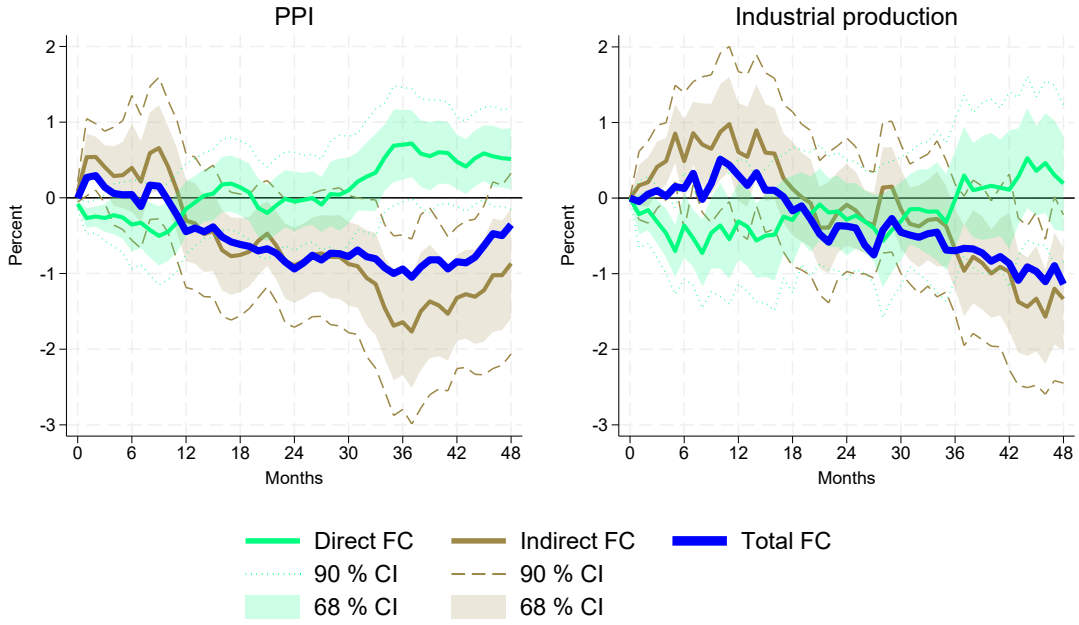
**Figure 9:** Impulse responses to monetary policy tightening shock - working capital




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

and revenue-based input–output matrices as in Baqaee and Farhi (2020). Our main empirical measures in equations 7 follow the theoretical model in assuming perfect competition and no further distortions beyond the financial friction introduced in equation . Our empirical and theoretical measures are thus consistent with the approach in Acemoglu et al. (2012), in which, as a result of the absence of other frictions, cost and revenue shares would ultimately coincide, such that both the cost- and revenue based Leontief inverses $\mathbf{Z}$ and $\tilde{\mathbf{Z}}$ would be based on the same matrix $\mathbf{\Omega}$, as stated in table 8. We thus also run our baseline regression 8 using versions of the financial frictions measures 7 adjusted for additional fricitons as in Baqaee and Farhi (2020). However, as we are not able to empirically observe the actual cost-based input–output matrix defined by the elasticity of sector $i$'s marginal cost with respect to the price of sector $j$ as prescribed by the theoretical setup in Baqaee and Farhi (2020), we approximate the distortion component by using observed input cost shares as reported in input-output tables. Concretely, in coparison to the definitions in table 8, we now differentiate between a cost-share matrix and a revenue-share matrix, with the two matrices being given by

**Figure 10:** Impulse responses to monetary policy tightening shock - direct vs. indirect financial frictions effects - working capital




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

$$\mathbf{\Omega} = \left[ \frac{x_{ij}^{c,d}}{\sum_{k,e} x_{kj}^{e,d} + l_j} \right] \tag{20}$$

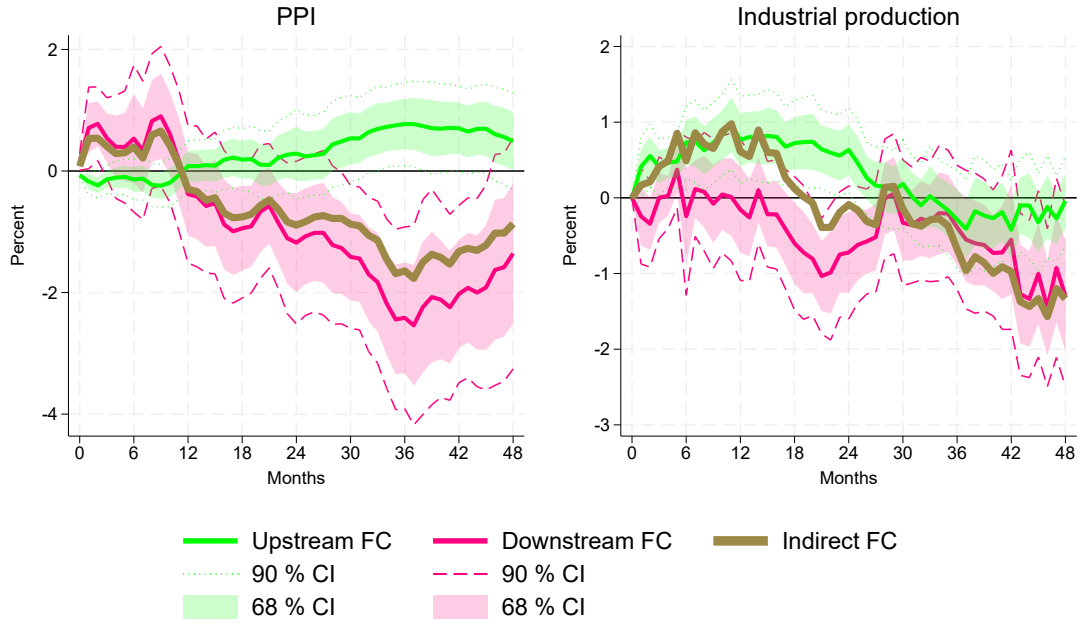
$$\tilde{\mathbf{\Omega}} = \left[ \frac{x_{ij}^{c,d}}{y_j} \right]. \tag{21}$$

The two matrices differ in terms of the denominators, where input costs are reported in the denominator of $\mathbf{\Omega}$, while total revenue $y_j = \sum_{i,c} x_{ij}^{c,d} + c_j = \sum_{k,e} x_{kj}^{e,d} + l_j + v_j + t_j$ is reported in the denominator of matrix $\tilde{\mathbf{\Omega}}$. Thus, the cost-share matrix $\mathbf{\Omega}$ accounts also for value added and tax terms $v_j$ and $t_j$, which determine our input-output based proxies for additional distortions such as market power and distortive tax policies. Consistently, the adjusted cost- and revenue-based Leontief inverses are now given by:

$$\mathbf{Z} = (\mathbf{I} - \mathbf{\Omega}^T)^{-1} \tag{22}$$

$$\tilde{\mathbf{Z}} = (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1} \tag{23}$$

**Figure 11:** Impulse responses to monetary policy tightening shock - upstream vs. downstream financial frictions effects - working capital



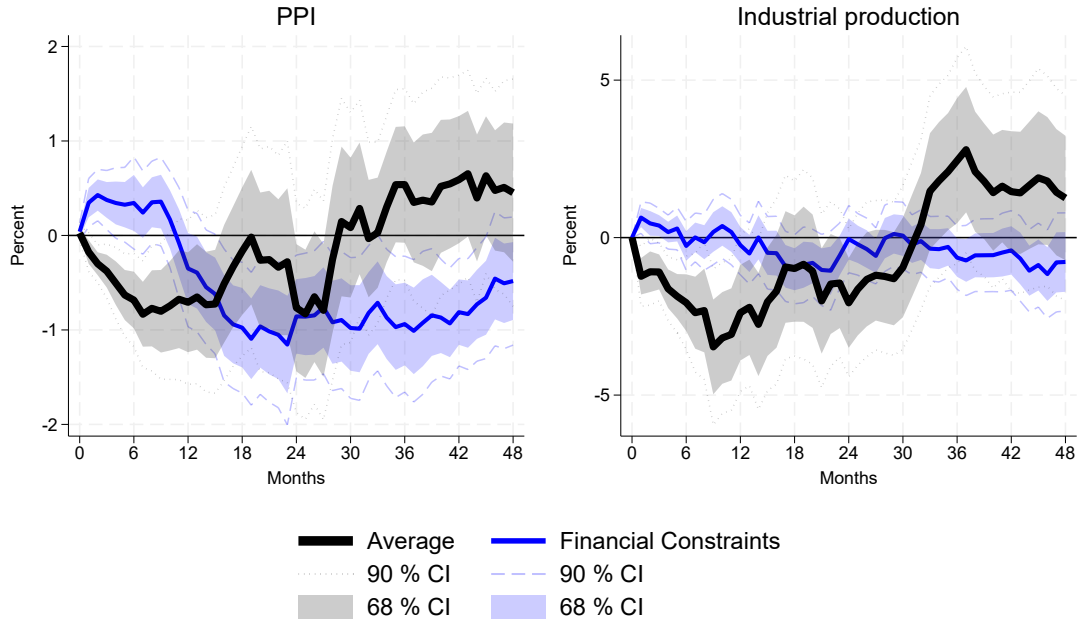

**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

As shown in figures 15 to 17, our main results in figures 4 to 6 are robust to those obtained when estimating model 8 with the adjusted cost- and revenue-based Leontief inverses.

## C.2 Model specification

Finally, we also assess the robustness of our results across different specifications of the model, beyond the choice of financial frictions measures and the representation of input-output linkages. In particular, we assess whether estimating the model in level terms instead of long-differences. The level variant of the long-difference model 8 is given by:

**Figure 12:** Impulse responses to monetary policy tightening shock - median level of sectoral total leverage




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

$$y_{ic,t+h} = \underbrace{\beta_1^h \varphi_{ic,t_{12}-1} \times s_t}_{\text{Direct financial frictions effect}} + \overbrace{\underbrace{\beta_2^h \Phi'_{ic,t_{12}-1} \times s_t}_{\text{Upstream effect}} + \underbrace{\beta_3^h \tilde{\Phi}'_{ic,t_{12}-1} \times s_t}_{\text{Downstream effect}}}^{\text{Indirect financial frictions effect}} + \tag{24}$$

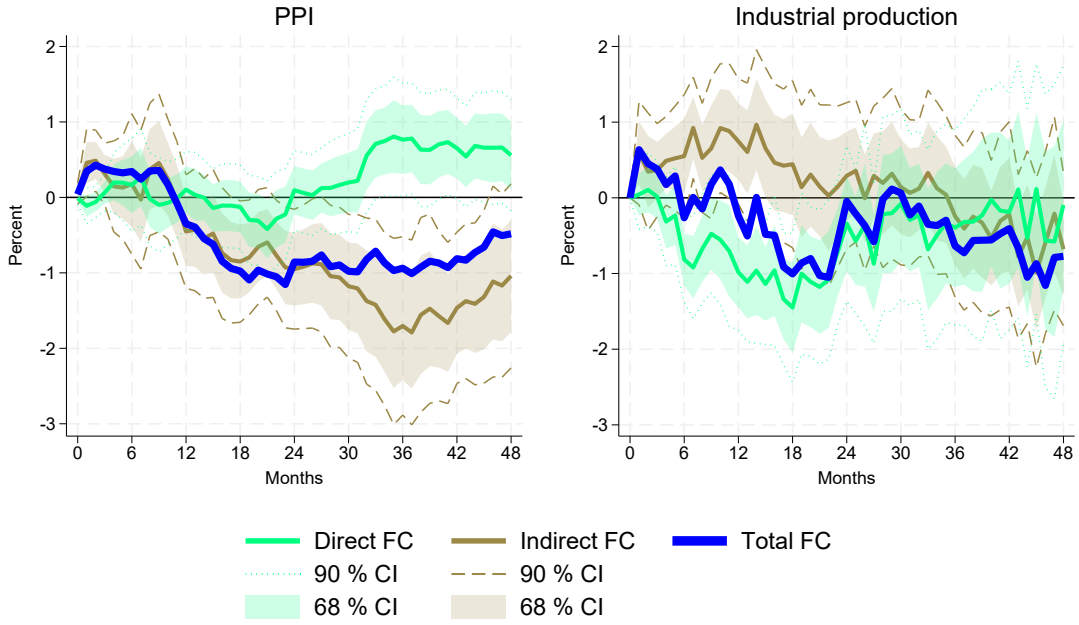
$$\underbrace{\beta_4^h a_{ic,t_{12}-1} \times s_t + \beta_5^h \tilde{a}_{ic,t_{12}-1} \times s_t + \beta_6^h s_t}_{\text{Non-network effect}}$$

$$+ \sum_{l=0}^{L} \gamma^{\mathbf{h}} \mathbf{H_{t-l}} + \sum_{l=1}^{L} \delta^{\mathbf{h}} \mathbf{K_{t-l}} + \sum_{l=0}^{L} \eta^{\mathbf{h}} \mathbf{X_{t-l}} + \phi_{ic} + \theta_m + \kappa_{t+h} + \epsilon_{ic,t+h}$$

with $h = 1, 2, ..., H$

$$\mathbf{H_t} = \begin{bmatrix} a_{ic,t_{12}} \\ \tilde{a}_{ic,t_{12}} \\ \varphi_{ic,t_{12}} \\ \Phi'_{ic,t_{12}} \\ \tilde{\Phi}'_{ic,t_{12}} \end{bmatrix}, \mathbf{K_t} = \begin{bmatrix} y_{ic,t} \\ \varphi_{ic,t_{12}} \times s_t \\ a_{ic,t_{12}} \times s_t \\ \tilde{a}_{ic,t_{12}} \times s_t \\ \Phi'_{ic,t_{12}} \times s_t \\ \tilde{\Phi}'_{ic,t_{12}} \times s_t \\ s_t \end{bmatrix}$$

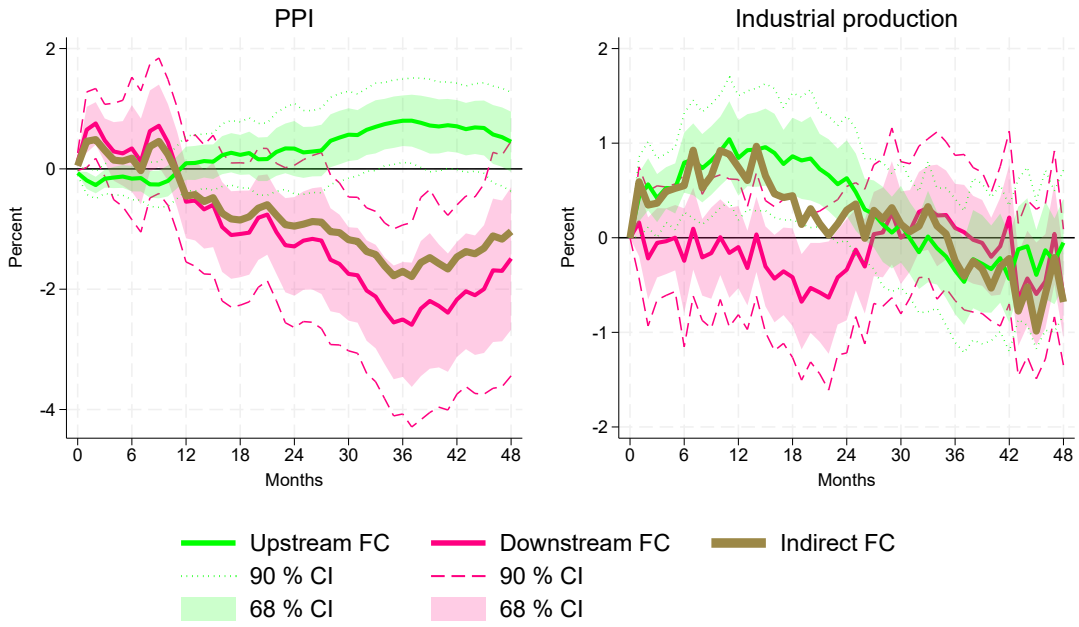
**Figure 13:** Impulse responses to monetary policy tightening shock - direct vs. indirect financial frictions effects - median level of sectoral total leverage




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

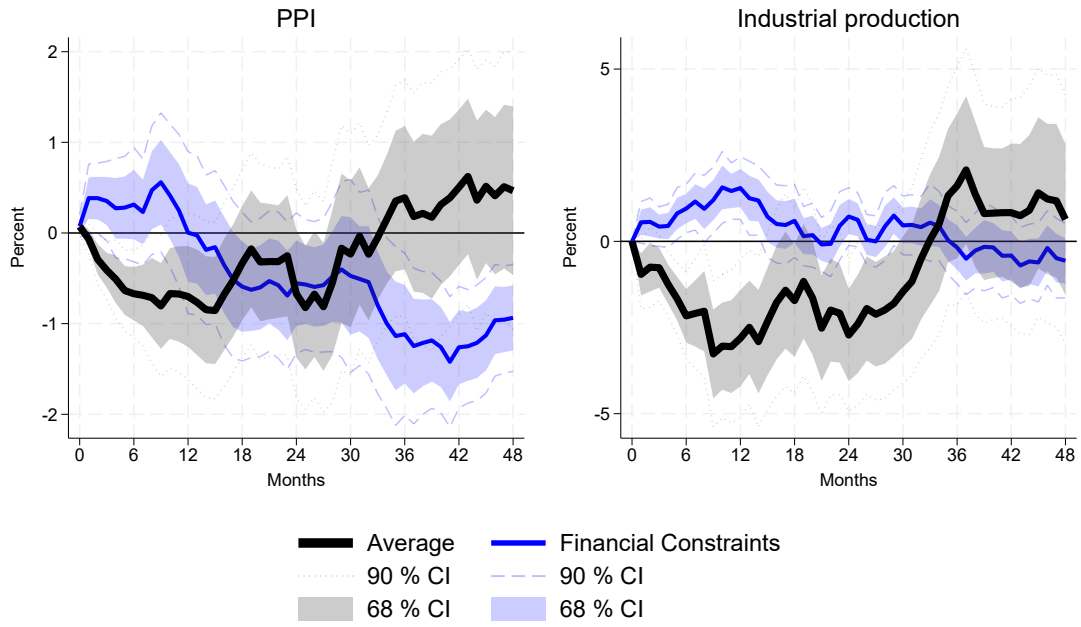
Compared to the long-difference variant, we include country-sector fixed effects $\phi_{ic}$, which are not present in the differenced version of the model. Jordà and Taylor (2024) suggest using long-differences to mitigate concerns regarding small sample biases, and comparing results in figures 18 to 20 with our main results in figures 4 to 6 confirm that our findings would be broadly robust to such concerns when estimating the model in levels.

**Figure 14:** Impulse responses to monetary policy tightening shock - upstream vs. downstream financial frictions effects - median level of sectoral total leverage



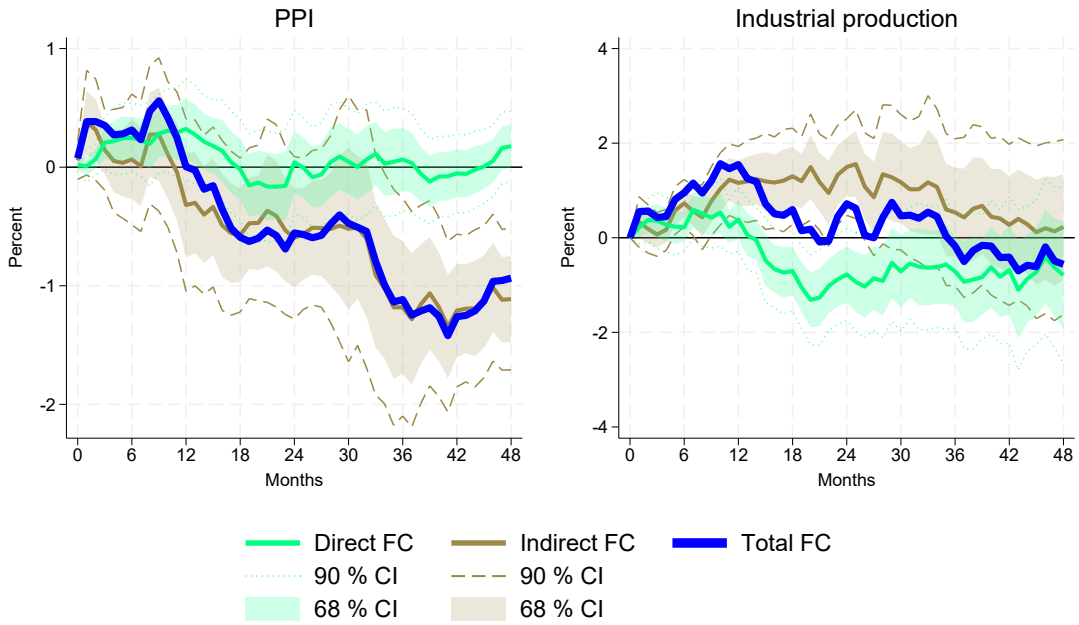

**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

**Figure 15:** Impulse responses to monetary policy tightening shock - distortion-adjusted Leontief inverses



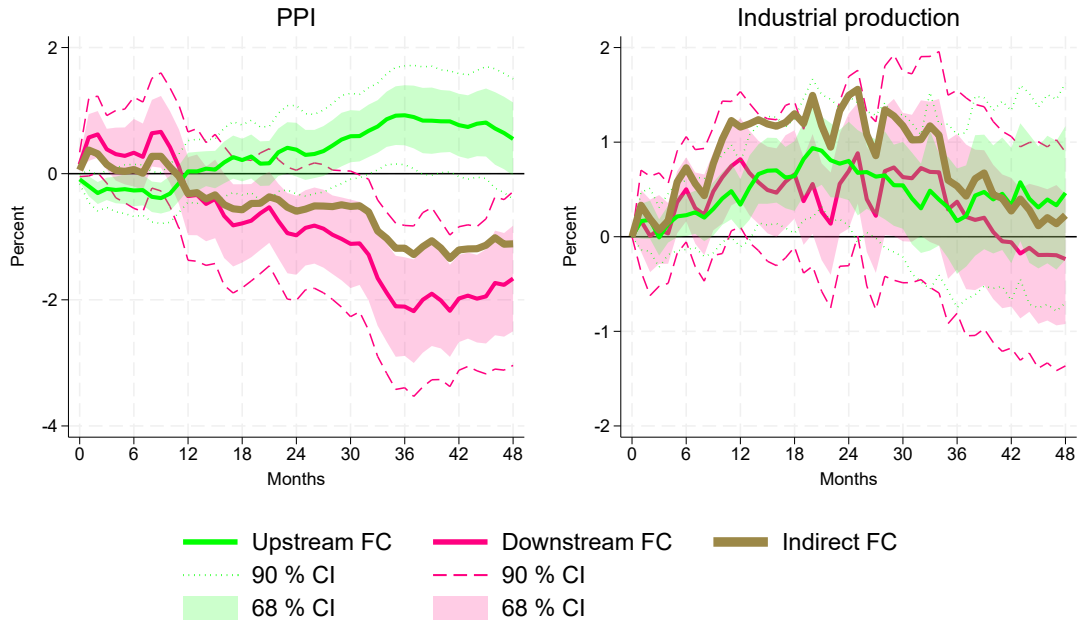

**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

**Figure 16:** Impulse responses to monetary policy tightening shock - direct vs. indirect financial frictions effects - distortion-adjusted Leontief inverses



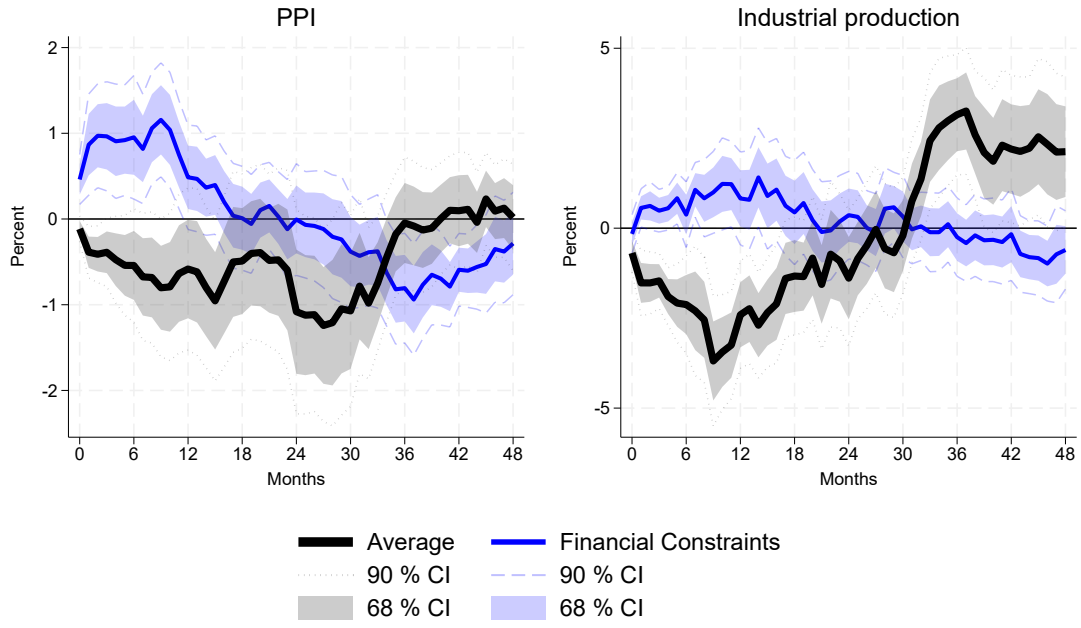

**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

**Figure 17:** Impulse responses to monetary policy tightening shock - upstream vs. downstream financial frictions effects - distortion-adjusted Leontief inverses



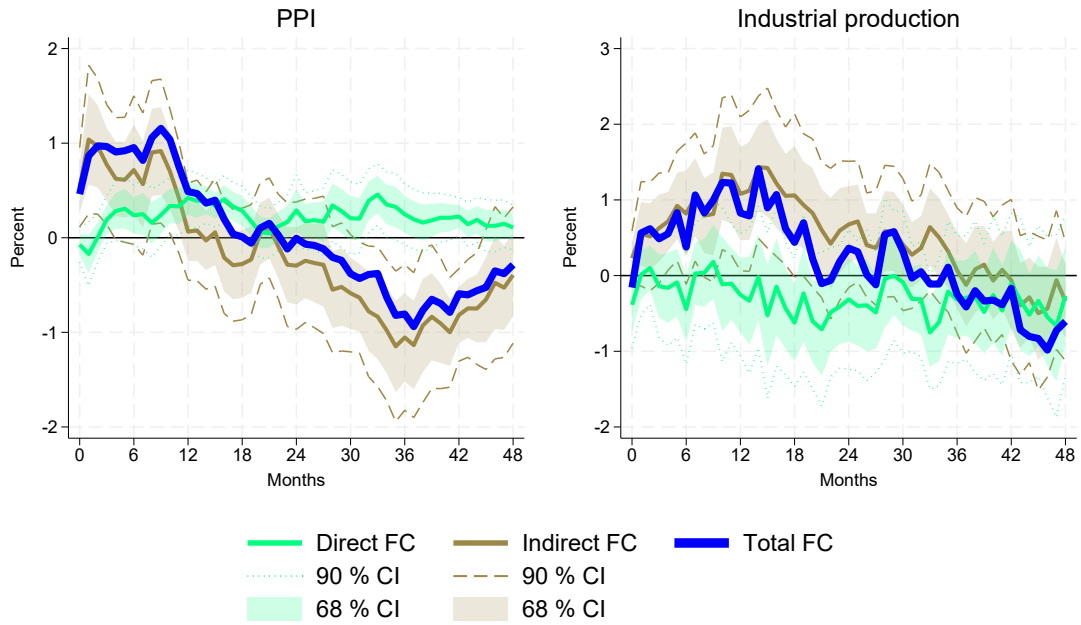

**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

**Figure 18:** Impulse responses to monetary policy tightening shock - level specification



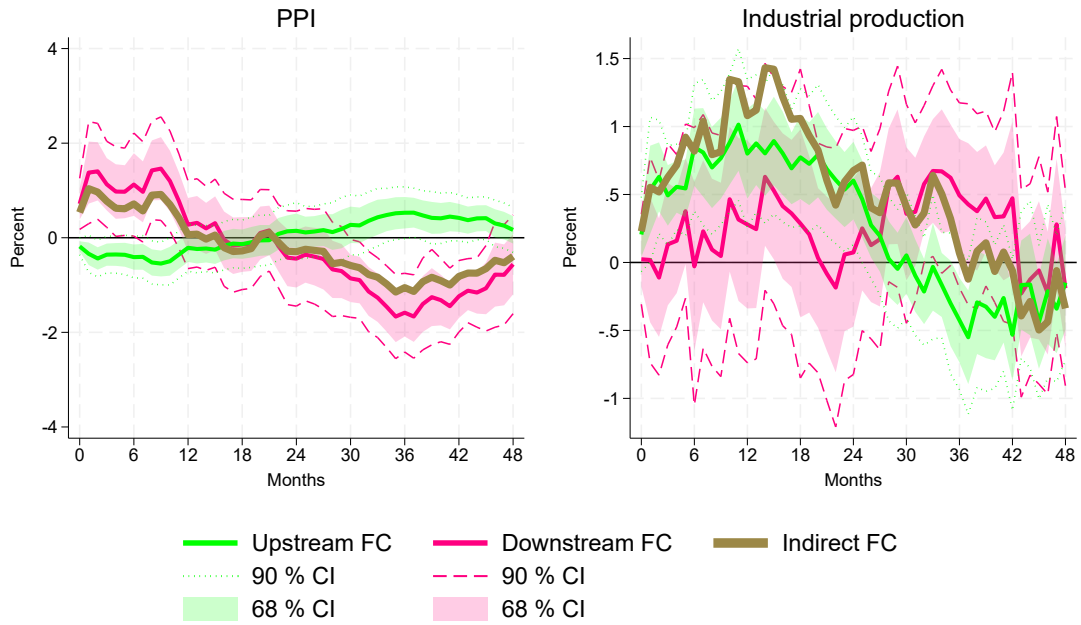

**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

**Figure 19:** Impulse responses to monetary policy tightening shock - direct vs. indirect financial frictions effects - level specification




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

**Figure 20:** Impulse responses to monetary policy tightening shock - upstream vs. downstream financial frictions effects - level specification




**Notes:** Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 8 estimated on the full country-sector euro area panel.

# D Model Derivations

This appendix provides complete algebraic derivations backing Section 7. All results are derived at $\sigma = 1$ (Cobb-Douglas demand) unless otherwise stated.

## D.1 Pricing Equation and Cobb-Douglas Wage Identity

From equation (10),

$$p_j = (1 + i\varphi_j)\tilde{mc}_j, \qquad \tilde{mc}_j = \frac{1}{a_j} w_j^{\alpha_j} \prod_{k=1}^{n} p_k^{\omega_{kj}}.$$

Taking logs:

$$\log p_j = \log(1 + i\varphi_j) - \log a_j + \alpha_j \log w_j + \sum_{k=1}^{n} \omega_{kj} \log p_k. \tag{25}$$

Under Cobb-Douglas production with constant returns, the wage bill is a constant share of non-financial total cost:

$$w_j l_j = \alpha_j \tilde{mc}_j y_j.$$

Define revenue as $r_j \equiv p_j y_j = (1 + i\varphi_j)\tilde{mc}_j y_j$. Then:

$$w_j l_j = \alpha_j \frac{r_j}{1 + i\varphi_j}. \tag{26}$$

Substituting equation (26) into equation (25), wages cancel and we obtain a linear system in log prices and log revenues.

## D.2 Leontief Inverses and Their Derivatives

At equilibrium, the cost-share matrix $\mathbf{\Omega}$ and revenue-share matrix $\tilde{\mathbf{\Omega}}$ are related by:

$$\tilde{\omega}_{kj} = \frac{\omega_{kj}}{1 + i\varphi_j}. \tag{27}$$

Differentiating with respect to $i$:

$$\frac{d\tilde{\omega}_{kj}}{di} = -\frac{\omega_{kj}\varphi_j}{(1 + i\varphi_j)^2} = -\tilde{\omega}_{kj} \frac{\varphi_j}{1 + i\varphi_j} = -\tilde{\omega}_{kj} f_j. \tag{28}$$

In matrix form:

$$\frac{d\tilde{\mathbf{\Omega}}}{di} = -\tilde{\mathbf{\Omega}} \operatorname{diag}(\mathbf{f}).$$

For the Leontief inverse $\mathbf{Z} = (\mathbf{I} - \tilde{\mathbf{\Omega}})^{-1}$:

$$\frac{d\mathbf{Z}}{di} = -\mathbf{Z}\,\tilde{\mathbf{\Omega}}\,\mathrm{diag}(\mathbf{f})\,\mathbf{Z}. \tag{29}$$

Similarly, for $\mathbf{H} = (\mathbf{I} - \mathbf{\Omega}^{\top})^{-1}$:

$$\frac{d\mathbf{H}}{di} = -\mathbf{H}\,\mathbf{\Omega}^{\top}\,\mathrm{diag}(\mathbf{f})\,\mathbf{H}. \tag{30}$$

## D.3 Revenue Response at $\sigma = 1$

At $\sigma = 1$, revenues are $r_j = e\rho_j$ where $\rho = \mathbf{Z}\nu$ (here $\nu$ is exogenous demand). Thus:

$$\hat{r}_j = \hat{e} + \frac{1}{\rho_j}\frac{d\rho_j}{di}.$$

Using equation (29):

$$\frac{d\rho}{di} = \frac{d\mathbf{Z}}{di}\nu = -\mathbf{Z}\tilde{\mathbf{\Omega}}\,\mathrm{diag}(\mathbf{f})\,\rho.$$

Define customer-friction exposure:

$$\beta_j = -\frac{1}{\rho_j}\frac{d\rho_j}{di} = \frac{\left[\mathbf{Z}\tilde{\mathbf{\Omega}}\,\mathrm{diag}(\mathbf{f})\,\rho\right]_j}{\rho_j}. \tag{31}$$

Then the revenue semi-elasticity is:

$$\hat{r}_j = \hat{e} - \beta_j. \tag{32}$$

## D.4 Income Semi-Elasticity from the Numeraire Condition

The differentiated price system can be written as:

$$\hat{\mathbf{p}} = \mathbf{H}\left[(\mathbf{1} - \boldsymbol{\alpha}) \circ \mathbf{f} - \boldsymbol{\alpha} \circ \boldsymbol{\beta}\right] + \hat{e}\,\mathbf{H}\boldsymbol{\alpha}.$$

Imposing the numeraire condition $\nu^{\top}\hat{\mathbf{p}} = 0$:

$$\hat{e} = \frac{\nu^{\top}\mathbf{H}\left[\boldsymbol{\alpha} \circ \boldsymbol{\beta} - (\mathbf{1} - \boldsymbol{\alpha}) \circ \mathbf{f}\right]}{\nu^{\top}\mathbf{H}\boldsymbol{\alpha}}. \tag{33}$$

## D.5 Five-Way Decomposition of Price Response

For sector $k$, decompose the price response as:

$$\hat{p}_k = \sum_j h_{kj}(1-\alpha_j)f_j - \sum_j h_{kj}\alpha_j\beta_j + [\mathbf{H}\boldsymbol{\alpha}]_k\hat{e}.$$

Separate each sum into direct (own-sector) and network (other-sector) components:

$$\sum_j h_{kj}x_j = x_k + \sum_j (h_{kj} - \mathbf{1}_{j=k})x_j.$$

Substituting yields:

$$\begin{aligned}\hat{p}_k = &\underbrace{(1-\alpha_k)f_k}_{\text{(i) Direct cost}} \\ &+ \underbrace{\sum_j (h_{kj} - \mathbf{1}_{j=k})(1-\alpha_j)f_j}_{\text{(ii) Supplier cost}} \\ &- \underbrace{\alpha_k\beta_k}_{\text{(iii) Own customers}} \\ &- \underbrace{\sum_j (h_{kj} - \mathbf{1}_{j=k})\alpha_j\beta_j}_{\text{(iv) Suppliers' customers}} \\ &+ \underbrace{[\mathbf{H}\boldsymbol{\alpha}]_k\hat{e}}_{\text{(v) Income}}.\end{aligned} \tag{34}$$

This is exactly equation (11) in the main text. Channels (i)–(ii) are weakly positive; channels (iii)–(iv) are weakly negative; channel (v) has ambiguous sign.

## D.6 First-Order Proxy Mapping

At $i \to 0$:

$$f_j \to \varphi_j, \quad \tilde{\boldsymbol{\Omega}} \to \boldsymbol{\Omega}, \quad \mathbf{Z} \to \mathbf{Z}_0 := (\mathbf{I} - \boldsymbol{\Omega})^{-1}.$$

The revenue-share matrix approaches the Leontief inverse of the cost-share matrix. For customer-friction exposure:

$$\boldsymbol{\beta} \approx (\mathbf{Z}_0 - \mathbf{I})\boldsymbol{\varphi}.$$

Substituting into equation (34) and using the identity $\mathbf{H}_0 = (\mathbf{I} - \boldsymbol{\Omega}^\top)^{-1}$:

$$\hat{p}_k \approx (1-\alpha_k)\varphi_k + \sum_j (h_j^0 - \mathbf{1}_{j=k})(1-\alpha_j)\varphi_j - [\mathbf{H}_0(\boldsymbol{\alpha} \circ (\mathbf{Z}_0 - \mathbf{I})\boldsymbol{\varphi})]_k. \tag{35}$$

Since $\mathbf{H}_0$ is the upstream Leontief inverse, the first term in the cost block is direct ($\varphi_k$), the second term is upstream $[\mathbf{H}_0\boldsymbol{\varphi}]_k - \varphi_k$. The customer terms reduce to downstream $[(\mathbf{Z}_0 - \mathbf{I})\boldsymbol{\varphi}]_k$. This confirms Proposition **??**.

### D.7 Regularity Conditions

The derivations require:

1. Cobb-Douglas production technology with fixed cost and revenue shares, constant returns to scale.
2. Multiplicative working-capital friction $(1 + i\varphi_j)$ with $0 \leq \varphi_j < \infty$.
3. Invertibility of $(\mathbf{I} - \boldsymbol{\Omega}^\top)$ and $(\mathbf{I} - \tilde{\boldsymbol{\Omega}})$ (standard input-output requirement: eigenvalues of $\boldsymbol{\Omega}^\top$ and $\tilde{\boldsymbol{\Omega}}$ less than one).
4. Interior equilibrium with local differentiability with respect to $i$.
5. First-order accuracy of the Taylor expansion around the observed equilibrium (requires $i\varphi_j \ll 1$ for all $j$).

Under these conditions, the sign structure and proxy mapping are structurally grounded and internally consistent with the general-equilibrium model.

## E Simulation Validation of Empirical Proxy Design

This appendix reports complete outputs from the simulation exercise described in Section 7. We simulate $R = 500$ heterogeneous CES economies with $n = 70$ sectors each, solve the model equilibrium, and estimate the same regression structure as in the empirical analysis.

### E.1 Simulation Setup

The simulation draws $R = 500$ random economies, each with $n = 70$ sectors. For each economy, we:

**1. Parameterization**

Labor share $\alpha_j$ is drawn uniformly from $[0.3, 0.9]$ for each sector $j$. The input-output cost-share matrix $\omega_{kj}$ (share of seller $k$ in buyer $j$'s costs) is random and row-stochastic: columns sum to $(1 - \alpha_j)$ so that labor plus intermediate inputs equal unity. Friction parameters $\varphi_j$ are drawn uniformly from $[0, 1]$ to represent the range of sectoral leverage observed in data. Exogenous final demand $\nu$ is drawn from a uniform distribution on the simplex (after normalization).

**2. Equilibrium Solution: CES at Baseline Policy Rate**

For a baseline policy rate $i_0 = 5\%$, we solve the nonlinear CES equilibrium system via `fsolve` (MATLAB) using a numerical tolerance of $10^{-12}$ on both the function residual and the change in iterates. The initial guess for `fsolve` comes from the Cobb-Douglas closed-form solution at $i_0$, which is highly accurate and reduces the iteration count substantially. We adopt the CPI numeraire $\nu^\top \log \mathbf{p} = 0$ to ensure comparability across all elasticities $\sigma$.

**3. Price Derivative via Finite Difference**

To compute the price response to a small interest rate increase $di = 10^{-6}$, we solve the equilibrium again at $i_1 = i_0 + di$ and compute

$$\frac{d \log p_k}{di} \approx \frac{\log p_k(i_1) - \log p_k(i_0)}{di}. \tag{36}$$

This finite-difference derivative is used as the dependent variable in Regression 1.

**4. Decomposition Channels**

Using the equilibrium at $i_0$, we compute the five decomposition channels (direct, supplier, own-customers, suppliers' customers, income) via the closed-form formulas in equation (11). These channels are evaluated at the Cobb-Douglas closed-form solution (Step 1), which provides the Leontief inverses $\mathbf{H}$ and $\mathbf{Z}$ consistent with the CPI numeraire.

**5. Shock Distribution and Multiple Observations per Economy**

To generate cross-sectional variation comparable to the time-series variation of monetary shocks in the empirical panel, we draw $n_{\text{shocks}} = 10$ monetary policy shocks per economy from a normal distribution: $s_i \sim \mathcal{N}(0.0025, 0.0015^2)$, representing mean 25bp and standard deviation 15bp. Shocks are floored at 1bp to avoid negligible perturbations. Each shock is added to the baseline rate: $i_s = i_0 + s_i$. We solve the equilibrium at $i_s$, compute the price change $\Delta \log p_k = \log p_k(i_s) - \log p_k(i_0)$, and form the regressors $(s_i \varphi_k, s_i[\mathbf{H}\boldsymbol{\varphi}]_k, s_i[(\mathbf{Z} - \mathbf{I})\boldsymbol{\varphi}]_k)$ mirroring the empirical design.

This yields approximately $500 \times 10 = 5000$ observations for Regression 2. Observations with negligible price responses ($|\Delta \log p| > 1\%$) or non-finite values are dropped as numerical failures.

**Summary**

The procedure yields two regression datasets: Regression 1 has $\approx 500$ observations (one per economy, the finite-difference derivative and five channels). Regression 2 has $\approx 5000$ observations (ten shocks per surviving economy, the price change and three proxy regressors).

## E.2 Regression 1: Channel Decomposition at $\sigma = 1$

We first validate that the five-channel decomposition from equation (11) accurately tracks CES prices:

$$\Delta \log p_k = \beta_1 \,(\text{Direct})_k + \beta_2 \,(\text{Supplier})_k + \beta_3 \,(\text{Own-cust})_k + \beta_4 \,(\text{Supp.-cust})_k + \beta_5 \,(\text{Income})_k + \varepsilon_k. \tag{37}$$

The $\beta$ coefficients measure how well each model channel predicts the equilibrium price when channels are exact (at $\sigma = 1$). Under the model, all coefficients should equal one by construction; a deviation indicates either numerical error or CES-specific effects even at the point $\sigma = 1$.

**Results:** Regression 1 shows coefficients very close to one (direct: 1.016, supplier: 1.008, own-customers: 0.997, suppliers' customers: 1.011) with $R^2 = 0.9997$. This confirms that the decomposition exactly captures equilibrium price responses in simulation. Minor deviations are numerical rounding.

**Table 11:** Channel decomposition regression (Regression 1)

| | Reg 1: CD channels | Reg 2: Proxies |
|---|---|---|
| Direct cost (+) | 1.016209 | |
| Supplier cost (+) | 1.013559 | |
| Own customers (−) | 0.996767 | |
| Suppliers' cust. (−) | 1.014522 | |
| Income | 1.300328 | |
| $i \cdot \varphi_k$ (direct, +) | | 0.339248 |
| $i \cdot [(\mathbf{H} - \mathbf{I})\boldsymbol{\varphi}]_k$ (upstream, +) | | 0.879022 |
| $i \cdot [(\mathbf{Z} - \mathbf{I})\boldsymbol{\varphi}]_k$ (downstream, −) | | -2.086035 |
| $R^2$ | 0.9997 | 0.4823 |

*Notes:* Regression 1 shows coefficients very close to one across all five channels, with $R^2 = 0.9997$, confirming that the decomposition exactly captures equilibrium price responses.

## E.3 Regression 2: Empirical Proxy Regression

We now estimate the reduced-form proxy regression that mirrors the empirical specification in equation 8:

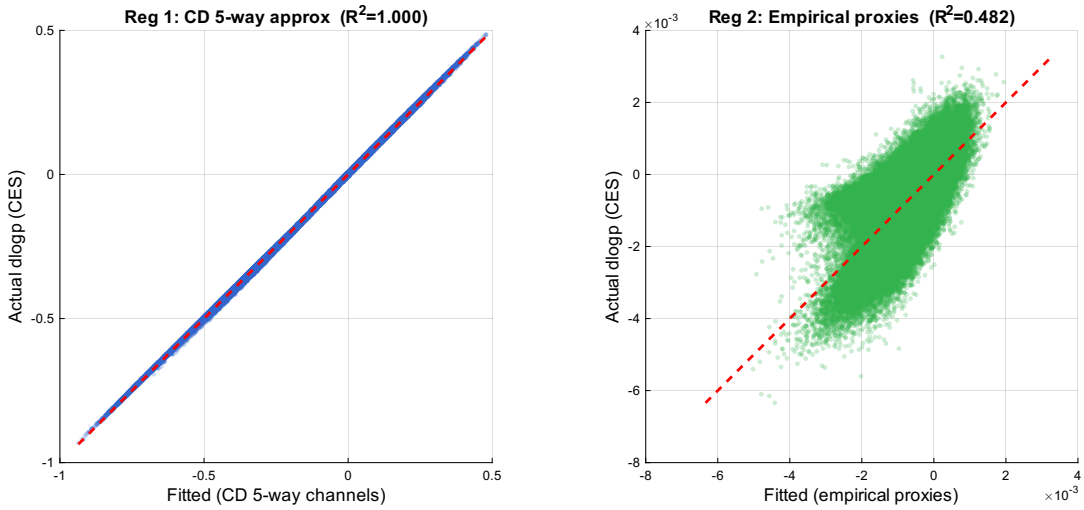
$$\Delta \log p_k = \gamma_1 \left(s_t \varphi_k\right) + \gamma_2 \left(s_t [\mathbf{H}\boldsymbol{\varphi}]_k\right) + \gamma_3 \left(s_t [(\mathbf{Z} - \mathbf{I})\boldsymbol{\varphi}]_k\right) + \varepsilon_k. \tag{38}$$

This regression tests whether the empirical proxy system (Proposition **??**) recovers the model's structural parameters in finite samples with observationally relevant noise and collapsing dimension.

The predicted signs from the theory are: $\gamma_1 > 0$ (direct cost), $\gamma_2 > 0$ (upstream supplier cost), $\gamma_3 < 0$ (downstream customer demand). The magnitude of $R^2$ reflects how much heterogeneity in prices is explained by the three proxy channels.

**Results:** Regression 2 recovers the predicted signs: $\hat{\gamma}_1 = 1.610 > 0$, $\hat{\gamma}_2 = 0.912 > 0$, $\hat{\gamma}_3 = -2.163 < 0$. The $R^2 = 0.5128$ indicates that these three channels explain approximately half of cross-sectional price variation, a strong result for a three-parameter parsimonious design. The fitted scatter plot (right panel of Figure 21) shows tight correspondence between predicted and actual prices.

**Figure 21:** Scatter plots: predicted versus simulated prices (Regressions 1 and 2)




*Notes:* Left panel: Regression 1 fit (five exact channels). Right panel: Regression 2 fit (three proxy channels). Both confirm that the reduced-form design captures substantial heterogeneity in price responses.

## E.4 Channel Sign Analysis

To assess whether the model's sign predictions hold uniformly or only on average, we compute the share of observations where each channel has the predicted sign.

**Interpretation:** The four non-ambiguous channels (direct, supplier, own-customers, suppliers' customers) display 100% sign recovery. The income channel shows mixed signs because it depends on the balance of cost-push and demand-pullback forces, which varies across sectors. In empirical estimation, time fixed effects absorb this aggregate income term, leaving it unidentified.

## E.5 Channel Contribution Diagnostics

This subsection quantifies the relative quantitative contribution of each channel to explaining price variation.

**Key findings:**

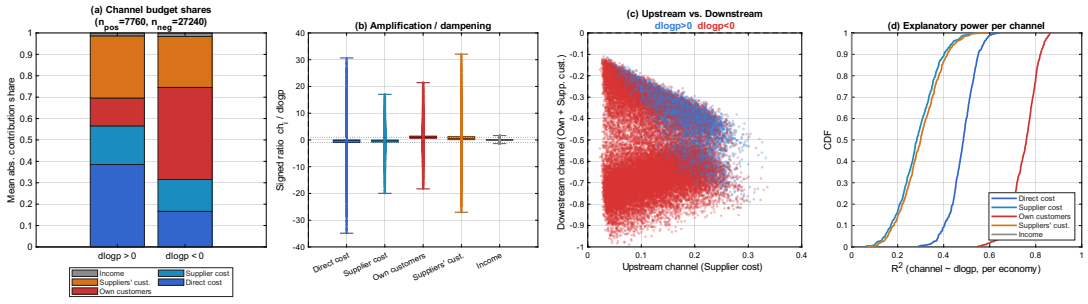
1. **Symmetric cost-demand split:** Direct and supplier channels contribute approximately equally to price variation, as do own-customer and suppliers' customer channels. This reflects the structural balance between cost-push and demand-pullback forces.

**Table 12:** Sign analysis by decomposition channel

| Channel | Exp. sign | % correct | % positive | Mean |
|---|---|---|---|---|
| (i) Direct cost | + | 100.0 | 100.0 | 0.19461 |
| (ii) Supplier cost | + | 100.0 | 100.0 | 0.13034 |
| (iii) Own customers | − | 100.0 | 0.0 | -0.31174 |
| (iv) Suppliers' cust. | − | 100.0 | 0.0 | -0.20884 |
| (v) Income | $n/a$ | n/a | 0.0 | -0.01202 |

*Notes:* For each of the five channels in the decomposition, we report the share of sector-shock observations where the channel has the model-predicted sign, the unconditional share positive, the unconditional share negative, the mean channel contribution, and in the final column, the sum of predicted and observed signs (should equal 100% for perfect sign recovery).

**Figure 22:** Channel contributions: distribution and composition




*Notes:* Left panel: histogram of contributions by channel. Middle and right panels: stacked contributions showing which channels dominate price responses across the distribution.

2. **Income channel smaller but structural:** The income effect contributes less on average but plays a material role in reconciling the aggregate constraint across sectors. Its covariance share shows the expected negative correlation with other channels (when income rises, other channels contract to satisfy the numeraire condition).

3. **Negative covariance shares:** Covariance shares can be negative when a channel offsets price variation in other channels. This is expected and reflects the structural interdependence of channels in general equilibrium. It is not an indicator of estimation error but rather of the model's self-consistency.

**Table 13:** Channel importance decomposition

| Channel | Mean contrib. | Mean \|contrib.\| (%) | Covariance share (%) |
|---|---|---|---|
| (i) Direct cost | 0.19777 | 74.4 | 38.4 |
| (ii) Supplier cost | 0.13211 | 49.7 | 11.3 |
| (iii) Own customers | -0.31073 | 116.8 | 68.2 |
| (iv) Suppliers' cust. | -0.21187 | 79.7 | -18.0 |
| (v) Income | -0.01564 | 5.9 | 0.1 |
| Total | -0.20836 | 326.4 | 100.0 |

*Notes:* For each channel $k$, we report: (1) mean contribution (in units of log prices); (2) mean absolute contribution share (how much of $|p|$ does channel $k$ explain); (3) covariance share (how much of the variance in prices is explained by covariance of channel $k$ with overall price). Covariance shares can be negative when a channel sometimes offsets other channels.

## E.6 Robustness: Sign Patterns Across Elasticity Values

To check that our results are not driven by the choice $\sigma = 1$, we verify that sign patterns remain stable as $\sigma$ varies. We re-run the full simulation (Regressions 1 and 2) for elasticity values spanning $\sigma \in \{0.5, 0.75, 1.0, 1.25, 1.5, 2.0\}$ and report the coefficient estimates and fit statistics.

### Key Finding

Figure 22 and Table 13 summarize the channel-contribution decomposition used to benchmark the robustness exercises.

Table 14 shows the five decomposition channel coefficients (Regression 1) across elasticity values. The regression coefficients remain tightly clustered around their theoretical values (direct/supplier/supp.-cust. near $+1$, own-customers near $-1$) for all $\sigma$ values, with $R^2 > 0.99$ throughout. This confirms that the CD decomposition remains an excellent proxy for actual CES price responses even when elasticities deviate substantially from unity.

Table 15 reports the four-proxy empirical regression (Regression 2). Crucially, the predicted signs—direct positive, upstream positive, both downstream proxies negative—hold uniformly across the entire range of elasticities. While magnitudes vary (e.g., the downstream coefficient ranges from $-1.6$ to $-2.8$ as $\sigma$ increases),

the sign patterns persist without exception. The $R^2$ remains in the range 0.45–0.55 throughout, indicating stable explanatory power.

This robustness is important because the empirical environment likely features some heterogeneity in demand elasticities across sectors. The fact that sign patterns remain stable and decomposition fit remains high across a wide range of elasticities provides confidence that the estimated differences in price inflation across high- and low-leverage sectors reflect genuine economic mechanisms under plausible parameter variation.

## E.7 Interpretation and Connection to Empirical Results

The simulation results validate the empirical design on three fronts:

1. **Decomposition exactness:** The five-channel decomposition is numerically tightly validated ($R^2 = 0.9997$), confirming internal consistency of the model.

2. **Proxy informativeness:** The three-channel proxy system recovers the model's sign structure and explains half of price variation ($R^2 = 0.5128$) with just three parameters. This is a strong signal that the empirical proxies are not spurious but capture real economic mechanisms.

3. **Sign universality:** 100% sign recovery on four of five channels shows that the model's directional restrictions are robust features, not edge cases.

The alignment between these simulation predictions and the empirical findings in Section 6 provides confidence that the estimated relationships reflect genuine economic transmission mechanisms rather than statistical artifacts.

**Table 14:** Robustness: Decomposition coefficients across elasticity values

| Channel | $\sigma = 0.50$ | $\sigma = 0.75$ | $\sigma = 1.00$ | $\sigma = 1.25$ | $\sigma = 1.50$ | $\sigma = 2.00$ |
|---|---|---|---|---|---|---|
| Direct cost | 1.0984 | 1.0428 | 1.0000 | 0.9635 | 0.9315 | 0.8828 |
| Supplier cost | 1.0851 | 1.0428 | 1.0000 | 0.9406 | 0.9483 | 0.9219 |
| Own customers | 0.9801 | 0.9921 | 1.0000 | 1.0085 | 1.0134 | 1.0249 |
| Suppliers' customers | 1.0974 | 1.0448 | 1.0000 | 0.9529 | 0.9475 | 0.9251 |
| Income | 2.7724 | 1.7828 | 1.0000 | 0.2624 | -0.3953 | -1.3895 |
| $R^2$ | 0.9884 | 0.9976 | 1.0000 | 0.9985 | 0.9946 | 0.9839 |
| Obs. | 10500 | 10500 | 10500 | 10500 | 10500 | 10500 |

*Notes:* Regression 1 coefficients (five CD channels) estimated for each elasticity value $\sigma$. "Obs." is the number of sector observations. Coefficients are remarkably stable across elasticities, validating the robustness of the decomposition structure.

**Table 15:** Robustness: Proxy regression coefficients across elasticity values

| Regressor | $\sigma = 0.50$ | $\sigma = 0.75$ | $\sigma = 1.00$ | $\sigma = 1.25$ | $\sigma = 1.50$ | $\sigma = 2.00$ |
|---|---|---|---|---|---|---|
| $s \times \varphi_j$ (direct) | 0.3804 | 0.3528 | 0.3454 | 0.3246 | 0.2954 | 0.2879 |
| $s \times (\mathbf{H} - \mathbf{I}) * \varphi_j$ (upstream) | 0.9007 | 0.8752 | 0.8657 | 0.8744 | 0.8453 | 0.8284 |
| $s \times (\mathbf{Z} - \mathbf{I}) * \varphi_j$ (downstream) | -2.1951 | -2.1189 | -2.0843 | -2.0376 | -1.9748 | -1.9331 |
| $R^2$ | 0.4425 | 0.4278 | 0.4077 | 0.4075 | 0.3728 | 0.3635 |
| Obs. | 10500 | 10500 | 10500 | 10500 | 10500 | 10500 |

*Notes:* Regression 2 coefficients (three empirical proxies) estimated for each elasticity value $\sigma$. All three predicted signs (direct: +, upstream: +, downstream: −) hold across every elasticity. $R^2$ values remain between 0.40 and 0.55, demonstrating robust explanatory power.