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

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Abstract

This paper explores the dynamics of U.S. sectoral producer prices in a large Bayesian vector autoregressive (BVAR) model with prior that incorporates information from the Input-Output (IO) matrix to structure the long-run relationships between these time series. The forecasts of headline inflation generated with this model have accuracy comparable to those from the Survey of Professional Forecasters (SPF) and greater than the ones generated by a standard BVAR with Minnesota priors, confirming that the IO matrix long-run prior conveys relevant information about the data. We analyze the effects of different types of shocks on sectoral prices and aggregate inflation, identified via external instruments – a sectoral shock (cereal price), an aggregate shock (monetary policy) and oil supply shock – to gain insight into the role of production networks in price dynamics, studying the sectoral sources of inflation fluctuations, as well as the propagation through the production network of aggregate shocks. Our findings contribute to understanding the role of production networks in price dynamics, the sectoral sources of inflation fluctuations, and the implications for monetary and fiscal policy in an economy with heterogeneous sectoral price adjustments. It offers insights for monetary and fiscal policy decisions in the face of inflationary pressures.

1 Introduction

The rapid increase in inflation since early 2021 in the U.S. and mid-2021 in the European Union can be explained by several concomitant factors. One part of the story lies in the fast reopening of economies after the COVID-19 crisis, leading to an increase in demand that could not be met with the reduced supply capacity following the pandemic lockdowns, such as in shipping and semiconductors. Demand was further boosted by the stimulative fiscal policies enacted by governments in response to the pandemic. In addition, companies adjusted their prices in response to rising energy and commodity costs, which, further exacerbated by the war in Ukraine, reached extraordinary levels and spread to other sectors, amplifying headline inflation.

While economists broadly agree on these drivers (see, e.g., Guerrieri et al. (2023)), there is far less consensus on the relative importance of these factors in shaping inflation dynamics. Indeed, the lively debate between Team Transitory - economists who argued that inflation was primarily driven by supply-side disruptions and would fade as shortages eased - and Team Persistent - economists who suggested that overheating demand caused by the fiscal stimulus, rather than supply-side issues were to blame - is not yet fully settled.

In this paper we aim to shed light on this question by modeling the transmission of sectoral and aggregate shocks to prices in different sectors as well as headline inflation. In particular, we study what contributes to the pass-through and persistence of such shocks in different prices. We do so by modeling sectoral producer price dynamics with a Bayesian autoregressive (BVAR) model the incorporates prior information from the Input-Output matrix. We identify three key shocks using external instruments: a cereal price shock (micro-level), an oil price shock (meso-level), and a monetary policy shock (macro-level). 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. Moreover, 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.

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* component, without distinguishing between sectoral shocks that spill over to other sectors and aggregate shocks. In such a framework, the sum of sectoral shocks across all sectors appears indistinguishable from a common shock, making it difficult to separate sectoral transmission mechanisms from macro-level inflation drivers.

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) 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 to capture these *pipeline pressures* or *inflation spillovers* across sectors. These models have shown that pipeline pressures, depending on the production architecture, take more or less time to materialize and contribute to inflation volatility and persistence. The heterogeneity in nominal rigidity changes the sectors from which aggregate fluctuations originate. This leads to important policy implications as the most important sectors for GDP and aggregate price volatility differ in a sticky price economy from a frictionless economy.

This paper builds on this literature by investigating how different types of shocks, ranging from sectoral disturbances to aggregate macroeconomic shocks, affect price dynamics across sectors and headline inflation. While sector-specific shocks, such as a cereal price shock, propagate through production linkages and affect downstream prices, economy-wide shocks, such as monetary policy shocks, influence sectoral inflation primarily by altering aggregate demand and financing conditions. But in both cases, the heterogeneity across sectors has important implications for monetary or fiscal policy. Understanding how different sectors respond to a micro shock that propagates to the economy and whether a monetary policy tightening affects

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

the sectoral prices in a homogeneous or heterogeneous way should enable a better response to a possible surge in inflation in the future.

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 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 change over time in the selling prices received by domestic producers for their output, producer prices are directly in relation with the production network. 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. The paper shows across a range of different DSGE models that the rankings of the sectors' responses (in magnitude) are similar. The paper 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) opts for a VARX model and uses the Diebold and Yilmaz Connectedness Index to represent a network of inflation spillover. While such a framework can show useful results it is subject to many issues such as the poor estimation of classical VARs for large panels of data. Finally many empirical models that address the effects of idiosyncratic shocks on other time series rely on a factor analysis to clean for common comovement and, as stressed before in this discussion, end up with only the direct effect of sectoral shocks (i.e. show no propagation at all).

The latter elements motivate our choice to study sectoral producer prices dynamics via a hierarchical Bayesian vector autoregressive (BVAR) model. Hierarchical BVARs have already shown very good forecasting performances and enable to at least *partially* solve some of the issues when one wishes to analyse producer prices dynamics empirically. First of all, the Bayesian approach is known for its ability to overpass the curse of dimensionality issue, when dealing with a large number of variables relative to the number of observations as prior information can act as a regularization mechanism. Second, such a model still indirectly captures common factors by the inclusion of a large set of variables. Finally, BVARs still offer a large set of identification strategies to recover the impacts of structural shocks on the model variables. Specifically, 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 while still allowing for flexibility in the data-driven estimation of the coefficients.

Unlike the approach of Schneider (2023) that builds on *similarities* in rankings between different theoretical modelings, our approach allows to test for *different* assumptions for constructing the prior for the long run, for example testing whether the Leontief inverse built from the Input-Output matrix allows for better forecasting performances.

Our contribution is also 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.

Finally, our contribution shares features with Yilmazkuday (2023) that estimates the pass-through of different shocks into different U.S. prices but does not include disaggregated price series. The pass-through of a shock is defined as the ratio between the cumulative impulse response of a price variable and the cumulative impulse response of the shock variable to its own shock. His analysis provides suggestions for monitoring consumer prices, which can be completed by the responses of sectoral prices that are presented in this paper.

2 Theoretical model framework

2.1 Hierarchical BVAR with a long run prior

We model sectoral producer prices dynamics with a hierarchical Bayesian Vector Autoregressive (BVAR) model enriched with a long run prior, adopting the approach of Giannone, Lenza, and Primiceri (2019). Such a model allows to represent a large number N of variables as following a vector autoregressive process with p lags, with prior information on the long run relationships between variables. The long run prior developed by Giannone, Lenza, and Primiceri (2019) 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 writes 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 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. Such a prior assumes an inverse Wishart distribution for the covariance matrix Σ 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 minimum that guarantees the existence of the mean of Σ. Regarding the scale matrix Ψ, 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 Ω, the Minnesota prior assumes the following moments for the coefficient matrices :

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

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

As shown in the second moment of the coefficient matrices, the hyperparameter λ controls for the *tightness* of the prior. Indeed, for $\lambda = 0$, the posterior equals the prior mean while as $\lambda \to \infty$ the posterior coincides with the OLS estimates. Adopting the *hierarchical* approach, we do not fix the hyperparameter λ. Instead, it is well known that for such a model, the marginal likelihood is available in closed form as a function of the hyperparameter. It is thus possible to estimate the hyperparameters by maximizing the marginal likelihood of the data as a function of these 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 level and differences as:

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

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 rewriting of the model 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:

$$\Delta Y_t = a + \Lambda \tilde{Y}_{t-1} + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + e_t$$

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 ΔY_t

In this setup, the construction of a reasonable prior for Λ depends on the H matrix, that 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 Λ and thus for Π. For example, if a specific linear combination is completely irrelevant for the estimation of ΔY_t, a reasonable prior for the corresponding column in the Λ matrix should be a vector of zero values.

In their paper, Giannone, Lenza, and Primiceri (2019) show how this formulation of the VAR can be used to elicit a prior for the VAR that provides guidance on the joint dynamics of the time series in the long run. Indeed, economic theory can provide useful information for choosing a matrix H for which we know *a priori* that the linear combinations formed by the variables will be useful or not to model ΔY_t. 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. In this 2-variables example, we see that it is thus possible to build a prior for the Λ matrix that is economically grounded.

The possibility to do so depends on the H matrix, which in this example would be the simple 2×2 following matrix.

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

Given an H matrix that makes sense economically, and to then elicit a prior for the Λ matrix, Giannone, Lenza, and Primiceri (2019) propose a specific *a priori* distribution for the columns of the Λ matrix:

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

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 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:

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

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.

However, the authors to not impose a specific value for the hyperparameters ϕ_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 ϕ_i values.

We notice that, 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 $(Y_t - I_t)$. The inclusion of the trend $(Y_t + I_t)$ represented by the first line of the matrix is however also informative. Indeed, this will then shape the prior for $\Pi = \Lambda H$.

While we refer to Giannone, Lenza, and Primiceri (2019) for more details about the long run prior, we will now show how the long run prior framework can be used to incorporate information about the production structure in the BVAR.

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

The long-run prior framework introduced by Giannone, Lenza, and Primiceri (2019) provides a interesting way to incorporate information about the production structure of the economy into a BVAR model studying sectoral prices 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 for example summarizes these dependencies, making it a candidate for specifying economically meaningful long-run relationships in a BVAR model of sectoral producer price indices. The core idea is to impose an H matrix based on the input-output matrix to test whether the production linkages defined by the Input-Output matrix indeed allow to better understand and model the dynamics of sectoral prices.

To understand this, we consider a small-scale vector auto-regression (VAR) model for three sectoral producer price indices (PPIs):

- PPI_A - Price index for Sector A (e.g., Energy),
- PPI_B - Price index for Sector B (e.g., Manufacturing),
- PPI_C - Price index for Sector C (e.g., Services).

The production structure of the economy is represented by the following 3×3 IO matrix:

$$IO = \begin{bmatrix} 0.5 & 0.4 & 0.1 \\ 0.3 & 0.6 & 0.1 \\ 0.1 & 0.2 & 0.7 \end{bmatrix}. \tag{2.5}$$

where each element IO_{ij} represents the proportion of input costs in sector i that comes *directly* from sector j.

Another interesting matrix derived from the Input-Output matrix is its Leontief inverse $(I - IO)^{-1}$. The Leontief inverse can be decomposed into

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

where each nth power of the Input-Output matrix represents the intermediates from one sector to another via 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.

For both these matrices, even if the price indices are log-transformed, each entry of the matrix provides some information about how one sector depends on another sector. Each line of the matrix defines a linear combination of variables that are linked together through production linkages so that might be cointegrated. Whether the linear combination formed by a row of the Input-Output or Leontief inverse matrix is stationary or not does not matter: event if the linear combination is non-stationary (such as $Y_t + I_t$) in the previous example from Giannone, Lenza, and Primiceri (2019), it will help to shrink to zero the corresponding column in the Λ matrix and thus provides information for the construction of the prior on Π. In our small example, it appears clearly that sectors A and B are strongly related while sector C shows less dependence on the other sectors. A shock affecting the sector A (in this example energy) would probably impact much more sector B than sector C and sectors A and B could even show a common trend due to this cross-dependence.

This small example motivates the following choices for the H matrix in our long-run prior BVAR. To the information from the Input-Output matrix, we also add two lines 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, where the top left 35×35 corner with the *IO* matrix can also be replaced by the Leontief inverse.

$$\tilde{Y}_t = \underbrace{\begin{pmatrix} \mathbf{IO} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ \mathbf{0} & 0 & -1 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}}_{H} \underbrace{\begin{pmatrix} \textbf{35 sectoral prices}_t \\ \text{industrial production}_t \\ \text{headline inflation } \pi_t \\ \text{oil price}_t \\ \text{cereals price}_t \\ \text{inflation expectations}_t \\ \text{excess bond premium}_t \\ \text{shadow rate}_t \end{pmatrix}}_{Y_t} \tag{2.6}$$

This choice of linear combinations is only a proposition to better model eventual cointegration relationships between our variables but for each linear combination i, the hierarchical approach allows to estimate the corresponding hyperparameter ϕ_i. We also note that other possibilities could be considered regarding the choice of linear combinations on aggregate variables. Here we focus on this simple choice because our interest is mainly to test the use of the Input-Output matrix. As we do not propose linear combinations on all variables of the models, the H matrix here above is not full rank so the code automatically completes H with $Hcompl$ which is constructed as the null space.

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 impact 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 :

$$Y_t = a + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + s_t e_t \tag{2.7}$$

Then, the authors assume specific values for s_t. For all months before March 2020, s_t is fixed to 1, which does not change the baseline VAR specification. Then for the months of March that we denote by $t*$, April, May and the following months, 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 coefficients. The Covid-19 correction proposed is completely suitable 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 July 2023. 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 in 35 sectors as in Smets, Tielens, and Van Hove (2019) and look at their monthly index from January 2004 to June 2023. Among the 35 sectoral producer price indices (PPI) included in our analysis, 7 series did not have a complete data coverage from 2004 onward, starting in 2005 or 2006. To ensure a consistent sample length across all variables and given the little impact of that specific years and sectors, we *backcasted* these missing early observations with the help of an arima model.

To the 35 sectoral PPI indices, we add some key aggregate variables, mostly retrieved from the Fred's database : industrial production, consumer price index, oil price, cereals price, the Michigan inflation expectations, the excess bond premium of Gilchrist and Zakrajšek and the shadow rate of Wu and Xia.

Our BVAR is hence estimated with a total of 42 variables. Sectoral prices, industrial production, cereals and oil prices are log-transformed ($y_t = 100 \times log(Y_t)$). Michigan expectations, 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 ($\pi_t = diff(100 \times log(Y_t))$).

The input-output matrix is constructed using the same methodology as in Schneider (2023), Smets, Tielens, and Van Hove (2019) or Pasten, Schoenle, and Weber (2021). It is based on the MAKE and USE tables provided by the Bureau of Economic Analysis (BEA). We use the investment flow matrix from Smets, Tielens, and Van Hove (2019). The Leontief inverse matrix is just a transformation of the Input-Output matrix (Leontief matrix = $(I - IO)^{-1}$) where I is the identity matrix.

3.2 Forecasting performances

To discriminate between the different priors and assess the validity of using such a level of disaggregation in a large BVAR as well as the idea of using a PLR BVAR to incorporate production network data in modeling sectoral prices dynamics, we look at the forecasting performances of different models for the aggregate Consumer Price Index, that is one of the key variables of the BVAR model. Our results are obtained by a pseudo-out-of-sample recursive forecasting exercise. In this exercise, we forecast the aggregate Consumer Price Index at different horizons and compare our findings with the Survey of Professional Forecasters. To do so, we:

- Use real-time data for the CPI time series, as done in the Survey of Professional Forecasters. However, we do not have access to real-time data for the sectoral price series.

- Consider all data up to the quarter that precedes the forecast, even though the SPF forecasts also uses the first month of the first quarter they forecast. For example, in the forecasting exercise of 2019-Q1, the SPF already knows the headline inflation for January 2019 while we use data only up to December 2018.

- Use monthly data to estimate our models and forecast and then transform the results in annualized quarter-on-quarter change, as presented in the SPF documentation. Root-mean-squared error are computed on the annualized quarter-on-quarter changes, using today's known realisations.

We this forecasting exercise, we aim to compare the BVARs with long run priors to the SPF forecast but also to the Minnesota BVAR without any long run prior. In total, we thus look at the forecasting performances of six variations of the model.

1. MN: The Minnesota BVAR
2. MN-C: The Minnesota BVAR with the Covid-19 correction
3. LR: The Minnesota BVAR with the Covid-19 correction and with the long run prior imposing as only linear combinations the two last lines of the H matrix defined above, i.e. the nominal trend shared by inflation and the interest rate.
4. LR-IO: The Minnesota BVAR with the Covid-19 correction and with the long run prior defined in the description of the model, i.e using the input-output matrix is the upper left corner of the left matrix H.
5. LR-L: The Minnesota BVAR with the Covid-19 correction and with the long run prior defined in the description of the model but using the Leontief inverse in the upper left corner of the left matrix H.
6. LR-I-IO: The Minnesota BVAR with the Covid-19 correction and with the long run prior defined in the description of the model but using the difference between the identity matrix and the IO matrix ($I_{35\times 35} - IO$) in the upper left corner of the left matrix H.

While our first idea is to use directly the Input-Output structure or the Leontief inverse in the construction of the long run prior, we motivate the idea of testing the sixth model (PLR-I-IO) as each linear combination is then an approximation of the relation between a sectoral price index (in log-level) and the weighted sum of the sectoral price indices (in log-level) from which it directly depends for its inputs.

For each model, we forecast inflation for 15 periods in the future then compute the quarterly inflation rates to allow for a comparison with the SPF forecast. As our sample is quite limited (starting only in 2004), we use an iterated forecast exercise. The first iteration uses data from 2004Q1 up to 2017Q4 to forecast the five following quarters (so from 2018Q1 to 2019Q1). The last iteration uses data from 2004Q1 up to 2021Q1 to forecast the five following quarters (so from 2021Q1 to 2022Q2). We also present some results in which we only do the iterated forecast up to 2021Q2 so as to see how the models perform outside of the very high inflation period. As a reminder, inflation in the US starts early 2021 and the annualized QoQ inflation rate already reaches 7.5% in 2021Q2.

The comparisons between the BVARs forecasts and the Survey of Professional Forecasters are displayed below on tables 1 and 2. As can be seen on the tables, our forecasts often compare to the ones of the SPF. Moreover, in some cases (in bold in the tables), the BVAR models perform better than the SPF. Plus, the BVAR with alternative priors often allows to forecast headline inflation better than the parsimonious specification of the Minnesota prior.

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)					
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf	LR-L/spf	LR-I-IO/spf
h=0Q	0.6100	1.1645	1.0555	1.0576	**0.9721**	**0.9101**	1.2597
h=1Q	1.0412	1.1234	1.0423	1.0042	1.1918	1.2014	1.2485
h=2Q	1.1204	1.2812	1.1046	1.2391	1.1006	1.0770	1.0868
h=3Q	1.1379	1.5393	1.3158	2.0237	1.0005	**0.9941**	**0.8811**
h=4Q	1.1322	1.2825	1.2918	1.0494	**0.9716**	**0.9584**	**0.9581**

Table 1: RMSE and RMSE ratios for CPI forecasts. BVAR(2)

While we show more details on the forecasting results in the appendix to confirm the robustness of our results, here we want to stress that with the shortest iterated forecasting exercise (in which we drop the iterated forecast that try to forecast the very high inflation period), the BVARs are showing quite good improvements to the Survey of Professional Forecasters as illustrated by the table 2.

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)					
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf	LR-L/spf	LR-I-IO/spf
h=0Q	0.5684	**0.6712**	**0.8360**	**0.7379**	**0.6117**	**0.6077**	1.2860
h=1Q	0.9150	1.2861	1.2071	1.2119	1.0008	1.0086	1.2705
h=2Q	0.9097	**0.9966**	**0.9495**	**0.9508**	**0.9300**	**0.9226**	**0.9841**
h=3Q	0.9241	1.2746	1.1856	**0.9541**	**0.8998**	**0.8930**	**0.9750**
h=4Q	0.8952	1.6242	1.6240	1.1201	**0.9552**	**0.9420**	1.2138

Table 2: RMSE and RMSE ratios for CPI forecasts, shorter iterated forecasting exercise excluding the four quarters from 2021Q3 to 2022Q2. BVAR(2)

The aim of this forecasting exercise is twofold. We first wanted to validate the idea of using information from the production network to inform about long-run dynamics of sectoral prices. The results show that even if the Long-Run BVARs perform so far less good as the number of lags in the model increase, they always allow to improve over the Minnesota BVAR. Moreover, on the fifth foretasted quarter, the production network informed Long-Run BVARs allow to improve over the Survey of Professional Forecasters predictions. The second purpose of the forecasting exercise was to distinguish between the three production network informed models (so between LR-IO, LR-L and LR-I-IO). Tables 1 and 2 do not enable to do so as the results are very similar. However, given the poorer forecasting results of the last model in the iterated forecast that excludes the high inflation period, the LR-IO (with the Input-Output matrix) and LR-L (with the Leontief inverse) models are preferred. We then use these two models for the analysis of sectoral prices dynamics that follows, in which we look at the responses of our model variables to three shocks ranging from micro to macro.

3.3 Identification of structural shocks

We identify three types of shocks, going from a *micro* cereal price shock to a *meso* oil price shock and finally to a *macro* monetary policy shock. We identify each of these shocks using external instruments.

1. For the cereal price shock we consider as instrument the agricultural supply news surprises from Jo and Adjemian (2023). The authors construct agricultural supply news surprises by comparing USDA (United States Department of Agriculture) forecast revisions for crop production to market expectations derived from futures prices. The surprises are defined as the difference between the actual USDA revisions and the expected changes implied by market prices, isolating unexpected supply shocks.

2. 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.

3. Finally, concerning the monetary policy shock, we test two different instrumental variables:

    - The monetary policy surprises from Bauer and Swanson (2023). The authors use high-frequency asset price changes around FOMC (Federal Open Market Committee) announcements to isolate unexpected monetary policy shifts.
    - The monetary policy surprises from Miranda-Agrippino and Ricco (2021). Also based on high-frequency movements, the constructed surprises aim to solve for the *information bias effect* by applying a dynamic factor model in order to isolate the component of financial market movements that reflects true monetary policy innovations.

For each of these shocks, we looked 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(3) model.

3.3.1 The cereal price shock

While energy price shocks have traditionally been at the center of inflation analysis, the recent sharp increase in global food prices has highlighted the importance of micro shocks like cereals price shocks in shaping inflationary pressures. Despite their relevance, cereal price shocks remain however understudied in the macroeconomic literature, particularly in the context of inflation dynamics. Here we rely on the surprise series constructed by Jo and Adjemian (2023) to investigate how a shock in cereals price may transmit to other sectoral or aggregate variables. We impose a 5% shock in the US cereals price using the surprises described above as the external instrument. While all impulse responses are shown in the appendix, here we comment on the most important variables. We see on figure 1 that the cereals price shock has a quite persistent

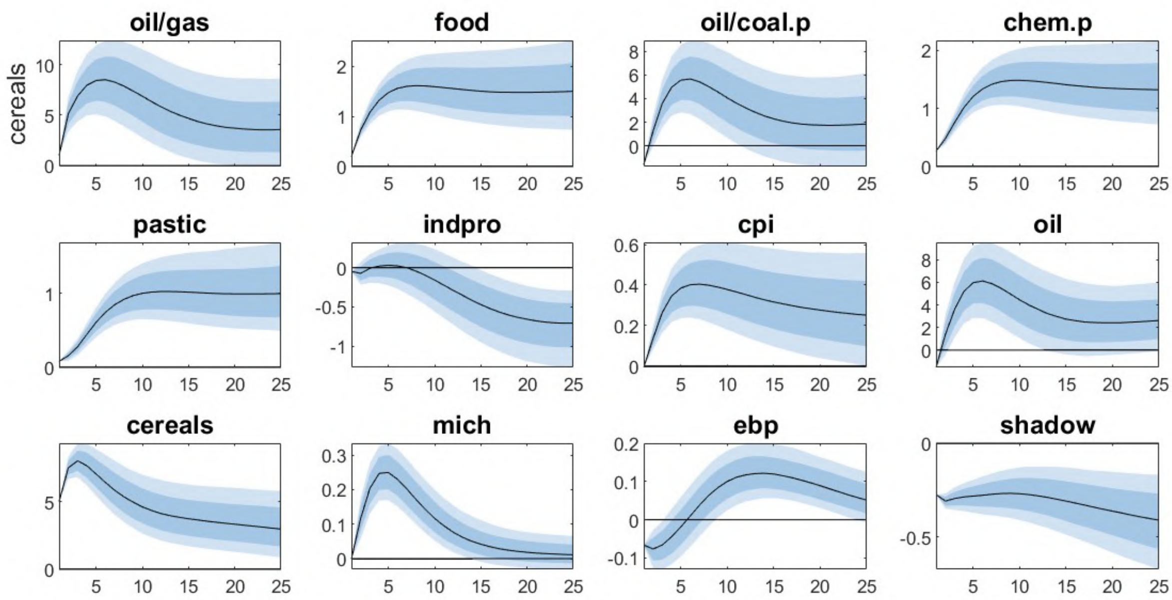

Figure 1: Impulse responses to a **cereals price shock** using Adjemian and Jo surprises in a BVAR(2) model with Input-Output informed Long-Run prior.

impact on *food producer prices*. But it is also followed by a rise in *oil prices* and thus in the *oil and gas sector*, *oil and coal products* sector and also in *chemical products* or *plastics*. If the Jo and Adjemian (2023) instrument is partially correlated with global commodity market conditions, it may capture supply disruptions that affect multiple raw materials, including oil, rather than isolating a cereal-specific shock. The link between cereal and oil prices could also be driven by financial market dynamics, where commodities are traded as part of diversified portfolios, leading to correlated price movements even in the absence of direct sectoral spillovers. Finally, we see that the *consumer price index* also increases and in a quite persistent way but it is thus hard to define whether this comes from a cereal price shock that spills over to the network or from a broader commodity price shock. Surprisingly, the monetary policy response is negative. Since our data starts only in 2004, this could be due to the post-2008 period characterized by low interest rates and unconventional monetary policy. Further work is however needed to better understand the mechanisms at play. Another interesting graph is the figure 2 that displays the weighted sum of producer price indices responses through time. This allows two things: compare the aggregated producer price response to the consumer price response and show which are the sectors that contribute to the aggregated PPI the most.

On figure 2 as expected the *food and beverage* sector responds to the cereal price shock (in light green). Our results however also show surprising aspects such as the high contribution of the *professional and business services* sector (in light pink). It also appears that the aggregated PPI response is almost twice the size of the consumer price response. This could provide support for the hypothesis that micro shocks in sectors might impact only slightly headline inflation or

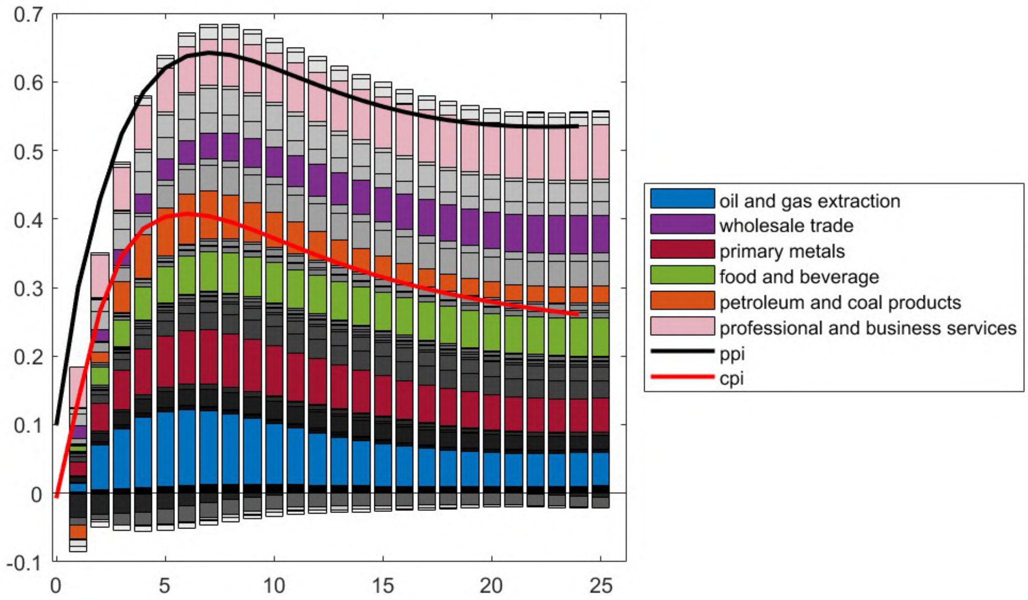

Figure 2: Contributions to aggregated PPI of sectoral PPIs responses to a **cereals price shock** using Adjemian and Jo surprises in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer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

at least that raw material costs increase substantially, but not all of this increase is passed on to consumers.

3.3.2 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. Unlike cereal price shocks, which are typically seen as micro shocks, affecting other prices through direct cost pass-through, oil price shocks have a much broader reach, impacting directly production costs, transportation but also the financial markets. This is why it can be seen less as a micro shock but as a *meso* shock, that shares features both with micro shocks (transmitting through production costs for example) and macro shocsk. The transmission of oil supply shocks even if widely studied is complex and deserves attention. To analyze these dynamics, 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. As for the analysis of the responses to a cereals price shock, the impulse responses of all variables are provided in the appendix, and we highlight the key sectoral and aggregate effects in the discussion below.

As expected, the rise in oil prices is transmits quite rapidly to the *oil and gas extraction* sector and to *oil and coal products*. We also see that while the *oil and gas extraction* sector response goes back to zero, the responses of the *oil and coal products* sector is already more persistent and the ones for the *chemical products*, *plastic* or *transportation* are even more persistent. We also see that a sector like *construction* can show no response for a few months and then increase, contributing also to the persistence of the shock in the economy. The response of the shadow rate is not very surprising as it is know that policymakers often "look through" supply-side oil price shocks. The ECB and the Fed have historically stated that they 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.). This is often motivate by the negative effect such a raise of interest rate can have on production. What is more surprising is the response of the excess bond premium, and further work would be needed to fully investigate that question.

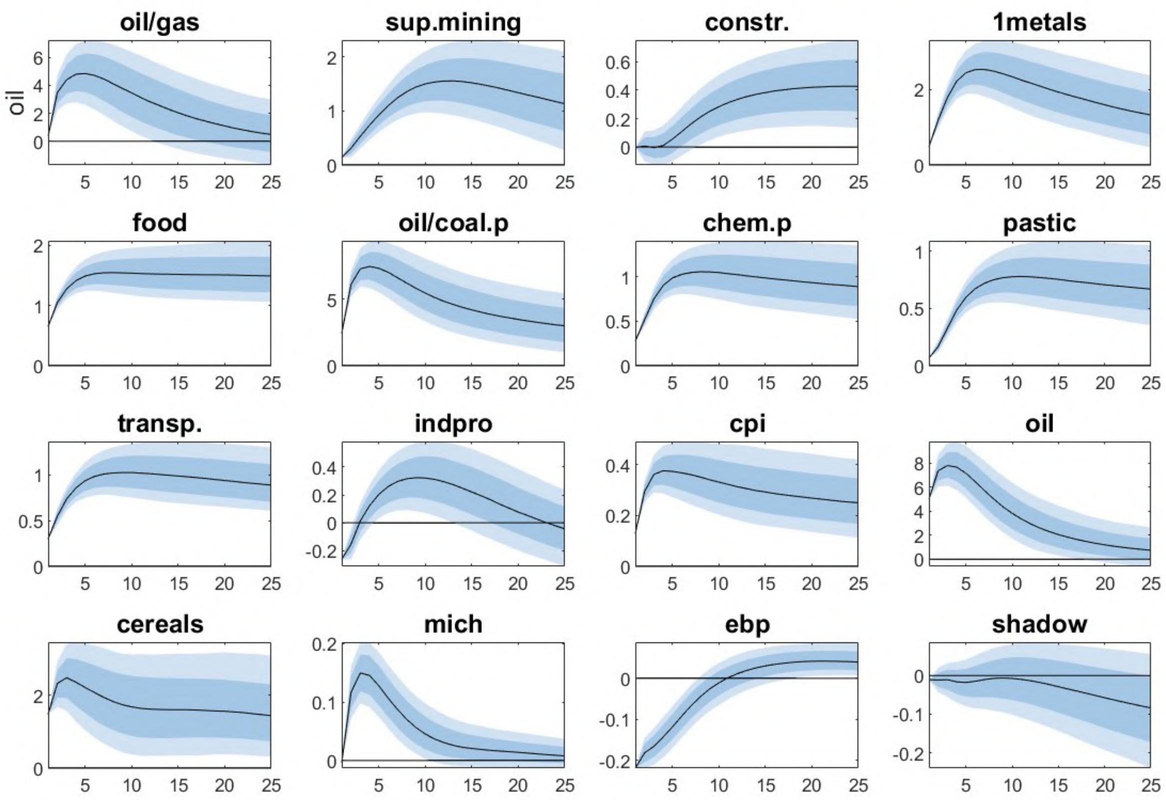

Figure 3: Impulse responses to an **oil price shock** using Kanzig's surprises in a BVAR(2) model with Input-Output informed Long-Run prior.

As done with the cereals price shock, we look on figure 4 at the weighted sum of producer price indices responses through time. A first look at the figure already shows that interestingly the aggregated PPI response is now very close to the CPI response. This could indicate that indeed, oil price shocks, because they impact more directly the final consumer prices (for example through energy prices or fuel), are transmitted not only indirectly via the production network but also directly. As with the cereal price shock, we find a surprising response for the *professional and business services*. We also see as stated above that while the *oil and gas extraction* sector responds rapidly to the oil shock, its contribution fades away while the ones of the *petroleum and coal products* or *transportation* sectors are much more persistent. We also highlight in yellow in the figure the contribution of the *construction* sector.

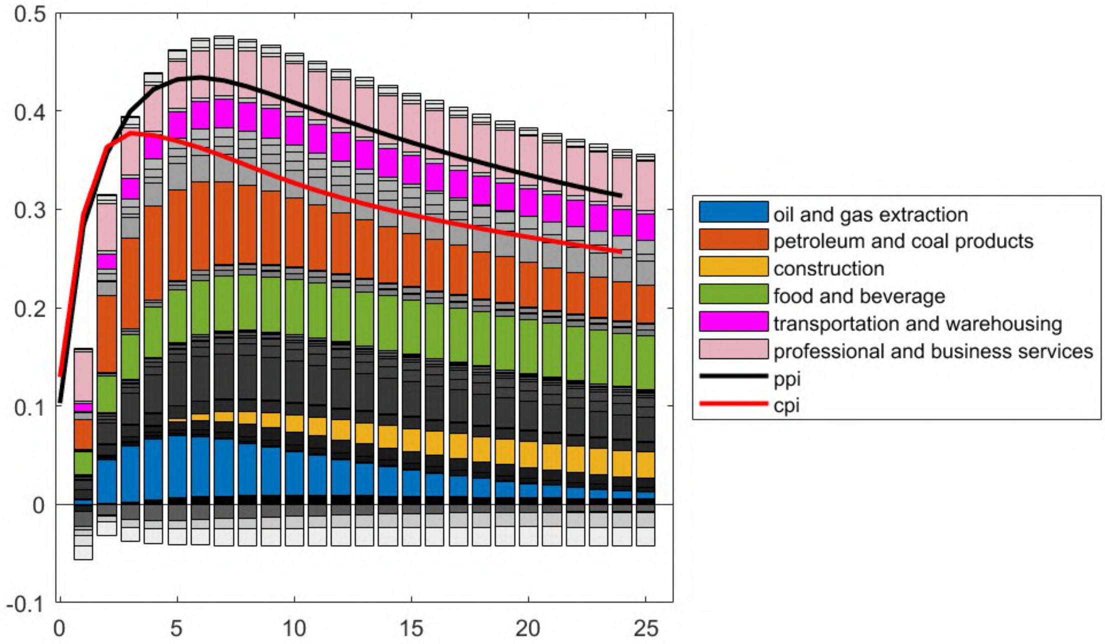

Figure 4: Contributions to aggregated PPI of sectoral PPIs responses to an **oil price shock** using Kanzig's surprises in a BVAR(2) model with Input-Output informed Long-Run prior. The weighted sum of all the producer prices responses is the black line while the response of headline consumer price index 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.

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. Understanding these sectoral asymmetries is crucial for evaluating the broader macroeconomic consequences of energy price shocks, as industries with slower price adjustments may contribute to inflation persistence, even after the initial shock dissipates. Another interesting aspect is the quite important response of food producer prices. While a rise in food producer prices after an oil price shock is not surprising, the response of food PPI exhibits notable persistence, suggesting that rising energy costs may have prolonged effects on food production and distribution.

3.3.3 The monetary policy shock

As a final analysis, we then look at the responses of the different sectors to a rise in the interest rate (here the shadow rate). To do so, we used two different instrumental variables, from Bauer and Swanson (2023) and from Miranda-Agrippino and Ricco (2021). We start by the impulse responses of the macro variables of the model leaving aside the sectoral responses. Figures

5 and 6 show the responses of the main aggregate variables to a 0.25% rise in the shadow rate. The responses to the shock identified using Bauer and Swanson (2023) monetary policy surprise seem more natural because of the rise observed in the excess bond premium, which 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. Also, the inflation expectations that are expected to decrease show in both cases an initial positive response but are then clearly negative only for the monetary policy shock identified via Bauer and Swanson (2023) surprises. The initial positive response of inflation expectations in both cases is however unexpected, 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. However, both set of responses show an expected decline in industrial production and in the consumer price index.

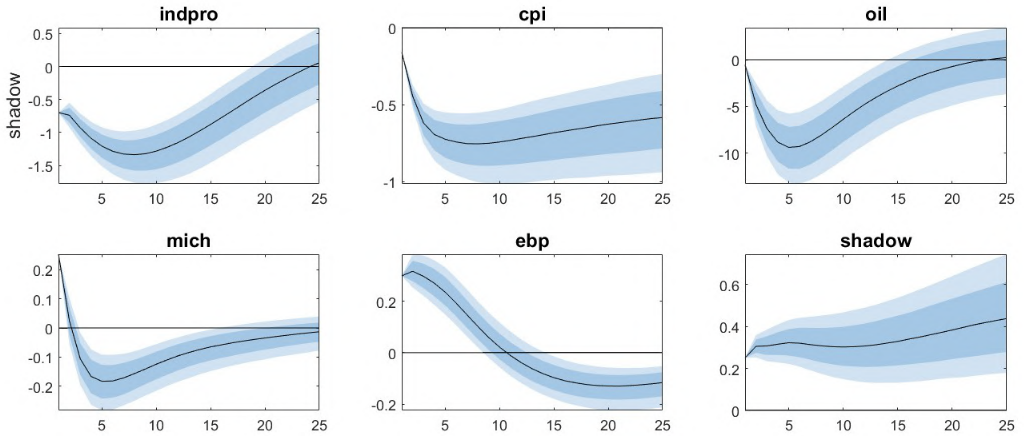

Figure 5: Impulse responses to a **monetary policy shock** using Bauer and Swan surprises in a BVAR(2) model with Input-Output informed Long-Run prior.

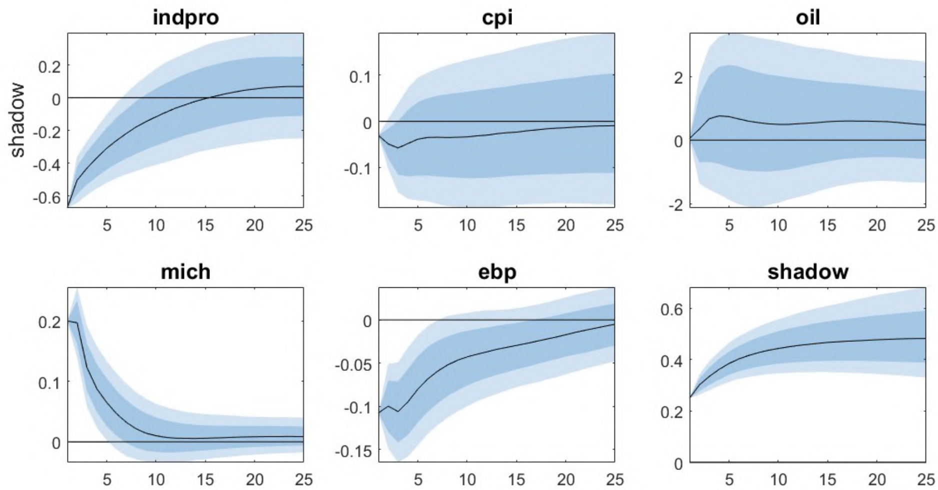

Figure 6: Impulse responses to a **monetary policy shock** using Miranda-Agrippino and Ricco surprises in a BVAR(2) model with Input-Output informed Long-Run prior.

On figure 7 we now show the responses of sectoral producer price indices to the monetary policy shock identified with Bauer and Swanson (2023) instrument. The objective is to highlight the heterogeneity in the responses of the different sectors to a rise in the interest rate. While some sectoral responses remain surprising, such as the positive answer in the *vehicles* sector, most of the responses are negative and show that a certain time is needed for the rise in the interest rate to have an impact on producer prices.

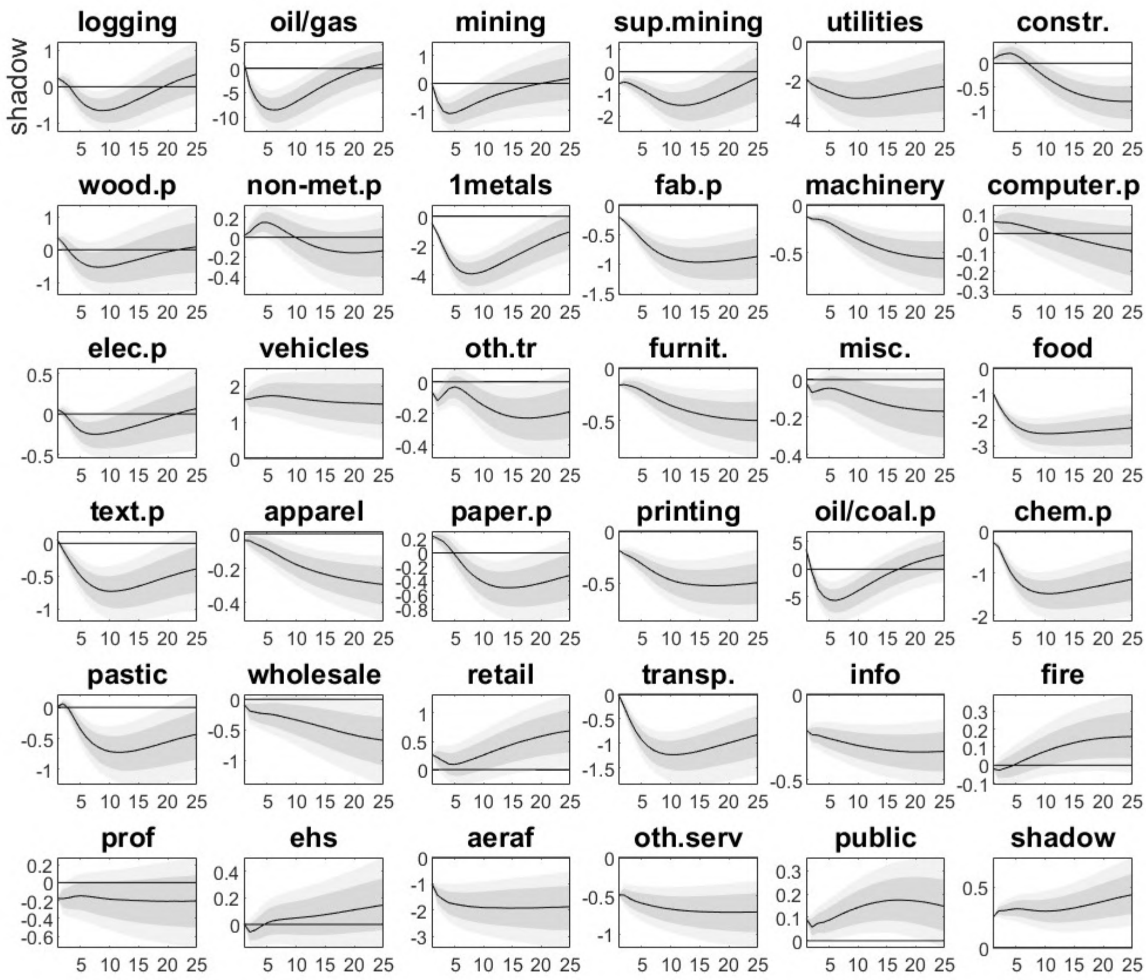

Figure 7: Impulse responses of the sectoral producer prices to a **monetary policy shock** using Bauer and Swan surprises in a BVAR(2) model with Input-Output informed Long-Run prior.

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 results 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. they also show that incorporating production network data in disaggregated models bring an added value in terms of forecasting performances.

The use of disaggregated producer price indices also allow to show through impulse responses how micro shocks can transmit to the different sectors, leading to an increase in the aggregate producer price index. Even though the consumer price index only responds to a lesser extent to a cereal price shock than the aggregated producer price index, the response of headline inflation to a cereal price shock is positive and quite persistent. Oil price shocks seem to influence both producer and consumer prices in a more similar manner. The widespread reliance on energy across sectors may amplify the inflationary impact of oil price fluctuations.

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 interest rate to oil price shocks suggests that policymakers "look through" supply-side disturbances, focusing instead on core inflation and second-round effects.

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 however contributes to a more nuanced understanding of how inflation evolves across different layers of the economy.

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Appendix

A. Shorter iterated forecasting exercise for the BVAR(1) and BVAR(3) models.

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)					
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf	LR-L/spf	LR-I-IO/spf
h=0Q	0.6100	1.1630	1.0732	1.1133	**0.9967**	**0.9736**	**0.9942**
h=1Q	1.0412	1.1613	**0.9859**	1.0517	1.1424	1.1301	1.0157
h=2Q	1.1204	1.4545	1.0987	1.1872	1.0034	**0.9952**	**0.8984**
h=3Q	1.1379	2.0039	1.5951	1.7777	**0.9587**	**0.9538**	**0.8867**
h=4Q	1.1322	1.1950	1.1460	1.0564	**0.9358**	**0.9295**	**0.9576**

Table 3: RMSE and RMSE ratios for CPI forecasts. BVAR(1)

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)					
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf	LR-L/spf	LR-I-IO/spf
h=0Q	0.5684	0.7386	0.7987	0.8156	0.7206	0.7196	0.9830
h=1Q	0.9150	1.2692	1.1784	1.2328	0.9386	0.9597	1.2894
h=2Q	0.9097	0.7823	0.7456	0.7173	0.8576	0.8590	0.8610
h=3Q	0.9241	1.0737	1.0843	1.0377	0.9119	0.9106	0.9007
h=4Q	0.8952	1.6652	1.6651	1.5643	0.9230	0.9069	1.1518

Table 4: RMSE and RMSE ratios for CPI forecasts, shorter iterated forecasting exercise excluding the four quarters from 2021Q3 to 2022Q2. BVAR(1)

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)					
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf	LR-L/spf	LR-I-IO/spf
h=0Q	0.6100	1.2083	1.1001	1.3144	1.0979	1.0873	1.4168
h=1Q	1.0412	1.1795	1.1010	1.3678	1.2497	1.2045	1.2351
h=2Q	1.1204	1.3224	1.1924	1.3006	1.1840	1.1471	1.1671
h=3Q	1.1379	1.6018	1.4293	1.3275	1.0225	1.0078	**0.8769**
h=4Q	1.1322	1.2565	1.3363	1.5155	**0.9609**	**0.9506**	**0.9614**

Table 5: RMSE and RMSE ratios for CPI forecasts. BVAR(3)

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)					
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf	LR-L/spf	LR-I-IO/spf
h=0Q	0.5684	0.6018	0.8375	1.0449	0.7968	0.7908	1.3831
h=1Q	0.9150	1.2698	1.2193	1.4846	1.1182	1.1270	1.1921
h=2Q	0.9097	0.9617	0.9169	1.0597	0.9932	0.9945	1.0200
h=3Q	0.9241	1.2552	1.1494	1.5165	0.9104	0.8992	0.9514
h=4Q	0.8952	1.4929	1.4926	2.1474	0.9555	0.9457	1.1952

Table 6: RMSE and RMSE ratios for CPI forecasts, shorter iterated forecasting exercise excluding the four quarters from 2021Q3 to 2022Q2. BVAR(3)

B. Impulse response functions of all the variables of the shocks.

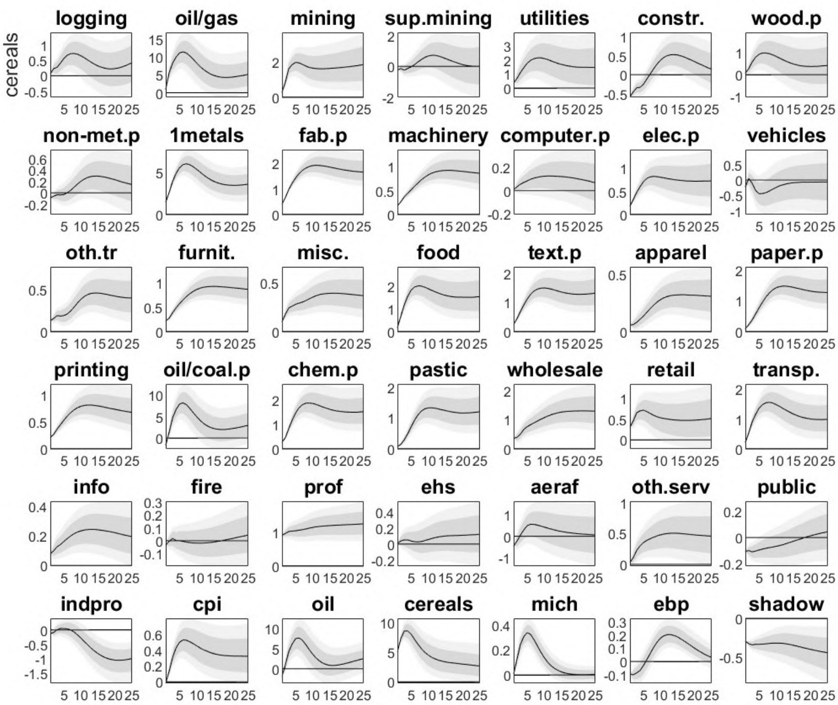

Figure 8: Impulse response functions of all the variables to a 5% cereals price shock identified via Jo and Adjemian (2023) agricultural surprises.

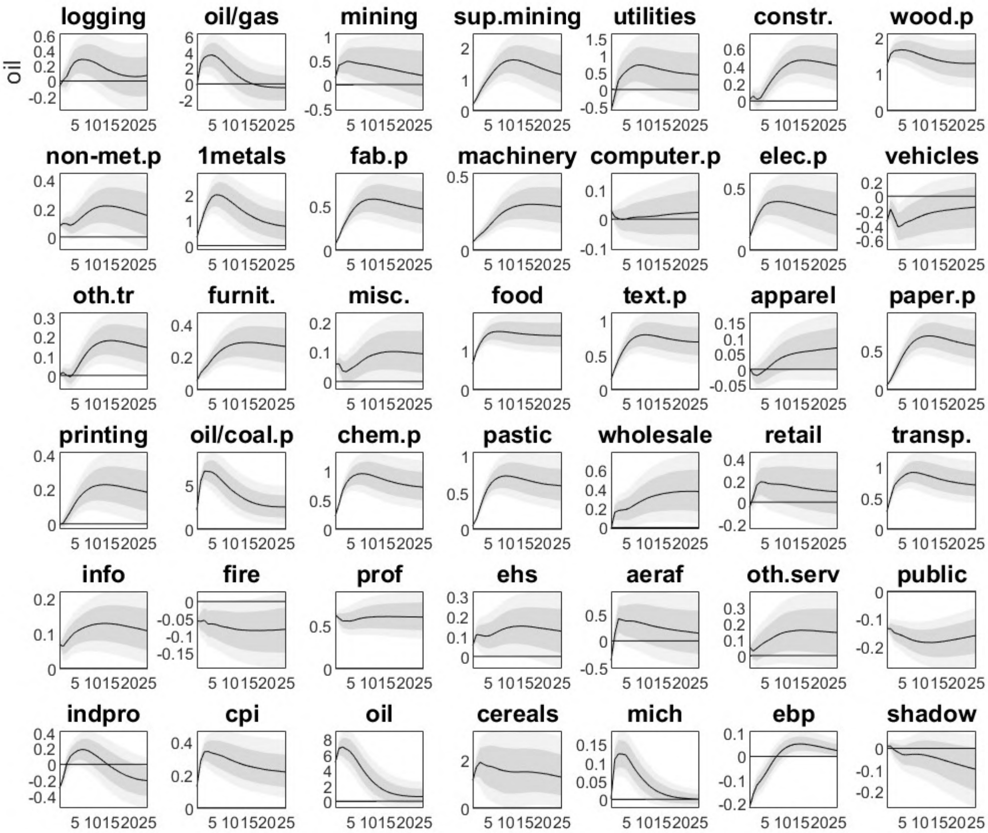

Figure 9: Impulse response functions of all the variables to a 5% oil price shock identified via Känzig (2021) oil price supply surprises.

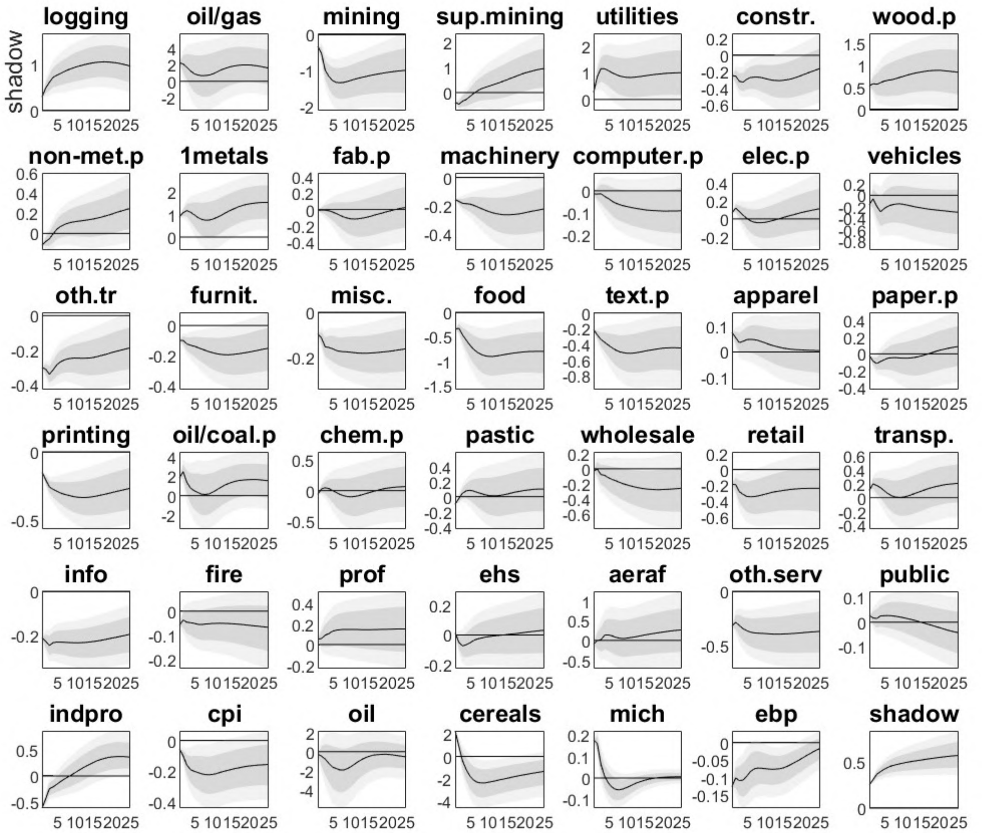

Figure 10: Impulse response functions of all the variables to a 0.25% monetary policy shock identified via Bauer and Swanson (2023) monetary policy surprises.

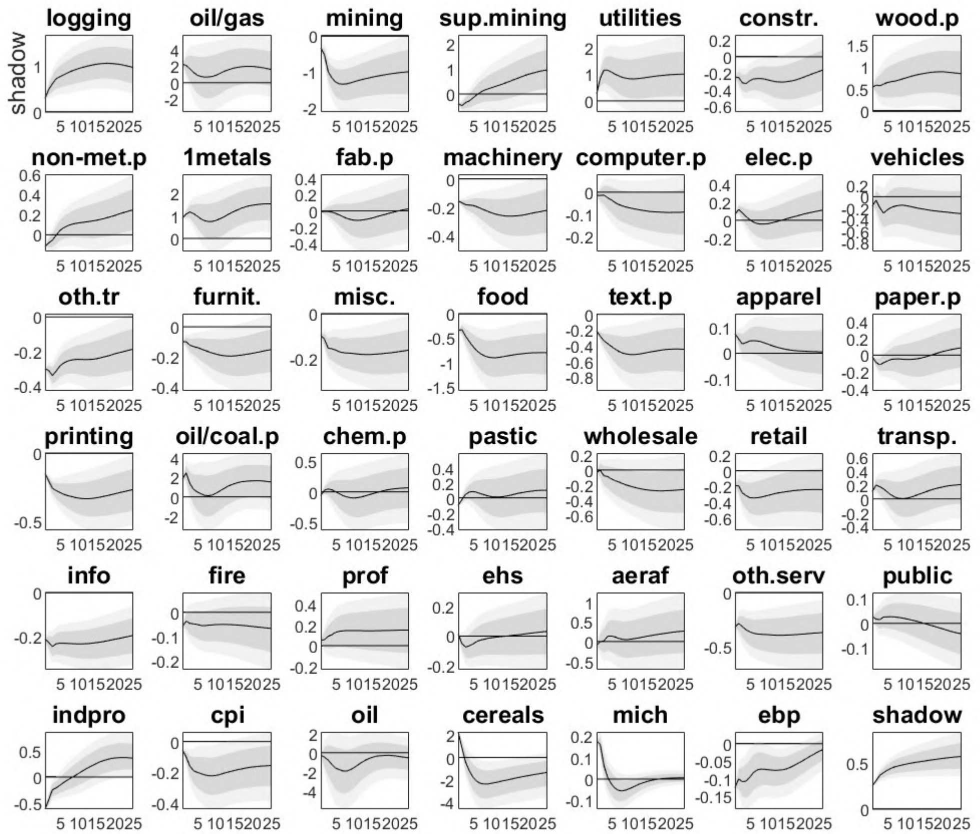

Figure 11: Impulse response functions of all the variables to a 0.25% monetary policy shock identified via Miranda-Agrippino and Ricco (2021) monetary policy surprises.

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