

Financial constraints across the production network and the transmission of monetary policy

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February 25, 2025
PRELIMINARY DRAFT

Abstract

We analyze how the interplay between production network linkages and sector-specific financial constraints affects the transmission of monetary policy. Using a granular country-sector dataset for the euro area, we document substantial heterogeneity in the response of producer prices and output across sectors. We account for cross-sectoral flows by incorporating information from input-output tables and study the importance of financial constraints among upstream suppliers and downstream customers in the pricing and production decisions of firms in a specific sector. To this end, we develop a novel set of empirical measures of upstream and downstream financial tightness, and we find that these measures significantly affect the transmission of monetary policy shocks through the production network. We provide theoretical foundations of our empirical measures by assessing the impact of sectoral financial frictions in a canonical multi-sector model.

JEL: C32, C33, C67, E31, E32, E44, E50, E52

Keywords: Monetary policy, inflation, production networks, input-output, financial frictions, local projections

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The views in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank or the Eurosystem. We thank Hassan Afrouzi, Rubén Domínguez-Díaz, Mishel Ghassibe, Christophe Kamps, Sujit Kapadia, Keith Kuester, Philip R. Lane, Óscar Jordà, and participants at the Banque de France Conference on “Financial Intermediation and Monetary Policy: Recent Trends and New Challenges” for valuable comments.

1 Introduction

Over the years, economists have identified different channels through which monetary policy can affect the economy. In this paper, we focus on two aspects that have been highlighted as important by the literature, namely financial constraints and production networks. The role of financial frictions and the acceleration of monetary policy via financial constraints has been first illustrated by the seminal work of [Bernanke and Gertler \(1995\)](#) and [Bernanke et al. \(1999\)](#) and found empirical validation in a number of papers. At the same time, researchers and policymakers have identified production networks as a key determinant for the transmission of shocks across the economy ([Acemoglu et al., 2012, 2016](#)). More recently, they featured prominently in the debate on the role of supply-side versus demand-side factors in the inflation surge following the Covid-19 pandemic.¹

In this paper, we bring together these two aspects and investigate to what extent the transmission of monetary policy depends on financial constraints across the production network. In doing so, we assess the importance of both direct and indirect channels through which financial constraints across the production network may amplify or dampen the transmission of monetary policy. First, financial constraints directly applying to firms in a specific sector i may amplify the transmission of a monetary policy shock following the traditional balance-sheet channel ([Bernanke and Gertler, 1995](#)).² Second, the balance-sheet channel may also be indirectly amplified via the production network, depending on both the degree of interconnections across sectors and their level of financial constraints. For instance, the ability of financially constrained firms in sector i to purchase intermediate inputs from other firms and sectors may be limited once rising interest rates imply a tightening of financial constraints. In turn, this may put downward pressure on prices charged

¹See for instance [Blanchard and Bernanke \(2023, 2024\)](#); [Giannone and Primiceri \(2024\)](#).

²In short, this channel prescribes that due to frictions in credit intermediation for instance related to agency costs banks face when monitoring the credit quality of borrowers, the external finance premium, i.e. the firm's cost on externally obtained funding over the cost of internal funds (e.g. retained earnings) is inversely related with the financial position of the firm, i.e. with the amount of collateral the firm holds on its balance sheet. This relationship implies that firms may face binding borrowing constraints once their collateral positions deteriorates, with a monetary policy tightening likely aggravating the issue of binding constraints as both financing costs rise and the value of collateral assets such as government bonds and other fixed-rate assets may fall as interest rates rise. In this way, the balance sheet channel directly amplifies the effect of monetary policy on prices and output, as firms are forced to adjust their production plans in light of their own exposure to financial constraints.

and output provided by upstream suppliers to these firms. At the same time, financially constrained firms may try to raise selling prices to alleviate tight financial constraints by generating revenue, potentially putting upward pressure on prices faced by downstream customers. As we show, not accounting for such indirect financial constraints effects results in understating the full impact that a monetary policy shock may have on the economy. In addition, explicitly accounting for the role of upstream and downstream financial constraints sheds light on the timing of the transmission mechanism and on the relative importance of upstream “cost” and a downstream “demand” channels in the transmission of a monetary policy shock across the production network.

We therefore assess how both direct and indirect up- and downstream financial constraints across the production network affect monetary policy transmission. To this end, we develop new measures of financial constraints for suppliers (“upstream financial constraints”) and customers (“downstream financial constraints”) and study their interaction with monetary policy shocks in a panel local projections model (Jordà and Taylor, 2016; Jordà, 2005). The analysis is based on a euro area country-sector panel dataset at monthly frequency that includes sector-level data on prices, quantities, inter-sectoral linkages, as defined by euro area input-output (IO) tables, and sector-specific financial frictions.

We derive three key results from the analysis. First, we find that the sector-specific transmission of monetary policy tightening shocks varies substantially across sectors regarding the strength, timing, and persistence of the dampening effect on prices and output. Second, our results show that both direct and indirect financial constraints significantly amplify the dampening effect of a monetary policy tightening shock, with indirect financial constraints accounting for a large share in the overall effect of financial constraints on prices and output. Finally, we find that while downstream financial constraints seem to reinforce the decline in prices and output following a monetary policy tightening shock, upstream constraints tend to partly mitigate these effects. While a tightening of financial constraints seems to lower downstream customers’ demand for intermediate goods produced by sector i (“demand channel”), it may foster incentives for upstream suppliers to raise prices and/or gain market share to alleviate financial constraints (“cost channel”).

The rest of the paper is organised as follows: section 2 reviews the relevant literature, section 3 describes the data, section 4 shows how we construct the sector-specific financial constraint measures, section 5 outlines the econometric strategy,

and section 6 presents the empirical results. We rationalize our empirical financial constraints measures in a simple discrete time multi-sector economy model in section 7, before robustness checks on these measures in section 8. Finally, section 9 concludes.

2 Literature

Our work intersects with multiple strands of existing literature. First, it aligns with theoretical studies on production networks and their impact on shock propagation. Following the foundational work of [Acemoglu et al. \(2012\)](#), extensive research has explored how demand and supply shocks travel through supply chains. Interest in the amplification effects of production networks, especially in terms of supply-side shocks, has grown significantly since the onset of the Covid-19 pandemic. Our focus on the role of production networks in the transmission of monetary policy finds its underpinning in a number of recent theoretical papers that have established the importance of this mechanism. [La'O and Tahbaz-Salehi \(2022\)](#) examine the influence of production networks on optimal monetary policy, finding that the optimal approach involves stabilizing a price index that assigns greater weight to industries that are larger, exhibit higher price stickiness, and are positioned further upstream, as well as those with less sticky upstream suppliers but more rigid downstream customers. Similarly, [Rubbo \(2023\)](#) demonstrate that in a multi-sector economy with input-output linkages, the "divine coincidence" — the simultaneous stabilization of both output and prices via monetary policy — no longer holds. Additionally, [Bigio and La'O \(2020\)](#) show that the US input-output structure amplified financial distortions by a factor of approximately two during the Great Financial Crisis. We provide empirical evidence of an unexplored channel in the transmission of shocks, that is the interaction of sector-level financial constraints with inter-sectoral flows.

Second, we contribute to the empirical literature on monetary policy shock transmission across production networks by providing new evidence for the Euro Area. Despite the growing body of theoretical studies assessing the transmission of shocks in production network models, the empirical evidence is still relatively limited and focused primarily on the United States. One of the first contribution to the topic is [Ozdagli and Weber \(2017\)](#), where the authors analyse the impact on monetary policy shocks around press releases by the Federal Reserve on financial markets. Using data on stock returns, they find a large and immediate effect of monetary

policy on financial markets and that between 50% and 85% of the overall effect is attributable to indirect network effects. More recently, [Ghassibe \(2021\)](#) employs monthly data on US final 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 rises in the frequency of price non-adjustment and intermediates intensity. From a methodological point of view, Our study most closely aligns with [Borağan Aruoba and Drechsel \(2024\)](#), who use disaggregated price data to examine monetary policy transmission, focusing on consumer prices in the US. In contrast, we analyze the production side, highlighting the role of financial constraints within production networks. Integrating financial variables into our empirical model reveals a new cost channel of monetary policy, extending [BarthIII and Ramey \(2002\)](#). In our framework, this cost channel operates directly through firms’ financial constraints and indirectly through the constraints on their suppliers.

[Durante et al. \(2022\)](#) find that young firms are more sensitive to monetary policy shocks, with high leverage holdings amplifying the effect.

Third, our work relates to the vast literature on the role of financial frictions in the transmission of monetary policy shocks. The importance of financial frictions for the transmission of shocks has been acknowledged starting with [Bernanke and Gertler \(1995\)](#) and [Bernanke et al. \(1999\)](#) and featured prominently in macro-financial research since then. However, the role of financial frictions at the micro-level for the transmission of shocks to the macroeconomy has only relatively recently been investigated. [Ottonello and Winberry \(2020\)](#) show that financially constrained firms invest significantly less following a monetary policy shock compared to non-constrained firms. They rationalise their empirical findings in a heterogeneous firm New Keynesian dynamic stochastic general equilibrium (DSGE) model featuring default risk, showing that firms prone to high default risks respond less to monetary policy due to steeper marginal costs of financing investment projects. Our work is closely related to [Jeenas \(2023\)](#), which assesses the differences in how non-financial firms respond to high frequency identified monetary policy shocks conditional on various measures of financial conditions. He finds that firms with low liquid asset holdings invest less after unexpected policy rate increases, regardless of other characteristics like leverage or size. This suggests that recent trends in corporate liquidity management influence monetary policy transmission and that firms’ liquidity significantly impacts their investment behavior. [Holm-Hadulla and Thürwächter \(2024\)](#) examine how corporate leverage influences monetary policy transmission us-

ing firm-level data for the euro area and find that increased leverage enhances the impact of monetary policy on the price level but not on real GDP. They show that higher leverage leads to stronger contractions in domestic demand while mitigating declines in exports through improving terms of trade. These findings highlight the significant role of leverage in creating heterogeneity in monetary policy transmission across different euro area countries. Our study complements these findings by showing that sector-specific responses to monetary policy shocks depends not only on the financial structure of firms active in the specific sector under consideration, but also on the financial structure of its customers and suppliers. In this regard, our study relates in part to [Adelino et al. \(2023\)](#) who study the role of trade credit in the transmission of unconventional monetary policy from eligible firms to their clients.

Finally, we contribute to the vast empirical literature studying the effect of monetary policy shocks on macro-financial outcomes employing local projections. Given their flexibility, the limited amount of assumptions on the data generating process needed, and the straightforward way to integrate exogenously identified shocks, a vast literature on assessing monetary policy shocks in local projections emerged, and the relative advantage of local projections compared to other empirical strategies like structural vector autoregression (VAR) models have been extensively discussed in the empirical macroeconomic literature.³ Recently, [Borağan Aruoba and Drechsel \(2024\)](#) have studied the heterogeneous impact of monetary policy shocks on highly disaggregated consumer price indices. Their local projection setup builds on [Jordà \(2005\)](#)’s early work and the more recent surveyed evidence from [Ramey \(2016\)](#). They also provide a survey of the empirical literature on the effects of monetary policy on prices. By differentiating the impact of monetary policy across varying levels of financial constraints, our empirical results also connect to the state-dependent local projections proposed by [Ramey and Zubairy \(2018\)](#).

³As discussed e.g. by [Plagborg-Møller and Wolf \(2021\)](#) and [Li et al. \(2024\)](#), local projections and VARs estimate the same impulse response functions asymptotically, with the latter being characterized by a higher bias and a lower variance in finite samples. At the same time, the need to correct standard errors for serial correlation in the regression residuals has commonly been identified as a drawback of using local projections. However, [Montiel Olea and Plagborg-Møller \(2021\)](#) show that this issue is alleviated by augmenting the local projection setup with lags of controls, shocks and dependent variables. In this case, local projections tend to be more robust than VARs.

3 Data

We construct a country-sector panel at monthly frequency for the 20 euro area countries, with sector-specific information reported at the NACE-2 level.⁴ Our dataset is composed of four major building blocks: 1) a set of main macroeconomic indicators reported at the country level, including aggregate monetary policy shocks; 2) a dataset including information on sector-specific producer prices and activity reported at the NACE-2 level; 3) data on input-output linkages for 64 sectors reported at this level capturing bilateral cross-sector flows for all euro area countries; and 4) firm-level balance sheet data obtained from Orbis aggregated at country-sector-year level to obtain information on sector-specific financial constraints. The resulting dataset spans from January 1999 to December 2024. In the following, we describe each of these building blocks in greater detail. Table 1 reports summary statistics for each category.

Country-level macroeconomic 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 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 shocks as high-frequency changes in the 3-months OIS rate over the event window coinciding with stock prices movements in the opposite direction.⁵

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 Eu-

⁴See [Eurostat \(2008\)](#) for an explanation of the NACE categorization applied to euro area sector-specific data.

⁵We show that our results are robust to identifying monetary policy shocks at different frequencies in section 8.

Table 1: Summary statistics of used variables

| | N | Mean | SD | Median |
|--------------------------|---------|-------------|-------------|------------|
| <i>Euro area level</i> | | | | |
| CISS | 312 | 0.18 | 0.15 | 0.12 |
| EUR/DOL exchange rate | 312 | 1.18 | 0.16 | 1.17 |
| Reference 10y 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 |
| Sign-instrumented shock | 312 | 0.00 | 0.03 | 0.00 |
| <i>Country level</i> | | | | |
| Real GDP | 2,363 | 474.56 | 893.63 | 54.31 |
| GDP Deflator | 2,256 | 88.37 | 15.53 | 89.15 |
| Unemployment | 7,093 | 8.80 | 4.14 | 8.00 |
| Hours worked | 2,329 | 10633201.16 | 19787134.50 | 1673727.00 |
| Number of employed | 1,955 | 29989.61 | 53716.30 | 2539.70 |
| HICP | 6,409 | 95.51 | 15.81 | 97.96 |
| QE holdings | 3,424 | 100227.86 | 208248.89 | 12576.88 |
| 10y yield | 2,974 | 2.60 | 1.83 | 2.85 |
| <i>Sector level</i> | | | | |
| PPI (SA) | 145,986 | 52.81 | 48.01 | 74.04 |
| IP (SA) | 197,951 | 84.83 | 88.09 | 92.59 |
| Turnover (SA) | 220,521 | 101.23 | 2533.46 | 83.60 |
| Employment index (SA) | 98,710 | 42.77 | 53.98 | 0.00 |
| Hours worked index (SA) | 87,323 | 33.06 | 53.37 | 0.00 |
| Job Vacancy rate (SA) | 3,768 | 1.96 | 4.12 | 1.20 |
| Gross wages (SA) | 96,507 | 34.09 | 45.79 | 0.00 |

Sources: Eurostat, MDP, IMF

rostat. As STS does not have price indices for the trade sector (namely NACE codes G00, G45, G46, G47), we compute them dividing the nominal turnover by real turnover,⁶ consistent with the methodology employed by Eurostat. In addition, we proxy the PPI for the construction sector (NACE code F00) with the PPI of residential buildings construction (i.e. CPA code F411X, which covers "new buildings" only and is the main component of sector F41). Moreover, STS does not cover agriculture, so we complement the PPI for agricultural sector (A01) with information from other Eurostat datasets⁷. These indices are, however, at quarterly frequency only, so we linearly interpolate them to obtain monthly observations. We also complement industrial production indices for agriculture (A01) with another dataset provided by Eurostat⁸, which however is only at annual frequency.

In STS, data on employment, hours worked, and wages are available at quarterly frequency, or monthly on voluntary basis⁹, while data on prices, industrial production, and turnover are available both at monthly and quarterly frequency, depending on the country, the sector and the time period¹⁰. To maximize the number of observations while preserving the consistency of the dataset, we linearly interpolate quarterly series to monthly and we take the original monthly series or the quarterly interpolation depending on which one has more observations.

For all available indices, we use seasonally adjusted series¹¹ and perform a four-step cleaning procedure:

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).

⁶More precisely we divide Turnover (value) by the Volume of sales (deflated turnover).

⁷Specifically we rely on the Price indices of agricultural products.

⁸Namely the "Economic accounts for agriculture - indices: volume, price, values (aact_eaa05)".

⁹See STS regulations [here](#).

¹⁰This means that for a given country-sector we may have only monthly observation, only quarterly or both. Moreover, when both monthly and quarterly observations are available, they may not overlap perfectly, as they may also not overlap at all.

¹¹We derive seasonally adjusted series in cases for which the seasonal adjustment is not directly carried out by Eurostat by performing a LOESS transformation.

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. We report the dropped series in appendix

Input-output linkages

We derive information on industry-by-industry input-output (IO) linkages from the annual EU inter-country input-output tables in Eurostat’s FIGARO database¹². These tables are available from 2010 to 2022, so to cover the entire period of interest we extrapolate the 2010 figures to preceding years and the 2022 table for the subsequent years. We take comfort in doing so from the fact that IO linkages are changing only very gradually over time, and we report summary statistics on the evolution of the IO tables in our sample in the appendix . Table 2 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 2: Simplified Multi-Country Input-Output Table

| | A1 | A2 | B1 | B2 | Final Consumption |
|--------------|----------------|----------------|----------------|----------------|--------------------------|
| A1 | $z_{11}^{A,A}$ | $z_{12}^{A,A}$ | $z_{11}^{A,B}$ | $z_{12}^{A,B}$ | y_1^A |
| A2 | $z_{21}^{A,A}$ | $z_{22}^{A,A}$ | $z_{21}^{A,B}$ | $z_{22}^{A,B}$ | y_2^A |
| B1 | $z_{11}^{B,A}$ | $z_{12}^{B,A}$ | $z_{11}^{B,B}$ | $z_{12}^{B,B}$ | y_1^B |
| B2 | $z_{21}^{B,A}$ | $z_{22}^{B,A}$ | $z_{21}^{B,B}$ | $z_{22}^{B,B}$ | y_2^B |
| Labor | VA_1^A | VA_2^A | VA_1^B | VA_2^B | VA |
| Taxes | T_1^A | T_2^A | T_1^B | T_2^B | T |

First, we calculate the share of each sector’s labour expenses, taxes and value added in total input expenses. In our simplified table, this would be given by

$$a_{1A} = \frac{VA_1^A + T_1^A}{z_{11}^{A,A} + z_{21}^{A,A} + z_{11}^{B,A} + z_{21}^{B,A} + VA_1^A + T_1^A} \quad (1)$$

for industry 1 in country A.¹³ This represents the share of a sector’s upstream inputs that are not coming in the form of intermediate input goods from the production network.

¹²FIGARO stands for ”Full international and global accounts for research in input-output Analysis”. See Eurostat for more details.

¹³In the actual IO tables, we calculate the share of each sector’s input coming from outside the production network by dividing all the rows containing W2 (compensation of employees, operating surplus, other gross value added and net taxes) by the total expenses for production.

Second, we compute the share of output used for final consumption, i.e. the share of a sector's downstream output that is not re-used for production. For sector 1 in country A, this would be given by¹⁴

$$\tilde{a}_{1A} = \frac{y_1^A}{z_{11}^{A,A} + z_{12}^{A,A} + z_{11}^{A,B} + z_{12}^{A,B} + y_1^A} \quad (2)$$

We then take the square IO matrix:

$$\mathbf{A} = \begin{bmatrix} z_{11}^{A,A} & z_{12}^{A,A} & z_{11}^{A,B} & z_{12}^{A,B} \\ z_{21}^{A,A} & z_{22}^{A,A} & z_{21}^{A,B} & z_{22}^{A,B} \\ z_{11}^{B,A} & z_{12}^{B,A} & z_{11}^{B,B} & z_{12}^{B,B} \\ z_{21}^{B,A} & z_{22}^{B,A} & z_{21}^{B,B} & z_{22}^{B,B} \end{bmatrix} \quad (3)$$

and calculate the matrix of technical coefficients \mathbf{B} by dividing each element of matrix \mathbf{A} by the total of the respective column where the element is located, obtaining

$$\mathbf{B} = \begin{bmatrix} \nu_{11}^{A,A} & \nu_{12}^{A,A} & \nu_{11}^{A,B} & \nu_{12}^{A,B} \\ \nu_{21}^{A,A} & \nu_{22}^{A,A} & \nu_{21}^{A,B} & \nu_{22}^{A,B} \\ \nu_{11}^{B,A} & \nu_{12}^{B,A} & \nu_{11}^{B,B} & \nu_{12}^{B,B} \\ \nu_{21}^{B,A} & \nu_{22}^{B,A} & \nu_{21}^{B,B} & \nu_{22}^{B,B} \end{bmatrix} \quad (4)$$

In a similar vein, one obtains the matrix of allocation coefficients \mathbf{C} by dividing each element of matrix \mathbf{A} by the total of the rows:

$$\mathbf{C} = \begin{bmatrix} \tilde{\nu}_{11}^{A,A} & \tilde{\nu}_{12}^{A,A} & \tilde{\nu}_{11}^{A,B} & \tilde{\nu}_{12}^{A,B} \\ \tilde{\nu}_{21}^{A,A} & \tilde{\nu}_{22}^{A,A} & \tilde{\nu}_{21}^{A,B} & \tilde{\nu}_{22}^{A,B} \\ \tilde{\nu}_{11}^{B,A} & \tilde{\nu}_{12}^{B,A} & \tilde{\nu}_{11}^{B,B} & \tilde{\nu}_{12}^{B,B} \\ \tilde{\nu}_{21}^{B,A} & \tilde{\nu}_{22}^{B,A} & \tilde{\nu}_{21}^{B,B} & \tilde{\nu}_{22}^{B,B} \end{bmatrix} \quad (5)$$

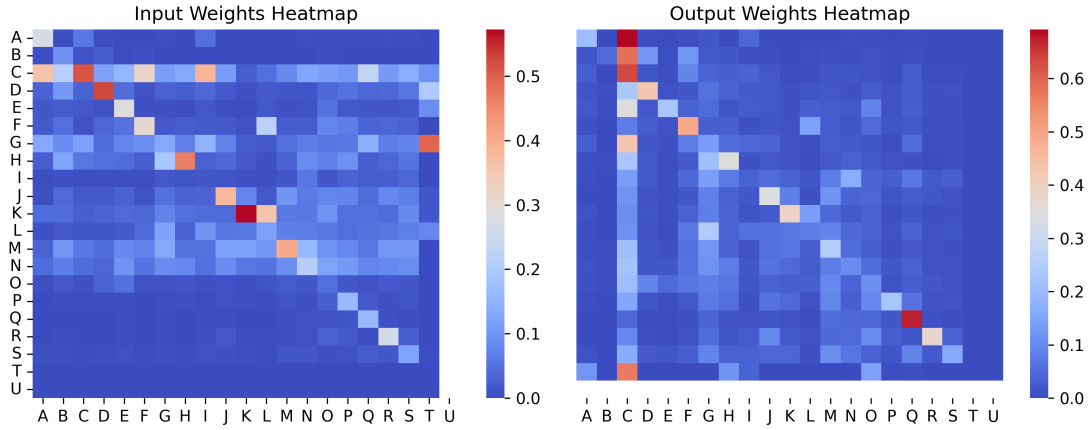
Figure 1 presents heatmaps illustrating the technical coefficients (empirical counterpart of equation 4) and allocation coefficients (empirical counterpart of equation 5) for NACE 1-digit sectors in the euro area. These coefficients quantify inter-sectoral dependencies by mapping the flow of goods and services across sectors.

In the left heatmap, red shades indicate that the sector in the corresponding row is a key supplier to the sector in the corresponding column. In the right heatmap,

¹⁴In the actual IO tables, we calculate the share of each sector's output used for final consumption by dividing the sum of consumption columns ("P3_S" and P5) by the sum of total output.

red-shaded cells indicate that the sector in the corresponding column is purchasing strongly from the sector in the corresponding row. 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 1: Heatmaps of technical and allocation coefficients for NACE 1-digit at EA level for 2015



Notes: The heatmaps show input-output tables as given by 4 and 5 for the euro area (2023, 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 technical coefficients \mathbf{B} and the matrix of allocation coefficients \mathbf{C} 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 through 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 Leontief and Gosh inverses, given by $\mathbf{L} \equiv (\mathbf{I} - \mathbf{B})^{-1}$ and $\mathbf{G} \equiv (\mathbf{I} - \mathbf{C})^{-1}$, where \mathbf{I} is the identity matrix:

$$\mathbf{L} = \begin{bmatrix} \omega_{11}^{A,A} & \omega_{12}^{A,A} & \omega_{11}^{A,B} & \omega_{12}^{A,B} \\ \omega_{21}^{A,A} & \omega_{22}^{A,A} & \omega_{21}^{A,B} & \omega_{22}^{A,B} \\ \omega_{11}^{B,A} & \omega_{12}^{B,A} & \omega_{11}^{B,B} & \omega_{12}^{B,B} \\ \omega_{21}^{B,A} & \omega_{22}^{B,A} & \omega_{21}^{B,B} & \omega_{22}^{B,B} \end{bmatrix} \quad (6)$$

$$\mathbf{G} = \begin{bmatrix} \tilde{\omega}_{11}^{A,A} & \tilde{\omega}_{12}^{A,A} & \tilde{\omega}_{11}^{A,B} & \tilde{\omega}_{12}^{A,B} \\ \tilde{\omega}_{21}^{A,A} & \tilde{\omega}_{22}^{A,A} & \tilde{\omega}_{21}^{A,B} & \tilde{\omega}_{22}^{A,B} \\ \tilde{\omega}_{11}^{B,A} & \tilde{\omega}_{12}^{B,A} & \tilde{\omega}_{11}^{B,B} & \tilde{\omega}_{12}^{B,B} \\ \tilde{\omega}_{21}^{B,A} & \tilde{\omega}_{22}^{B,A} & \tilde{\omega}_{21}^{B,B} & \tilde{\omega}_{22}^{B,B} \end{bmatrix} \quad (7)$$

In the following, we test both the direct weights from the IO network (matrices 4 and 5) and the Leontief and Gosh matrices (matrices 6 and 7) when deriving the up-and downstream measures for financial constraints in section 4.

Firm-level data and financial constraints measures

We collect firm-level data from Orbis to derive sector-specific financial constraints measures such as sector-level leverage, the working capital share, interest expenditures, and distance to default. We follow [Gopinath et al. \(2017\)](#) and [Kalemli-Ozcan et al. \(2015\)](#) in cleaning the data, and report all cleaning steps in the appendix. Table 3 lists the set of financial constraints measures we derive from firm-level data and incorporate in our empirical setup in section 5, and table 4 shows summary statistics for these sector-level measures.

To ensure that the firm-level financial constraints variables match the level of aggregation of the sectoral price and production data, we compute the financial constraints measures by NACE-2 sector using the sector-specific weighted average of the ratios, with weights derived from firm sales. As a robustness check, we derive two alternative variants of the measures in addition to using median values. First, we recompute the financial constraints measures by using the sectoral median level of the financial constraints measure in the computations. Second, we derive the measures by taking sector-specific sums of balance sheet items before calculating the respective aggregate ratios. We compare the different variants of measures in section 4, where we compare the sector-specific measures with the up-and downstream financial constraints measures.

Table 3: Definitions of the financial constraints measure

| Measure | Definition |
|------------------------------|--|
| Total leverage | Ratio of total liabilities excluding shareholders funds to total assets. |
| Financial leverage | Ratio of loans and long term debt to total assets, with loans including short-term financial debts and long term debt including long-term borrowings from credit institutions and bonds issued. |
| Short-term leverage | Ratio of current liabilities to total assets, with current liabilities including loans (short-term financial debt), trade credit, and other current liabilities (including liabilities arising due to pensions, staff costs etc.). |
| Adjusted short-term leverage | Ratio of current liabilities net of cash and cash equivalents to total assets, with cash and cash equivalents including balances in bank accounts and highly liquid short-term investments. |
| 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 4: Financial constraint measures: sector level descriptive statistics

| | N | Mean | SD | Median |
|------------------------------|---------|------|------|--------|
| Total leverage | 249,144 | 0.59 | 0.16 | 0.60 |
| Financial leverage | 249,144 | 0.16 | 0.12 | 0.15 |
| Short-term leverage | 249,144 | 0.40 | 0.16 | 0.40 |
| Adjusted short-term leverage | 249,144 | 0.27 | 0.19 | 0.27 |
| Working capital share | 249,144 | 0.15 | 0.15 | 0.14 |

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

4 Up- and downstream financial constraint measures

In this section, we derive a set of novel financial constraints measures indicating how much firms in sector i are exposed to financial constraints their suppliers and customers face. All measures are derived from the IO and financial constraints measures data reported in section 3. In particular, we define:

$$\begin{aligned}\Lambda_{ic,t_{12}} &= (1 - a_{ic,t_{12}}) \sum_{j,d} 1(j \neq i, d \neq c) \nu_{ic,jd,t_{12}} \times \lambda_{jd,t_{12}} \\ \tilde{\Lambda}_{ic,t_{12}} &= (1 - \tilde{a}_{ic,t_{12}}) \sum_{j,d} 1(j \neq i, d \neq c) \tilde{\nu}_{ic,jd,t_{12}} \times \lambda_{jd,t_{12}}\end{aligned}\quad (8)$$

$$\begin{aligned}\Lambda_{ic,t_{12}} &= (1 - a_{ic,t_{12}}) \sum_{j,d} (\omega_{ic,jd,t_{12}} - 1_{j=i,d=c}) \times \lambda_{jd,t_{12}} \\ \tilde{\Lambda}_{ic,t_{12}} &= (1 - \tilde{a}_{ic,t_{12}}) \sum_{j,d} (\tilde{\omega}_{ic,jd,t_{12}} - 1_{j=i,d=c}) \times \lambda_{jd,t_{12}}\end{aligned}\quad (9)$$

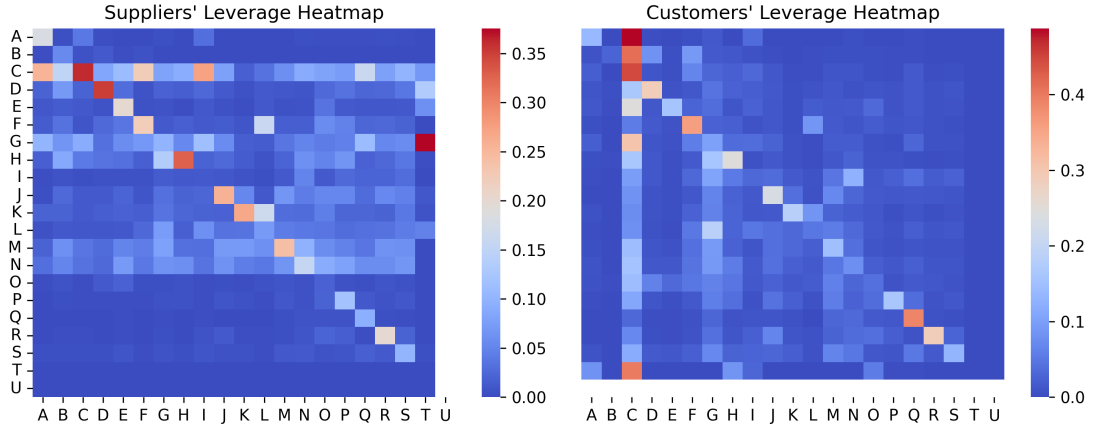
where variables $\Lambda_{ic,t_{12}}$ and $\tilde{\Lambda}_{ic,t_{12}}$ are annual measures for up- and downstream financial constraints, respectively.¹⁵ They are obtained by summing the products of sector i 's exposure to each supplier (customer) sector $j \in J$ in country $d \in D$ – as measured by the respective bilateral objects from the input-output tables – the technical and allocation matrices 4 and 5 (equation 8, the baseline case used for results presented in section 6) or the Leontief and Gosh inverse matrices 6 and 7 (equation 9) – and the degree of financial constraints in sector j in country d , $\lambda_{jd,t_{12}}$, given by the respective measure in table 3 under consideration.

Following Acemoglu et al. (2016), we account for indirect effects stemming from a sector's exposure to its own level of financial constraints by either taking it out (equation 8) or subtracting a value of one from the diagonal elements of matrices 6 and 7 (equation 9) when $j = i$ and $d = c$. This procedure yields a weighted measure of a sector i 's exposure to financial constraints accruing to sectors it is interacting with, net of the impact of financial constraints in i itself. As discussed in the previous section, we take sectoral weighted averages of the financial constraints measure $\lambda_{jd,t_{12}}$ in each sector in the interaction with IO table information.

¹⁵To highlight the difference in frequency, we label all variables at annual frequency with the subscript 12.

Figure 2 illustrates intersectoral financial dependencies among NACE-1 sectors at the euro area level. Following the specification in equation 8, the respective heatmaps are generated by multiplying the two heatmaps in figure 1 (reflecting $\nu_{ic,jd,t_{12}}$ and $\tilde{\nu}_{ic,jd,t_{12}}$, respectively) with the vector of total leverage, as defined in table 3 (reflecting $\lambda_{jd,t_{12}}$), resulting in the set of bilateral exposures to financial constraints across the 20 NACE-1 sectors in the euro area. Concretely, in the left panel of figure 2, cell values are computed as $\nu_{i,j,t_{12}}^{EA} \times \lambda_{j,t_{12}}^{EA}$. Summing across rows within a given column yields $\sum_{j,d}(\nu_{i,j,t_{12}}^{EA}) \times \lambda_{j,t_{12}}^{EA}$. Similarly, the right panel shows $\tilde{\nu}_{i,j,t_{12}}^{EA} \times \lambda_{j,t_{12}}^{EA}$, where summing the columns in a specific row results in $\sum_{j,d}(\tilde{\nu}_{i,j,t_{12}}^{EA}) \times \lambda_{j,t_{12}}^{EA}$.

Figure 2: Heatmaps of bilateral leverage exposures for NACE 1-digit sectors at EA level for 2015

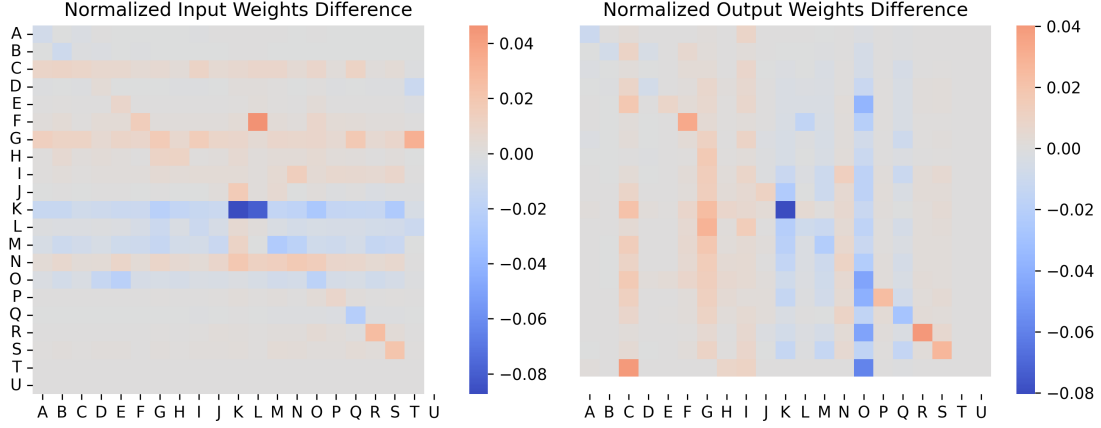


Notes: Heatmaps for the interaction of technical (left) and allocation (right) coefficients with the vector of leverages of 1-digit NACE sectors at the EA level.

Figure 3 illustrates how the relative significance of upstream (suppliers) and downstream (customers) financial constraints 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 4 shows the obtained measures using total leverage for a selection of production and services sectors reported at NACE-1 level. Both direct (blue lines) and

Figure 3: Change in relative importance of upstream and downstream for NACE 1-digit sectors at EA level for 2015



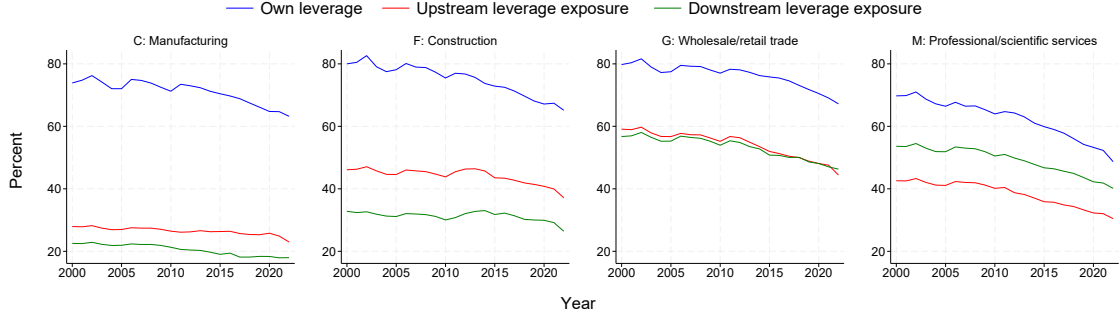
Notes: This figure illustrates changes in the relative importance of upstream (suppliers) and downstream (customers) financial constraints across NACE 1-digit sectors in the euro area when leverage is considered. The left panel shows how a sector’s importance as a supplier changes relative to a model based solely on intersectoral flows of goods and services, with blue cells indicating a decline in importance. The right panel highlights shifts in a sector’s role as a buyer, where red cells signify an increase in relative importance

indirect (red and green lines) financial constraints measures based on total leverage follow a downward trend across all sectors, as commonly found for financial constraints measures derived from Orbis (Beck et al., 2023). Furthermore, while upstream financial constraints measures seem to be relatively higher than downstream measures in the interest-rate sensitive manufacturing and construction sector, services-oriented sectors like wholesale/retail trade and professional services including legal, accounting, marketing, scientific and research services are exposed to higher downstream customer related financial constraints.

5 Econometric Strategy

In the following, we integrate our network financial constraints measures in a country-sector panel local projection setup similar to that used in Jordà and Taylor (2016). This framework is particularly suited for studying the transmission of externally-identified shocks, as is our case, and requires limited assumptions on the data generating process needed.

Figure 4: Sector-specific financial constraints measures - total leverage



Notes: Time series of sector-specific financial constraints measures, as defined in equation 8, with $\lambda_{jd,t_{12}}$ referring to total leverage defined in table 3.

We first assess the transmission of monetary policy shocks in a simple baseline local projections model only estimating for the composite effect of a monetary policy shock on sector-specific variables of interest. We then study the specific role and non-linear interactions of production networks and financial constraints in our main model. We present the simple and complete models in sections 5.1 and 5.2, respectively, and report results in section 6.

5.1 Baseline local projections

Our simple baseline local projection model abstracting from network financial constraints effects is given by:

$$y_{ic,t+h} - y_{ic,t-1} = \beta_1^h s_t + \sum_{l=1}^L \delta^h \mathbf{K}_{t-l} + \sum_{l=0}^L \eta^h \Delta \mathbf{X}_{t-l} + \theta_{t_{12}} + \kappa_{t+h} + \epsilon_{ic,t+h} \quad (10)$$

with $h = 1, 2, \dots, H, \mathbf{K}_t = \begin{bmatrix} \Delta y_{ic,t} \\ s_t \end{bmatrix}$

We follow Jordà and Taylor (2024) and estimate the model in long-differences, with $\Delta x_t = x_t - x_{t-1}$. We are particularly interested in the response of prices and output reported for sector i in country c to a monetary policy shock. Specifically, we assess the impact of a monetary policy shock on sectoral producer prices (PPI) and industrial production, our key variables of interest included in vector $y_{ic,t+h}$. Coefficient β_1 accounts for the period $t + h$ impact of a monetary policy shock in t on the economy and matrix \mathbf{K}_t collects lags of the dependent variable $y_{ic,t}$ and

the shock variables. Matrix \mathbf{X}_t contains contemporaneous values and lags of 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 Index, the euro area harmonized index of consumer prices (HICP) and the euro area unemployment rate. It also includes lags of our sector-specific financial constraints measure $\lambda_{ic,t_{12}-1}$ ¹⁶ as well as sectoral turnover and employment which we add as additional sector-specific macroeconomic controls. θ_i depict month fixed-effects,¹⁷ and we control for the Covid-19 pandemic by adding a forward dummy κ_{t+h} entering the model at the same horizon as the dependent variable.¹⁸

In order to discuss sector-specific heterogeneity in the responses of industrial production and producer prices to monetary policy shocks, we estimate sector-specific regressions for each of the NACE-2 subsectors following

$$y_{ic,t+h} - y_{ic,t-1} = \beta_{1,i}^h s_t + \sum_{l=0}^L \gamma^h \mathbf{H}_{t-l} + \sum_{l=1}^L \delta^h \mathbf{K}_{t-l} + \sum_{l=0}^L \eta^h \Delta \mathbf{X}_{t-l} + \theta_{t_{12}} + \kappa_{t+h} + \epsilon_{ic,t+h} \quad (11)$$

with $h = 1, 2, \dots, H$

$$\mathbf{H}_t = \begin{bmatrix} a_{ic,t_{12}} \\ \tilde{a}_{ic,t_{12}} \\ \tilde{\Lambda}_{ic,t_{12}} \end{bmatrix}, \mathbf{K}_t = \begin{bmatrix} \Delta y_{ic,t} \\ \lambda_{ic,t_{12}} \times s_t \\ a_{ic,t_{12}} \times s_t \\ \tilde{a}_{ic,t_{12}} \times s_t \\ s_t \end{bmatrix}$$

with the only difference to model 10 being that $\beta_{1,i}^h$ is now specific to the NACE-2 sector i taken up in the respective single-sector regression.

¹⁶Similarly 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.

¹⁷We only account for time fixed-effects as long-differencing eliminates entity fixed effects. We obtain identical results when estimating the model in levels including both month and country-sector fixed-effects. As shown in section 8, results are robust to other fixed-effects specifications.

¹⁸The 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.

5.2 Local projections with production network and financial constraints

Our main model specification explicitly accounts for the role of production networks and financial constraints in the transmission of monetary policy shocks. We estimate the following model

$$\begin{aligned}
 y_{ic,t+h} - y_{ic,t-1} = & \underbrace{\beta_1^h \lambda_{ic,t_{12}-1} \times s_t}_{\text{Direct financial constraints effect}} + \underbrace{\beta_2^h \Lambda_{ic,t_{12}-1} \times s_t}_{\text{Upstream effect}} + \underbrace{\beta_3^h \tilde{\Lambda}_{ic,t_{12}-1} \times s_t}_{\text{Downstream effect}} + \underbrace{\beta_4^h a_{ic,t_{12}-1} \times s_t + \beta_5^h \tilde{a}_{ic,t_{12}-1} \times s_t + \beta_6^h s_t}_{\text{Non-network effect}} \\
 & + \sum_{l=0}^L \gamma^h H_{t-l} + \sum_{l=1}^L \delta^h K_{t-l} + \sum_{l=0}^L \eta^h \Delta X_{t-l} + \theta_{t_{12}} + \kappa_{t+h} + \epsilon_{ic,t+h}
 \end{aligned} \tag{12}$$

with $h = 1, 2, \dots, H$

$$H_t = \begin{bmatrix} a_{ic,t_{12}} \\ \tilde{a}_{ic,t_{12}} \\ \lambda_{ic,t_{12}} \\ \Lambda_{ic,t_{12}} \\ \tilde{\Lambda}_{ic,t_{12}} \end{bmatrix}, K_t = \begin{bmatrix} \Delta y_{ic,t} \\ \lambda_{ic,t_{12}} \times s_t \\ a_{ic,t_{12}} \times s_t \\ \tilde{a}_{ic,t_{12}} \times s_t \\ \Lambda_{ic,t_{12}} \times s_t \\ \tilde{\Lambda}_{ic,t_{12}} \times s_t \\ s_t \end{bmatrix}$$

where $\lambda_{ic,t_{12}-1}$ refers again to the lag of the country-sector-specific measure of financial constraints¹⁹ sector i in country c was exposed to in the previous year.

We estimate model 12 to study the importance of nonlinear interactions between production networks and financial constraints for the overall transmission of monetary policy shocks s_t .²⁰ In our model, the full shock impact is determined by the sum of three separate transmission channels. First, we account for a “direct financial constraints” channel captured by the coefficient β_1^h on the interaction of the monetary policy shock s_t with the respective sector’s level of financial constraints as measured by $\lambda_{ic,t}$. This channel can be interpreted as a sector-level representation

¹⁹In the rest of the paper we test different measures of financial constraints, as discussed below in more detail.

²⁰While model 12 is specified in long-differences, we obtain identical results as shown in section 6 when estimating the model in levels.

of the traditional balance sheet channel (Bernanke and Gertler, 1995) affecting a sectors’ own borrowing capacities.

We then identify an additional “indirect financial constraints” 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 constraints measures $\Lambda_{ic,t_{12}}$ and $\tilde{\Lambda}_{ic,t_{12}}$ derived in section 4 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 constraints measure. This approach also allows us to disentangle the overall “indirect financial constraints channel” explicitly into downstream (β_2^h) and upstream (β_3^h) financial constraints 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 $a_{ic,t}$, the share of production sold to final customers outside the network as given by equation 2 (β_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 $\tilde{a}_{ic,t}$, the share of production inputs purchased by sector i from outside the network, as given by equation 1 (β_5^h). Finally, coefficient β_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 constraints and the broader production network.²¹ In the main results presented in section 6.2, we refer to coefficients β_4^h to β_6^h jointly as “non-network effects”.

In the full model, 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. As for the simple baseline model of section 5.1, 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 contemporaneous values and lags of the same set of macroeconomic control variables reported in the previous subsection, and θ_i and κ_{t+h} again depict month fixed-effects and the Covid-19 forward dummy, respectively.

²¹Such 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.

6 Results

In section 6.1, we report results for the simple baseline model presented in section 5.1 before discussing our main findings on the role of production networks and financial constraints obtained with the full model presented in section 5.2 in results section 6.2. We show results using total leverage as our financial constraint measure of interest, $\lambda_{ic,t_{12}-1}$, and we ensure consistency in units between $\lambda_{ic,t_{12}-1}$, $\Lambda_{ic,t_{12}-1}$, $\tilde{\Lambda}_{ic,t_{12}-1}$, $a_{ic,t_{12}-1}$ and $\tilde{a}_{ic,t_{12}-1}$ by subtracting the population mean from observations, and by scaling the beta coefficients of the interaction terms such that a one-unit change as measured by the coefficients refers to a 10 percent deviation of leverage from the mean. 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.²² We use cluster-robust standard errors in all specifications by clustering at the country-sector level.²³

6.1 Baseline model results

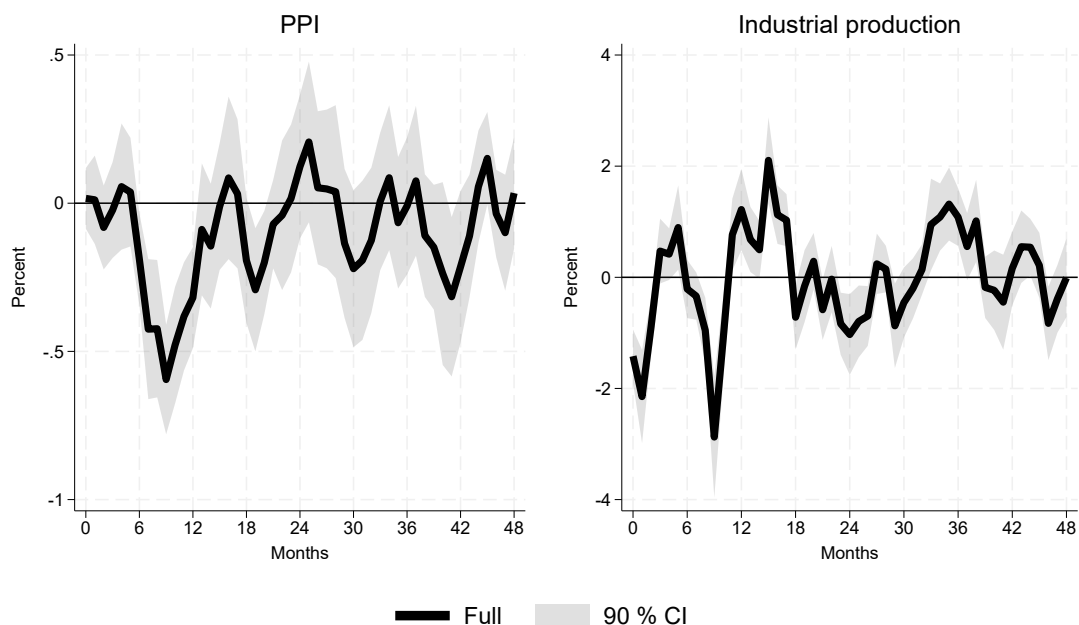
Figure 5 shows the impulse responses for producer prices and industrial production obtained from estimating model 10. Both prices and output drop within the first year after the shock, with the trough impact of the shock on prices implying a decline by 0.5 percent, while industrial production declines by approx. 3 percent in response to a 25bp peak monetary policy tightening shock. Both sector-specific producer prices and production return to the baseline level after approximately 12 months.

Figure 6 reveals a substantial degree of heterogeneity in the sector-specific responses to a monetary policy shock. Overall, the size of trough effects (y-axes in figure 6), the timing at which the trough is reached (x-axes in figure 6), and the persistence with which the monetary policy effect materializes (bubble size in figure 6) differ substantially across sub-sectors and for prices and output. While the trough impact of a monetary policy shock on producer prices (left panel) falls within zero to

²²See appendix section A for details on the scaling routine.

²³Following 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. However, we report estimates using the Driscoll and Kraay (1998) standard errors in section 8.

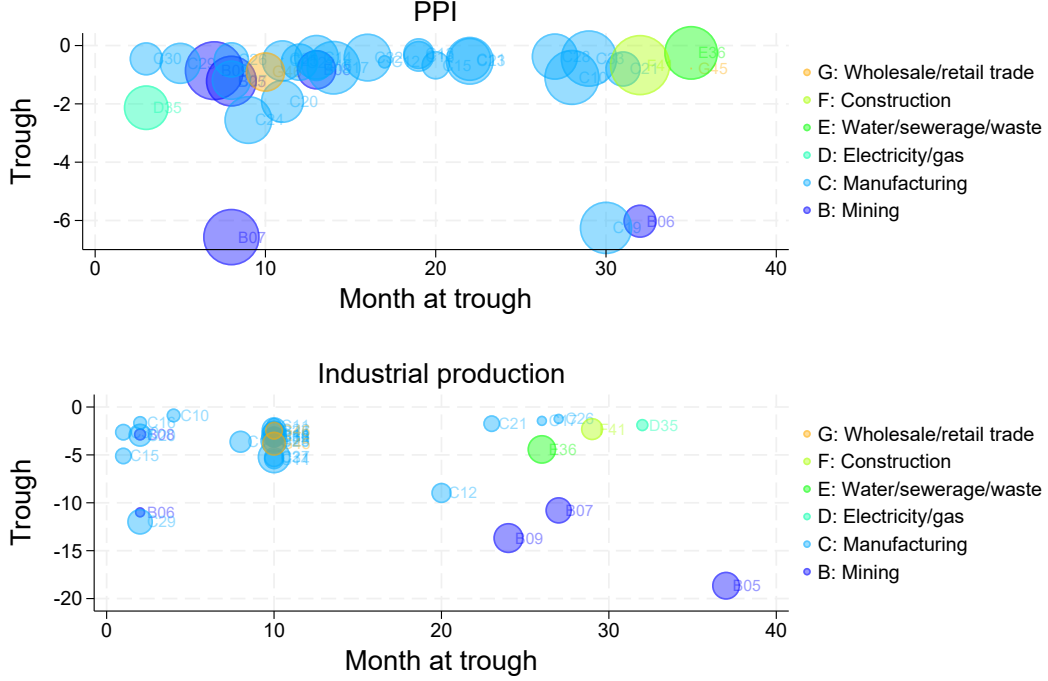
Figure 5: Impulse responses to monetary policy tightening shock - baseline model



Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 10 estimated on the full country-sector euro area panel with cluster-robust standard errors.

two percent for most sectors, a few sectors in the mining (B) and manufacturing (C) industries see prices dropping by up to 6-8 percent in response to a 25bp monetary policy tightening shock. In particular, prices drop substantially in response to a tightening shock for crude oil and natural gas extraction (B06), the mining of metal ores (B07), and relatedly, the manufacturing of coke and refined petroleum products (C19). Regarding industrial production (right panel of figure 6), the trough impact is again particularly pronounced for crude oil and gas extraction (B06), the mining of metal ores (B07), and related support service activities (B09), with trough effects of more than 10 percent. On the manufacturing side, the production of tobacco products (C12) and motor vehicles (C29) drop by more than 10 percent at the trough, with the drop in tobacco output occurring only two months after the shock.

Figure 6: Sector-specific impulse responses to monetary policy tightening shock - baseline model



Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 11 estimated on each individual country-sector with cluster-robust standard errors.

6.2 The importance of production networks and financial constraints

In the following, we discuss results for estimating the complete model 12 allowing for network and financial constraints nonlinearities. As shown in figure 7, both PPIs and production fall in response to a monetary policy tightening shock as in the case of the simple model of section 10. However, the declines in prices and output are quantitatively more pronounced and occur later for PPIs when allowing for network-financial constraints interactions, compared to results obtained in the baseline model 10 reported in figure 5, highlighting the importance of considering nonlinear effects stemming from production networks and financial constraints. For PPIs, the average effect of a monetary policy shock, i.e. with all financial constraints measures at the mean (black line in the LHS panel of figure 7), amounts to a trough decline of 1.2 percent almost 3 years after the shock. In addition, the blue line in figure 7 reports the *additional* overall effect of an increase in all financial constraints measures derived using total leverage by 10 percent above the mean, as measured by the linear

combination of coefficients β_1^h , β_2^h , and β_3^h . At the trough, the additional dampening effect of a monetary policy shock due to a 10 percent increase of financial constraints amounts to approximately 0.6 percent. The average decline in production stands at approximately 4 percent 9 months after the shock (black line in the RHS panel of figure 7), with an additional significant dampening effect of the monetary policy shock due to financial constraints materializing after approximately 2 years (blue line in the RHS panel of figure 7).

In addition to impulse responses, we follow [Jordà and Taylor \(2024\)](#) and report results of a joint significance test in figure 7, with the null hypothesis given by

$$H_0 : \mathcal{R}(h) \equiv E[y_{ic,t+h}|s_t; \mathbf{x}_t] - E[y_{ic,t+h}|\mathbf{x}_t] = 0 \quad (13)$$

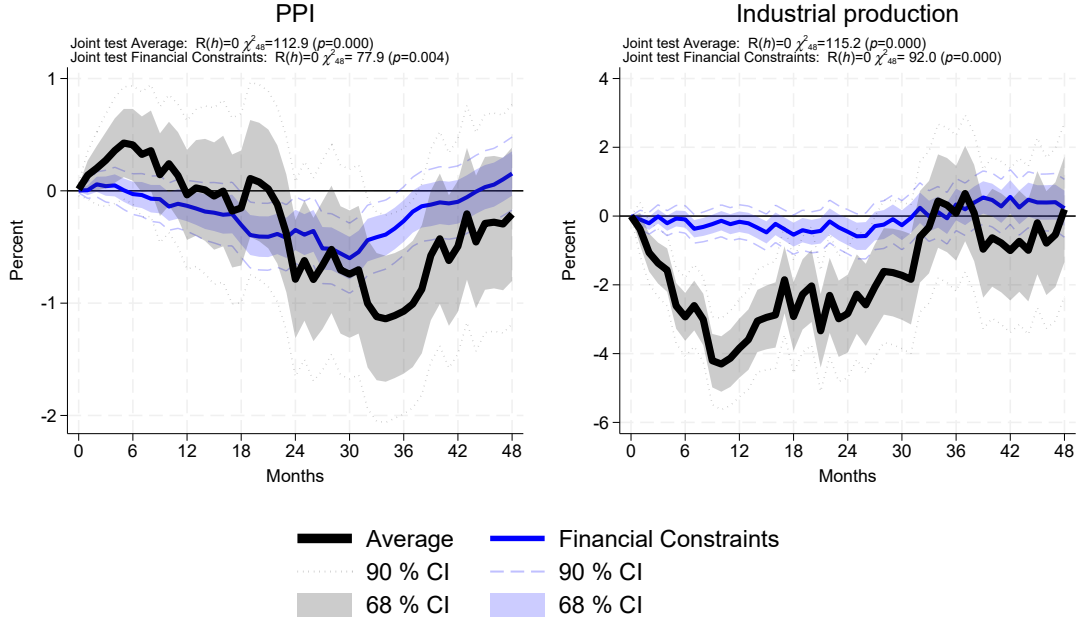
where \mathbf{x}_t denotes a matrix of exogenous and predetermined variables. Stating the joint hypothesis test in terms of the regression coefficients in figure 7, the null hypothesis can be expressed as

$$H_0 : \check{\beta}^0 = \dots = \check{\beta}^H = 0 \quad (14)$$

with $\check{\beta}^h$ referring to the linear combination of regression coefficients under consideration evaluated at horizon h . Results for the joint hypothesis tests indicate that the null hypothesis can be rejected for all impulse responses, i.e. that responses for average and financial constraints effects of a monetary policy shock on PPIs and industrial production are different from zero for at least one horizon $h \in H$.

Figure 8 decomposes the overall financial constraints effect reported in blue in figure 7 into the direct financial constraints effect related to the interaction of the monetary policy shock with the respective sector's own level of total leverage (as measured by β_1^h in equation 12), and the indirect effect of financial constraints in the transmission of monetary policy shocks (as measured by the linear combination of β_2^h and β_3^h in equation 12). Figure 8 shows that both direct and indirect financial constraints significantly dampen PPIs 2.5 years after the shock (green and brown lines in LHS panel), with direct effects explaining the larger share of overall financial constraints effects. However, the share of indirect effects in total financial constraints effects is only marginally smaller than the direct effect for PPIs, and both effects' shares broadly balance for industrial production (RHS panel in figure 8), where the trough impact of both direct and indirect financial constraints is reached after around 2 years.

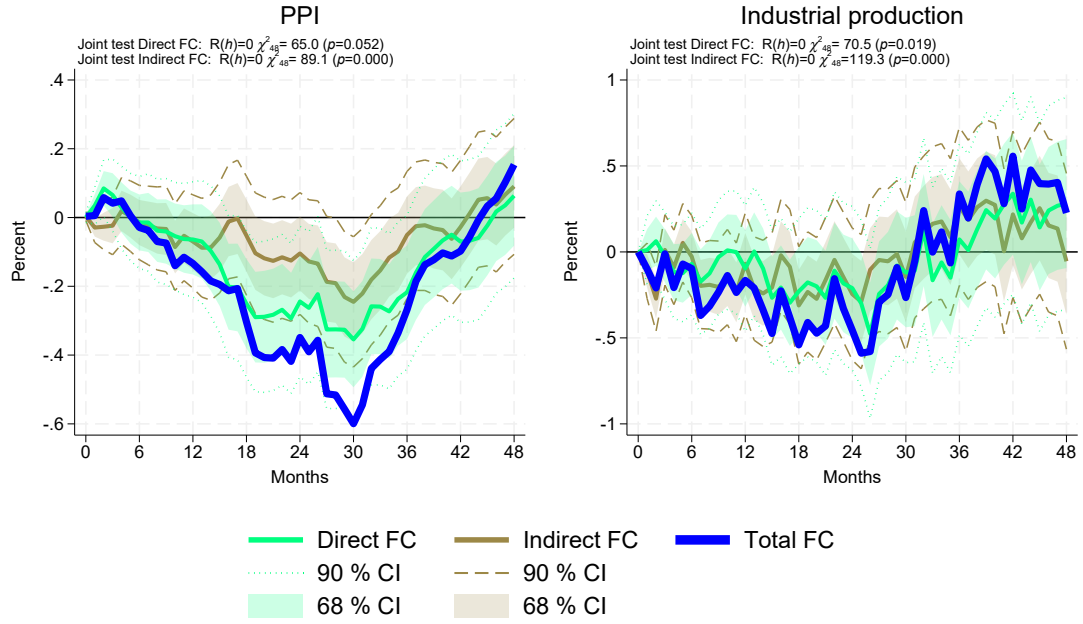
Figure 7: Impulse responses to monetary policy tightening shock



Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

Finally, figure 9 provides a breakdown of the indirect financial constraints effects reported by the brown lines in figure 8 into up- and downstream financial constraints (as measured by β_2^h and β_3^h in equation 12, respectively). While downstream financial constraints seem to reinforce the decline in prices and output following a monetary policy tightening shock (pink lines in figure 9), upstream constraints tend to partly mitigate these effects (green lines in figure 9). In particular, the overall drop in prices associated to the interaction of the monetary policy shock and indirect financial constraints (brown line LHS panel of figure 9) can be largely attributed to downstream financial constraints, while the impulse response function associated to the upstream financial constraints interaction term remains positive for most of the horizon. Similarly, downstream financial constraints seem to amplify the drop in industrial production two years after the shock (pink line RHS panel of figure 9), while upstream financial constraints seem to counteract this additional drop to some extent over the same horizon (green line RHS panel of figure 9). Results thus indicate that a tightening of financial constraints 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

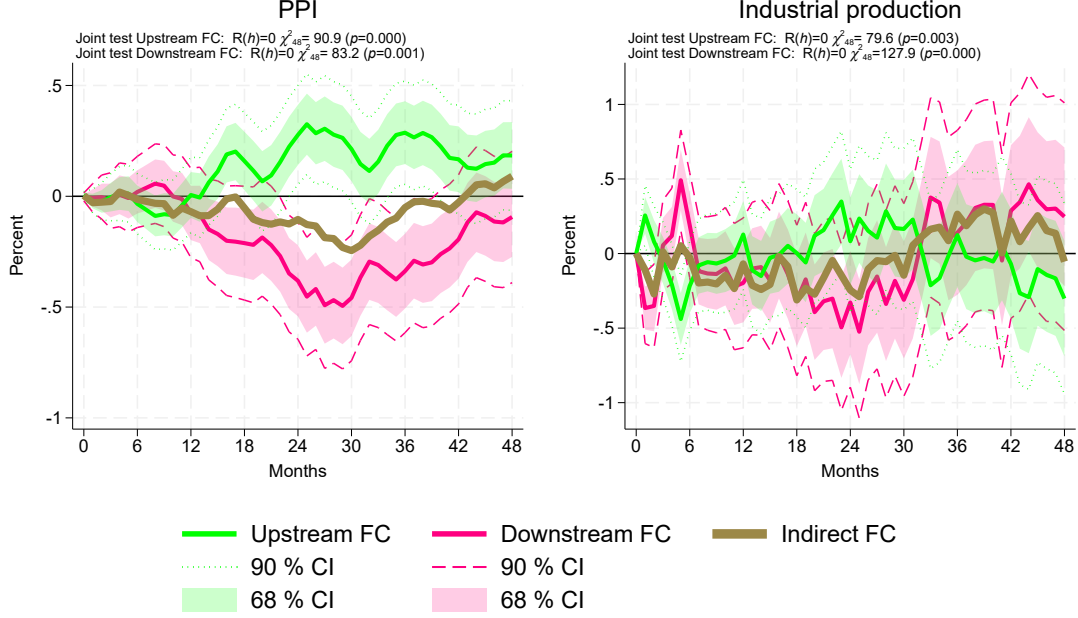
Figure 8: Impulse responses to monetary policy tightening shock - direct vs. indirect financial constraints effects



Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

and/or gain market share to alleviate financial constraints (in line with a sector-specific “cost channel”).

Figure 9: Impulse responses to monetary policy tightening shock - direct vs. indirect financial constraints 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 12 estimated on the full country-sector euro area panel.

7 Theoretical model

In this section, we derive a simple model for a canonical multi-sector economy with intersectoral flows and financial constraints to validate our empirically derived financial constraints measures and to discuss the underlying mechanism of the empirically identified cost-channel dynamics. The model broadly represents a simplified version of the framework developed in Acemoglu et al. (2012) and Bigio and La'O (2020), which we extend by incorporating a specific sector-specific financial constraints parameter, which allows us to derive model-based cross-sectoral financial constraints measures resembling the empirical measures derived in equations 8 and 9. Importantly, the modeling choice regarding the financial frictions parameter allows for a generic interpretation the underlying source of the friction, and nests the set of different empirical measures reported in table 3. The model is static and only features two agents: firms and households.

7.1 The model economy

Firms

There is a continuum of firms in each sector. The production technology is identical for firms within the same sector but heterogeneous across sectors. The production of firm i in sector k is a constant returns-to-scale Cobb-Douglas technology given by

$$y_{k,i} = z_k l_{k,i}^{\alpha_k} x_{k,i}^{1-\alpha_k},$$

where $y_{k,i}$ is the firm's output, $l_{k,i}$ its labor, and $x_{k,i}$ is a composite of the firm's intermediate inputs. The parameter α_k denotes the sector-specific labor share and z_k is a sector-specific productivity shock. As in Ghassibe (2021), the firm's intermediate goods basket is a Cobb-Douglas composite given by

$$x_{k,i} = \prod_{r \in K} \omega_{kr}^{-\omega_{kr}} x_{kr,i}^{\omega_{kr}}$$

where $x_{kr,i}$ is the amount it purchases of the sectoral commodity r , ω_{kr} denotes the share of good r in this composite.

Each firm in sector k needs to finance portion φ_k of its working capital. On this fraction, the firm needs to pay interest.²⁴ Profits of sector firm k in sector i are given by

$$\begin{aligned} \pi_{k,i} &= p_{k,i} y_{k,i} - \left(l_{ik} + \sum_{r \in K} p_r x_{kr,i} \right) - i_t \times \varphi_k \left(l_{ik} + \sum_{r \in K} p_r x_{kr,i} \right) \\ &\rightarrow \pi_{k,i} = p_{k,i} y_{k,i} - (1 + i_t \varphi_k) \left(l_{ik} + \sum_{r \in K} p_r x_{kr,i} \right) \end{aligned}$$

where $p_{k,i}$ is its own output price, and p_r is the price at which it purchases input $x_{kr,i}$. We set labor as the numeraire input, thereby normalizing the wage rate to one.

²⁴Alternatively, one could interpret φ_k as a sector-specific interest rate shifter, i.e. as an exogenous shock to the interest rate the firm has to pay on its working capital. While such a disturbance may be due to both aggregate shocks (i.e. stemming from unexpected changes in monetary policy) or idiosyncratic sectoral shocks (e.g. changes in investor risk perception towards specific sectors), we treat the source of variation in φ_k as exogenously determined here.

Firms within a sector are monopolistically competitive. Within each sector k , we assume there is a producer aggregating sectoral goods according to the following CES production function with elasticity of substitution θ_k :

$$y_k = \left[\int y_{k,i}^{\frac{\theta_k-1}{\theta_k}} dk \right]^{\frac{\theta_k}{\theta_k-1}}$$

This aggregator firm acts under perfect competition, i.e., it takes all prices as given and maximizes profits, which are given by

$$\pi_k = p_k y_k - \int p_{k,i} y_{k,i} di,$$

where p_k is the price of good k . We include this aggregator firm, which adds zero value and makes zero profits, for exposition only: it ensures that a homogeneous good is produced by each industry while at the same time allowing for monopolistic competition among firms within the industry.

Problem of the aggregator firm

The problem of the aggregator firm is given by maximizing profits following

$$\max_{\{y_{k,i}\}_{i \in I}} \pi_k = p_k y_k - \int p_{k,i} y_{k,i} di,$$

subject to the production function:

$$y_k = \left[\int y_{k,i}^{\frac{\theta_k-1}{\theta_k}} dk \right]^{\frac{\theta_k}{\theta_k-1}}$$

The solution to this problem yields the following sectoral demand functions:

$$y_{k,i} = \left[\frac{p_{k,i}}{p_k} \right]^{-\theta_k} y_k$$

with the price index for sector k being given by:

$$p_k = \left(\int p_{k,i}^{1-\theta_k} di \right)^{\frac{1}{1-\theta_k}}$$

Problem of the monopolistically competitive firm

The monopolistically competitive firm i in sector k maximizes profits

$$\pi_{k,i} = p_{k,i} y_{k,i} - (1 + i_t \varphi_k) (l_{ik} + P^k x_{k,i})$$

subject to its production technology

$$y_{k,i} = z_k l_{k,i}^{\alpha_k} x_{k,i}^{1-\alpha_k}, \quad x_{k,i} = \prod_{r \in K} \omega_{kr}^{-\omega_{kr}} x_{kr,i}^{\omega_{kr}}$$

and subject to the demand for its input:

$$y_{k,i} = \left[\frac{p_{k,i}}{p_k} \right]^{-\theta_k} y_k$$

and taking the price of inputs as given, with P^k being the aggregate price for intermediate inputs, which we derive below as a result of the firm's optimization problem.

The firm's problem can be split into two parts. First, the firm solves an *outer problem* to maximize profits, given by

$$\pi_{k,i} = \max_{\{y_{k,i}, p_{k,i}\}} p_{k,i} y_{k,i} - (1 + i_t \varphi_k) mc_{k,i} y_{k,i}$$

subject to the firm's demand function

$$y_{k,i} = \left[\frac{p_{k,i}}{p_k} \right]^{-\theta_k} y_k$$

where $mc_{k,i}$ is the firm's marginal cost of producing goods $y_{k,i}$. Substituting in the firm's demand function, this problem reduces to

$$\max_{\{y_{k,i}, p_{k,i}\}} p_{k,i} \left[\frac{p_{k,i}}{p_k} \right]^{-\theta_k} y_k - (1 + i_t \varphi_k) mc_{k,i} y_{k,i}$$

or

$$\max_{\{y_{k,i}\}} p_k \left[\frac{y_{k,i}}{y_k} \right]^{-\frac{1}{\theta_k}} y_{k,i} - (1 + i_t \varphi_k) mc_{k,i} y_{k,i}$$

Solving the optimization problem yields the following optimality condition:

$$\frac{\theta_k - 1}{\theta_k} \left(\frac{y_{k,i}}{y_k} \right)^{-\frac{1}{\theta_k}} p_k = (1 + i_t \varphi_k) mc_{k,i}$$

By symmetry of all firms within the sector, we obtain

$$\frac{\theta_k - 1}{\theta_k} p_k = (1 + i_t \varphi_k) mc_k$$

with the price in sector k being determined by a markup on the marginal cost of sector k including the financing cost φ_k .

Second, the *inner problem* of the firm is given by a dual a cost minimization problem determining the firms marginal cost function. First, the firm minimizes

$$mc_{k,i} y_{k,i} = \min_{\{l_{k,i}, x_{k,i}\}} l_{k,i} + P^k x_{k,i}$$

subject to the firm's production function

$$y_{k,i} = z_k l_{k,i}^{\alpha_k} x_{k,i}^{1-\alpha_k},$$

The first-order conditions of this problem with respect to $x_{kr,i}$ and $l_{k,i}$ are given by

$$P^k = \lambda_{k,i} (1 - \alpha_k) \frac{y_{k,i}}{x_{k,i}},$$

$$1 = \lambda_{k,i} \alpha_k \frac{y_{k,i}}{l_{k,i}},$$

Hence

$$\frac{l_{k,i}}{x_{k,i}} = \frac{(1 - \alpha_k)}{\alpha_k} \frac{1}{P^k},$$

Using the expression above for total expenditure, we obtain:

$$mc_{k,i} y_{k,i} = l_{k,i} + P^k x_{k,i} = \lambda_{k,i} \alpha_k y_{k,i} + \lambda_{k,i} (1 - \alpha_k) y_{k,i} = \lambda_{k,i} y_{k,i}$$

where the last step obtains because $\sum_{r \in K} \omega_{kj} = 1 \forall k$. Hence $\lambda_{k,i} = mc_{k,i}$.

Substituting the optimal labour and intermediate good input, one obtains

$$mc_{k,i} \equiv mc_k = \frac{(1 - \alpha_k)^{\alpha_k - 1}}{\alpha_k^{\alpha_k}} (P^k)^{1 - \alpha_k},$$

where we have dropped the index i because of symmetry across firms in a specific sector.

Finally, the firm decides on the mix of intermediate inputs in order to minimize:

$$P^k x_{k,i} = \sum_{r \in K} p_r x_{kr,i},$$

subject to

$$x_{k,i} = \prod_{r \in K} \omega_{kr}^{-\omega_{kr}} x_{kr,i}^{\omega_{kr}},$$

This leads to the following expression for the input price mix

$$P^k = \prod_{r \in K} p_r^{\omega_{k,r}},$$

Partial equilibrium relations Using the expression for the input price index for sector k , we obtain

$$mc_k = \frac{(1 - \alpha_k)^{\alpha_k - 1}}{\alpha_k^{\alpha_k}} \left(\prod_{r \in K} p_r^{\omega_{k,r}} \right)^{1 - \alpha_k},$$

Using the profit maximizing condition for firm k yields

$$\frac{\theta_k - 1}{\theta_k} p_k / (1 + i_t \varphi_k) = mc_k = \frac{(1 - \alpha_k)^{\alpha_k - 1}}{\alpha_k^{\alpha_k}} \left(\prod_{r \in K} p_r^{\omega_{k,r}} \right)^{1 - \alpha_k},$$

$$p_k = (1 + i_t \varphi_k) \frac{\theta_k}{\theta_k - 1} \frac{(1 - \alpha_k)^{\alpha_k - 1}}{\alpha_k^{\alpha_k}} \left(\prod_{r \in K} p_r^{\omega_{k,r}} \right)^{1 - \alpha_k},$$

Combining with the profit maximizing relation for all r suppliers of sector k gives

$$p_k = (1 + i_t \varphi_k) \frac{\theta_k}{\theta_k - 1} \frac{(1 - \alpha_k)^{\alpha_k - 1}}{\alpha_k^{\alpha_k}} \left(\prod_{r \in K} \left(\frac{\theta_r}{\theta_r - 1} (1 + i_t \varphi_r) mc_r \right)^{\omega_{k,r}} \right)^{1 - \alpha_k},$$

To simplify the interpretation of this equation, we take the logarithm of this expression:

$$\begin{aligned} \log(p_k) &= \log(1 + i_t \varphi_k) + \log(\theta_k) - \log(\theta_k - 1) + (\alpha_k - 1) \log(1 - \alpha_k) - \alpha_k \log(\alpha_k) \\ &+ (1 - \alpha_k) \left(\sum_{r \in K} \omega_{k,r} \log \left(\frac{\theta_r}{\theta_r - 1} \right) + \sum_{r \in K} \omega_{k,r} \log(1 + i_t \varphi_r) + \sum_{r \in K} \omega_{k,r} \log(mc_r) \right) \end{aligned}$$

Taking the derivative of this expression with respect to i_t yields:

$$\frac{d}{di_t} \log(p_k) = \frac{\varphi_k}{1 + i_t \varphi_k} + (1 - \alpha_k) \sum_{r \in K} \omega_{k,r} \frac{\varphi_r}{1 + i_t \varphi_r} + (1 - \alpha_k) \sum_{r \in K} \omega_{k,r} \frac{mc'_r(i_t)}{mc_r(i_t)}$$

Finally, using the logarithm approximation for $\log(1 + i_t \varphi_r)$, we obtain

$$\frac{d}{di_t} \log(p_k) \approx \varphi_k + (1 - \alpha_k) \sum_{r \in K} \omega_{k,r} \varphi_r + (1 - \alpha_k) \sum_{r \in K} \omega_{k,r} \frac{mc'_r(i_t)}{mc_r(i_t)} \quad (15)$$

The first term (φ_k) on the right hand side corresponds to the model-based counterpart of our empirical measures for the degree of financial tightness in the firm's own sector, with the latter given by the λ_{ic} terms in equations 8, 9 and 12. The second term $((1 - \alpha_k) \sum_{r \in K} \omega_{k,r} \varphi_r + (1 - \alpha_k) \sum_{r \in K} \omega_{k,r} \frac{mc'_r(i_t)}{mc_r(i_t)})$ instead, corresponds to the upstream financial constraints exposure given by the Λ_{ic} terms in the empirical specification. Intuitively, equation 15 shows that while keeping the marginal costs in other sectors fixed, an increase in the interest rate will have a direct effect on the price in sector k through sector k 's own financial constraints (φ_k). Interest payment increase for sector k , and an indirect effect stemming from suppliers' financial constraints, which increase prices due to the marginal increase in financing costs for an additional unit of production. The latter effect depends on sector k 's unput purchases from other sectors: sectors using only labor as input will only be exposed to interest rate changes through own leverage φ_k .

Households

This block straightforwardly follows the framework laid out in [Bigio and La'O \(2020\)](#). Preferences of the representative household are given by

$$\max U(C) - V(L)$$

where C is its final consumption basket and L its labor supply. We assume the following regularity conditions: U and V are twice differentiable with

$$U' > 0, \quad V' > 0, \quad U'' < 0,$$

and satisfy the Inada conditions. The final consumption basket is a Cobb-Douglas composite of the sectoral goods:

$$C = \prod_{k \in K} c_k^{v_k}, \quad \sum_{k=1}^K v_k = 1$$

s.t.

$$\sum_{k \in K} p_k c_k \leq L + \sum_{k \in K} \left[\int \pi_{k,i} di + \pi_k \right] + T$$

Market clearing and distortions

While closely following [Bigio and La'O \(2020\)](#), we adjust market clearing conditions to incorporate the financial constraints parameter applied to interest rate payments carried out by monopolistically competitive firms in each sector. We allow for a sector-specific proportion δ_k of these payments to be wasted.

$$\begin{aligned}
 h_k &= \delta_k \varphi_k i_t \int \left(l_{k,i} + \sum_{j \in K} p_j x_{kr,i} \right) di \\
 T &= \sum_{k \in K} (1 - \delta_k) \varphi_i \int \left(l_{k,i} + \sum_{j \in K} p_j x_{kr,i} \right) di \\
 y_k &= c_k + h_k + \sum_{j \in K} x_{j,k} \\
 L &= \sum_{k \in K} l_k, \quad l_k = \int l_{k,i} di
 \end{aligned}$$

7.2 Comparative statics

XXX TO BE ADDED XXX

8 Robustness checks

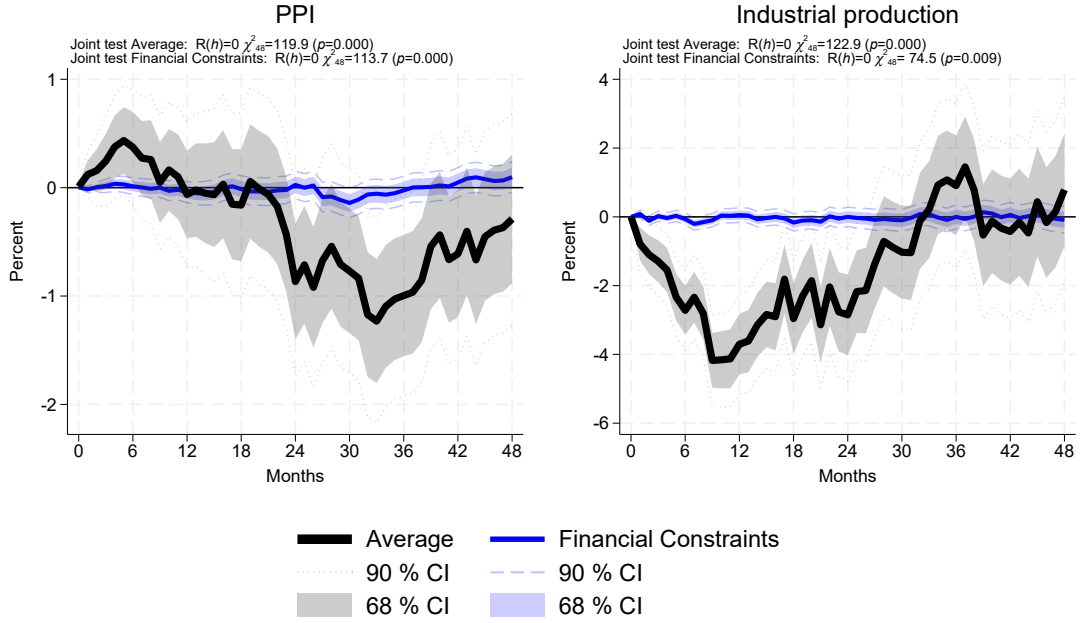
In the following, we provide robustness checks to the results obtained with empirical model presented in section 6.2. We particularly assess the robustness of our main empirical results in figures 7 to 9 to using different specifications of financial constraints measures listed in table 3, and across using input-output weights (matrices 4 and 5) or Leontief and Gosh inverses (matrices 6 and 7).

8.1 Financial constraints measures

In this section, we show that our results remain broadly robust when using alternative empirical financial constraints measures for λ in equations 8, 9, and 12. Figures 10 to 12 show the same set of impulse response as depicted in figures 7 to 9 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 3). 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 upward price effects stemming from upstream financial constraints playing out significantly slightly later (figures 9 vs. 12). At the same time, significance when separating direct from indirect effects turns out lower when using the working capital share, also indicated by the fact that the joint null hypothesis cannot be rejected for PPI and industrial production (figures 8 vs 11).

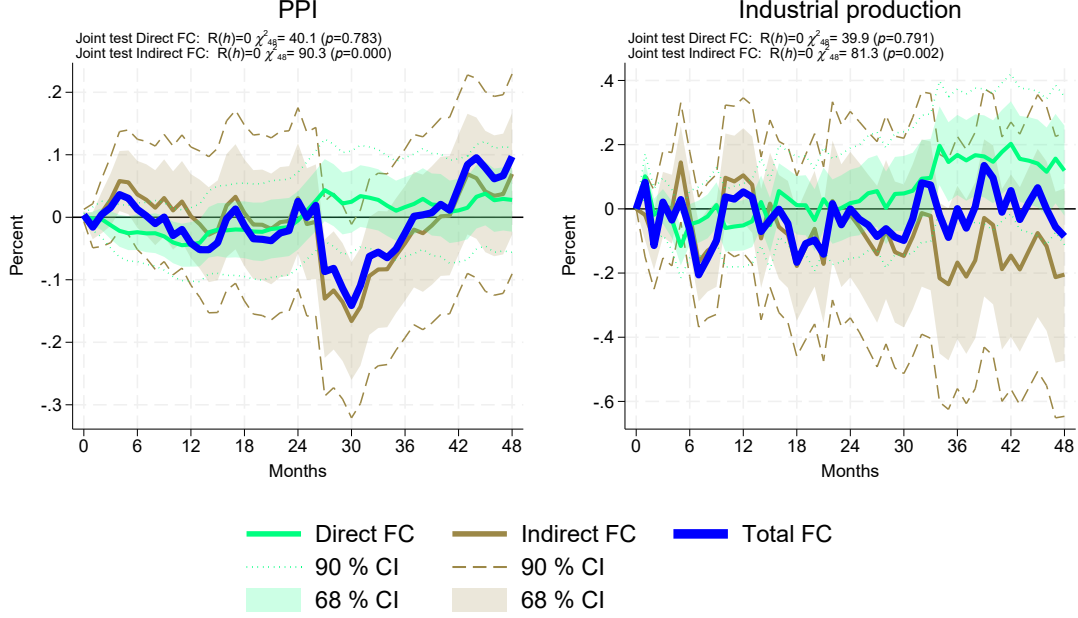
Figure 10: Impulse responses to monetary policy tightening shock - working capital



Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

We also test for differences in aggregating firm-level data on financial constraints measures to the sectoral level. While main results in figures 7 to 9 were derived using sales-based weighted averages of firm level data to generate sectoral measures, figures 13 to 15 show the same set of results when sectoral levels of total leverage reflect the median firm's leverage holdings. While results remain broadly consistent, the trough effect of the average monetary policy shock on PPIs turns out stronger than in the main results (figure 13), and an upward drift in the direct financial constraints effect plays out over the latter part of the projection horizon (figure 14).

Figure 11: Impulse responses to monetary policy tightening shock - direct vs. indirect financial constraints 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 12 estimated on the full country-sector euro area panel.

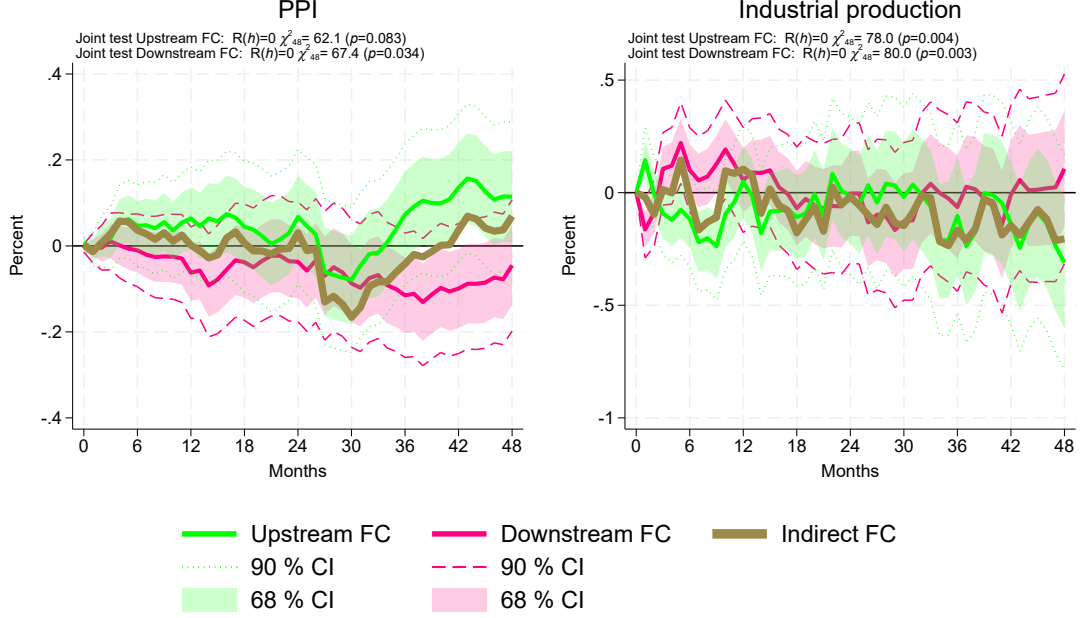
8.2 Production network measures

XXX TO BE ADDED XXX

8.3 Model specification

We also assess the robustness of our results across different specifications of the model, beyond the choice of financial constraints measures and the representation of input-output linkages. First, we assess whether estimating the model in level terms instead of long-differences. The level variant of the long-difference model 12 is given by:

Figure 12: Impulse responses to monetary policy tightening shock - upstream vs. downstream financial constraints effects - working capital



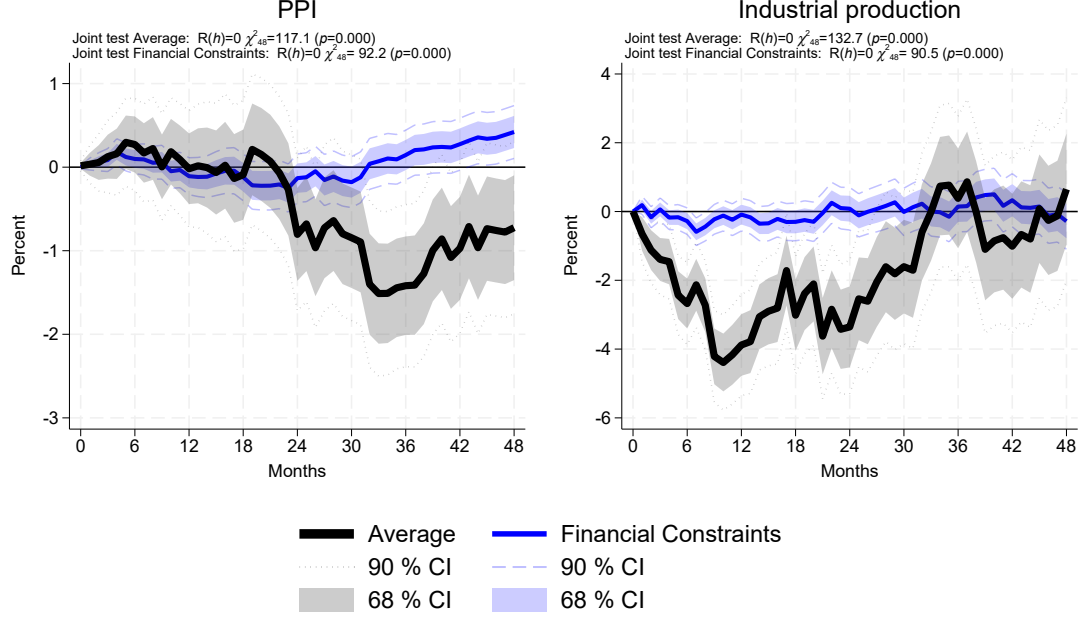
Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

$$\begin{aligned}
y_{ic,t+h} = & \underbrace{\beta_1^h \lambda_{ic,t_{12}-1} \times s_t}_{\text{Direct financial constraints effect}} + \underbrace{\beta_2^h \Lambda_{ic,t_{12}-1} \times s_t + \beta_3^h \tilde{\Lambda}_{ic,t_{12}-1} \times s_t}_{\text{Indirect financial constraints effect}} + \\
& \underbrace{\beta_4^h a_{ic,t_{12}-1} \times s_t + \beta_5^h \tilde{a}_{ic,t_{12}-1} \times s_t + \beta_6^h s_t}_{\text{Non-network effect}} \\
& + \sum_{l=0}^L \gamma^h H_{t-l} + \sum_{l=1}^L \delta^h K_{t-l} + \sum_{l=0}^L \eta^h X_{t-l} + \phi_{ic} + \theta_{t_{12}} + \kappa_{t+h} + \epsilon_{ic,t+h}
\end{aligned} \tag{16}$$

with $h = 1, 2, \dots, H$

$$H_t = \begin{bmatrix} a_{ic,t_{12}} \\ \tilde{a}_{ic,t_{12}} \\ \lambda_{ic,t_{12}} \\ \Lambda_{ic,t_{12}} \\ \tilde{\Lambda}_{ic,t_{12}} \end{bmatrix}, K_t = \begin{bmatrix} y_{ic,t} \\ \lambda_{ic,t_{12}} \times s_t \\ a_{ic,t_{12}} \times s_t \\ \tilde{a}_{ic,t_{12}} \times s_t \\ \Lambda_{ic,t_{12}} \times s_t \\ \tilde{\Lambda}_{ic,t_{12}} \times s_t \\ s_t \end{bmatrix}$$

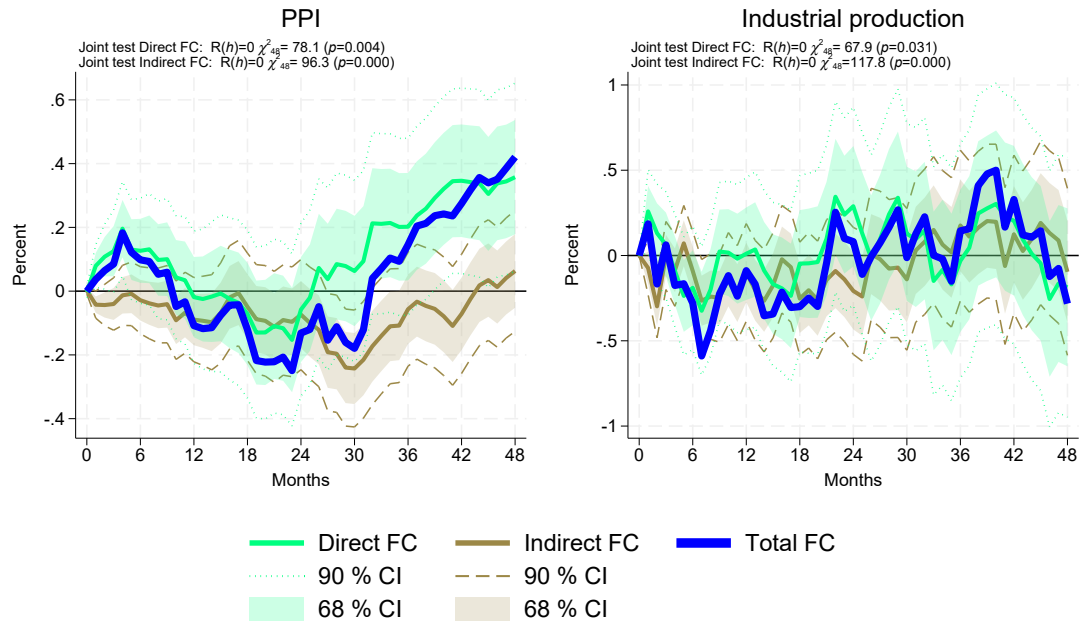
Figure 13: Impulse responses to monetary policy tightening shock - median level of sectoral total leverage



Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

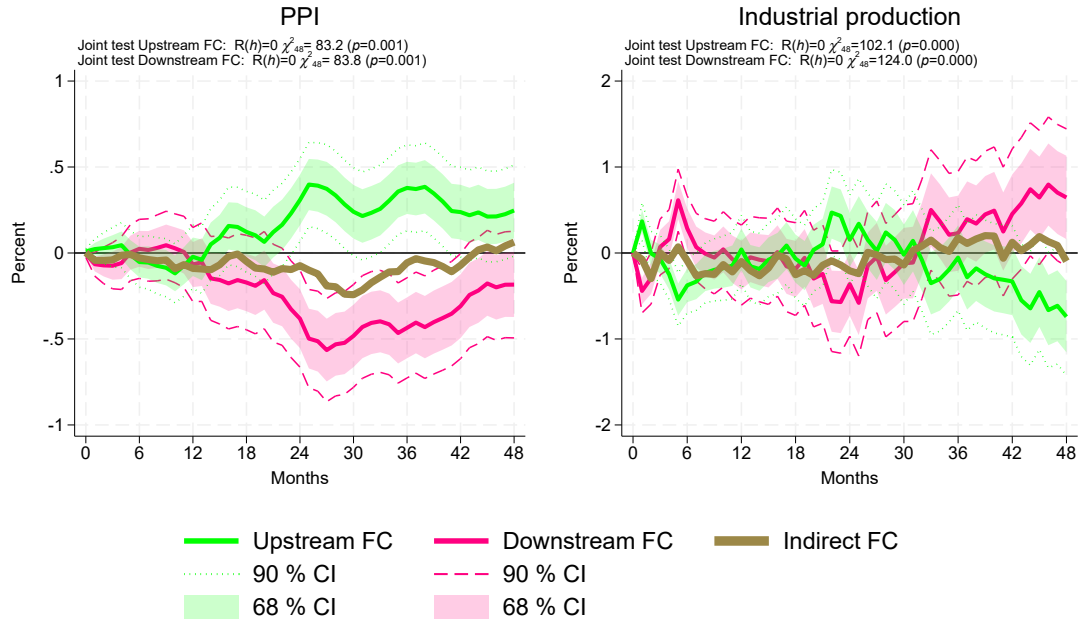
Compared to the long-difference variant, we include country-sector fixed effects ϕ_{ic} , which are not present in the differenced version of the model. Jordà and Taylor (2024) suggest using long-differences to mitigate concerns regarding small sample biases, and comparing results in figures 16 to 18 with our main results in figures 7 to 9 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 - direct vs. indirect financial constraints effects - median level of sectoral total leverage



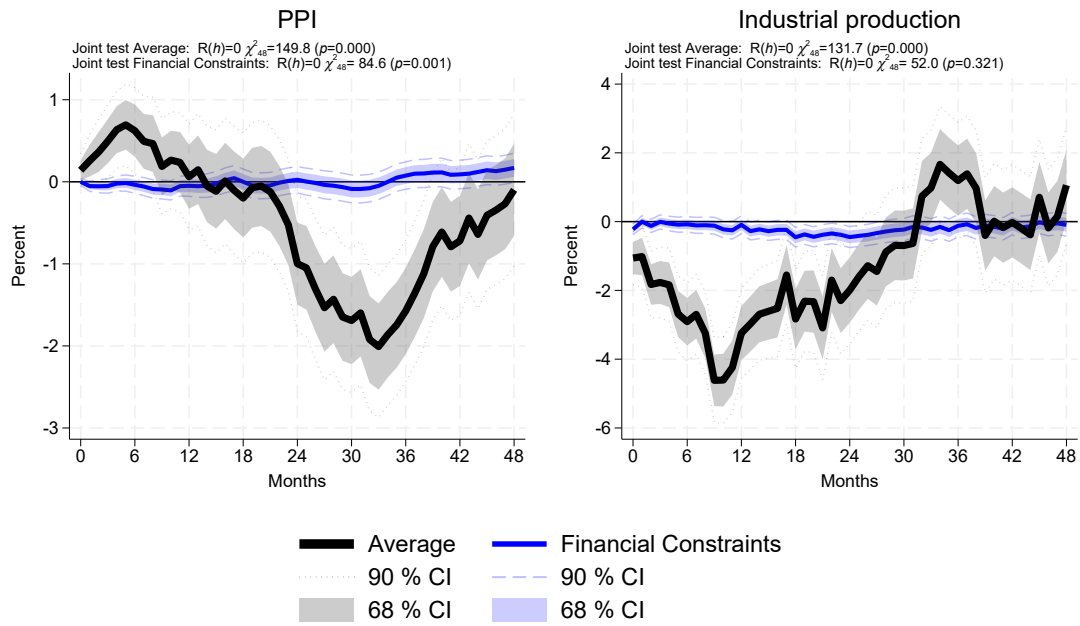
Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

Figure 15: Impulse responses to monetary policy tightening shock - upstream vs. downstream financial constraints effects - median level of sectoral total leverage



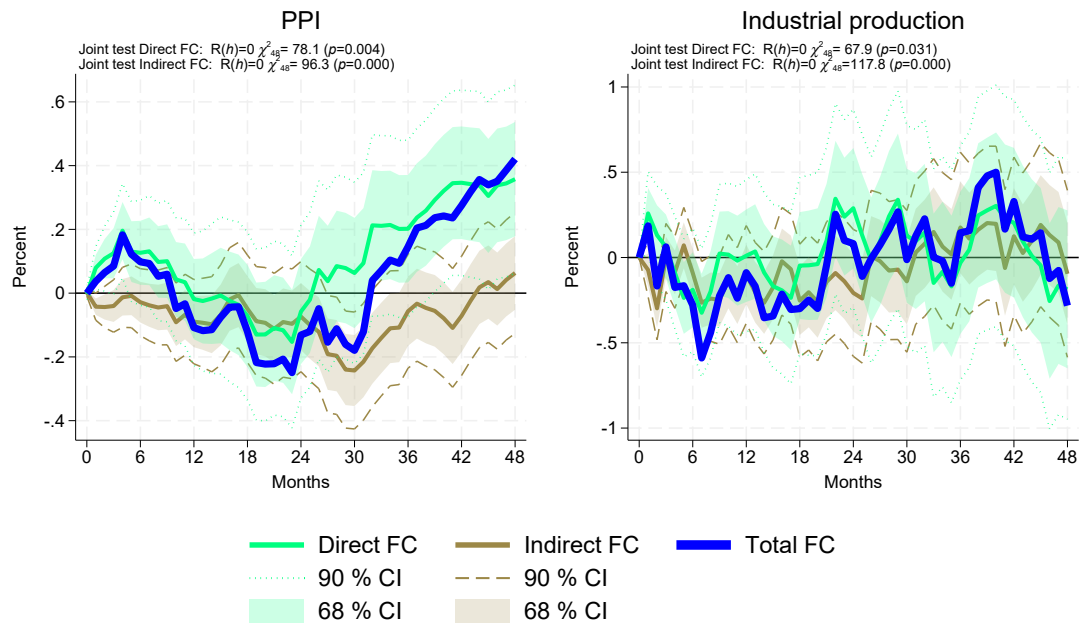
Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

Figure 16: Impulse responses to monetary policy tightening shock - level specification



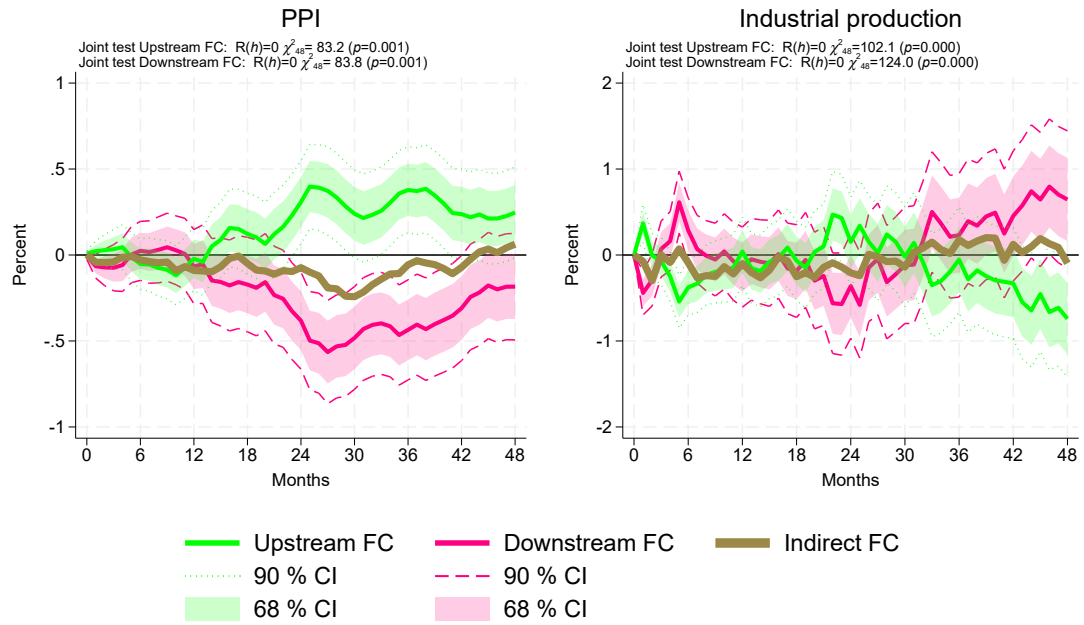
Notes: Impulse responses to a monetary policy tightening shock scaled to a peak increase in the 3m OIS rate of 25bp. Estimates for model 12 estimated on the full country-sector euro area panel.

Figure 17: Impulse responses to monetary policy tightening shock - direct vs. indirect financial constraints 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 12 estimated on the full country-sector euro area panel.

Figure 18: Impulse responses to monetary policy tightening shock - upstream vs. downstream financial constraints 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 12 estimated on the full country-sector euro area panel.

9 Conclusion

In this paper, we provide new evidence on the transmission of monetary policy along the production network, taking the role of sector-specific financial constraints into account. We do so using a comprehensive dataset that combines sectoral information at the disaggregated NACE-2 level with granular firm-level balance sheet information. We then build a set of novel measures of sectoral financial constraints that allowing us to account for the role of financial tightness along the production chain. We show that this interaction between the network structure and sectoral financial constraints matters for the transmission of monetary policy, and validate the choice of empirical measures in a canonical multi sector model.

First, we find that the sector-specific transmission of monetary policy tightening shocks varies substantially across sectors regarding the strength, timing, and persistence of the dampening effect on prices and output. Second, our results show that both direct and indirect financial constraints significantly amplify the dampening effect of a monetary policy tightening shock, with indirect financial constraints accounting for a large share in the overall effect of financial constraints on prices and output. Finally, we find that while downstream financial constraints seem to reinforce the decline in prices and output following a monetary policy tightening shock, upstream constraints tend to partly mitigate these effects. While a tightening of financial constraints seems to lower downstream customers' demand for intermediate goods produced by sector i ("demand channel"), it may foster incentives for upstream suppliers to raise prices and/or gain market share to alleviate financial constraints ("cost channel").

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A Impulse response scaling

We scale the size of a monetary policy tightening shock z_t in models 10, 11 and 12 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 25bs 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 the baseline panel model 10, 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 ψ 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 τ as a scaling parameter in the impulse response functions of industrial production and producer prices shown in section 6.

The euro area aggregate model is given by:

$$y_{t+h} = \beta_1^h s_t + \sum_{l=1}^L \delta^h \mathbf{K}_{t-l} + \sum_{l=0}^L \eta^h \mathbf{X}_{t-l} + \epsilon_{t+h} \quad (17)$$

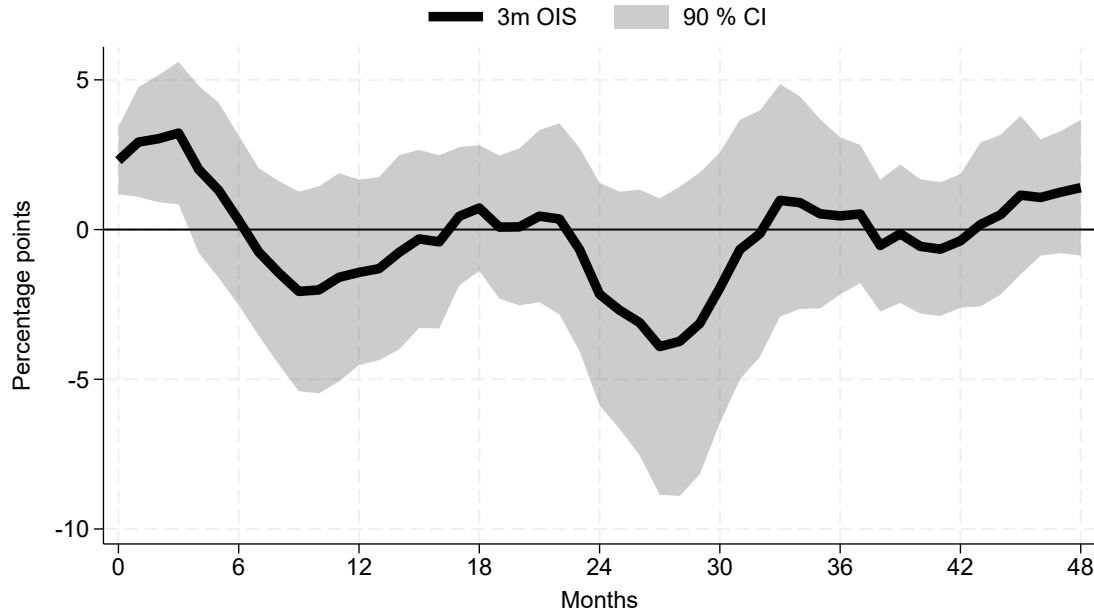
with $h = 1, 2, \dots, H, \mathbf{K}_t = \begin{bmatrix} y_t \\ s_t \end{bmatrix}$

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 models 10, 11, and 12, 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 19 shows the impulse response function to a monetary policy tightening shock as obtained from model 17. 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 β_1^h in equation 17 and shown in figure 19 turns out large.²⁵ Within the first year, the peak increase of 3.2 percentage points in response the OIS 3m rate amounts to percentage points and is reached three months after the shock. In turn, this implies that $\tau \approx 0.078$.

Figure 19: Impulse responses to monetary policy tightening shock - aggregate model



Notes: Impulse responses to a monetary policy tightening shock. Estimates for model 17 estimated on aggregate euro area data with Newey and West (1987) standard errors.

²⁵As 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).