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# The transmission of shocks across sectors and the dynamics of sectoral prices*

Francesca Monti[1,2] and Leïla Van Keirsbilck[1]

[1]UCLouvain
[2]CEPR

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**Abstract**

This paper explores the dynamics of U.S. sectoral producer prices in a large BVAR model where the Input-Output (IO) matrix is used to structure their long-run relationships, allowing to capture flexibly the propagation of micro shocks to aggregate variables. This model's forecasts of headline inflation have accuracy comparable to the Survey of Professional Forecasters' and greater than those generated by a standard BVAR with Minnesota priors, confirming that the IO matrix long-run prior conveys relevant information about the data. We identify three key shocks - an oil price shock, a cereal price shock, and a monetary policy shock - using instrumental variables and find that sectoral linkages play a significant role in their transmission. Sectoral asymmetries are crucial for evaluating the macroeconomic consequences of energy price shocks, as industries with slower price adjustments amplify inflation persistence, even after the shock dissipates. And the impact of a sector-specific shock like the cereals price shock is non-negligible once the production network accounted for.

JEL Classification: C11; C55; E30
Keywords: BVAR, production networks, sectoral shocks

## 1 Introduction

The inflation surge of early 2021 in the U.S. and mid-2021 in the European Union was the backdrop for a heated debate among economists supporting the idea that inflation was "transitory" – due mainly to supply chain pressures following the fast reopening

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of economies after the COVID-19 crisis – and those in the "persistent" camp – who suggested that inflation was mainly boosted by the stimulative fiscal policies enacted by governments in response to the pandemic. While economists now broadly agree on the coexistence of these drivers (see, e.g., Guerrieri et al. (2023)), there is still debate about their relative contribution and their propagation through the sectors of the economy.

Our goal in this paper is to shed some light on these questions, by assessing the degree of pass-through and persistence of sectoral and aggregate shocks to sectoral prices as well as to headline inflation. We do so by modeling sectoral producer price dynamics with a Bayesian autoregressive (BVAR) model that incorporates prior information from the Input-Output matrix, which summarizes the production structure of an economy, *i.e.* defines how each sector depends on other production sectors through intermediate input linkages. We identify three key shocks using instrumental variables: an oil price shock, a cereal price shock, and a monetary policy shock and we document each sector's role in the transmission of shocks, highlighting how the contribution of some sectors to headline inflation is more persistent than that of other sectors.

Our results confirm that sectoral linkages play a significant role in the transmission of inflationary shocks, highlighting the importance of production networks in shaping price dynamics. For example, when studying energy price shocks, understanding sectoral asymmetries is crucial for evaluating their broader macroeconomic consequences, as industries with slower price adjustments, such as the construction sector, may contribute to inflation persistence, even after the initial shock dissipates. Together with Mlikota (2023), our paper is among the very few that explicitly account for production networks when modeling price dynamics outside the multi-sector DSGE literature. It is encouraging to see that many results obtained in the multi-sector DSGE framework are also confirmed here, where the model introduces sectoral interactions through the prior and lets the data determine their relative importance. Overall, we find that sectoral linkages increase both the size and the persistence of price index responses to an oil price shock. We also show that the impact of sector-specific shocks, such as a cereals price shock, becomes non-negligible once the production network is taken into account. Finally, a counterfactual analysis demonstrates that while production linkages amplify the persistence of inflation following an oil shock, the fundamental inflation–output trade-off remains.

Comovement of price indices across different sectors of the economy has traditionally been attributed to aggregate shocks. The lion's share of the literature studying headline or sectoral price dynamics indeed decomposes inflation volatility into aggregate and sector-specific origins as done, among others, in Altissimo et al. (2006), Maćkowiak, Moench, and Wiederholt (2009) or Boivin, Giannoni, and Mihov (2009).[1] However, these approaches typically rely on dynamic factor models, which decompose inflation series into a *common* component and an *idiosyncratic*, possibly weakly correlated, component. In such a framework, though, a sectoral shock that affects all sectors, such as an oil price shock, and a common shock are indistinguishable.

The recognition that micro shocks can have macro consequences has led to the development of macroeconomic models embedding production networks information (e.g. Gabaix (2011), Foerster, Sarte, and Watson (2011), Acemoglu et al. (2012) and Baqaee and Farhi (2019)) and models that formally describe this cascade effect of sectoral price shocks, also called *pipeline pressures*. It is the case of the dynamic stochastic general equilibrium models presented in Smets, Tielens, and Van Hove (2019), Carvalho, Lee, and Park (2021) or Pasten, Schoenle, and Weber (2021), which enable us to capture these *pipeline pressures* or *inflation spillovers* across sectors. These models have shown that pipeline pressures take more or less time to materialize and contribute to inflation volatility and persistence, depending on the production architecture and the relative price rigidity of the sectors.

Recent studies, such as Ferrante, Graves, and Iacoviello (2023) and Di Giovanni and Hale (2022), have examined how monetary policy shocks or demand reallocation shocks influence inflation through input-output interactions and nominal rigidities. Notably, Di Giovanni and Hale (2022) decomposes the transmission of U.S. monetary policy into direct and network effects, showing that production linkages amplify monetary policy effects, with the network component contributing to nearly 70% of the total transmis-

[1] More recently in De Graeve and Walentin (2015) or Andrade and Zachariadis (2016)

sion. Moreover, as emphasized by La'O and Tahbaz-Salehi (2022), sectoral technological differences influence the efficiency of monetary policy, challenging the assumption that monetary shocks affect all firms uniformly.

Within this context, this paper aims to study *inflation spillovers* of sectoral and aggregate shocks into U.S. producer prices. Sectoral producer prices have been less studied than consumer prices. Yet, they influence consumer prices and are of great interest to track cost-push mechanisms. As they reflect the average selling prices received by domestic producers for their output, producer prices are more directly linked to the production network than consumer price indices. However, there is not an *obvious* representation of sectoral inflation spillovers. Schneider (2023) addresses a similar problem for the dynamics of personal consumption expenditures (PCE) inflation, showing, across a range of different DSGE models, that the magnitudes of sectoral responses are similar. He thus opts for a factor-augmented vector autoregressive (FAVAR) model that uses the theoretically-driven ranking to identify the sectoral shocks. Bilgin and Yilmaz (2018) opt for a VARX model and use the Diebold and Yilmaz Connectedness Index to represent a network of inflation spillover. While such a framework can provide useful insights, it is subject to many issues such as the poor estimation of classical VARs for large panels of data.

In short, many empirical models that study the effects of idiosyncratic shocks on other time series rely on a factor analysis to clean for common comovement and, as stressed before, end up with only the direct effect of sectoral shocks (i.e. show no propagation at all). These considerations motivate our choice to study sectoral producer price dynamics via a hierarchical Bayesian vector autoregressive (BVAR) model. Hierarchical BVARs can handle the inclusion of a large set of variables and have already shown very good forecasting performances. Importantly, such a model does not require the explicit identification of common factors and idiosyncratic components, therefore allowing to capture more naturally the possible propagation from micro shocks to aggregate variables. Finally, BVARs also offer a large set of identification strategies to recover the impacts of structural shocks on the model variables.

We employ the Prior for the Long Run (PLR) BVAR framework developed by Giannone, Lenza, and Primiceri (2019), which allows for flexible long-run relationships between the variables of the model. Unlike traditional BVARs, the PLR prior explicitly incorporates economic restrictions on long-run behavior. This approach is particularly useful for studying sectoral price spillovers, as it enables us to impose economically meaningful priors based on the Input-Output matrix, ensuring that intersectoral linkages are reflected in the estimated model.

Our contribution is close to the work of Mlikota (2023). The author builds a *Network VAR* model: a vector auto-regression in which innovations transmit cross-sectionally via bilateral links only. For example, concerning the dynamics of sectoral prices, the Network VAR (NVAR) model takes the following form $x_\tau = \delta_1 A x_{\tau-1} + ... + \delta_p A x_{\tau-p} + \nu_\tau$ where the $A$ matrix is fixed to the Input-Output matrix while the $\delta_i$ coefficients are estimated. While our model shares the idea of using production linkages to structure inflation dynamics, the use of the prior for the long run BVAR offers a much more flexible way to incorporate production information in the model, compared to the NVAR in which the network transmission of shocks is directly determined by sectoral linkages. Instead of forcing sectoral propagation to match Input-Output relationships as in NVAR, the PLR prior allows the production network to guide, but not rigidly constrain, the estimation of sectoral interactions. The PLR prior shrinks the coefficient matrices toward economically plausible long-run values but does not force sectoral interactions to follow a fixed propagation matrix. Our contribution is also close to Aruoba and Drechsel (2024) that study how monetary policy contraction impacts the Personal Consumption Expenditures (PCE) price index in the U.S. on disaggregated data. Their findings share features with ours, such as the heterogeneity of impulse responses across sectors that helps to better understand the aggregate response. Their paper is however centered on PCE indices while our paper focuses on PPI indices. Moreover, while Aruoba and Drechsel (2024) contribute importantly to the literature of sectoral prices dynamics by providing inference for the re-aggregation of the sectoral responses, they do not include in the model any *network* information, such as the one contained in the Input-Output matrix.

# 2 Theoretical model framework

## 2.1 Hierarchical BVAR with a long run prior

We model sectoral producer price dynamics with a hierarchical Bayesian Vector Autoregressive (BVAR) model with $p$ lags enriched with a long run prior, adopting the approach of Giannone, Lenza, and Primiceri (2019). The long run prior is conjugate and can be implemented using Theil mixed estimation, i.e. by adding a set of artificial (or dummy) observations to the original sample. It can thus be added to the more classic flat or Minnesota BVARs. Before delving into the details of the long-run prior, we first review the Minnesota BVAR, which serves as the foundation to which the long-run prior will be incorporated.

Letting $Y_t$ represent the $N$-dimensional vector of (transformed) variables, a reduced-form VAR model can be written as

$$Y_t = a + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + e_t \tag{2.1}$$

where $A_p$ is the $p$-th lag coefficient matrix and $e_t$ is a Normally-distributed multivariate white noise process, with covariance matrix $\Sigma$. Bayesian VARs allow us to explicitly provide prior information for the distributions of the parameters $a$, $A_i (i \in 1, ..., p)$ and $\Sigma$. As in Giannone, Lenza, and Primiceri (2015) we use a conjugate prior for our parameters: the Normal-Inverse Wishart prior, which assumes an inverse Wishart distribution for the covariance matrix $\Sigma$ and a multivariate Normal distribution for the coefficient matrices $A_i$. If we define $\beta = vec([a, A_1, ..., A_p]')$,

$$\begin{aligned} &\Sigma \sim IW(\Psi, d) \\ &\beta|\Sigma \sim N(b, \Sigma \otimes \Omega) \end{aligned} \tag{2.2}$$

We fix the degrees of freedom of the Wishart distribution $d$ to $N + 2$, the minimal value that guarantees the existence of the mean of $\Sigma$. Regarding the scale matrix $\Psi$, we depart from Giannone, Lenza, and Primiceri (2015) and opt for the more classical approach that considers this matrix as diagonal with the $N \times 1$ vector fixed using sample information. For the other parameters $b$ and $\Omega$, we use the Minnesota prior, which assumes that each variable follows a random walk process. For that reason, it is more convenient to express the prior for $b$ and $\Omega$ directly using the first and second moments of the coefficient matrices:

$$\mathbb{E}[(A_s)_{ij}|\Sigma] = \begin{cases} 1 \text{ if } i = j \text{ and } s = 1 \\ 0 \text{ otherwise} \end{cases} \tag{2.3}$$

$$\mathbb{C}\text{ov}[(A_s)_{ij}, (A_r)_{hm}|\Sigma] = \begin{cases} \lambda^2 \frac{\Sigma_{ih}}{s^2 \psi_j} \text{ if } m = j \text{ and } s = r \\ 0 \text{ otherwise} \end{cases} \tag{2.4}$$

The prior mean expressed in (2.3) encodes the assumption that each variable follows a random walk: only the own first lag enters with coefficient one, while all other coefficients are shrunk towards zero.

As shown in (2.4), a hyperparameter $\lambda$ controls for the *tightness* of the prior. As $\lambda \rightarrow 0$, the posterior mean converges to the prior mean because the prior variance vanishes, while as $\lambda \rightarrow \infty$, the posterior mean coincides with the OLS estimate because the prior becomes flat. Adopting the *hierarchical* approach, we do not fix the hyperparameter $\lambda$, but rather estimate it by maximizing the marginal likelihood of the data as a function of this and other hyperparameters. Then, conditionally on a value for the hyperparameters, draw the VAR coefficients from their posterior distributions.

**Adding the long run prior to the Minnesota BVAR.** Turning now to the long run prior proposed in Giannone, Lenza, and Primiceri (2019), the authors show that the VAR model presented above can be re-written in terms of levels and differences as:

$$\Delta Y_t = a + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + e_t \tag{2.5}$$

where:

- $\Pi = (A_1 + \cdots + A_p) - I_N$ is a coefficient matrix of cointegration relationships

- $\Gamma_j = -(A_{j+1} + \cdots + A_p)$ with $j = 1, ..., (p-1)$ are the coefficient matrices of the lags of the differenced variables

This is the vector error correction (VECM) representation of the VAR and is used for data where the underlying variables are possibly cointegrated. The $\Gamma_j$ parameters of the model are often referred to as the short-run parameters, and $\Pi y_{t-1}$ is sometimes called the *long-run* part of the model. This is because if the rank of $\Pi$ is a constant $r > 0$ and there exist two $N \times r$ matrices $\alpha$ and $\beta$ such that $\Pi = \alpha\beta'$, then $Y_t$ is cointegrated of order $r$, meaning that some long-run cointegration relationships exist between the variables. The matrix $\beta$ then represents these long-run equilibrium cointegration relationships between the variables while $\alpha$ denotes the loading matrix, which indicates the speed at which the system corrects deviations from these equilibria.

In their paper, Giannone, Lenza, and Primiceri (2019) aim to elicit a prior for the $\Pi$ matrix that is centered around zero but has a covariance matrix that is guided by economic theory. To reach such a goal, they propose to rewrite the model as:

$$\Delta Y_t = a + \underbrace{\Lambda \tilde{Y}_{t-1}}_{\Pi H^{-1} H Y_{t-1}} + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + e_t \tag{2.6}$$

where:

- $\tilde{Y}_{t-1} = HY_{t-1}$ is an $n \times 1$ vector containing $n$ linearly independent combinations of the variables $Y_{t-1}$

- $\Lambda = \Pi H^{-1}$ is an $n \times n$ matrix of coefficients capturing the effect of these linear combinations on $\Delta Y_t$

In this setup, the construction of a reasonable prior for $\Lambda$ depends on the $H$ matrix, which plays a crucial role. Indeed, $HY_{t-1}$ represents a set of linear combinations of the variables (each line is a linear combination), that can help to guide the elicitation of a good prior for $\Lambda$ and thus for $\Pi$. If a specific linear combination is a priori likely to be nonstationary, one could impose more shrinkage on the elements of the corresponding column of the $\Lambda$ matrix towards a prior centered at zero. For example, given that the variables are log-transformed, investment minus output $(I_t - Y_t)$ represents a ratio that is expected to be stationary while investment plus output $(I_t + Y_t)$ is likely to have a common trend. The prior can thus shrink more strongly the coefficients associated with non-stationary linear combinations, while allowing stationary ones to play a larger role in explaining short-run dynamics. In this 2-variables example, we see that it is thus possible to build a prior for the $\Lambda$ matrix that is economically grounded. In this example, the matrix $H$ would be:

$$H = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}.$$

Giannone, Lenza, and Primiceri (2019) propose a specific *a priori* distribution for the columns of the $\Lambda$ matrix, conditional on $H$:

$$\Lambda_{\cdot i} | H_{i\cdot}, \Sigma \sim N(0, \tilde{\phi}_i(H_{i\cdot})\Sigma). \tag{2.7}$$

The idea is that the following prior indeed allows to push towards zero values the column of $\Lambda$ related to linear combinations of variables that do not play a role in explaining the short-run dynamics $\Delta Y_t$. This is done by pushing towards zero the $\tilde{\phi}_i(H_{i\cdot})$ value. The proposed reference value for $\tilde{\phi}_i(H_{i\cdot})$ is the following:

$$\tilde{\phi}_i(H_{i\cdot}) \sim \frac{\phi_i^2}{(H_{i\cdot}\bar{Y}_0)^2} \tag{2.8}$$

where $\phi_i$ is a scalar hyperparameter controlling the standard deviation of the prior on the elements of $\Lambda_{\cdot i}$, and $\bar{Y}_0$ is a column vector containing the average of the initial $p$ observations of each variable of the model. The key element of the prior for the columns of $\Lambda$ is thus the $\phi_i$ hyperparameters (one for each column of $\Lambda$). As $\phi_i$ gets closer to zero, it is equivalent to assuming that the corresponding linear combination does not help in explaining $\Delta Y_t$.

However, the authors do not impose a specific value for the hyperparameters $\phi_i$ but instead adopt a hierarchical interpretation of the model. As shown in their paper, this prior being conjugate, its marginal likelihood can be written in closed form and it is thus possible to express the marginal likelihood of the model in terms of its hyperparameters. Maximizing the marginal likelihood thus leads to an optimization of the hyperparameters, hence of the $\phi_i$ values.

Importantly, in the Giannone, Lenza, and Primiceri (2019) framework described above, even the non-stationary linear combinations provided in the $H$ matrix inform the model. To show this, let us use the 2-variables example again. A reasonable prior for $\Lambda$ would be that $\Lambda_{\cdot,1}$ should be tight around zero while $\Lambda_{\cdot,2}$ should be less tight around zero, hence allowing for the error-correction mechanism from the stationary linear combination $(I_t - Y_t)$. Even though $(I_t + Y_t)$ is non-stationary, including it in $H$ is still informative, since $\Pi = \Lambda H$. The trend combination affects the prior structure of $\Lambda$ and therefore $\Pi$.

## 2.2 A long run prior driven by the production structure of the economy

We exploit the long-run prior framework to incorporate information about the production structure of the economy into a BVAR model for sectoral price dynamics. The production structure of an economy defines how each sector depends on other production sectors through intermediate input linkages. The Input-Output (IO) matrix summarizes these dependencies, making it a natural candidate for specifying economically meaningful long-run relationships in the BVAR.

In equation (2.6), we set the $H$ matrix to reflect combinations of sectoral prices implied by the IO structure. More explicitly, if we assume (for the simplicity of the reasoning) that the vector of variables $Y_t$ is only composed of the sectoral producer prices indices, we set $H$ equal to the $IO$ matrix. In our implementation, the IO matrix is normalized such that each row sums to one, so that the linear combinations in $H$ define proper cost-share–weighted averages of sectoral log prices. These aggregates may be stationary (if relative price adjustments restore equilibrium) or non-stationary (if they share common stochastic trends); in both cases, the prior can shrink the corresponding elements of the $\Lambda$ matrix towards zero, thus guiding the long-run component $\Pi = \Lambda H$ towards an economically plausible structure.

For example, consider a VAR model for three sectoral producer price indices (PPIs) - $PPI_A$ (e.g., Energy), $PPI_B$ (e.g., Manufacturing), $PPI_C$ (e.g., Services) - and assume that the production structure of the economy is represented by the following $3 \times 3$ IO matrix:

$$IO = \begin{bmatrix} 0.5 & 0.4 & 0.1 \\ 0.3 & 0.6 & 0.1 \\ 0.1 & 0.2 & 0.7 \end{bmatrix}.$$

where each element $IO_{ij}$ represents the proportion of input costs in sector $i$ that comes *directly* from sector $j$. The first two rows indicate that sectors A and B are strongly linked through intermediate inputs, while sector C is more self-contained. In the long-run prior, this translates into linear combinations in $H$ where sectors A and B enter with relatively large weights. A shock to sector A (energy prices) is therefore expected to propagate more strongly to B than to C, and A and B may even share a common trend driven by their production interdependence.

**The Input-Output informed long-run prior BVAR as a Minnesota BVAR on *IO-weighted averages of log prices.*** An additional motivation for choosing $H$ based on the IO matrix comes from the fact that, within the PLR framework, a BVAR on sectoral prices with long-run restrictions $\Pi = \Lambda H$ (where $H$ contains the $IO$ matrix for the linear combinations on sectoral prices) is algebraically equivalent to a classic Minnesota BVAR on *input prices* $\tilde{Y}_t = HY_t$. To see this in the simple VAR(1) case, assuming $Y_t$ contains only sectoral prices, start from:

$$Y_t = A_1 Y_{t-1} + u_t. \tag{2.9}$$

Subtract $Y_{t-1}$ from both sides to obtain the VECM form:

$$\Delta Y_t = (A_1 - I)Y_{t-1} + u_t. \tag{2.10}$$

Under the PLR structure, we write:

$$\Delta Y_t = (A_1 - I)H^{-1}HY_{t-1} + u_t. \tag{2.11}$$

Multiplying through by $H$ gives:

$$\Delta \tilde{Y}_t = (HA_1H^{-1} - I)\tilde{Y}_{t-1} + \tilde{u}_t, \tag{2.12}$$

with $\tilde{Y}_t \equiv HY_t$.

This is exactly the VECM representation of a VAR in $\tilde{Y}_t$, showing that the PLR prior on $Y_t$ is equivalent to a standard Minnesota BVAR on the transformed variables $HY_t$. Each row of $H$ contains the cost shares of intermediate inputs used by a sector, taken from the IO matrix. Therefore, $HY_t$ stacks, for each sector, the *aggregate price index of its intermediate input bundle*. In levels, these are cost-weighted arithmetic means of prices; when $Y_t$ contains *log price indices*, they become cost-weighted averages of log prices, i.e. the logs of geometric means. The geometric-mean interpretation is standard in index number theory: Tornqvist and related indices aggregate prices using expenditure or cost shares as weights (see Diewert (1976) for a seminal contribution and Stanley (2024) for a recent BLS application). This interpretation also matches the log-linearized CES price aggregators commonly found in multi-sector DSGE models.

This equivalence shows that the long-run prior is not restricting arbitrary linear combinations of sectoral prices, but is instead shrinking toward plausible dynamics for economically interpretable aggregates — the prices of sector-specific input bundles implied by the production network. Using the IO matrix to construct $H$ thus embeds the network structure of the economy directly into the long-run component $\Pi = \Lambda H$ of the BVAR. The equivalence with the Minnesota BVAR on *IO-weighted averages of log prices* implies the shrinkage introduced by the long run prior targets these *IO-weighted input bundles*.

To the information from the Input-Output matrix, we also add two lines that take into account for the nominal trend shared by inflation and the interest rate. We summarize here below our choice of linear combinations on the variables.

$$\tilde{Y}_t = \underbrace{\begin{pmatrix} \mathbf{IO} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ \mathbf{0} & 0 & -1 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}}_{H} \underbrace{\begin{pmatrix} \textbf{35 sectoral prices}_t \\ \text{industrial production}_t \\ \text{headline inflation } \pi_t \\ \text{oil price}_t \\ \text{cereals price}_t \\ \text{inflation expectations}_t \\ \text{excess bond premium}_t \\ \text{shadow rate}_t \end{pmatrix}}_{Y_t} \tag{2.13}$$

This specification of linear combinations is intended as a baseline choice to capture potential cointegration relationships among the variables. For each linear combination $i$, the hierarchical prior framework allows us to estimate the corresponding hyperparameter $\phi_i$, letting the data determine the degree of shrinkage towards the prior mean. Other specifications of linear combinations for the aggregate variables could also be considered; here, we focus on this simple design in order to isolate and evaluate the contribution of the Input-Output matrix. Since we do not impose linear combinations on all variables in the model, the $H$ matrix is not full rank. The code therefore completes $H$ with an additional matrix $H_{\text{compl}}$, constructed as a basis for the null space of $H$, to ensure a full-rank transformation.

## 2.3 An addition: the Covid-19 correction

Also building on the hierarchical BVAR of Giannone, Lenza, and Primiceri (2015), Lenza and Primiceri (2022) propose to explicitly model the surge in shock volatility during the pandemic. Though our model is mainly focused on prices, we also include among our variables the US industrial production that was indeed greatly impacted by the pandemic, especially during the months of March, April and May 2020. To estimate properly a VAR during the Covid-19 period and account for the large variance of shocks during that period, Lenza and Primiceri (2022) modify the standard VAR by adding a *scaling* vector multiplying the error term. The standard VAR becomes :

$$Y_t = a + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + s_t e_t \tag{2.14}$$

Then, the authors assume specific values for $s_t$. For all months before March 2020, $s_t$ is fixed to 1, not impacting the baseline VAR specification. Then, letting March 2020 be denoted by $t*$, the authors assume that $s_{t*} = s_0$, $s_{t*+1} = s_1$, $s_{t*+2} = s_2$ and $s_{t*+j} = 1 + (s_2 - 1)\rho^{j-2}$ where $[s_0, s_1, s_2, \rho]$ is a vector of unknown parameters. These parameters are estimated jointly with the VAR parameters, typically via marginal likelihood maximization The Covid-19 correction proposed is fully compatible with the hierarchical approach from Giannone, Lenza, and Primiceri (2015) and with the long run prior. Hence, we include this modification in our model.

# 3 Estimation and identification of the hierarchical BVAR

## 3.1 Data

We estimate the model using monthly data on the U.S. economy from January 2004 to December 2024.[2] All sectoral price series are obtained from the Bureau of Labor Statistics (BLS) producer price data classified by the North American Industry Classification System (NAICS) index codes. Such price series are available at different levels of aggregation: we opt for a decomposition into 35 sectors as in Smets, Tielens, and Van Hove (2019). To the 35 sectoral PPI indices, we add some key aggregate variables: industrial production, consumer price index, oil price, cereals price, the Michigan inflation expectations, the

[2]For the detailed description of the data, the treatment of missing values and the transformations used, see Appendix A

updated series for the excess bond premium of Gilchrist and Zakrajšek (2012), and the shadow rate of Wu and Xia (2016).

Our BVAR is hence estimated with a total of 42 variables. We seasonally adjust the sectoral PPI series using the U.S. Census Bureau's X-13ARIMA-SEATS procedure. Macroeconomic aggregates that are already available in seasonally adjusted form from FRED, such as the Consumer Price Index (CPI) and the Industrial Production Index (INDPRO), were used as provided. Other series in the model (inflation expectations from the Michigan Survey of Consumers, the real oil price, the real cereal price index, the Excess Bond Premium, and the shadow federal funds rate) were retained in their original, non-seasonally adjusted form, as they do not exhibit strong or stable seasonal patterns. Sectoral prices, industrial production, cereals and oil prices are log-transformed. Inflation expectations from the Michigan Survey of Consumers, the excess bond premium or the interest rate are in level. The only variable that enters the VAR in difference is the headline consumer price index as we need the inflation rate to construct the long run prior linking inflation and the interest rate. The Input–Output matrix is constructed using the same methodology as in Schneider (2023), Smets, Tielens, and Van Hove (2019), and Pasten, Schoenle, and Weber (2021). It is based on the annual MAKE and USE tables provided by the Bureau of Economic Analysis (BEA). Although the Input–Output matrix changes slightly over time, these variations are relatively small during the period considered. We tested the model with IO matrices from different years and found the impact negligible; therefore, we use an average Input–Output matrix over 2004–2021.

## 3.2 Forecasting performance

We evaluate the predictive accuracy of the IO-informed BVAR against several benchmark specifications for U.S. headline CPI, one of the key variables in our system. The evaluation is based on a pseudo-out-of-sample recursive forecasting exercise. At each forecast origin, the model is estimated on all available data up to the quarter preceding the forecast quarter, and used to generate monthly forecasts for up to 15 months ahead. These monthly forecasts are then aggregated to annualized quarter-on-quarter (QoQ) inflation rates, matching the format used in the Survey of Professional Forecasters (SPF).

Our baseline design follows the SPF in using real-time CPI data, but differs in two respects. First, we lack real-time data for variables other than CPI. Second, we deliberately exclude the first month of the forecast quarter from our information set. For instance, when forecasting for 2019Q1, we use data only up to December 2018, making our comparison a relatively strict test of forecasting performance. By contrast, SPF respondents conduct their forecasts in mid-quarter and may therefore have a minor informational advantage.[3] Forecast accuracy is measured using the root mean squared error (RMSE) of the annualized QoQ inflation forecasts, computed using the latest available realizations. The baseline evaluation sample covers the quarters for which forecast accuracy is assessed, while the forecast sample refers to the data used for estimation at each forecast origin. In our recursive design, the forecast sample runs from January 2004 up to December 2017 and is expanded by three months at each iteration, so that each new forecast origin adds one quarter of observations to the estimation window. The evaluation sample runs from 2018Q1 to 2024Q4. We also report results for a shorter evaluation period ending in 2021Q2, to assess performance outside of the very high inflation episode that began in early 2021.

We compare the following BVAR specifications:

1. **MN**: Minnesota prior.
2. **MN-C**: Minnesota prior with Covid-19 correction.
3. **LR**: Minnesota prior with Covid-19 correction, augmented with a long-run prior on two nominal-trend linear combinations (inflation and interest rate) from the $H$ matrix.
4. **LR-IO**: Minnesota prior with Covid-19 correction, augmented with a long-run prior whose $H$ matrix includes the Input–Output matrix in its upper-left block.

[3] In the Philadelphia Fed's real-time vintage database, the first month of the current quarter is included. However, it is uncertain whether SPF forecasters actually incorporate this first-month inflation release at the time of submitting their forecasts. In Appendix B.3, we report results using the full vintage data (including the first month of the current quarter). The results are very similar, except that current-quarter forecasts improve.

All baseline forecasts are produced with a BVAR(2). Robustness checks with one and three lags are presented in Appendix B.1. In Appendix B.2, we also replace the IO matrix in $H$ with the Leontief inverse $(I - IO)^{-1}$[4]. The Leontief inverse is $(I - IO)^{-1}$, which can be decomposed into

$$(I - IO)^{-1} = I + IO + IO^2 + IO^3 + \cdots$$

where each $n$th power of the Input-Output matrix represents the intermediates from one sector to another via network paths of length $n$. So in the Leontief inverse, each element $((I - IO)^{-1})_{ij}$ represents the proportion of input costs in sector $i$ that comes *indirectly* from sector $j$.

Tables 1 and 2 report the root mean squared error (RMSE) for the Survey of Professional Forecasters (SPF) as a benchmark, along with RMSE ratios for each BVAR specification, defined as $\text{RMSE}_{\text{model}}/\text{RMSE}_{\text{spf}}$. An RMSE ratio below one therefore indicates that the BVAR outperforms the SPF benchmark, while a ratio above one implies lower forecast accuracy relative to the SPF. Each forecast that is significantly worse/better than the SPF is highlighted in bold (Diebold-Mariano test). Across most horizons, the BVAR forecasts are comparable to those of the SPF, despite the latter's informational advantage at the now-cast horizon.

Importantly, in all cases the IO-based long-run prior yields more accurate forecasts than the parsimonious Minnesota prior, indicating that Input–Output linkages embed useful information for inflation dynamics. The IO-based long-run prior also yields more accurate forecasts than the other competitor models (Minnesota with the Covid adjustment and Long-Run Prior without the IO) at almost all horizons.

Although forecasting is not the primary aim of this paper, these results provide reassurance that the proposed framework maintains competitive predictive accuracy while offering a richer, more disaggregated structure for analyzing the transmission of shocks.

[4]As our definition of the IO matrix is row-normalized - as standard in multi-sector macroeconomic models see for example Schneider (2023) or Pasten, Schoenle, and Weber (2021), please note the interpretation of the $(I - IO)^{-1}$ differs from the standard Leontief Input-Output model where elements $ij$ represent shares of $j$'s output going to sector $i$ (column-normalization).

| | | Ratios rmse(BVARs) / rmse(spf) (< 1 → better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.3721 | 1.6367 | 1.3600 | 1.2662 | 1.2102 |
| h=1Q | 0.6144 | **1.5524** | **1.4191** | **1.3670** | 1.4504 |
| h=2Q | 0.6665 | **1.6776** | **1.4471** | **1.3468** | 1.2741 |
| h=3Q | 0.6811 | **1.6968** | **1.3778** | 1.3026 | 1.0678 |
| h=4Q | 0.6815 | **2.0848** | **1.6840** | **1.5862** | 0.9978 |

Table 1: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(2) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Full evaluation sample : 2018Q1 up to 2024Q4.

When limiting the evaluation sample to 2021Q2 (excluding high inflation in evaluation data), the BVARs, and especially the IO-informed BVAR, are showing quite good improvements to the Survey of Professional Forecasters as illustrated by Table 2. It also confirms that the IO-informed Long-Run BVAR still improves on the competitor models, which confirms the relevance of the information coming from the Input-Output matrix.

| | | Ratios rmse(BVARs) / rmse(spf) (< 1 → better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.5640 | 0.8292 | 0.8424 | 0.7867 | 0.5853 |
| h=1Q | 0.9177 | 1.4015 | 1.2580 | 1.4307 | 0.9754 |
| h=2Q | 0.9119 | 1.1616 | 1.0198 | 1.1008 | 0.9700 |
| h=3Q | 0.9255 | 1.1059 | 0.9713 | 0.9492 | 0.9189 |
| h=4Q | 0.8972 | **1.5594** | **1.5597** | 1.3621 | 0.9834 |

Table 2: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(2) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Shorter evaluation sample : 2018Q1 up to 2021Q2.

## 3.3 Identification of structural shocks

This model can trace the propagation of micro-shocks to aggregate variables, as well as study how aggregate shocks transmit heterogeneously across sectors. We study three types of shocks – an oil price shock, a cereal price shock, and a monetary policy shock – using external and internal instruments.

1. For the oil price shock, we use the oil supply news surprises from Känzig (2021). Narrative-based, Känzig's oil supply surprises have been widely adopted in macroeconomics, finance, and energy economics. They are now considered a benchmark measure for exogenous oil supply shocks.

2. The cereal price shock on which we base our identification is by Jo and Adjemian (2023). The authors employ an external instruments approach within a Vector Autoregression (VAR) framework to identify agricultural supply news shocks. They utilize high-frequency changes in futures prices of U.S. field crops around the release times of key USDA (U.S. Department of Agriculture) reports. These price changes serve as proxies for market reactions to new information about crop supply, allowing the authors to isolate exogenous shocks to agricultural supply expectations. Their methodology is thus close to what Känzig (2021) applies for oil surprises. However, the authors do not make available the original proxy so we use the pre-identified shock series from Jo and Adjemian (2023) to trace impulse responses. To do so, we treat the cereal price shock series as an internal instrument, running the model with this shock as first variable. We obtain the impact vector for the agricultural shock by looking at the first column of the Cholesky matrix.

3. Finally, concerning the monetary policy shock, we opt for the monetary policy surprises from Bauer and Swanson (2023), in which the authors use high-frequency asset price changes around FOMC (Federal Open Market Committee) announcements to isolate unexpected monetary policy shifts. In Appendix, we also show the impulse responses obtained via the monetary policy surprises from Miranda-Agrippino and Ricco (2021).

For each of these shocks, we look at the responses provided by the LR-IO (Input-Output) and LR-L (Leontief) informed models but, as they are very similar, we only show here the responses to shocks from the LR-IO BVAR(2) model. Impulse responses for the LR-L (Leontief) BVAR(2) model are included in Appendix C.

### 3.3.1 The oil price shock

Oil price shocks have long been recognized as a major driver of macroeconomic fluctuations, influencing inflation, output, and monetary policy responses. They stem from the oil sector but have a much broader reach, directly impacting production costs, transportation, and also the financial markets. We rely on the oil supply news surprises constructed by Känzig (2021) to isolate exogenous variations in oil prices. We impose a 5% oil price shock using these surprises as an external instrument, allowing us to examine the propagation of energy price shocks across sectoral and macroeconomic variables. The impulse responses of all variables are provided in the Appendix C, and we highlight the key sectoral and aggregate effects in the discussion below. Figure 1 compares the impulse responses obtained from the Minnesota BVAR(2) (in red) with the ones obtained from the IO-informed long-run prior BVAR(2) (in blue).

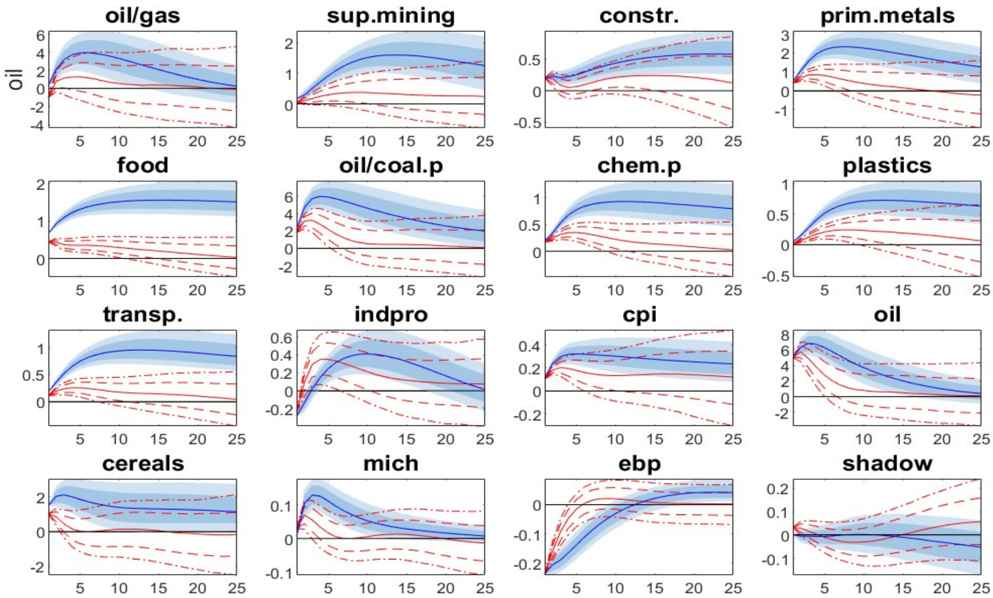


Figure 1: Impulse responses to an **oil price shock** using Känzig's surprises in a BVAR(2) model with Input-Output informed Long-Run prior and Covid-19 correction (in blue) versus in the standard Minnesota BVAR(2) (in red). We focus on the following variables: *oil/gas - Oil and gas extraction PPI*, *sup.mining - Support for mining activities PPI*, *constr. - Construction PPI*, *prim.metals - Primary metals PPI*, *food -Food, beverage and tobacco PPI*, *oil/coal.p - Oil and coal products PPI*, *chem.p - Chemical products PPI*, *plastics - Plastic products PPI*, *transp. -Transportation PPI*, *indpro - Industrial production*, *cpi - Consumer price index*, *oil - Crude oil price (WTI)*, *cereals - Cereals price*, *mich - Michigan inflation expectation*, *ebp - Excess bond premium*, *shadow - Shadow rate*

As evident in Figure 1, the oil supply news shock initially has the strongest effect on the *oil and gas extraction* sector and to *oil and coal products*, but this unwinds within a couple of years. The responses of the *chemical products*, *plastic products* and *transportation* sectors – typically energy-intensive sectors – are instead less strong initially, but are very persistent. Some sectors, like *construction* and *food, beverage and tobacco*, can show subdued responses for a few months and then increase, thus contributing to the persistence of the shock in the economy.

The response of the shadow rate could reflect the fact that policymakers often "look through" first-round effects of energy shocks, focusing instead on whether they lead to persistent second-round effects (wage-price spirals, inflation expectations, etc.).[5] This is often motivated by the negative effect that such an interest rate rise could have on production.

The response of the excess bond premium (EBP) might appear at first more surprising. However, the initial decline may reflect the forward-looking characteristic of Känzig (2021) supply news surprises (the economic fundamentals are not yet impacted while the oil price increase may boost profits in the energy sector), as well as the fact that investors may expect the Fed to maintain interest rates or to, at least, delay any tightening. Moreover, after a year, the EBP response is slightly above zero, meaning that the initial decline was after a moment compensated by the materialization of the real economic impact of the oil price shock.

When compared with the impulse responses obtained with the standard Minnesota BVAR (in red), the IO-informed BVAR leads to much tighter credible intervals. The IO-informed shrinkage thus appears stronger and better targeted. It reduces posterior uncertainty because it replaces the assumption of independent sectoral random walks with a structured view: prices inherit their persistence from input-cost bundles. This shrinks the effective number of free stochastic trends, aligning the prior with the production network. As a result, impulse responses are estimated with tighter credible intervals.

We also find that, when including the IO network, the responses to an oil price shock are more persistent and that the sectoral producer price indices and consumer price index respond more strongly to the oil shock. This is in line with the story that sectoral links increase headline inflation and its persistence, as shown in Rubbo (2023) or Afrouzi and Bhattarai (2023). It is however of great interest to see that such a finding appears not only in multi-sector DSGE models in which the pricing chain spillover channel is explicit in the equations of the model but also in our BVAR framework in which the network structure

[5]See recent speeches of central banks for example Lagarde (2025) for the ECB or Powell (2023) for the Fed.

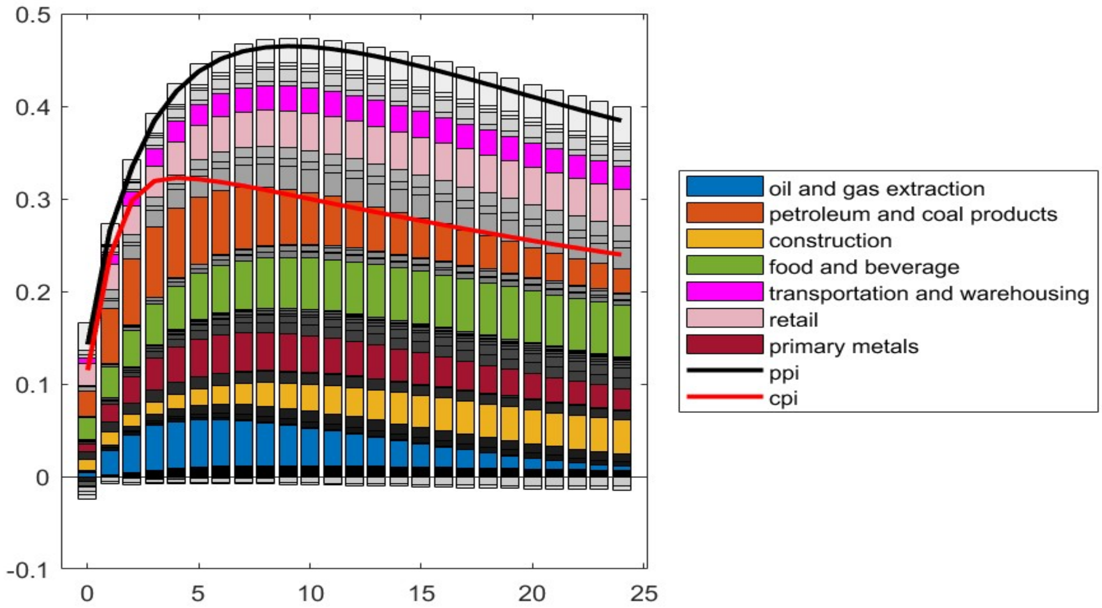


Figure 2: Contributions to aggregated PPI of sectoral PPIs responses to an **oil price shock** using Känzig's surprises in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer price index is the red line. Each color represents a sector that we decided to highlight (ex: oil and gas extraction in blue) while the non-highlighted sectors are in shades of grey.

only appears in the prior. By embedding the production linkages only through the prior, our model shows that the data themselves validate the importance of production networks, even without hard-wiring the transmission channel into the structural equations.

Figure 2 plots the contributions of the different sectors in transmitting the oil supply news shock to the weighted sum of producer price indices responses, highlighting the biggest contributing sectors and how they change in time. Although the *oil and gas extraction* sector responds rapidly to the oil shock, its contribution fades rapidly, in line with the findings of Afrouzi and Bhattarai (2023) who also find that the *oil and gas extraction* sector passes substantially through the impact on aggregate inflation, but the effects are very transient. The contributions of the *petroleum and coal products*, *food, beverage and tobacco* or *transportation* sectors are much more persistent. We notice however that the contributions of the *Petroleum and coal products* or *primary metals* sectors already start decreasing after a year while the *food, beverage and tobacco* or *retail* sectoral contributions still show no decrease after two years. The contribution of the *construction* sector (yellow) is small at first but grows over time. The observed lag in

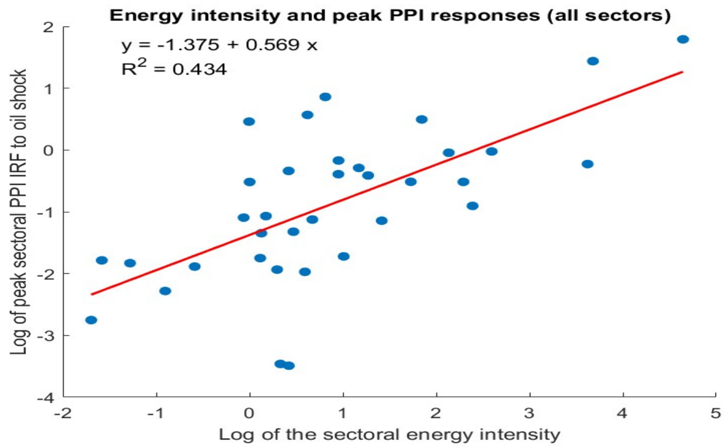


Figure 3: Sectoral energy intensity vs. Peak sectoral PPI IRF to an oil price shock

price adjustments for some industries, particularly construction, may indicate the role of contract rigidities, where firms absorb short-term price fluctuations before passing costs onto consumers. This is in contrast to fuel and energy-intensive goods, where price adjustments are almost immediate and the effects are more short-lived. The aggregated PPI response is above the CPI response, suggesting that not all increases in producer prices are passed on to consumers.

To investigate further the oil price shock, we study the relationship between the peak response of sectoral producer prices to the oil shock and each sector's *energy intensity*. We define energy intensity as the total cost share of intermediate inputs that originate, directly or at second-order, from the *oil and gas extraction* sector. Concretely, for each sector $i$, we compute the sum of the column *oil and gas extraction* in the Input–Output matrix and in its square, $IO + IO^2$, capturing both first-order and second-order linkages. This is because some sectors in the Input-Output matrix do not use as direct (first-order) intermediate goods from the *oil and gas extraction* sector. As can be seen on Figure 3, there is a clear positive relationship between the *oil intensity* and the peak impulse response to an oil shock. A simple cross-sectional regression yields a slope coefficient of 0.57 and an 0.434. In a recent work, Pinchetti (2025) studies geopolitical shocks that raise oil prices and also finds that sectors characterized by higher energy intensity are subject to larger price increases in response to geopolitical energy shocks (i.e. shocks raising energy prices).

### 3.3.2 The cereal price shock

The recent sharp increase in global food prices has highlighted the importance of micro shocks such as cereal price shocks in shaping inflationary pressures. Despite their relevance, cereal price shocks remain understudied in the macroeconomic literature, particularly in the context of inflation dynamics. Here, we rely on the shock series estimated by Jo and Adjemian (2023) to investigate how a shock in cereal price may transmit to sectoral producer prices or aggregate variables. We impose a 5% shock in the US cereal price by adding the shock series as the first variable to the model.

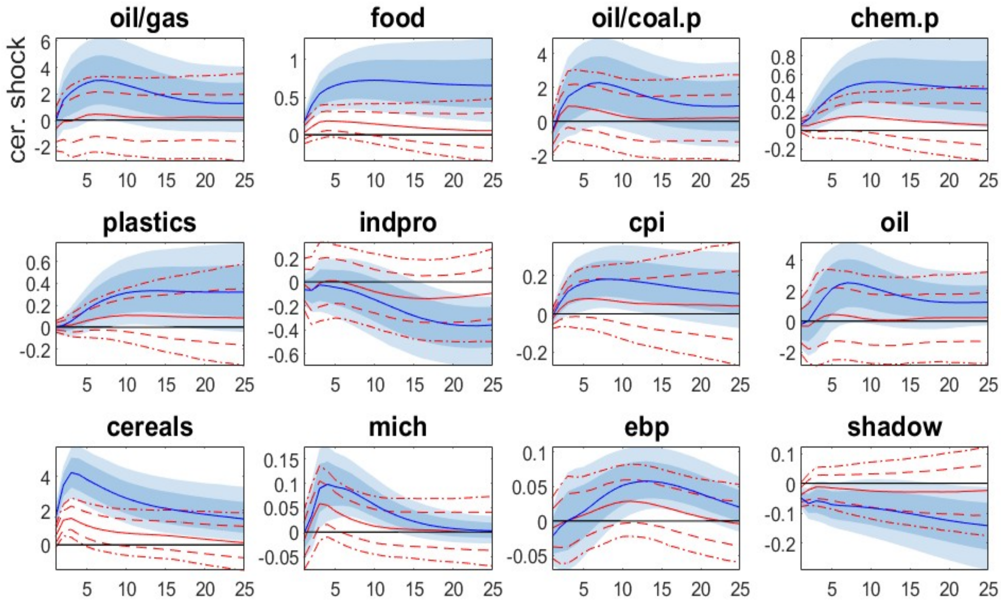


Figure 4: Impulse responses to a **cereal price shock** using Adjemian and Jo shock series in a BVAR(2) model with Input-Output informed Long-Run prior and Covid-19 correction (in blue) versus in the standard Minnesota BVAR(2) (in red). The shown variables are the following: *oil/gas - Oil and gas extraction PPI*, *food -Food, beverage and tobacco PPI*, *oil/coal.p - Oil and coal products PPI*, *chem.p - Chemical products PPI*, *plastics - Plastic products PPI*, *transp. -Transportation PPI*, *indpro - Industrial production*, *cpi - Consumer price index*, *oil - Crude oil price (WTI)*, *cereals - Cereals price*, *mich - Michigan inflation expectation*, *ebp - Excess bond premium*, *shadow - Shadow rate*

The impulse responses for all variables are shown in the Appendix C, while here we focus on the most relevant for the transmission. Again, we compare the impulse responses obtained from the Minnesota BVAR(2) (in red) with the ones obtained from the IO-informed long-run prior BVAR(2) (in blue). We see in Figure 4 that, as expected, the cereal price shock has a sizable and persistent impact on the producer price index for the *food, beverage and tobacco* sector. With the Minnesota BVAR(2) (in red), instead, we observe that the response of the *food, beverage and tobacco* sector would be close to zero. Similarly, many important sectors that show non-zero responses in the Input-Output informed Long-Run BVAR have close to zero responses in the Minnesota BVAR(2) (in red). This is also the case for headline CPI, indicating the inclusion of production linkages allows to capture how sectoral shocks can lead to aggregate responses.

The cereal price shock is also followed by a rise in *oil prices* and by a rise in the producer price indices of the *oil and gas extraction*, *oil and coal products* and also in *chemical products* or *plastic products* sectors. As the correlation between the oil price shock and the cereal price shock is 0.03 and as the angle between the two impact vectors is 105.57 degree, it means that the two shocks are capturing something different. Economically, cereal and oil are not directly linked in the IO table—cereals are downstream of oil, not the reverse. The fact that our IO-BVAR generates oil-related price responses to a cereal shock should be read as evidence that the prior couples them through shared cost-bundle modes. This is consistent with the empirical observation that global commodity prices often co-move (e.g. cereals, fertilizers, and oil during supply disruptions or biofuel booms). Surprisingly, the monetary policy response to the cereal price shock is expansionary. This could be due to the post-2008 period characterized by low interest rates and unconventional monetary policy, as well as to the post-COVID inflationary period during which the Fed arguably responded with some delay.

Figure 5 reports the responses to the cereal price shock of the aggregated producer price and the consumer price, showing which sectors contribute to the aggregate dynamics of PPI. As expected, the *food, beverage and tobacco* sector responds persistently to the cereal price shock (in light green). The *wholesale trade* sector, interestingly, responds to the cereal price shock with some delay. It could indicate that the rise in food prices caused by cereal prices only shows up in wholesale trade after a few months. The contribution of the oil and gas extraction sector is also important and persistent. However, Figure 5 is based on mean responses, while, as shown in Figure 4 the credible interval around the oil and gas extraction sector is quite large.

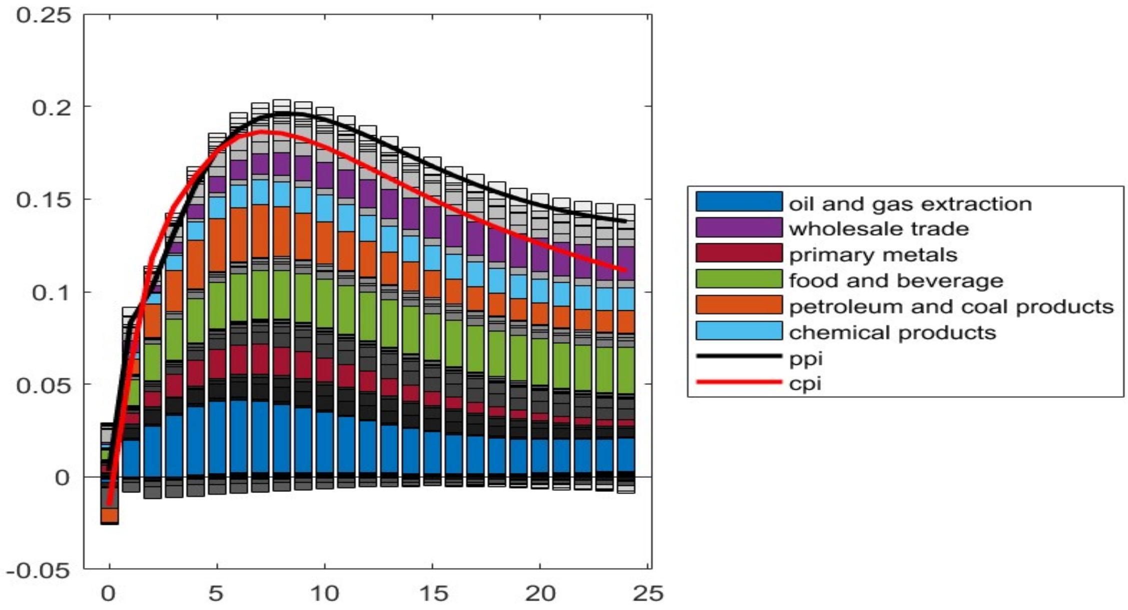


Figure 5: Contributions to aggregated PPI of sectoral PPIs responses to a **cereal price shock** using Adjemian and Jo shock series in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer price index is the red line. Each color represents a sector that we decided to highlight (ex: oil and gas extraction in blue) while the non-highlighted sectors are in shades of grey.

Interestingly, the aggregate PPI and CPI responses to the cereals price shock are now closely aligned, both in magnitude and persistence. This stands in contrast with the oil price shock, where producer prices rise more sharply and more persistently than consumer prices. The similarity between CPI and PPI in the cereals case could reflect the more direct position of agricultural goods in the production network: cereals are inputs mainly for final-consumption sectors such as food and beverages, so cost increases could be passed on more rapidly and almost completely to consumers. Moreover, food producers and retailers could tend to pass cost increases more directly to final consumers because margins are thin and substitution possibilities are limited.

### 3.3.3 The monetary policy shock

We look at the responses of the different variables in our model to a rise in the policy rate (here the shadow rate). To do so, we used the instrumental variable from Bauer and Swanson (2023).

Figure 6 shows the responses of the main aggregate variables to a 0.25% increase

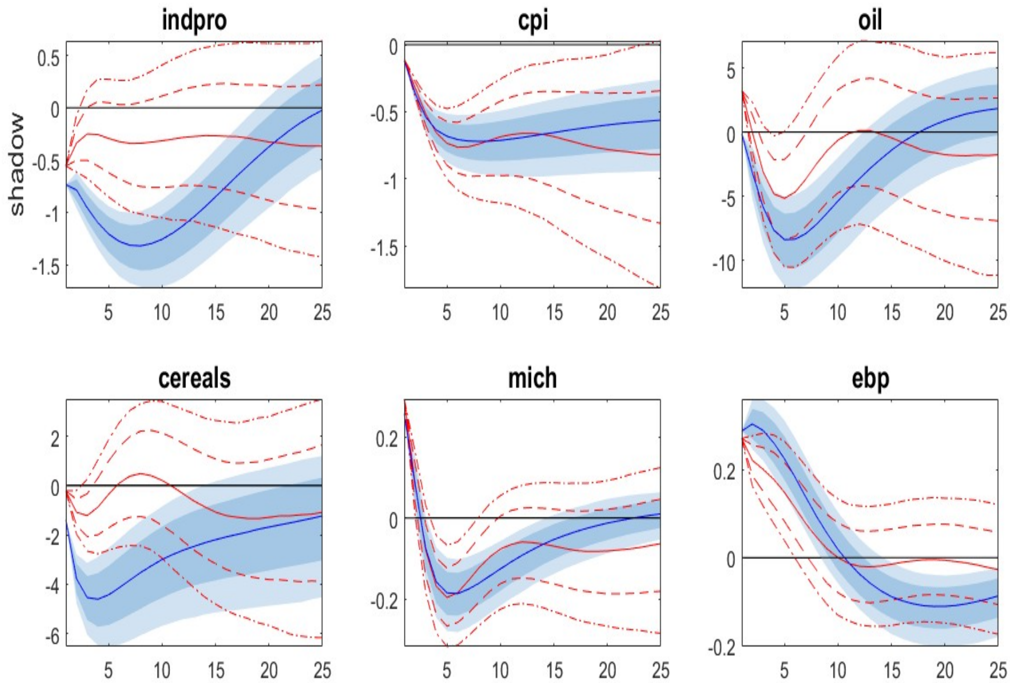


Figure 6: Impulse responses to a **monetary policy shock** using Bauer and Swanson surprises in a BVAR(2) model with Input-Output informed Long-Run prior and Covid-19 correction (in blue) versus in the standard Minnesota BVAR(2) (in red). The shown variables are the following: *indpro - Industrial production*, *cpi - Consumer price index*, *oil - Crude oil price (WTI)*, *mich - Michigan inflation expectation*, *ebp - Excess bond premium*, *shadow - Shadow rate*

in the shadow rate. The sectoral responses are available in Appendix C, along with the responses using Miranda-Agrippino and Ricco (2021) surprises. The rise observed in the excess bond premium makes sense as a rise in the interest rate signals tighter financial conditions, which can lead to higher risk premia to compensate for higher uncertainty.

The initial positive response of inflation expectations is however somewhat puzzling, as monetary policy tightening is typically associated with lower inflation expectations. A possible explanation is that financial markets initially interpret the rate hike as a response to rising inflationary pressures, before expectations decline later. The responses obtained with the Minnesota BVAR (in red) show that it is not the inclusion of the Input-Output long run prior that causes this small puzzle. The responses show an expected decline in industrial production and in the consumer price index.

Figure 7 completes the analysis of monetary policy shock in sectoral prices by looking, as done previously with the oil and cereal price shocks, to the contributions of the sectors to the aggregated PPI. Most of the contributions are negative and show that a certain

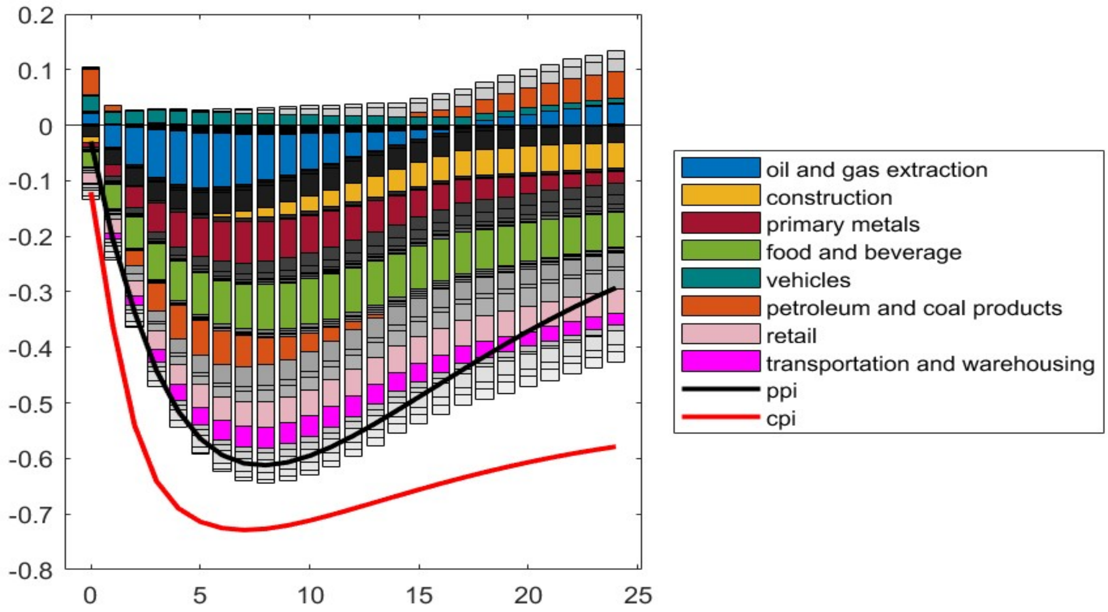


Figure 7: Contributions to aggregated PPI of sectoral PPIs responses to a **monetary policy shock** using the Bauer and Swanson surprises in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer price index is the red line. Each color represents a sector that we decided to highlight (ex: oil and gas extraction in blue) while the non-highlighted sectors are in shades of grey.

time is needed for the rise in the interest rate to have an impact on producer prices. Some sectoral contributions are more surprising, such as the positive contribution in the *vehicles* sector, but such a phenomenon has already been highlighted in other papers looking at the impact of monetary policy contraction on sectoral prices, as for example Aruoba and Drechsel (2024). The fact that a certain time is needed for the monetary policy shock to have an impact on aggregated PPI or CPI indices is also documented in Carvalho, Lee, and Park (2021) which finds that Input-Output linkages increase the persistence after an aggregate shock such as a monetary policy shock.

#### 3.3.4 A counterfactual analysis

The fact that the production linkages increase the size and persistence of price indices leads to questioning the pertinence for monetary policymakers to *look through* oil price shocks. To further assess the role of monetary policy in shaping the propagation of oil price shocks, we perform a counterfactual experiment in which the policy reaction is constrained to offset the inflationary effect of the oil shock. Specifically, we compute a

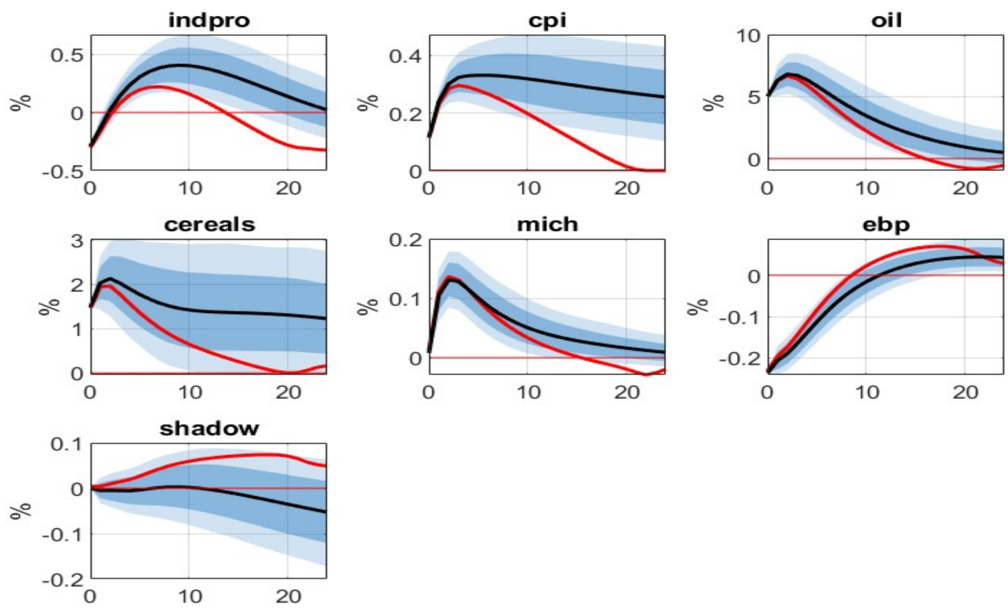


Figure 8: Counterfactual analysis comparing impulse responses to an oil shock (in blue) with a counterfactual situation in which monetary policy forces CPI's response to zero for horizons 22, 23 and 24 (last quarter of the two years horizon) (in red).

counterfactual impulse response that forces the CPI response to return to zero after two years (horizons 22–24). The resulting responses are shown in Figure 8: the blue impulse responses represent the baseline (Long-run prior with Input-Output matrix) model and the red lines the counterfactual paths under the stronger monetary policy reaction needed to shut down CPI at the last quarter of the two years horizon. In Appendix D we also provide the counterfactual scenario in which the policy reaction is constrained to offset the inflationary effect at the end of 1 year (i.e forcing CPI to zero for horizons 13 to 24). As expected, this further decreases the response of industrial production.

When monetary policy reacts to neutralize the inflationary pressure after two years, inflation is effectively contained, but at the cost of a pronounced and more persistent decline in industrial production. The shadow rate increases more strongly. This outcome mirrors the trade-off emphasized in Afrouzi and Bhattarai (2023): in their paper they find that if monetary policy responds by stabilizing aggregate inflation driven by a shock to the *oil and gas extraction* sector, it creates a large negative GDP gap.

# Conclusion

This paper explores the transmission of sectoral and aggregate shocks to producer prices using a Long-Run Prior BVAR framework that incorporates production network information. The long-run prior shrinks the model towards plausible dynamics for economically interpretable aggregates — the prices of sector-specific input bundles implied by the production network and is equivalent to the Minnesota BVAR on IO-weighted averages of log prices.

The results show that incorporating production network data in disaggregated models brings an added value in terms of forecasting performance. They also highlight the significant role of sectoral price spillovers in shaping inflationary dynamics, reinforcing the idea that sector-specific cost pressures can have broader macroeconomic implications. For example, we map how a cereal price shock transmits to the different sectors, leading to an increase in the aggregate producer price index or headline consumer price index, while it would not be the case if one does not take into account the production linkages.

The analysis of an oil price shock confirms many results highlighted in the multi-sector DSGE literature, such as the increased responses and persistence when taking into account production linkages. Oil intensive sectors clearly show stronger impulse responses.

The analysis of monetary policy shocks reveals that financial conditions play a central role in the inflation transmission mechanism. A contractionary policy shock leads to a decline in both inflation and industrial production. Interestingly, the response of inflation expectations suggests that financial markets may initially interpret policy rate hikes as a reaction to underlying inflationary pressures, before expectations adjust downward over time.

Furthermore, the muted response of the policy rate to oil price shocks suggests that policymakers "look through" supply-side disturbances, focusing instead on core inflation and second-round effects. However, we find with a counterfactual analysis that if policymakers reacted in order to offset inflation more rapidly, it would lead to a stronger decrease in output, confirming the well-known *inflation-output trade-off* for policymakers.

Importantly, this paper is, to our knowledge, the first to provide evidence of a sectoral spillover channel in driving headline inflation without imposing such a mechanism in the model's structure (as in DSGE models or in the NVAR framework of Mlikota (2023)). Since the Input–Output matrix enters only through the long-run prior, the model only suggests sectoral interactions and allows the data to determine the relative importance of this prior. This offers an innovative way to incorporate network linkages into the BVAR framework.

A deeper examination of sectoral heterogeneity in price responses could provide valuable insights into which industries drive inflation persistence, refining the framework for policy responses to inflationary pressures. By incorporating sectoral dynamics into macroeconomic analysis, this study contributes to a more nuanced understanding of how inflation evolves across different layers of the economy.

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# A Data Description and Sources

## A.1 Sectoral PPI series (35 sectors)

We collect 35 sectoral Producer Price Index (PPI) monthly indices from the BLS *Producer Price Index Industry Data*, from January 2004 up to December 2024. Series IDs are taken from the BLS list of industry data codes (`https://www.bls.gov/ppi/data-retrieval-guide/producer-price-index-industry-data-series-id-codes.txt`), and the time series are downloaded via the BLS portal (`https://data.bls.gov/series-report`). Data were last downloaded in July 2025. For most sectors we have a direct NAICS match and data starting before 2004M01. For some sectors we only take one sub-series as representative of the whole sector[6]. Out of the 35 sectors we find 6 sectors for which the available data starts after December 2003. In that case, we *backcast* the missing data. All PPI series are seasonally adjusted by us.

Table 3: BLS PPI Industry Series Used in the Paper

| # | Name in paper | BLS series code | Start | Remarks |
|---|---|---|---|---|
| 1 | Forestry and Logging | PCU1133–1133– | 198112 | Coverage narrow; only viable series. |
| 2 | Oil and gas extraction | PCU211—211— | 198512 | OK. |
| 3 | Mining, except oil and gas | PCU212—212— | 200312 | OK. |
| 4 | Support activities for mining | PCU213—213— | 200312 | OK (base date $\neq$ start date). |
| 5 | Utilities | PCU221—221– | 200312 | OK. |
| 6 | Construction | PCU236221236221 | 200412 | Warehouse building used for whole sector; starts 2004M12. |
| 7 | Wood products | PCU321—321— | 200312 | OK. |
| 8 | Nonmetallic mineral products | PCU327—327— | 198412 | OK. |
| 9 | Primary metals | PCU331—331— | 198412 | OK. |
| 10 | Fabricated metal products | PCU332—332— | 198412 | OK. |
| 11 | Machinery | PCU333—333— | 200312 | OK. |

*Continued on next page*

[6]For example, the Motor vehicles, bodies and trailers spans NAICS codes 3361-3363 but we only use the 3361 series after verification (see the file data_treatment.R) that the sub-series is strongly correlated with the other sub-series of the sector.

| # | Name in paper | BLS series code | Start | Remarks |
|---|---|---|---|---|
| 12 | Computer and electronic products | PCU334—334— | 200312 | OK. |
| 13 | Electrical equipment and appliances | PCU335—335— | 200312 | OK. |
| 14 | Motor vehicles, bodies and trailers | PCU3361–3361– | 200312 | OK, 3361 used for 3361–3363. |
| 15 | Other transportation equipment | PCU3364–3364– | 200312 | OK, 3364 used for 3364–3366, 3369. |
| 16 | Furniture and related products | PCU337—337— | 198412 | OK. |
| 17 | Miscellaneous manufacturing | PCU339—339— | 200312 | OK. |
| 18 | Food & beverage & tobacco products | PCU311—311— | 198412 | OK, 311 used for 311–312. |
| 19 | Textile mills & textile product mills | PCU313—313— | 200312 | OK, 313 used for 313–314. |
| 20 | Apparel & leather & allied products | PCU315—315— | 200312 | OK, 315 used for 315–316. |
| 21 | Paper products | PCU322—322— | 200312 | OK. |
| 22 | Printing and related support activities | PCU323—323— | 200312 | OK. |
| 23 | Petroleum and coal products | PCU324—324— | 198412 | OK. |
| 24 | Chemical products | PCU325—325— | 198412 | OK. |
| 25 | Plastics and rubber products | PCU326—326— | 198412 | OK. |
| 26 | Wholesale trade | pcuAWHLTRAWHLTR | 200612 | Aggregate; starts 2006M12. |
| 27 | Retail | pcuARETTRARETTR | 200612 | Aggregate; starts 2006M12. |
| 28 | Transportation and warehousing | pcuATRNWRATRNWR | 200612 | Aggregate; starts 2006M12. |
| 29 | Information | PCUAINFO-AINFO- | 200612 | Aggregate; starts 2006M12. |
| 30 | Finance, Insurance, Real Estate (FIRE) | PCU524—524— | 200312 | OK, 524 used for 52–53. |
| 31 | Professional & business services (PROF) | PCU5411–5411– | 199612 | OK, 5411 used for 54–56. |

*Continued on next page*

| # | Name in paper | BLS series code | Start | Remarks |
|---|---|---|---|---|
| 32 | Education, Health, Social assistance (EHS) | PCU622—622— | 199212 | OK, 622 (hospitals) used for whole 62 sector. |
| 33 | Arts/Rec/Accom/Food (AERAF) | PCU721—721— | 199612 | OK, 721 (accommodation) used for 71–72. |
| 34 | Other services, except government | PCU8113–8113– | 200606 | Only available; starts 2006M06. |
| 35 | Public sector | PCU491—491— | 198906 | Postal services proxy. |

## A.2 Macroeconomic variables

To the 35 sectoral PPI series, we add 7 additional series. The oil price and cereal price series are divided by the consumer price index to get real oil / cereals prices.

1. **Industrial Production (INDPRO)** — index 2017=100, SA (FRED).
2. **Consumer Price Index (CPIAUCSL)** — index 1982–84=100, SA (FRED).
3. **WTI oil price (DCOILWTICO)** — monthly average, USD/barrel, NSA (FRED).
4. **Primary commodity prices (IMF)** — NSA, used to construct the cereals price index; four cereals combined with weights from De Winne & Peersman (2021).
5. **Michigan inflation expectations (MICH)** — percent, NSA (FRED).
6. **Excess Bond Premium (EBP)** — NSA, Gilchrist & Zakrajšek (FEDS Notes).
7. **Wu–Xia shadow rate** — NSA, updated to 2023M6 (C. Wu's website) and completed afterwards with the federal funds rate (FEDFUNDS — percent, NSA (FRED)).

## A.3 Data treatment workflow

An `R` script (`data_treatment`) performs:

1. Reading/cleaning sectoral PPI files; reconciling sub-series where needed; backcasting to 2003M12 for sectors 6, 26–29, and 34.
2. Reading/cleaning additional macro series.
3. Producing a consolidated Excel file combining sectoral prices and macro data.

# B Recursive forecast robustness tests

## B.1 Changing the number of lags : BVAR(1) and BVAR(3) models

As seen in the tables 4 up to 7, changing slightly the number of lags does not impact the overall result that introducing the Input-Output matrix helps in comparison to the simpler (without network) BVAR specifications. As a reminder, MN is the simple Minnesota BVAR, MN-C adds the Covid variation, LR adds long-run priors on the interest rate and inflation rate and LR-IO is the full model, taking into account the Covid variation, and a long-run prior not only on the interest rate and inflation rate but also on the sectoral producer indices.

**BVAR(1)**

| | | Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.3721 | 1.7516 | 1.4353 | 1.3733 | 1.2560 |
| h=1Q | 0.6144 | **1.6598** | 1.3558 | **1.3677** | 1.3458 |
| h=2Q | 0.6665 | 1.7205 | 1.2934 | 1.1788 | 1.1755 |
| h=3Q | 0.6811 | 1.7449 | 1.2557 | 1.0705 | 1.0434 |
| h=4Q | 0.6815 | **2.1945** | **1.7431** | **1.4826** | 0.9839 |

Table 4: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(1) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Full evaluation sample : 2018Q1 up to 2024Q4.

| | | Ratios rmse(BVARs) / rmse(spf) (< 1 → better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.5640 | 0.8575 | 0.8160 | 0.8191 | 0.7675 |
| h=1Q | 0.9177 | **1.3752** | 1.2332 | 1.3001 | 0.9523 |
| h=2Q | 0.9119 | 1.0090 | 0.8233 | 0.8670 | 0.8811 |
| h=3Q | 0.9255 | 1.1112 | 0.9987 | 0.8564 | 0.9028 |
| h=4Q | 0.8972 | 1.7291 | 1.7293 | 1.4693 | 0.9350 |

Table 5: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(1) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Shorter evaluation sample : 2018Q1 up to 2021Q2.

**BVAR(3)**

| | | Ratios rmse(BVARs) / rmse(spf) (< 1 → better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.3721 | 1.6329 | 1.4129 | 1.3264 | 1.3198 |
| h=1Q | 0.6144 | **1.5349** | **1.4736** | **1.4003** | 1.5725 |
| h=2Q | 0.6665 | **1.6766** | **1.5301** | 1.5277 | 1.3838 |
| h=3Q | 0.6811 | **1.7852** | 1.5353 | **1.6031** | 1.1671 |
| h=4Q | 0.6815 | **2.1670** | **1.7889** | **1.8901** | 1.0922 |

Table 6: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(3) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Full evaluation sample : 2018Q1 up to 2024Q4.

| | | Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.5640 | 0.8412 | 0.8995 | 0.9306 | 0.7785 |
| h=1Q | 0.9177 | 1.4239 | 1.3140 | 1.5174 | 1.0785 |
| h=2Q | 0.9119 | 1.1929 | 1.1061 | 1.2034 | 1.0087 |
| h=3Q | 0.9255 | 1.1345 | 1.0142 | 1.1101 | 0.9190 |
| h=4Q | 0.8972 | **1.4041** | **1.4048** | 1.3855 | 0.9641 |

Table 7: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(3) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Shorter evaluation sample : 2018Q1 up to 2021Q2.

### B.2 Use the Leontief inverse instead of the IO matrix

In tables 8 and 9 we replace the IO matrix in $H$ with the Leontief inverse $(I - IO)^{-1}$. The Leontief inverse is $(I - IO)^{-1}$, which can be decomposed into

$$(I - IO)^{-1} = I + IO + IO^2 + IO^3 + \cdots$$

where each $n$th power of the Input-Output matrix represents the intermediates from one sector to another via network paths of length $n$. So in the Leontief inverse, each element $((I - IO)^{-1})_{ij}$ represents the proportion of input costs in sector $i$ that comes *indirectly* from sector $j$.

| | | Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-L/spf |
| h=0Q | 0.3721 | 1.6367 | 1.3600 | 1.2662 | 1.2705 |
| h=1Q | 0.6144 | **1.5524** | **1.4191** | **1.3670** | 1.4657 |
| h=2Q | 0.6665 | **1.6776** | **1.4471** | **1.3468** | 1.2843 |
| h=3Q | 0.6811 | **1.6968** | **1.3778** | 1.3026 | 1.1141 |
| h=4Q | 0.6815 | **2.0848** | **1.6840** | **1.5862** | 1.0128 |

Table 8: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-Leontief BVAR(2) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Full evaluation sample: 2018Q1–2024Q4.

| | | Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-L/spf |
| h=0Q | 0.5640 | 0.8292 | 0.8424 | 0.7867 | 0.6071 |
| h=1Q | 0.9177 | 1.4015 | 1.2580 | 1.4307 | 0.9927 |
| h=2Q | 0.9119 | 1.1616 | 1.0198 | 1.1008 | 0.9677 |
| h=3Q | 0.9255 | 1.1059 | 0.9713 | 0.9492 | 0.9180 |
| h=4Q | 0.8972 | **1.5594** | **1.5597** | 1.3621 | 0.9549 |

Table 9: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-Leontief BVAR(2) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Shorter evaluation sample: 2018Q1–2021Q2.

## B.3 Recursive forecast with one month of additional data

As discussed, in tables 10 and 11 we show a setup for the forecasting exercise in which the models have access to the first month of the forecasting quarter, matching the SPF vintage data. We here present the results for the BVAR(2) models.

| | | Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.3721 | 0.8956 | 1.0005 | 1.0481 | 0.8066 |
| h=1Q | 0.6144 | **1.8924** | **2.1070** | **1.9948** | 1.4567 |
| h=2Q | 0.6665 | **2.0952** | **2.0214** | **1.6502** | 1.3065 |
| h=3Q | 0.6811 | 2.3727 | 1.7835 | 1.3819 | 1.1004 |
| h=4Q | 0.6815 | 2.7748 | 1.8429 | 2.3879 | 0.9675 |

Table 10: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(2) models with one additional month in the information set, matching the SPF as forecasters do have access to the first month of the forecasting quarter. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Full evaluation sample: 2018Q1–2024Q4.

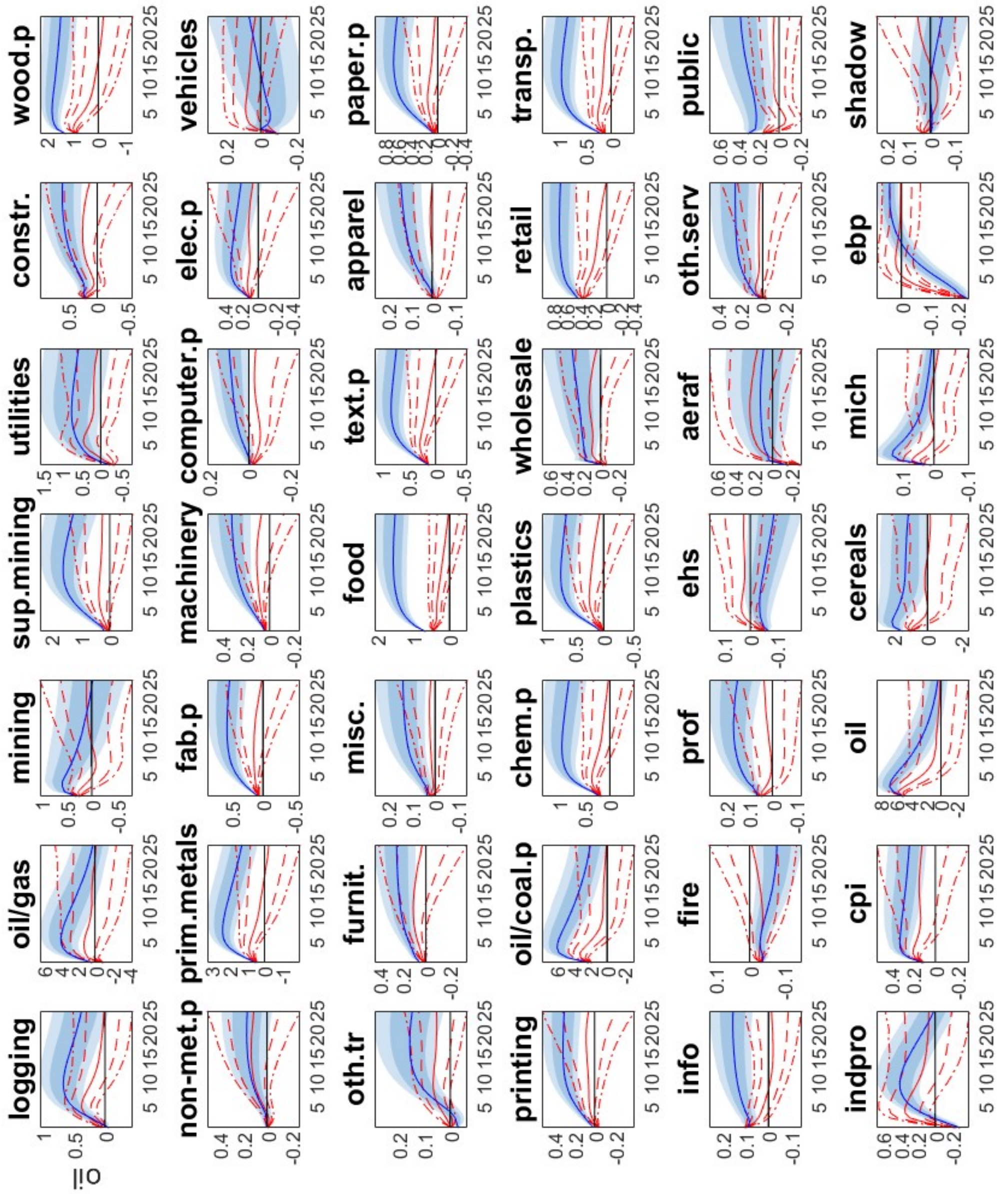
| | | Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf) | | | |
|---|---|---|---|---|---|
| | rmse(spf) | MN/spf | MN-C/spf | LR/spf | LR-IO/spf |
| h=0Q | 0.5640 | 0.8788 | 0.8987 | 0.9537 | 0.5209 |
| h=1Q | 0.9177 | 2.2188 | 2.2299 | 2.4264 | 0.9270 |
| h=2Q | 0.9119 | 2.1646 | 2.1430 | 1.9936 | 0.9615 |
| h=3Q | 0.9255 | 1.3584 | 1.3224 | 0.9034 | 0.9400 |
| h=4Q | 0.8972 | 0.8550 | 0.8568 | 3.4118 | 0.8357 |

Table 11: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(2) models with one additional month in the information set, matching the SPF as forecasters do have access to the first month of the forecasting quarter. No entries are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Shorter evaluation sample: 2018Q1–2021Q2.

# C Impulse response functions details

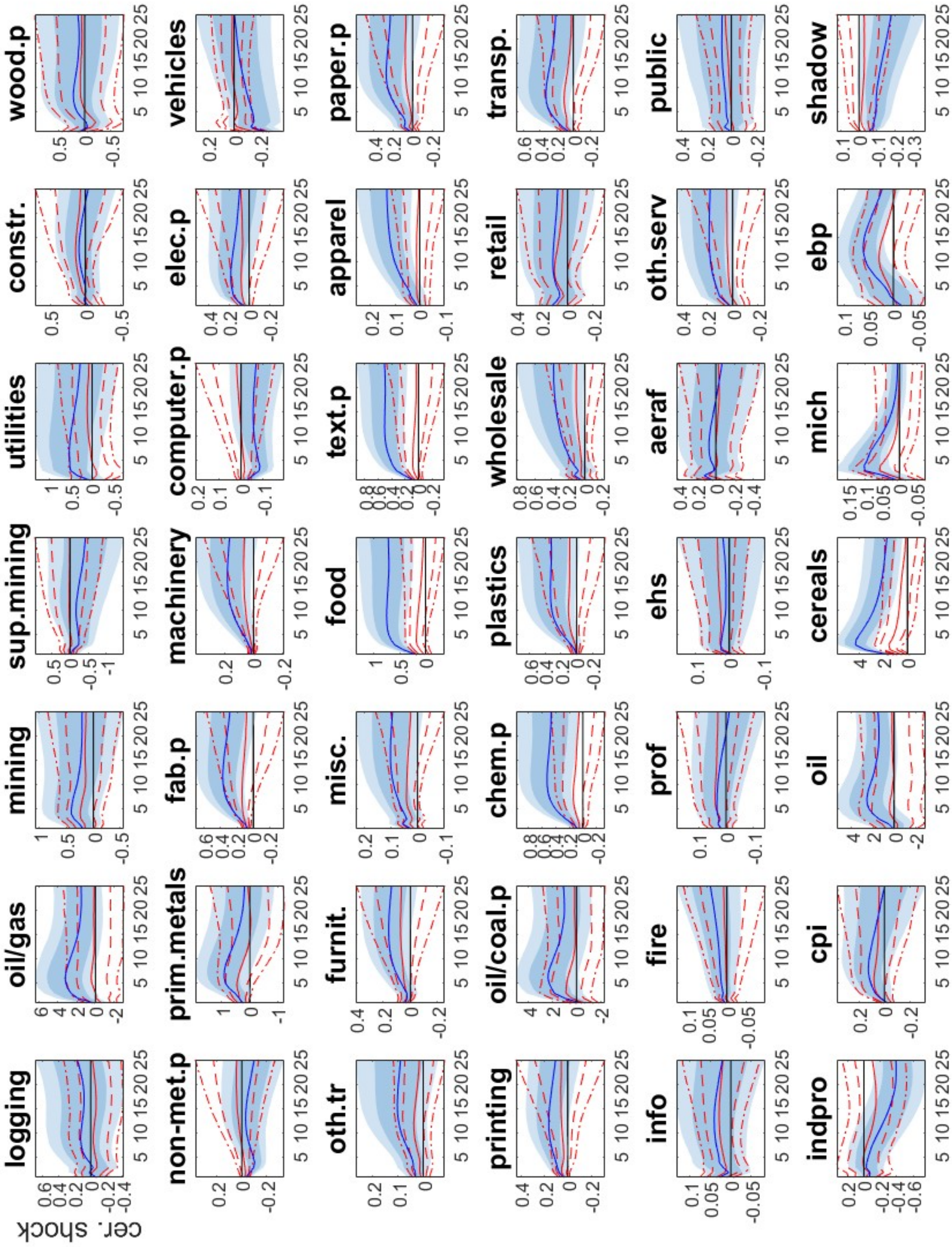
## C.1 Oil price shock - all impulse responses

Comparisons between the impulse responses using the IO-informed long-run BVAR(2) (in blue) and using the Minnesota BVAR(2) (in red). Refer to Appendix A for the full names of the sectors.



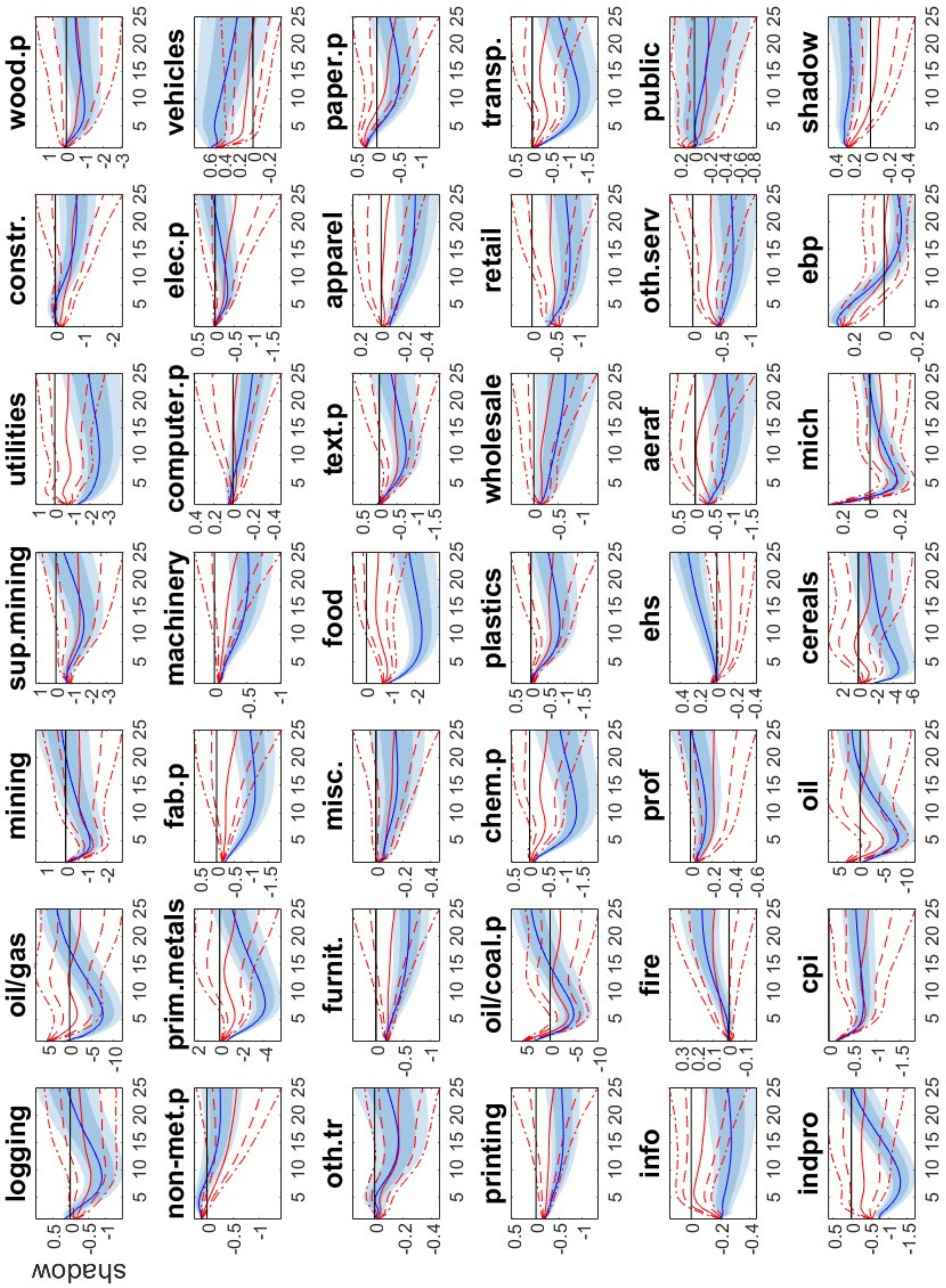
## C.2 Cereal price shock - all impulse responses

Comparisons between the impulse responses using the IO-informed long-run BVAR(2) (in blue) and using the Minnesota BVAR(2) (in red). Refer to Appendix A for the full names of the sectors.



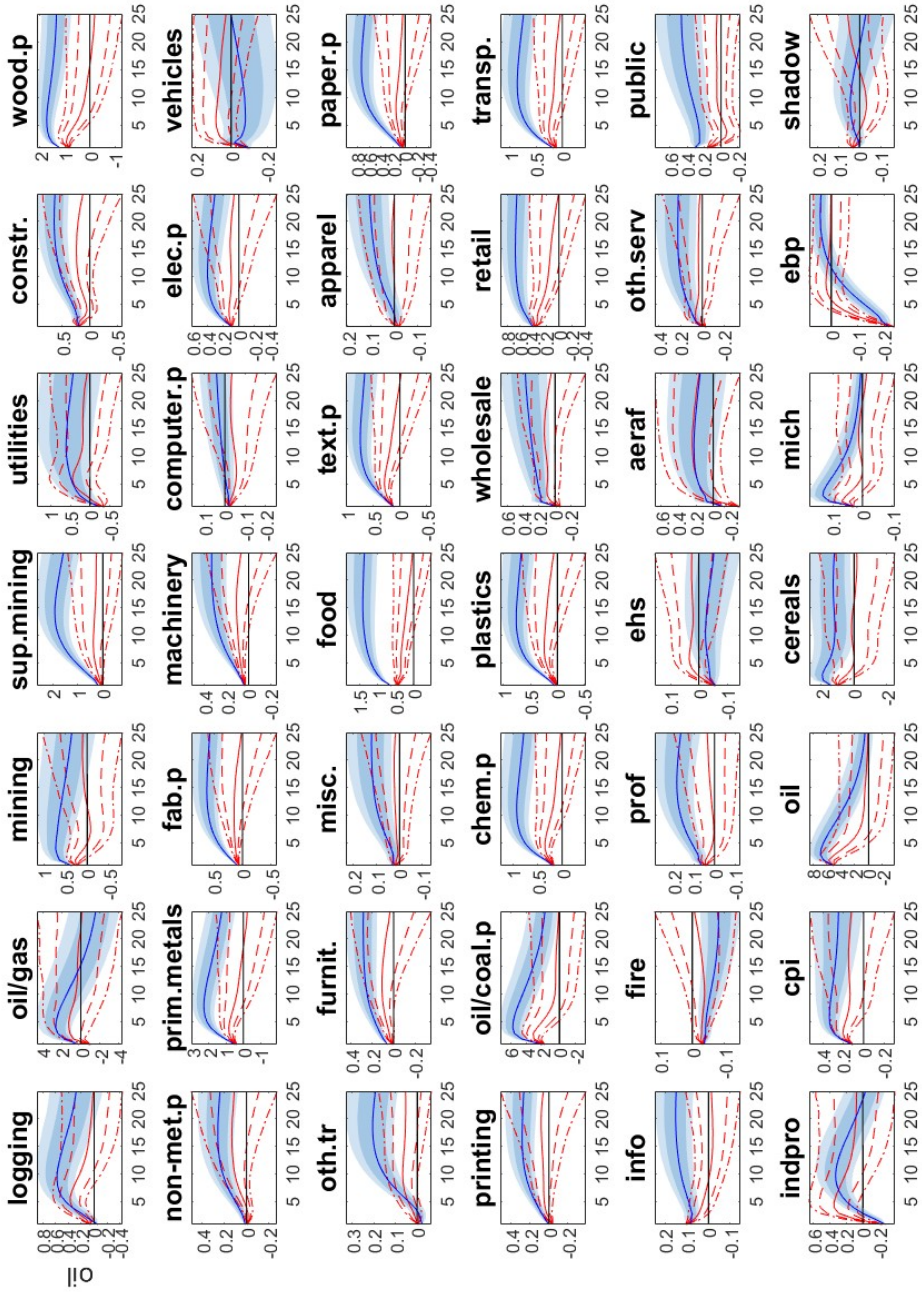
## C.3 Monetary policy shock - all impulse responses

Comparisons between the impulse responses using the IO-informed long-run BVAR(2) (in blue) and using the Minnesota BVAR(2) (in red). Refer to Appendix A for the full names of the sectors.



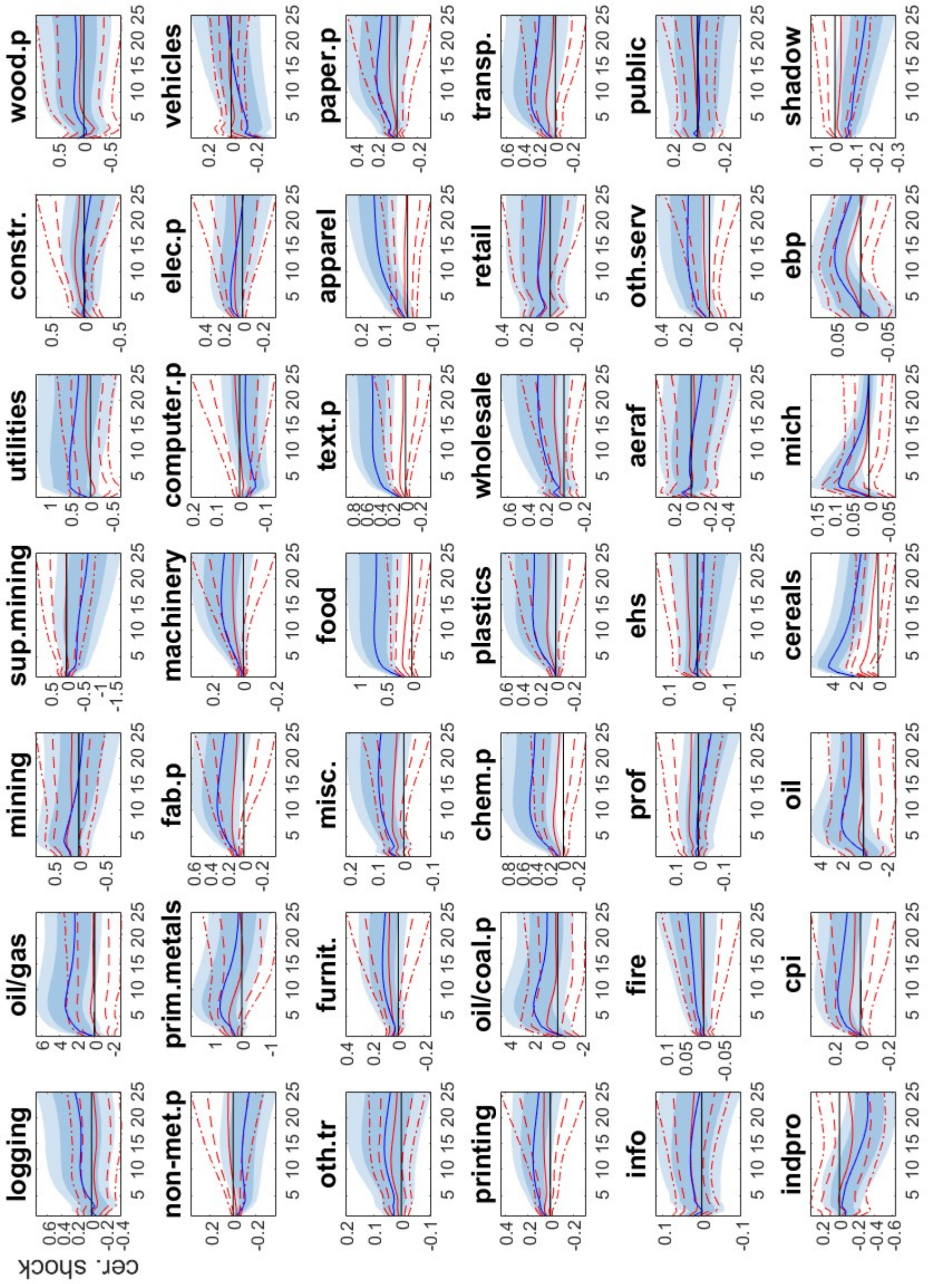
## C.4 Oil price shock - Leontief informed prior - all impulse responses

Comparisons between the impulse responses using the Leontief-informed long-run BVAR(2) (in blue) and using the Minnesota BVAR(2) (in red). Refer to Appendix A for the full names of the sectors.



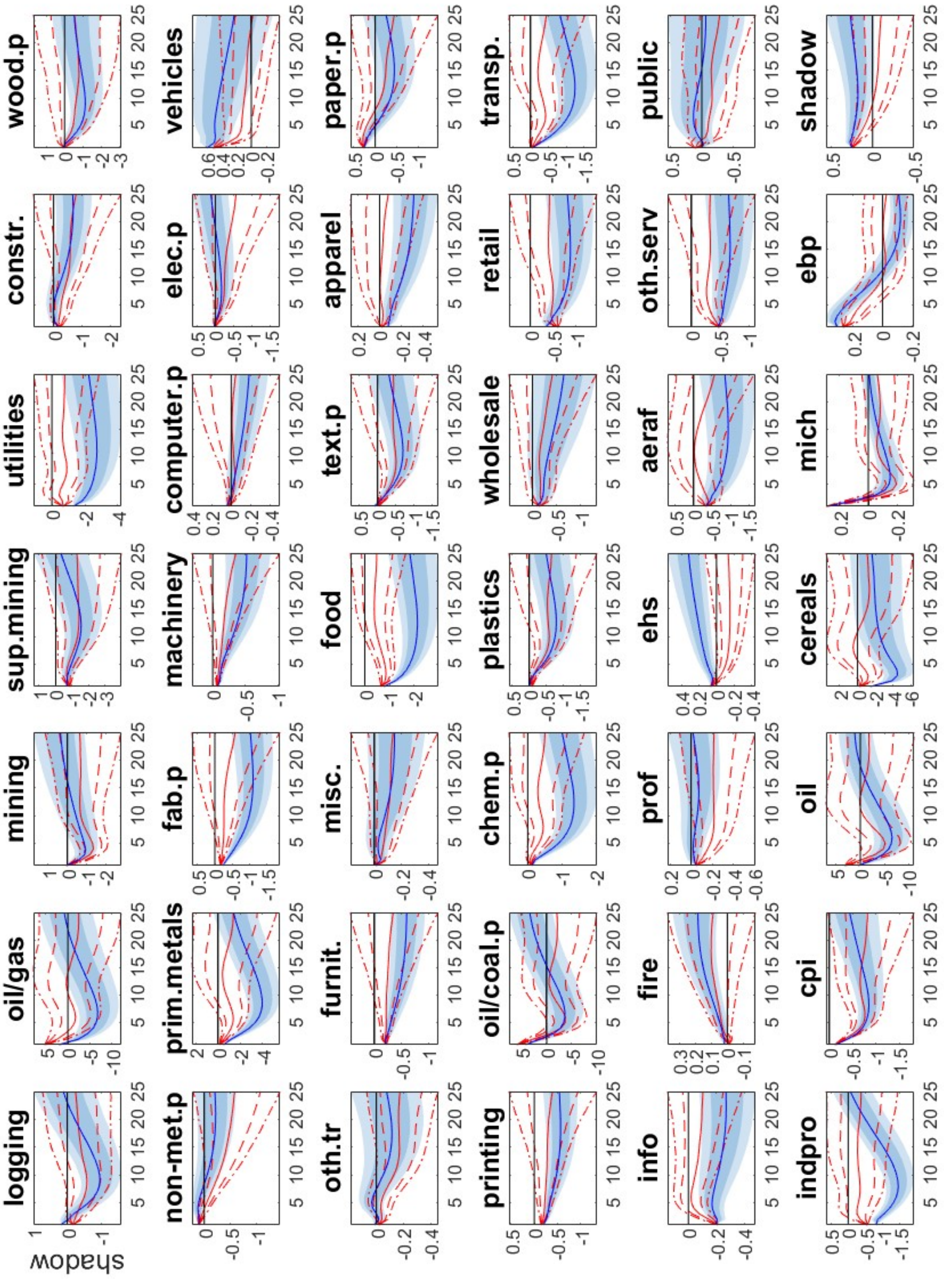
## C.5 Cereals price shock - Leontief informed prior - all impulse responses

Comparisons between the impulse responses using the Leontief-informed long-run BVAR(2) (in blue) and using the Minnesota BVAR(2) (in red). Refer to Appendix A for the full names of the sectors.



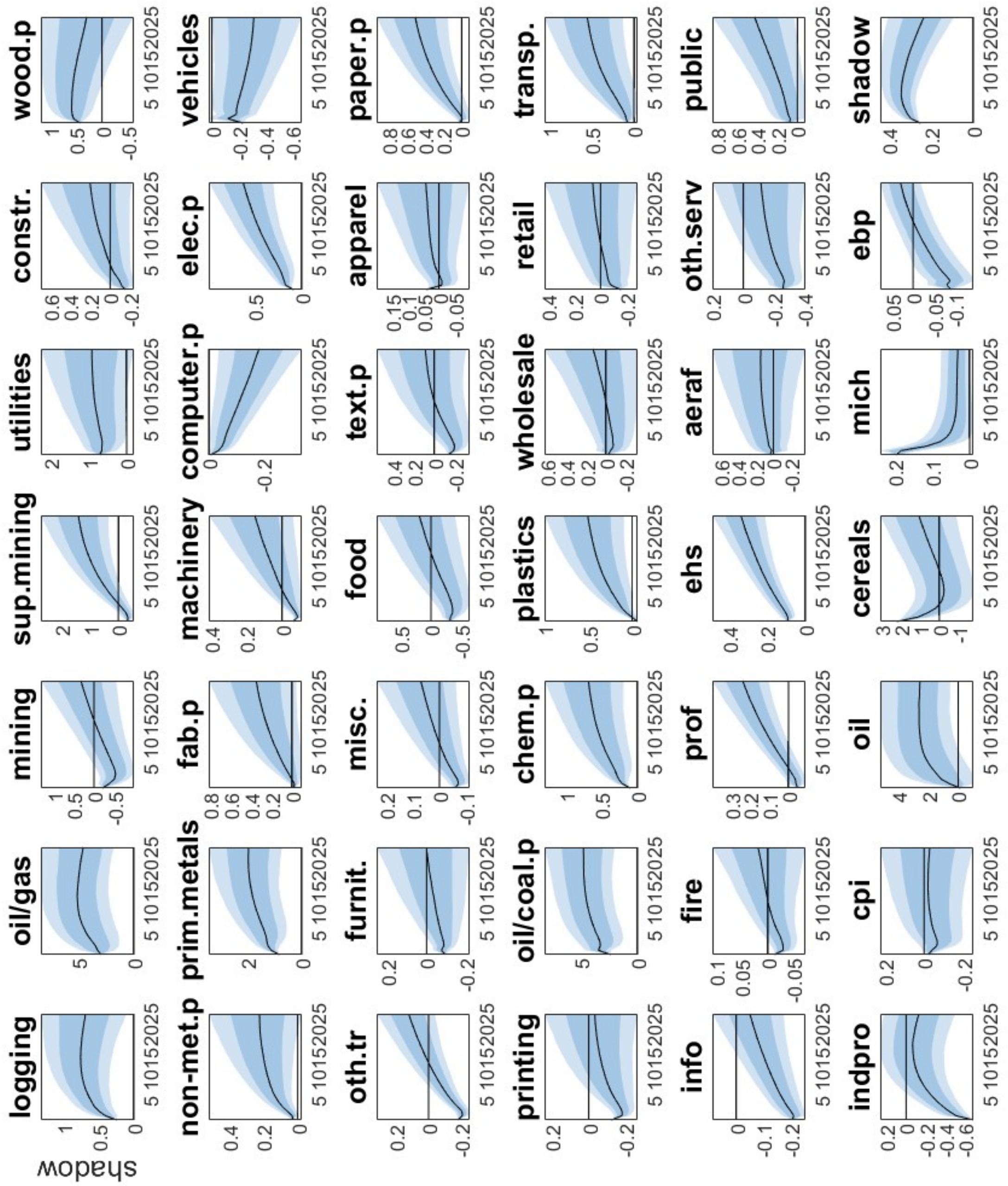
## C.6 Monetary policy shock - Leontief informed prior - all impulse responses

Comparisons between the impulse responses using the Leontief-informed long-run BVAR(2) (in blue) and using the Minnesota BVAR(2) (in red). Refer to Appendix A for the full names of the sectors.



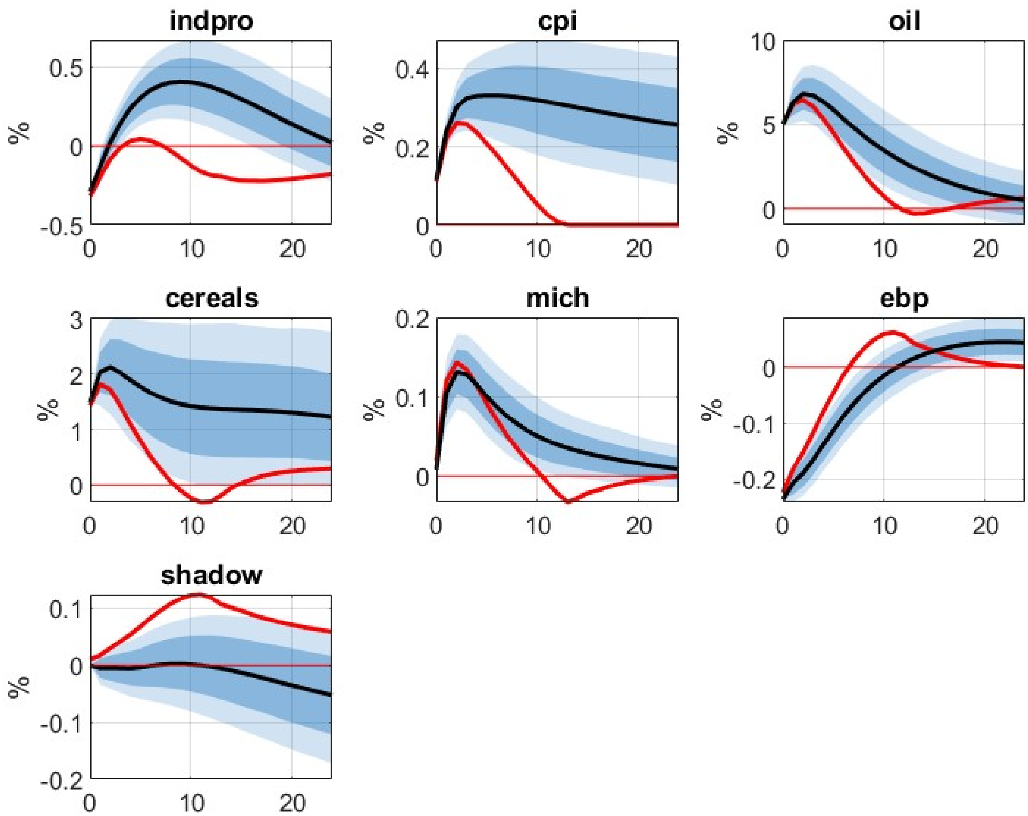
## C.7 Monetary policy shock - IO informed prior - Miranda-Agrippino and Ricco (2021) instrument

Impulse responses using the IO-informed long-run BVAR(2) and using the monetary policy surprises from Miranda-Agrippino and Ricco (2021) to identify the shock. Refer to Appendix A for the full names of the sectors.



# D Counterfactual exercise

Counterfactual analysis comparing impulse responses to an oil shock (in blue) with a counterfactual situation in which monetary policy forces CPI's response to zero for horizons 13 to 24 (last year of the two years horizon) (in red).



# E Input-Output matrix

| | Agriculture and forestry | Oil and gas extraction | Mining, except oil and gas | Support activities for mining | Utilities | Construction | Wood products | Nonmetallic mineral products | Primary metals | Fabricated metal products | Machinery | Computer and electronic products | Electrical equipment, appliances, and components | Motor vehicles, bodies and trailers, and parts | Other transportation equipment | Furniture and related products | Miscellaneous manufacturing | Food and beverage and tobacco products | Textile mills and textile product mills | Apparel and leather and allied products | Paper products | Printing and related support activities | Petroleum and coal products | Chemical products | Plastics and rubber products | Wholesale trade | Retail | Transportation and warehousing | Information | FIRE | PROF | EHS | AERAF | Other services, except government | Public sector |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Agriculture and forestry | 32 | 0 | 1 | 0 | 2 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 12 | 0 | 0 | 0 | 0 | 4 | 10 | 1 | 13 | 1 | 4 | 0 | 14 | 2 | 0 | 0 | 0 | 1 |
| Oil and gas extraction | 0 | 28 | 1 | 5 | 3 | 1 | 0 | 1 | 3 | 3 | 5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 4 | 0 | 4 | 0 | 6 | 2 | 12 | 16 | 0 | 0 | 0 | 2 |
| Mining, except oil and gas | 0 | 1 | 13 | 2 | 6 | 4 | 0 | 1 | 1 | 2 | 8 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 | 5 | 3 | 7 | 1 | 7 | 2 | 10 | 13 | 0 | 0 | 0 | 2 |
| Support activities for mining | 0 | 1 | 0 | 2 | 0 | 4 | 0 | 1 | 1 | 3 | 10 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 4 | 2 | 6 | 1 | 3 | 3 | 24 | 21 | 0 | 2 | 1 | 1 |
| Utilities | 0 | 21 | 5 | 0 | 11 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 1 | 0 | 3 | 1 | 12 | 3 | 7 | 13 | 0 | 1 | 0 | 6 |
| Construction | 0 | 0 | 2 | 0 | 1 | 0 | 6 | 9 | 1 | 11 | 4 | 1 | 5 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 2 | 4 | 9 | 11 | 3 | 2 | 7 | 10 | 0 | 0 | 1 | 1 |
| Wood products | 17 | 0 | 0 | 0 | 2 | 0 | 31 | 1 | 1 | 4 | 1 | 1 | 2 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 2 | 3 | 1 | 11 | 0 | 7 | 1 | 2 | 5 | 0 | 1 | 1 | 1 |
| Nonmetallic mineral products | 0 | 0 | 12 | 0 | 5 | 1 | 1 | 21 | 2 | 4 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | 2 | 6 | 2 | 8 | 1 | 11 | 2 | 5 | 8 | 0 | 1 | 1 | 2 |
| Primary metals | 0 | 0 | 9 | 0 | 4 | 0 | 0 | 1 | 43 | 4 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 1 | 1 | 13 | 0 | 7 | 1 | 3 | 5 | 0 | 0 | 1 | 2 |
| Fabricated metal products | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 1 | 34 | 18 | 2 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 4 | 1 | 8 | 0 | 3 | 2 | 5 | 10 | 0 | 1 | 1 | 1 |
| Machinery | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 15 | 12 | 15 | 4 | 6 | 6 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 2 | 3 | 11 | 1 | 2 | 2 | 4 | 9 | 0 | 0 | 0 | 1 |
| Computer and electronic prod. | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 4 | 5 | 1 | 35 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 3 | 2 | 9 | 0 | 3 | 3 | 5 | 22 | 0 | 0 | 0 | 1 |
| Electrical equipment, etc. | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 23 | 12 | 3 | 6 | 13 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 2 | 0 | 2 | 4 | 2 | 12 | 0 | 3 | 1 | 4 | 4 | 0 | 0 | 0 | 1 |
| Motor vehicles, bodies, etc. | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 10 | 9 | 5 | 4 | 1 | 39 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 2 | 5 | 11 | 1 | 2 | 1 | 1 | 4 | 0 | 0 | 0 | 0 |
| Other transportation equip. | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 6 | 7 | 3 | 8 | 1 | 3 | 37 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 2 | 6 | 1 | 2 | 2 | 5 | 11 | 0 | 0 | 0 | 1 |
| Furniture and related products | 0 | 0 | 0 | 0 | 1 | 0 | 15 | 1 | 8 | 7 | 0 | 2 | 0 | 1 | 0 | 8 | 0 | 0 | 6 | 0 | 3 | 0 | 1 | 4 | 8 | 11 | 1 | 5 | 2 | 6 | 7 | 0 | 1 | 0 | 1 |
| Miscellaneous manufacturing | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 9 | 7 | 2 | 4 | 1 | 1 | 0 | 0 | 8 | 0 | 3 | 0 | 3 | 0 | 1 | 8 | 7 | 11 | 1 | 4 | 3 | 7 | 13 | 0 | 1 | 1 | 1 |
| Food and beverage and tobacco prod | 33 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 0 | 0 | 4 | 0 | 1 | 2 | 3 | 9 | 1 | 6 | 1 | 2 | 5 | 0 | 0 | 0 | 1 |
| Textile and textile product mills | 5 | 0 | 0 | 0 | 3 | 0 | 0 | 1 | 1 | 2 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 1 | 2 | 0 | 2 | 27 | 1 | 8 | 1 | 4 | 1 | 3 | 7 | 0 | 0 | 0 | 1 |
| Apparel, leather & allied prod. | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 2 | 6 | 19 | 16 | 1 | 1 | 0 | 2 | 2 | 14 | 0 | 4 | 2 | 6 | 16 | 0 | 0 | 0 | 2 |
| Paper products | 4 | 0 | 1 | 0 | 4 | 1 | 4 | 0 | 0 | 4 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 2 | 0 | 33 | 0 | 2 | 9 | 3 | 9 | 1 | 6 | 1 | 2 | 5 | 0 | 0 | 1 | 2 |
| Printing and related support | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 3 | 3 | 4 | 0 | 1 | 0 | 0 | 0 | 2 | 1 | 2 | 17 | 5 | 4 | 11 | 2 | 7 | 4 | 5 | 3 | 6 | 13 | 0 | 1 | 1 | 2 |
| Petroleum and coal products | 0 | 78 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 2 | 0 | 3 | 0 | 5 | 0 | 0 | 2 | 0 | 0 | 0 | 1 |
| Chemical products | 2 | 2 | 1 | 0 | 3 | 0 | 0 | 0 | 0 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 0 | 6 | 46 | 3 | 10 | 1 | 3 | 1 | 3 | 9 | 0 | 0 | 1 | 2 |
| Plastics and rubber products | 1 | 0 | 0 | 0 | 3 | 0 | 1 | 1 | 1 | 5 | 1 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 3 | 0 | 2 | 38 | 11 | 8 | 0 | 5 | 1 | 3 | 6 | 0 | 1 | 1 | 1 |
| Wholesale trade | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 2 | 8 | 1 | 11 | 6 | 20 | 31 | 1 | 1 | 3 | 5 |
| Retail | 0 | 0 | 0 | 0 | 4 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 4 | 2 | 12 | 6 | 27 | 25 | 1 | 1 | 2 | 4 |
| Transportation and warehous. | 0 | 1 | 0 | 0 | 3 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 15 | 0 | 1 | 5 | 3 | 25 | 2 | 18 | 11 | 0 | 2 | 2 | 4 |
| Information | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 2 | 0 | 4 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 0 | 1 | 1 | 3 | 1 | 3 | 33 | 11 | 26 | 1 | 5 | 1 | 2 |
| FIRE | 0 | 0 | 0 | 0 | 3 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 2 | 4 | 51 | 19 | 0 | 3 | 1 | 3 |
| PROF | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 3 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 2 | 1 | 3 | 1 | 4 | 10 | 20 | 37 | 1 | 5 | 2 | 3 |
| EHS | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 4 | 3 | 0 | 0 | 1 | 1 | 1 | 7 | 1 | 6 | 1 | 2 | 5 | 28 | 21 | 4 | 4 | 2 | 3 |
| AERAF | 1 | 0 | 0 | 0 | 4 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 4 | 3 | 2 | 5 | 21 | 26 | 1 | 6 | 2 | 4 |
| Other services, except gov. | 0 | 0 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 1 | 2 | 2 | 1 | 6 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 2 | 2 | 2 | 5 | 3 | 2 | 6 | 32 | 16 | 2 | 2 | 3 | 3 |
| Public sector | 0 | 2 | 1 | 0 | 2 | 6 | 0 | 0 | 0 | 1 | 1 | 2 | 1 | 1 | 3 | 0 | 1 | 4 | 0 | 0 | 1 | 1 | 10 | 3 | 1 | 5 | 1 | 5 | 9 | 13 | 18 | 2 | 2 | 2 | 3 |