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

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Abstract

This paper studies the dynamics of U.S. sectoral producer prices in a large Bayesian Vector Auto Regression (BVAR) model where the Input-Output (IO) matrix is used to structure their long-run relationships. The model provides evidence of a sectoral spillover channel in driving headline inflation without imposing such a mechanism in the model's structure. Forecasts of headline inflation have accuracy comparable to the Survey of Professional Forecasters' and greater than those generated by a standard BVAR with the Minnesota prior, confirming that the IO matrix long-run prior conveys relevant information about the data. The study of an oil price shock shows that adding the production network prior alters the transmission of the shock, amplifying headline inflation. Across sectors, the peak price response to the oil shock increases with oil intensity. A narrowly sector-specific disturbance, such as a cereal price shock, has non-negligible aggregate effects once the production network is accounted for. Sectoral asymmetries are crucial for evaluating the macroeconomic consequences of macroeconomic shocks such as an energy price shock and a monetary policy shock, as industries with slower price adjustments amplify inflation persistence, even after the shock dissipates.

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

Non-technical summary

The surge in inflation observed in 2021–2022, with its concomitant spikes in food and energy prices, reignited fundamental questions about the origins and persistence of inflation pressures. In particular, how do shocks that originate in specific sectors of the economy, such as food or energy, spread to other sectors and ultimately shape aggregate inflation? Modern economies are deeply interconnected through supply chains: firms rely on intermediate inputs produced by other industries, so price increases in one sector can cascade through the production network. This paper proposes a data-driven model to study how sectoral shocks propagate across industries, how they contribute to headline inflation, and how the structure of production influences the persistence of inflationary pressures.

To address these questions, we build a Bayesian Vector Autoregression model of the U.S. economy that includes 35 sectoral producer price indices and key macroeconomic variables such as industrial production, consumer prices, and the policy rate. We incorporate information from the Input–Output tables on how sectors depend on each other through intermediate input linkages, not imposing rigid theoretical restrictions, but rather using this production network information to guide the long-run relationships in a flexible statistical framework. In this way, the model allows sectoral prices to move together in a manner consistent with supply-chain linkages, while still letting the data determine the strength and importance of these connections. We then identify three disturbances—an oil price shock, a cereal price shock, and a monetary policy shock—and trace their effects across sectors and onto aggregate inflation.

Our results show that accounting for the production-network structure plays a central role in shaping inflation dynamics. For example, when the network structure is taken into account, oil price shocks generate larger and more persistent increases in both producer and consumer prices than in models that ignore sectoral linkages. This heterogeneity across industries proves crucial. The analysis also shows that shocks that appear narrowly sector-specific can have broader macroeconomic consequences once supply-chain linkages are considered. A cereal price shock, for example, might seem confined to agriculture and food production. However, when production linkages are incorporated, its effects spread to other sectors and become non-negligible for aggregate inflation.

Monetary policy transmission is likewise shaped by the production network. A contractionary policy shock reduces inflation and output, but its effects differ across industries depending on their position in the network. Moreover, a counterfactual exercise shows that fully offsetting the inflationary impact of an oil shock would require a stronger monetary tightening and would entail a more pronounced decline in industrial production. Production networks therefore amplify the persistence of inflationary pressures.

1 Introduction

The inflation surge of early 2021 in the U.S. and mid-2021 in the European Union ignited a heated debate among economists about its drivers and persistence. Concomitant spikes in commodity and energy prices brought the role of sectoral disturbances in shaping the aggregate price dynamics to the forefront. Understanding how sectoral shocks transmit across sectors and ultimately affect aggregate inflation is crucial but challenging, given the input-output links of the production network and the large set of micro and macro shocks that affect them. This paper proposes a fully data-driven model to assess the degree of pass-through and persistence of sectoral and aggregate shocks to sectoral prices, as well as to headline inflation.

We model sectoral producer price dynamics with a Bayesian vector autoregressive (BVAR) model that incorporates prior information from the Input-Output matrix, which defines how each sector depends on other production sectors through intermediate input linkages and therefore summarizes the production structure of an economy. This long-run prior has a direct mapping to the Leontief price model and multi-sector DSGE model as Rubbo (2023). 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. In particular, 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. Indeed, 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.

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 transmission. 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 focuses on *inflation spillovers* of sectoral and aggregate shocks into U.S. producer prices. These are 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. Bilgin and Yilmaz (2018) opt for a VARX model and use the Diebold and Yilmaz Connectedness Index to represent a network of inflation spillovers. 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.

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. This choice is in line with the lion's share of the literature studying headline or sectoral price dynamics, which decomposes inflation volatility into aggregate and sector-specific origins with dynamic factor models, as done, among others, in Altissimo et al. (2006), Maćkowiak, Moench, and Wiederholt (2009) or Boivin, Giannoni, and Mihov (2009).[1] The drawback of using factor analysis to clean for the common component is that it risks understating the propagations on idiosyncratic shocks to the aggregate, given that all the common comovement is attributed to the common factors. VARs instead do not require the explicit identification of common factors and idiosyncratic components and therefore can capture more naturally the possible propagation from micro shocks to aggregate variables.

We employ the Prior for the Long Run (PLR) BVAR framework developed by Gi-

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

annone, 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 δ_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), who 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 Σ. Bayesian VARs allow us to explicitly provide prior information for the distributions of the parameters a, $A_i(i \in 1, ..., p)$ and Σ. As in Giannone, Lenza, and Primiceri (2015) we use a conjugate prior for our parameters: the Normal-Inverse Wishart prior. If we define $\beta = vec([a, A_1, ..., A_p]')$,

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

We fix the degrees of freedom of the inverse Wishart distribution d to $N+2$, the minimal value that guarantees the existence of the mean of Σ. Regarding the scale matrix Ψ, we take this matrix as diagonal with the $N \times 1$ vector fixed using sample information. For the other parameters b and Ω_β, 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 Ω_β 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 λ controls for the *tightness* of the prior. As $\lambda \to 0$, the posterior mean converges to the prior mean because the prior variance vanishes, while as $\lambda \to \infty$, the posterior mean coincides with the OLS estimate because the prior becomes flat. we estimate λ by maximizing the marginal likelihood of the data as a function of this and other hyperparameters, as in Giannone, Lenza, and Primiceri (2015). 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. Giannone, Lenza, and Primiceri (2019) show that the VAR model (2.1) can be re-written in terms of levels and differences as:

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

- $\Pi = (A_1 + \cdots + A_p) - I_N$ 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 Γ_j parameters of the model are often referred to as the short-run parameters, and Πy_{t-1} is sometimes called the *long-run* part of the model. This is because if the rank of Π is a constant $r > 0$ and there exist two $N \times r$ matrices α and β 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 β then represents these long-run equilibrium cointegration relationships between the variables while α 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 Π 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:

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

- $\tilde{Y}_{t-1} = HY_{t-1}$ 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 ΔY_t

In this setup, the construction of a reasonable prior for Λ depends on the H matrix, which plays a crucial role. Indeed, HY_{t-1} represents a set of linear combinations of the variables (each row is a linear combination), that can help to guide the elicitation of a good prior for Λ and thus for Π. 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 Λ 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 Λ 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 Λ 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 Λ related to linear combinations of variables that do not play a role in explaining the short-run dynamics ΔY_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 ϕ_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 Λ is thus the ϕ_i hyperparameters (one for each column of Λ). As ϕ_i gets closer to zero, it is equivalent to assuming that the corresponding linear combination does not help in explaining ΔY_t. This prior and its marginal likelihood can be written in closed form. The value of ϕ_i can then be chosen by maximizing the marginal likelihood.

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 Λ 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 Λ and therefore Π.

As emphasized by Giannone, Lenza, and Primiceri (2019), the family of priors proposed allow to solve for a specific issue in flat-prior VARs, which attribute an implausibly large share of the variation in observed time series to the deterministic component. The prior for the long run allows to shrink the VAR coefficients "towards values that imply little predictive power of the initial conditions of all these linear combinations of the variables, but particularly so for those that are likely to be nonstationary" (2019, p. 3).

Moreover, this approach does not require the researcher to be certain about the exact cointegration relations and common trends, that is, about the precise set of stationary and nonstationary linear combinations of the variables. Instead, the hyperparameter ϕ_i allows the data to adjust the strength of the prior associated with each linear combination.

2.2 The economy's production network as a long-run prior

We exploit the long-run prior framework to incorporate information about the production network of the economy into a BVAR model for sectoral price dynamics. Specifically, we use data from the Bureau of Economic Analysis (BEA) to construct an input-output matrix Ω summarizing the intermediate input linkages between sectors, with Ω_{ij} measuring the share of sector i's gross output spent on inputs from sector j. The Ω matrix is used in multi-sector New Keynesian models such as in Rubbo (2023) and is equivalent to the input-output matrix from the Leontief *price* model

$$p_t = \Omega p_t + v_t \quad \Leftrightarrow \quad p_t = (I - \Omega)^{-1} v_t. \tag{2.9}$$

The price-side Leontief model defines sectoral prices as the sum of intermediate input prices Ωp_t and value added v_t. The input-output coefficient Ω_{ij} measures the direct dependence of sector i on inputs produced by sector j: a change in the price of good j affects sector i's marginal cost in proportion to Ω_{ij}. If $(I - \Omega)$ is non-singular, $(I - \Omega)^{-1}$ exists and is known as the Leontief inverse. It accounts not only for this direct effect, but also for all higher-order propagation effects that arise as price changes pass through the production network. Formally, provided that the Neumann series converges,

$$(I - \Omega)^{-1} = I + \Omega + \Omega^2 + \Omega^3 + \cdots \tag{2.10}$$

Each term $(\Omega^n)_{ij}$ captures the exposure of sector i to sector j through production chains of length n.

In equation (2.6), we set the H matrix to reflect combinations of sectoral prices implied by the intermediate input linkages. More explicitly, if we assume (for the simplicity of the reasoning) that the vector of variables Y_t is only composed of the logarithms of sectoral producer prices indices, we set H equal to $I - \Omega$. Hence, we impose the linear combinations $(I - \Omega)Y_{t-1}$. Since Y_t contains logged price indices, the ith element of $(I - \Omega)Y_t$ can be written as

$$\big[(I - \Omega)Y_t\big]_i = \log\left(\frac{P_{i,t}}{\prod_j P_{j,t}^{\Omega_{ij}}}\right). \tag{2.11}$$

It therefore measures sector i's price relative to the *geometrically* weighted input-price component implied by the input-output matrix $\prod_j P_{j,t}^{\Omega_{ij}}$. This form is closely related to standard index-number formulas, such as Törnqvist-type and geometric Young indices, which aggregate prices through products weighted by expenditure or cost shares (Diewert (1976); Stanley (2024)). It is also consistent with the log-linearized constant elasticity of substitution (CES) price aggregators commonly used in multi-sector New Keynesian models, where sectoral price indices depend on weighted sums of logarithms of input-price indices.

Interestingly, the linear combinations defined by $(I - \Omega)Y_t$ display heterogeneous degrees of persistence across sectors. To illustrate this point, Figure 1 reports selected standardized elements of $(I-\Omega)Y_t$, ranked according to their estimated AR(1) coefficients. The combinations with the lowest estimated persistence are mostly energy-related and display more pronounced short-run reversals, consistent with the cyclical nature of commodity and energy prices. By contrast, the combinations with the highest estimated persistence are smoother and more trend-like, especially after 2021, capturing the inflation crisis. This ranking should therefore be interpreted as a persistence spectrum rather than as a classification between stationary and nonstationary combinations: even the least persistent combinations remain highly persistent in levels.

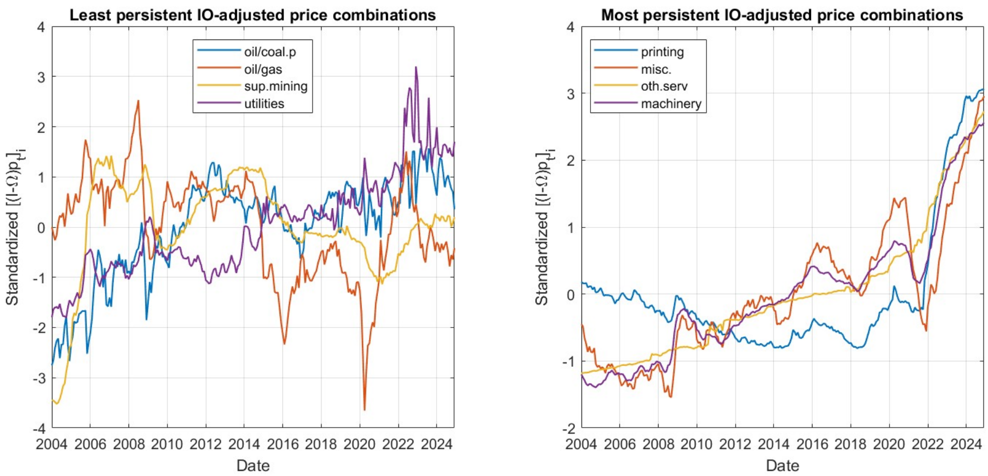

Figure 1: Selected elements of $(I - \Omega)Y_t$, ranked by AR(1) persistence.

This empirical finding is consistent with the interpretation of $(I - \Omega)Y_t$ suggested by multi-sector New Keynesian models. In Rubbo (2023), sectoral marginal costs, in the log-linearized model, satisfy

$$mc_t = \alpha w_t + \Omega p_t - \log A_t \tag{2.12}$$

In a long-run benchmark in which prices are aligned with marginal costs ($mc_t = p_t$) this implies

$$(I-\Omega)p_t = \alpha w_t - \log A_t \tag{2.13}$$

The transformed variables $(I-\Omega)p_t$ should therefore be interpreted as empirical proxy for sector-specific primary-cost components, combining labor-cost and productivity terms, which are themselves likely to be persistent, but with some heterogeneity, hence allowing the prior to shrink more strongly towards zero the columns of the Λ matrix associated with the most nonstationary linear combinations.

Two additional arguments motivate to use $HY_t = (I-\Omega)Y_t$ with Y_t being logged prices.

1. **The dummies directions correspond to the Leontief inverse columns.** In the long run prior framework, the prior being conjugate can be implemented by Theil mixed estimation, i.e. by adding artificial observations (dummies). Following Giannone, Lenza, and Primiceri (2019), the implementation of the long run prior defined above requires the following set of dummies:

$$y_{t_i^*} = y_{t_i^*-1} = \cdots = y_{t_i^*-p} = \frac{H_{i\cdot}\bar{y}_0}{\phi_i}[H^{-1}]_{\cdot i}, \qquad i = 1, \cdots, n \tag{2.14}$$

   With $H = (I-\Omega)$, the set of dummies becomes

$$p_{t_i^*} = p_{t_i^*-1} = \cdots = p_{t_i^*-p} = \underbrace{\frac{[(I-\Omega)\bar{p}_0]_i}{\phi_i}}_{\text{Initial primary cost}} \times \underbrace{[(I-\Omega)^{-1}]_{\cdot i}}_{\text{Leontief price propagation}} \tag{2.15}$$

   The scalar term is the initial value of the i-th proxy for primary costs, scaled by the tightness parameter ϕ_i. Under the Leontief price model, this transformed component corresponds to the i-th primary-cost component. The vector multiplying it is the i-th column of the Leontief inverse, which gives the sectoral price profile generated by a unit change in that primary-cost component after accounting for direct and indirect input-output propagation. In this sense, the dummy observations are not arbitrary artificial price vectors: they lie exactly in the price directions implied by the Leontief inverse. This matches the Leontief price model in which $p_t = (I-\Omega)^{-1}v_t$ or as in the New Keynesian framework in which $p_t = (I-\Omega)^{-1}(\alpha w_t - \log A_t)$.

2. **The prior tightness is economically scaled.** A second argument follows from the way the prior tightness is scaled in the framework of Giannone, Lenza, and Primiceri (2019). Conditional on a given matrix H, the long-run prior is specified column by column as in equation 2.7. In our application, setting $H = I - \Omega$ implies

$$\Lambda_{\cdot i} \mid H_{i\cdot}, \Sigma \sim N\left(0, \frac{\phi_i^2}{([(I-\Omega)\bar{p}_0]_i)^2}\Sigma\right). \tag{2.16}$$

If sector i's price is close to its intermediate-input price component at the beginning of the sample, then $|[(I-\Omega)\bar{p}_0]_i|$ is small. The corresponding prior variance is then larger, so the associated column of Λ is less tightly shrunk toward zero. Conversely, if the transformed price component has a large initial value, the prior places stronger shrinkage on its loading, reducing the ability of the VAR to explain subsequent price dynamics through a deterministic transition from that initial condition. In this sense, choosing $H = I - \Omega$ affects not only the directions of the dummies, but also the relative tightness assigned to these directions.

So far we have reasoned as if Y_t contained only sectoral prices. In the estimated model, Y_t is the full 42-dimensional vector stacking the 35 sectoral logged producer prices and seven macroeconomic variables (industrial production, the consumer price index, the oil price, the cereals price, inflation expectations, the excess bond premium and the shadow rate). We impose the production-network structure only on the price block: the matrix H contains the $(I-\Omega)$ combinations on the 35 sectoral prices and zeros on the seven macroeconomic columns. The long-run prior therefore shapes the joint dynamics of sectoral prices through their input-cost linkages, while remaining agnostic about the macroeconomic variables.

Because H has only 35 rows, it is of reduced row rank and must be completed to a full-rank transformation before the prior can be applied. We do not specify these complementary directions by hand. Instead, the framework completes H with an orthonormal basis of its null space. Since $(I-\Omega)$ is non-singular, the null space of H is spanned exactly by the seven macroeconomic directions. The completion therefore coincides, up to an orthonormal rotation, with the macroeconomic block $\begin{bmatrix}\mathbf{0}_{7\times 35} & I_7\end{bmatrix}$ that one would otherwise impose manually. The hierarchical prior then assigns a separate tightness hyperparameter ϕ_i to each of the 35 production-network price combinations, letting the data choose direction-specific shrinkage via marginal-likelihood maximization. A single hyperparameter governs the entire complementary block, under the *invariant* treatment of Giannone, Lenza, and Primiceri (2019).

We summarize here below our choice of linear combinations on the variables.

$$\tilde{Y}_t = \underbrace{\begin{pmatrix} \mathbf{I} - \mathbf{\Omega} & \mathbf{0}_{35\times 7} \\ & H_\perp \end{pmatrix}}_{H} \underbrace{\begin{pmatrix} \textbf{35 sectoral prices}_t \\ \text{industrial production}_t \\ \text{consumer price index}_t \\ \text{oil price}_t \\ \text{cereals price}_t \\ \text{inflation expectations}_t \\ \text{excess bond premium}_t \\ \text{shadow rate}_t \end{pmatrix}}_{Y_t} \tag{2.17}$$

where the lower block $H_\perp$ is the null-space completion described above, equivalent up to a rotation to $\begin{bmatrix} \mathbf{0}_{7\times 35} & I_7 \end{bmatrix}$.

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 include among our variables the US industrial production that was greatly impacted by the pandemic, especially during the months of March, April and May 2020. To 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 :

$$Y_t = a + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + s_t e_t \tag{2.18}$$

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 We include this Covid-19 correction which is fully compatible with the hierarchical approach from Giannone, Lenza, and Primiceri (2015) and with the long run prior.

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 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, consumer price index, 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 Input–Output matrix is constructed using the same methodology as in Pasten, Schoenle, and Weber (2021). However, we differ from their final matrix as they normalize the resulting industry-by-industry matrix by total intermediate input use, so that each row sums to one when we instead normalize by gross output, as in the Leontief price model or in Rubbo (2023). 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 Input-Output matrices from different years and found the impact negligible; therefore, we use an average Input–Output matrix over 2004–2017.

3.2 Forecasting performance

We evaluate the predictive accuracy of the PLR-IO BVAR for U.S. headline CPI using a pseudo–out-of-sample recursive exercise, benchmarking it against the Survey of

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

Professional Forecasters (SPF) and comparing it to a Minnesota BVAR with Covid-19 correction (MN-C). At each forecast origin, the model is estimated on data up to the quarter preceding the forecast quarter, and used to generate monthly forecasts for up to 15 months ahead. The 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 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 2019Q1 to 2024Q4. We also report results for a shorter evaluation period ending 2021Q2 to assess performance outside of the very high inflation episode starting early 2021. We compare two models:

1. **MN-C**: The Minnesota prior with Covid-19 correction.
2. **PLR-IO**: The Minnesota prior with Covid-19 correction, augmented with the production-network long-run prior whose H matrix imposes the $(I - \Omega)$ combinations on the sectoral price block.

All baseline forecasts are produced with a BVAR(2). Robustness checks with one and three lags are presented in Appendix C.1.

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

[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 C.2, we report results using full vintage data (including the first month of the current quarter). The results are very similar, except that current-quarter forecasts improve.

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, at almost all horizons the PLR-IO long-run prior yields more accurate forecasts than the Minnesota prior with the Covid-19 correction, indicating that Input-Output linkages embed useful information for inflation dynamics.

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.

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.8228	1.5452	1.4456
h=1Q	3.0099	1.8287	1.5756
h=2Q	3.2652	**1.8760**	<u>1.3150</u>
h=3Q	3.3366	1.8031	1.1462
h=4Q	3.3387	1.9217	1.0858

Table 1: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(2) models. Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level. Long evaluation sample: 2019Q1 up to 2024Q4.

When limiting the evaluation sample to 2021Q2 (excluding the high-inflation period from the evaluation data), the PLR-IO model shows good improvements relative to the Survey of Professional Forecasters, as illustrated by Table 2. The PLR-IO model still improves on the MN-C benchmark, confirming the relevance of the information coming from the Input-Output matrix.

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.7836	1.0114	0.8479
h=1Q	2.9021	1.3621	0.9950
h=2Q	2.8837	1.3240	0.9790
h=3Q	2.9267	1.0853	0.9610
h=4Q	2.8373	**1.2887**	<u>1.0266</u>

Table 2: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(2) models. Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level. Shorter evaluation sample: 2019Q1 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.

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 D, and we highlight the key sectoral and aggregate effects in the discussion below. Figure 2 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).

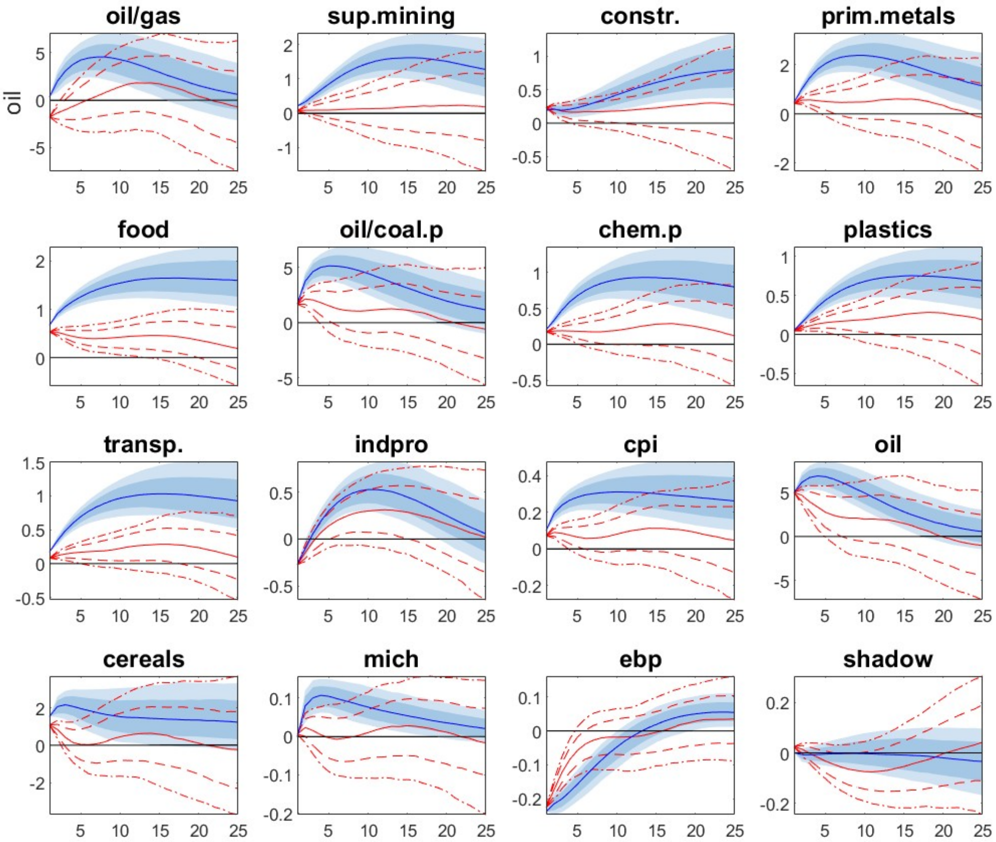

Figure 2: Impulse responses to an **oil price shock** using Känzig's surprises in a BVAR(2) model with Input-Output informed Long-Run prior and Covid-19 correction (in blue) versus in the standard Minnesota BVAR(2) (in red). We focus on the following variables: *oil/gas - Oil and gas extraction PPI*, *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 2, 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...).[4] This

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

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 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 3 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

the Fed.

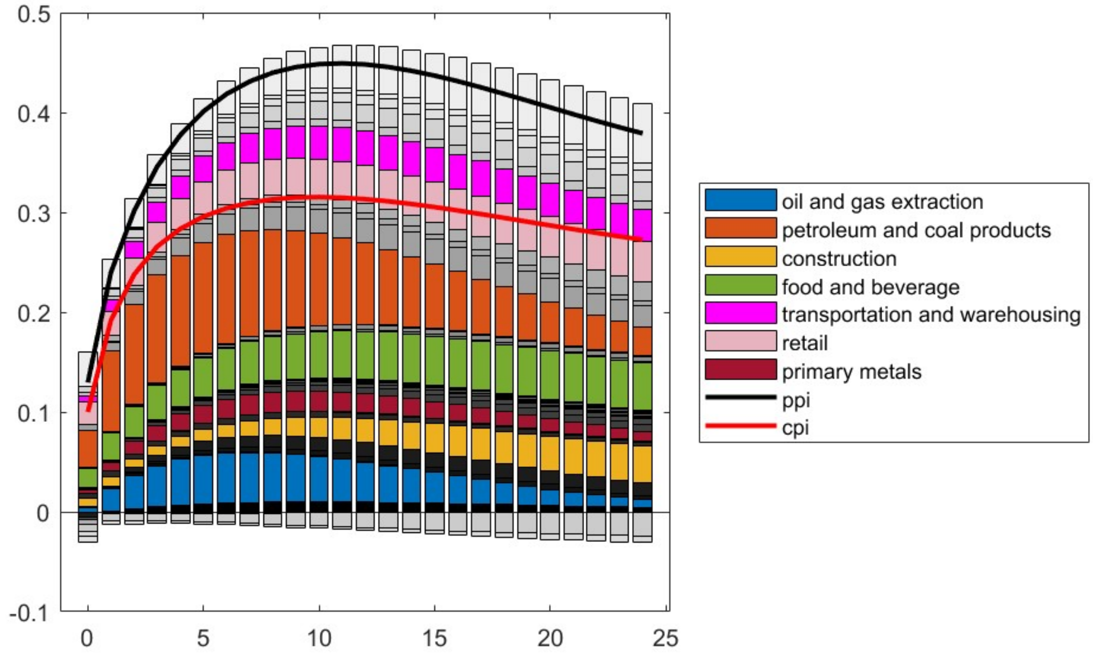

Figure 3: Contributions to aggregated PPI of sectoral PPIs responses to an **oil price shock** using Känzig's surprises in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer price index 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.

construction sector (yellow) is small at first but grows over time. The observed lag in 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, $\Omega + \Omega^2$, 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 4, 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 0.592 and an R^2 of 0.495. 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).

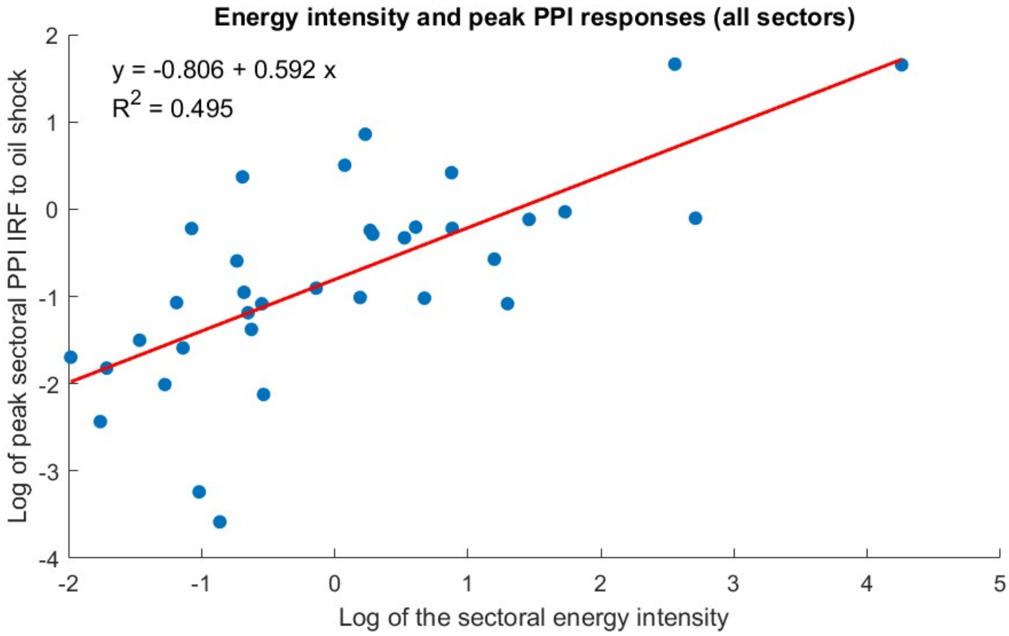

Figure 4: Sectoral energy intensity vs. Peak sectoral PPI IRF to an oil price shock

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.

The impulse responses for all variables are shown in the Appendix D, 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 5 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.

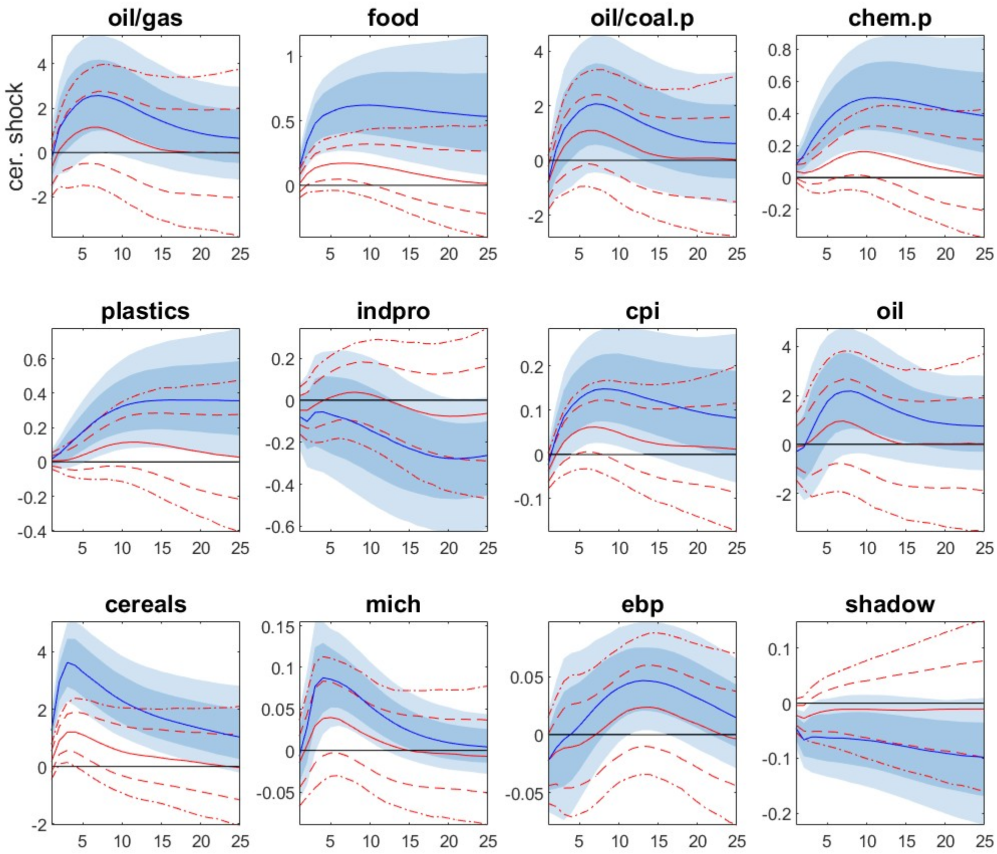

Figure 5: Impulse responses to a **cereal price shock** using Adjemian and Jo shock series in a BVAR(2) model with Input-Output informed Long-Run prior and Covid-19 correction (in blue) versus in the standard Minnesota BVAR(2) (in red). The shown variables are the following: *oil/gas - Oil and gas extraction 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 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 41.64 degree, it means that the two shocks are capturing something different. Economically, cereal and oil are not directly linked in the Ω Input-Output matrix, though they are indirectly (in the Leontief inverse) with cereals being downstream of oil, not the reverse. The fact that our PLR-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

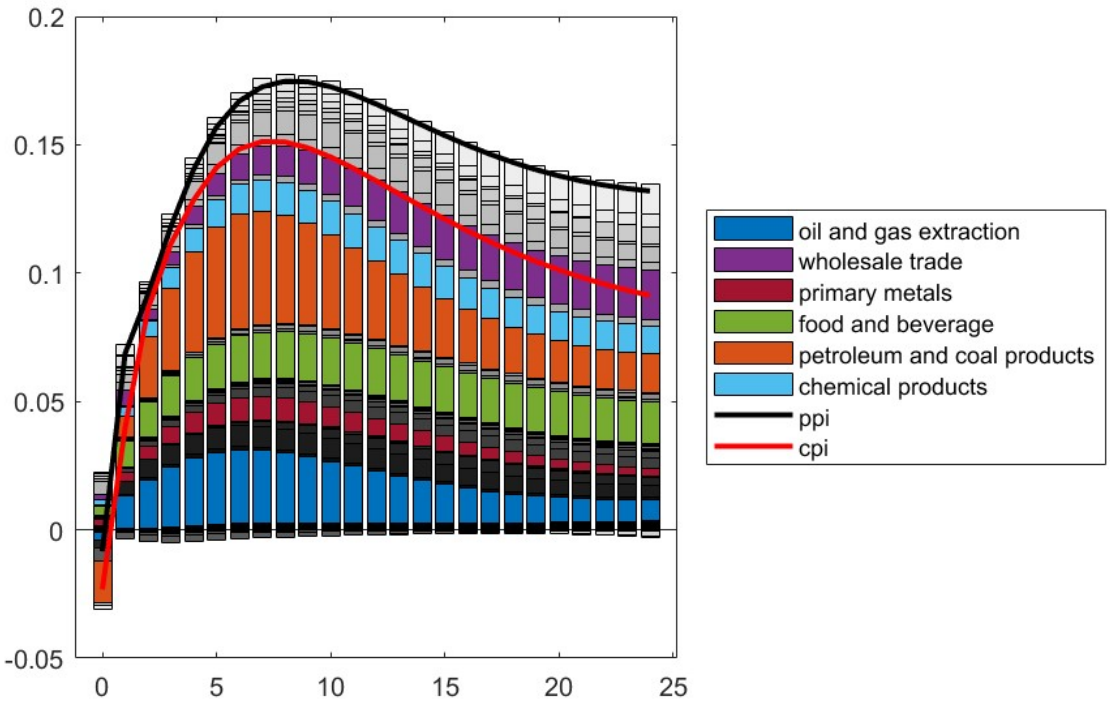

Figure 6: Contributions to aggregated PPI of sectoral PPIs responses to a **cereal price shock** using Adjemian and Jo shock series in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer 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.

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 6 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 6 is based on mean responses, while, as shown in Figure 5 the credible interval around the oil and gas extraction sector is quite large.

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

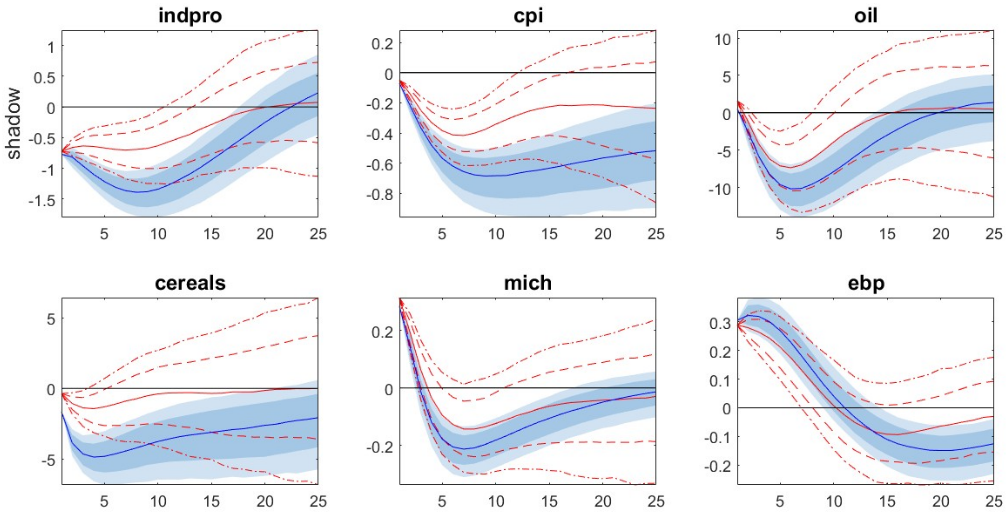

Figure 7: Impulse responses to a **monetary policy shock** using Bauer and Swanson surprises in a BVAR(2) model with Input-Output informed Long-Run prior and Covid-19 correction (in blue) versus in the standard Minnesota BVAR(2) (in red). The shown variables are the following: *indpro - Industrial production*, *cpi - Consumer price index*, *oil - Crude oil price (WTI)*, *mich - Michigan inflation expectation*, *ebp - Excess bond premium*, *shadow - Shadow rate*

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 7 shows the responses of the main aggregate variables to a 0.25% increase in the shadow rate. The sectoral responses are available in Appendix D 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 8 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

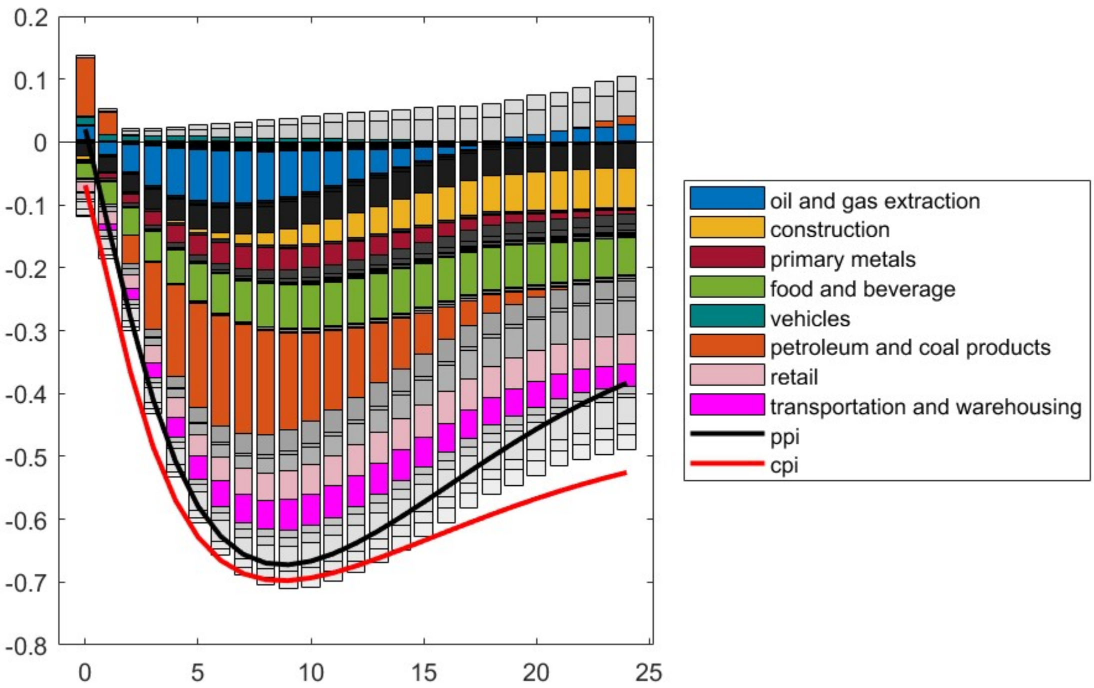

Figure 8: Contributions to aggregated PPI of sectoral PPIs responses to a **monetary policy shock** using the Bauer and Swanson surprises in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline 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.

to the aggregated PPI. Most of the contributions are negative and show that a certain 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 counterfactual impulse response that forces the CPI response to return to zero after two

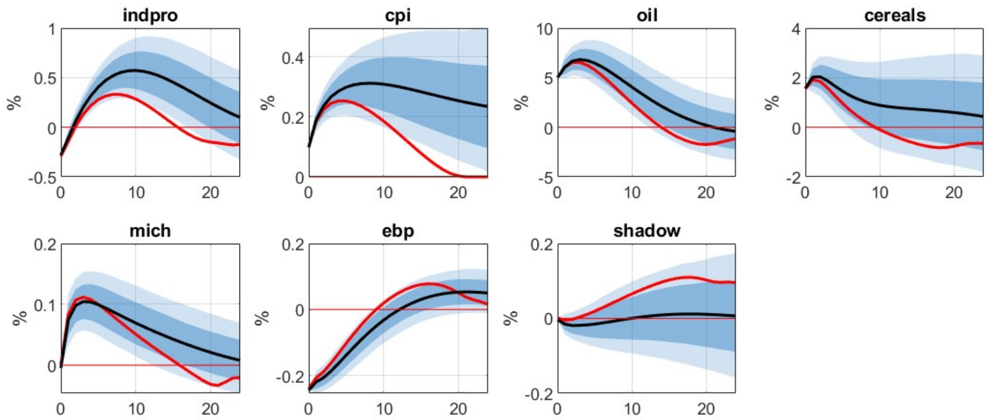

Figure 9: Counterfactual analysis comparing impulse responses to an oil shock (in blue) with a counterfactual situation in which monetary policy forces CPI's response to zero for horizons 22, 23 and 24 (last quarter of the two years horizon) (in red).

years (horizons 22–24). The resulting responses are shown in Figure 9: 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 E 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 is built from the $(I - \Omega)$ combinations of sectoral prices implied by the production network, which can be interpreted as proxies for sector-specific primary costs in a Leontief price model or in multi-sector New Keynesian models. It shrinks the coefficients associated with these economically interpretable directions while letting the data determine, through the hierarchical hyperparameters, how much each one matters.

The results show that incorporating production network data in disaggregated models improves 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 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.

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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[5]. 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.
12	Computer and electronic products	PCU334—334—	200312	OK.
13	Electrical equipment and appliances	PCU335—335—	200312	OK.

Continued on next page

[5] 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
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.
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.

B 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	Electrical equipment, ...	Motor vehicles, bodies ...	Other transportation	Furniture and related ...	Miscellaneous manufacturing
Agriculture and forestry	0,18	0	0,01	0	0,01	0	0	0	0	0	0,01	0	0	0	0	0	0
Oil and gas extraction	0	0,11	0	0,02	0,01	0,01	0	0	0,01	0,01	0,02	0	0	0	0	0	0
Mining, except oil and gas	0	0,01	0,06	0,01	0,03	0,02	0	0	0,01	0,01	0,04	0	0	0,01	0	0	0
Support activities for mining	0	0	0	0,01	0	0,02	0	0,01	0,01	0,01	0,05	0,01	0	0	0	0	0
Utilities	0	0,11	0,02	0	0,04	0,01	0	0	0	0	0	0	0	0	0	0	0
Construction	0	0	0,01	0	0	0	0,03	0,04	0	0,05	0,02	0,01	0,02	0	0	0,01	0
Wood products	0,12	0	0	0	0,01	0	0,21	0,01	0	0,03	0,01	0,01	0,01	0,01	0	0,01	0
Nonmetallic mineral products	0	0	0,07	0	0,03	0	0	0,12	0,01	0,02	0	0,01	0	0,01	0	0	0
Primary metals	0	0	0,06	0	0,03	0	0	0,01	0,29	0,02	0,01	0,01	0,01	0	0	0	0
Fabricated metal products	0	0	0	0	0,01	0	0	0	0,2	0,11	0,01	0,01	0,01	0	0	0	0
Machinery	0	0	0	0	0,01	0	0	0,01	0,09	0,07	0,09	0,02	0,03	0,04	0	0	0,01
Computer and electronic	0	0	0	0	0	0	0	0	0,01	0,02	0	0,13	0,01	0	0	0	0
Electrical equipment, ...	0	0	0	0	0,01	0	0	0,01	0,13	0,07	0,01	0,03	0,07	0	0	0	0,01
Motor vehicles, bodies ...	0	0	0	0	0	0	0,01	0,01	0,08	0,07	0,04	0,03	0,01	0,3	0	0	0
Other transportation	0	0	0	0	0	0	0	0	0,04	0,04	0,02	0,05	0,01	0,02	0,2	0	0
Furniture and related ...	0	0	0	0	0,01	0	0,09	0	0,05	0,04	0	0,01	0	0	0	0,05	0
Miscellaneous manufacturing	0	0	0	0	0,01	0	0,01	0,01	0,04	0,03	0,01	0,02	0,01	0	0	0	0,04
Food and beverage and tob.	0,24	0	0	0	0,01	0	0	0,01	0,01	0,02	0	0	0	0	0	0	0
Textile mills and	0,04	0	0	0	0,02	0	0	0	0,01	0,01	0	0,01	0	0	0	0	0
Apparel and leather	0	0	0	0	0,01	0	0	0	0	0,01	0	0	0	0	0	0	0,01
Paper products	0,02	0	0,01	0	0,03	0	0,03	0	0	0,03	0,01	0,01	0	0	0	0	0
Printing	0	0	0	0	0,01	0	0	0	0	0,02	0,01	0,02	0	0	0	0	0
Petroleum and coal products	0	0,62	0	0	0,01	0,01	0	0	0	0	0	0	0	0	0	0	0
Chemical products	0,01	0,01	0,01	0	0,02	0	0	0	0	0,01	0	0,01	0	0	0	0	0
Plastics and rubber products	0,01	0	0	0	0,02	0	0,01	0,01	0,01	0,03	0,01	0,01	0,01	0	0	0	0
Wholesale trade	0	0	0	0	0,01	0	0	0	0	0	0	0,01	0	0	0	0	0
Retail	0	0	0	0	0,02	0	0	0	0	0	0	0	0	0,01	0	0	0
Transportation	0	0	0	0	0,01	0,01	0	0	0	0,01	0	0	0	0,01	0,01	0	0
Information	0	0	0	0	0	0	0	0	0	0,01	0	0,02	0	0	0	0	0
FIRE	0	0	0	0	0,01	0,02	0	0	0	0	0	0	0	0	0	0	0
PROF	0	0	0	0	0	0	0	0	0	0	0	0,01	0	0	0	0	0
EHS	0	0	0	0	0,01	0	0	0	0	0	0	0	0	0	0	0	0,02
AERAF	0	0	0	0	0,02	0	0	0	0	0	0	0	0	0	0	0	0
Other services	0	0	0	0	0,01	0,01	0	0	0	0,01	0,01	0,01	0	0,02	0	0	0
Public sector	0	0,01	0	0	0,01	0,02	0	0	0	0	0	0,01	0	0	0,01	0	0

	Food and beverage and tob.	Textile mills and	Apparel and leather	Paper products	Printing	Petroleum and coal products	Chemical products	Plastics and rubber products	Wholesale trade	Retail	Transportation	Information	FIRE	PROF	EHS	AERAF	Other services	Public sector
Agriculture and forestry	0,07	0	0	0	0	0,02	0,06	0	0,07	0,01	0,02	0	0,08	0,01	0	0	0	0,01
Oil and gas extraction	0	0	0	0	0	0,01	0,01	0	0,01	0	0,02	0,01	0,04	0,05	0	0	0	0,01
Mining, except oil and gas	0	0	0	0	0	0,04	0,03	0,01	0,03	0	0,03	0,01	0,04	0,06	0	0	0	0,01
Support activities for mining	0	0	0	0	0	0,03	0,02	0,01	0,03	0	0,01	0,02	0,11	0,1	0	0,01	0,01	0,01
Utilities	0	0	0	0	0	0,04	0	0	0,01	0	0,05	0,01	0,03	0,05	0	0,01	0	0,02
Construction	0	0	0	0	0	0,04	0,01	0,02	0,04	0,06	0,02	0,01	0,03	0,05	0	0	0	0
Wood products	0	0,01	0	0,01	0	0,01	0,02	0,01	0,07	0	0,04	0,01	0,01	0,03	0	0	0	0,01
Nonmetallic mineral products	0	0	0	0,01	0	0,01	0,04	0,01	0,04	0	0,06	0,01	0,03	0,04	0	0	0,01	0,01
Primary metals	0	0	0	0,01	0	0,01	0,01	0	0,08	0	0,04	0,01	0,02	0,03	0	0	0	0,01
Fabricated metal products	0	0	0	0,01	0	0	0,02	0,01	0,04	0	0,02	0,01	0,03	0,06	0	0	0	0,01
Machinery	0	0	0	0,01	0	0,01	0,01	0,02	0,06	0,01	0,01	0,01	0,02	0,05	0	0	0	0,01
Computer and electronic	0	0	0	0	0	0	0,01	0,01	0,03	0	0,01	0,01	0,02	0,06	0	0	0	0
Electrical equipment, ...	0	0	0	0,01	0	0,01	0,02	0,01	0,06	0	0,01	0,01	0,02	0,02	0	0	0	0,01
Motor vehicles, bodies ...	0	0,01	0	0	0	0	0,01	0,04	0,08	0	0,01	0	0,01	0,03	0	0	0	0
Other transportation	0	0	0	0	0	0	0,01	0,01	0,03	0	0,01	0,01	0,03	0,06	0	0	0	0
Furniture and related ...	0	0,04	0	0,02	0	0,01	0,03	0,05	0,06	0,01	0,03	0,01	0,04	0,04	0	0	0	0,01
Miscellaneous manufacturing	0	0,01	0	0,01	0	0,01	0,04	0,03	0,05	0,01	0,02	0,01	0,04	0,06	0	0	0	0,01
Food and beverage and tob.	0,19	0	0	0,03	0	0	0,01	0,02	0,06	0,01	0,04	0,01	0,02	0,03	0	0	0	0,01
Textile mills and	0	0,17	0,01	0,01	0	0,01	0,19	0,01	0,05	0,01	0,02	0,01	0,02	0,04	0	0	0	0,01
Apparel and leather	0,03	0,11	0,1	0	0,01	0	0,01	0,01	0,07	0	0,02	0,01	0,04	0,09	0	0	0	0,01
Paper products	0,01	0,01	0	0,23	0	0,01	0,06	0,02	0,06	0	0,04	0,01	0,01	0,03	0	0	0,01	0,01
Printing	0,01	0	0,01	0,09	0,03	0,03	0,06	0,01	0,04	0,02	0,02	0,01	0,03	0,07	0	0,01	0	0,01
Petroleum and coal products	0	0	0	0	0	0,03	0,01	0	0,02	0	0,03	0	0	0,01	0	0	0	0
Chemical products	0,01	0	0	0,01	0	0,04	0,27	0,02	0,05	0,01	0,02	0,01	0,02	0,05	0	0	0	0,01
Plastics and rubber products	0	0,01	0	0,02	0	0,02	0,26	0,08	0,06	0	0,03	0,01	0,02	0,04	0	0	0	0,01
Wholesale trade	0	0	0	0	0,01	0	0	0,01	0,03	0	0,04	0,02	0,07	0,11	0	0	0,01	0,02
Retail	0	0	0	0	0	0	0	0	0,01	0,01	0,04	0,02	0,09	0,09	0	0	0,01	0,01
Transportation	0	0	0	0	0	0,08	0	0	0,02	0,01	0,12	0,01	0,09	0,05	0	0,01	0,01	0,02
Information	0	0	0	0	0,01	0	0	0	0,01	0	0,01	0,14	0,04	0,1	0	0,02	0	0,01
FIRE	0	0	0	0	0	0	0	0	0	0	0,01	0,02	0,19	0,07	0	0,01	0,01	0,01
PROF	0	0	0	0	0	0	0,01	0	0,01	0	0,01	0,03	0,07	0,13	0	0,02	0,01	0,01
EHS	0,01	0	0	0	0	0	0,03	0,01	0,02	0	0,01	0,02	0,1	0,08	0,01	0,02	0,01	0,01
AERAF	0,04	0	0	0	0	0	0	0	0,02	0,01	0,01	0,02	0,09	0,11	0	0,02	0,01	0,02
Other services	0	0	0	0	0	0,01	0,01	0,01	0,02	0,01	0,01	0,02	0,12	0,06	0	0,01	0,01	0,01
Public sector	0,01	0	0	0	0	0,04	0,01	0	0,02	0	0,02	0,03	0,04	0,06	0,01	0,01	0,01	0,01

B.1 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)).

B.2 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.

C Recursive forecast robustness tests

C.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)

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.8228	1.6594	1.2195
h=1Q	3.0099	1.8345	1.1494
h=2Q	3.2652	1.8793	1.0647
h=3Q	3.3366	1.7727	1.0423
h=4Q	3.3387	1.8257	**1.0499**

Table 4: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(1) models. Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level.

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.7836	1.0495	1.0315
h=1Q	2.9021	1.2467	1.0278
h=2Q	2.8837	1.1974	<u>0.9840</u>
h=3Q	2.9267	1.0802	0.9998
h=4Q	2.8373	**1.2515**	<u>1.0498</u>

Table 5: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(1) models. Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level. Shorter evaluation sample: 2019Q1 up to 2021Q2.

BVAR(3)

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.8228	1.5121	1.4558
h=1Q	3.0099	**1.7930**	1.6684
h=2Q	3.2652	**1.8207**	<u>1.4048</u>
h=3Q	3.3366	1.7500	1.1563
h=4Q	3.3387	1.8758	1.0711

Table 6: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(3) models. Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level.

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.7836	1.0138	0.8712
h=1Q	2.9021	1.4066	1.0707
h=2Q	2.8837	1.3614	1.0117
h=3Q	2.9267	1.0518	0.9510
h=4Q	2.8373	**1.2400**	<u>1.0143</u>

Table 7: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(3) models. Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level. Shorter evaluation sample: 2019Q1 up to 2021Q2.

C.2 Recursive forecast with one month of additional data

As discussed, in tables 8 and 9 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.

	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.8228	0.7769	0.8499
h=1Q	3.0099	1.7945	1.6577
h=2Q	3.2652	**1.9023**	1.4137
h=3Q	3.3366	**1.8055**	<u>1.1883</u>
h=4Q	3.3387	1.6709	1.0812

Table 8: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(2) models, with one month of additional data (SPF-matching vintage). Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level. Long evaluation sample.

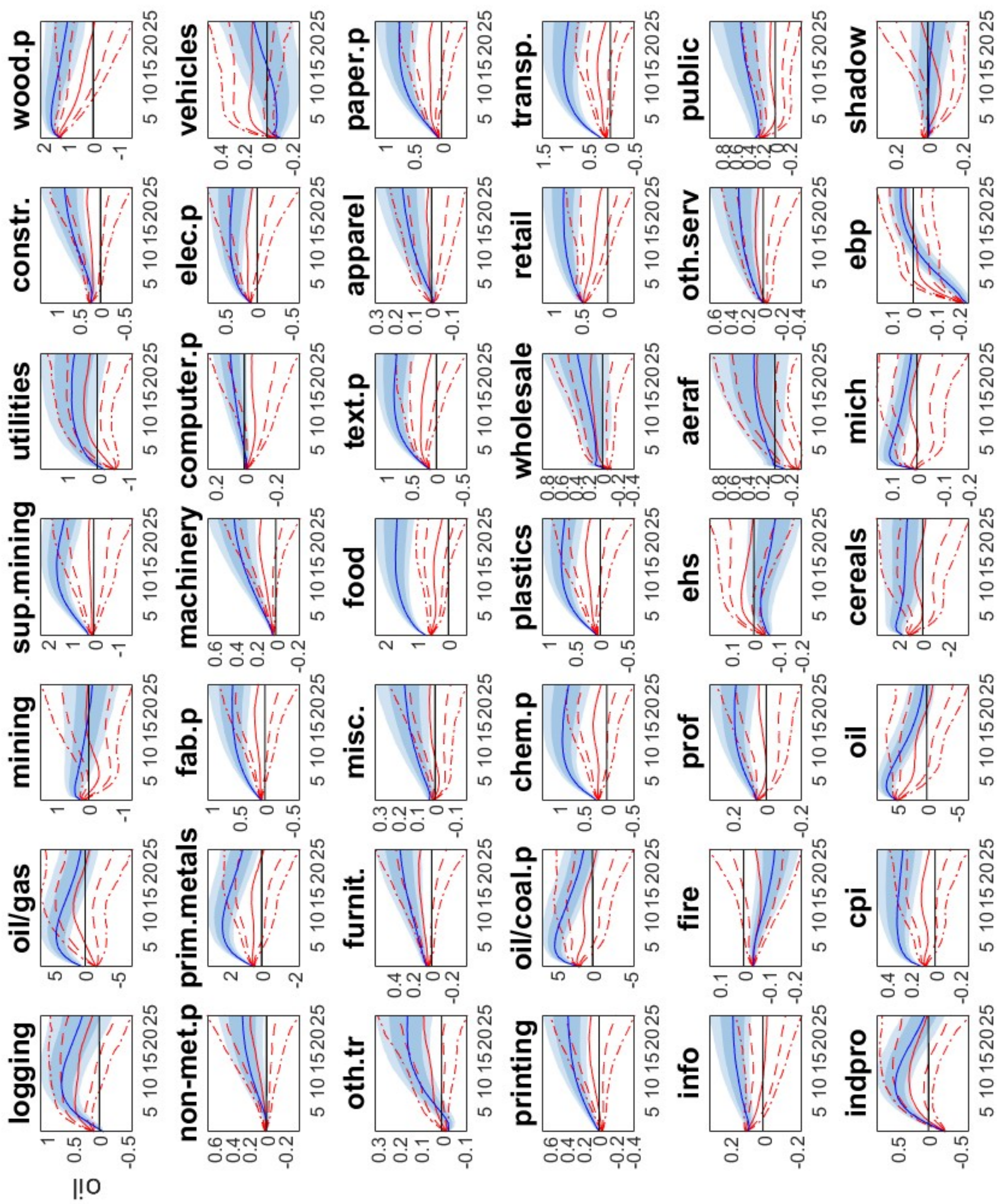
	rmse(spf)	rmse(MN-C)/rmse(spf)	rmse(PLR-IO)/rmse(spf)
h=0Q	1.7836	0.9318	<u>0.5846</u>
h=1Q	2.9021	2.1536	1.0810
h=2Q	2.8837	2.1618	0.9989
h=3Q	2.9267	1.7366	0.9601
h=4Q	2.8373	1.0676	<u>0.9660</u>

Table 9: SPF RMSE and RMSE ratios for CPI forecasts: Minnesota-Covid (MN-C) and PLR-IO BVAR(2) models, with one month of additional data (SPF-matching vintage). Bold entries indicate rejection of equal predictive accuracy relative to SPF forecasts at the 5% level (Diebold–Mariano test). Underlined entries indicate rejection of equal predictive accuracy between the Minnesota-Covid and PLR-IO models at the 5% level. Short evaluation sample.

D Impulse response functions details

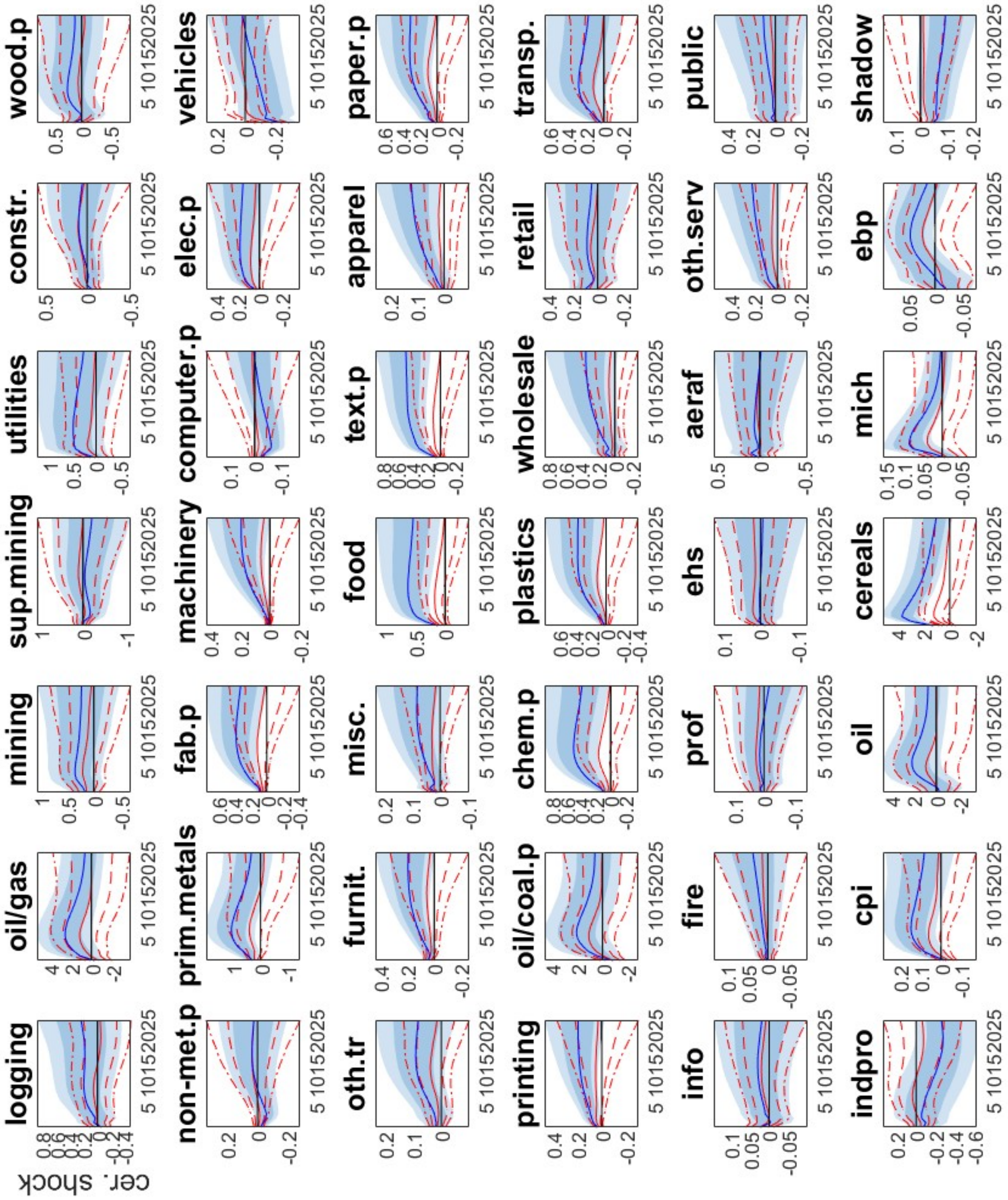
D.1 Oil price shock - all impulse responses

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.



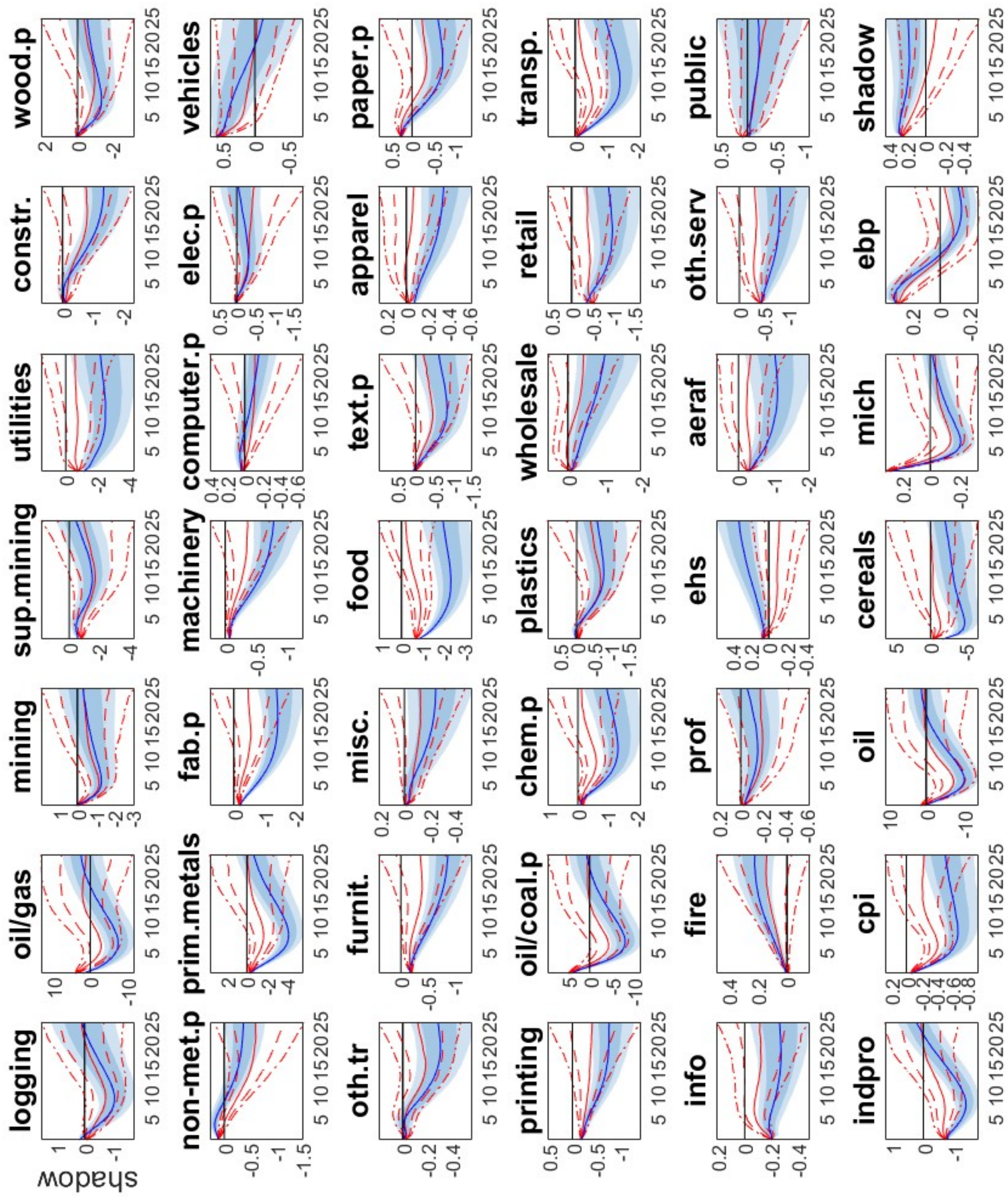
D.2 Cereal price shock - all impulse responses

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.



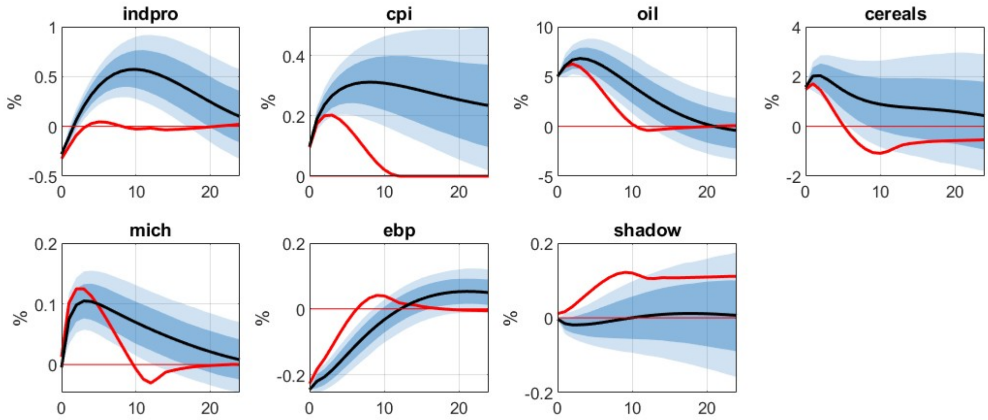
D.3 Monetary policy shock - all impulse responses

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.



E 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).



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