The Transmission of Keynesian Supply Shocks*

Ambrogio Cesa-Bianchi† Andrea Ferrero‡

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Abstract

Sectoral supply shocks can trigger shortages in aggregate demand when strong sectoral complementarities are at play. US data on sectoral output and prices offer support to this notion of "Keynesian supply shocks" and their underlying transmission mechanism. Demand shocks derived from standard identification schemes using aggregate data can originate from sectoral supply shocks that spillover to other sectors via a Keynesian supply mechanism. This finding is a regular feature of the data and is independent of the effects of the 2020 pandemic. In a New Keynesian model with input-output network calibrated to 3-digit US data, sectoral productivity shocks generate the same pattern for output growth and inflation as observed in the data. The degree of sectoral interconnection, both upstream and downstream, and price stickiness are key determinants of the strength of the mechanism. Sectoral shocks may account for a larger fraction of business cycle fluctuations than previously thought.

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†Bank of England, CEPR and CfM: Ambrogio.Cesa-Bianchi@bankofengland.co.uk

‡University of Oxford, CEPR and CfM: andrea.ferrero@economics.ox.ac.uk

1. Introduction

The economic shock associated with the Covid-19 pandemic has displayed both demand and supply-like features.[1] A clear distinction between the two, however, may be somewhat deceptive. Guerrieri et al. (2020) propose a model in which a supply shock that affects a subset of sectors may cause a demand-like response at the aggregate level if the economy displays enough complementarities.[2] These "Keynesian supply shocks," and the underlying mechanism that supports their transmission, suggest a different way to look at the Covid crisis and business cycles in general.

An example can help clarify the basic logic of Keynesian supply shocks, their transmission, and the role of complementarities. Suppose the economy consists of two sectors of roughly equal size: entertainment (offering movies in cinemas) and food (producing popcorn). A negative supply shock hits the entertainment sector so that the price of movie tickets increases.[3] What happens to the food sector? If the two goods are substitute, people switch from going to the movies to eating popcorn at home because of the pandemic. The demand for popcorn increases, and so does their price as to clear the market. If the two goods are complements, however, people do not enjoy eating popcorn without watching movies. In this case, the demand for popcorn falls and so does their price. Given that the two sectors are of similar size, the overall effect on prices is likely to be ambiguous. As a corollary, the behavior of aggregate prices and quantities per-se cannot be informative about the importance, or even the existence, of the Keynesian supply mechanism.

[1] A number of recent papers pursue different strategies to gauge the relative importance of demand and supply shocks in relation to the Covid crisis. del Rio-Chanona et al. (2020) distinguish between essential and non-essential industries and construct a remote labor index to measure the ability to work from home across occupations. Brinca, Duarte, and Faria-e-Castro (2020) focus on the US labor market. Balleer et al. (2020) analyze a survey of planned price changes among German firms. Bekaert, Engstrom, and Ermolov (2020) study real-time survey data on inflation and real GDP growth.

[2] The mechanism shares some similarities with the complementarities between consumption goods and distribution services in Corsetti, Dedola, and Leduc (2008).

[3] In this setting, the Covid shock would correspond to the extreme case in which the price of movie tickets goes to infinity since all cinemas close due to the lockdown.

The objective of this paper is to understand whether the data are supportive of a view of the world in which Keynesian supply shocks, and the underlying mechanism that supports their transmission, exist and play an important role for business cycle fluctuations. Our empirical findings offer support to the idea of Keynesian supply shocks using sectoral US data on gross output and prices.

Sectoral data are crucial for the analysis. Any approach that only relies on aggregate data would simply classify sectoral supply shocks with aggregate demand consequences as aggregate demand shocks. Yet, sectoral data per-se are not a silver bullet, as separating sectoral shocks that have aggregate consequences from true aggregate shocks poses severe identification challenges. Empirically, one way to solve this identification problem could be to rely on "granular" instruments (Gabaix and Koijen, 2020). Such instruments, however, are not always easy to come by. As an alternative, sufficient structure to recover supply shocks that spillover across sectors could come from economic theory, as in the work of Foerster, Sarte, and Watson (2011).

In this paper, we pursue a third route that does not require to explicitly separate aggregate shocks from sectoral shocks with aggregate consequences. The intuition for our approach is that while aggregate demand shocks and Keynesian supply shocks imply the same restrictions on the response of aggregate data—both giving rise to positive comovement between output and prices—the sectoral responses to these shocks are different. True aggregate demand shocks should move quantities and prices in the same direction in all sectors. Keynesian supply shocks should instead move quantities and prices in opposite directions for those sectors that are directly hit by the sectoral shocks.

We formalize this intuition by specifying a multi-sector VAR model with a factor structure to describe the sectoral dynamics of the US economy. In particular, we assume that sectoral quantities and prices load on a vector of unobserved common factors that capture the comovement across sectors. Following the approach in Cesa-Bianchi, Pesaran, and Rebucci (2020), we aggregate the sectoral models at the economy-wide level and obtain an estimate of the common factors through cross-sectional averages of the sectoral data, which correspond to aggregate output and aggregate inflation. We then impose sign restrictions on these aggregate variables to extract from the common factors two orthogonal innovations, one that leads to positive comovement between quantities and prices and another one that leads to negative comovement between quantities and prices. We label these innovations aggregate "demand-like" and aggregate "supply-like" shocks, respectively, as their effects might be the result of truly aggregate shocks as well as sector-specific shocks with aggregate effects.

We then estimate the sectoral loadings on the identified aggregate demand-like shock, which are key object of interest of our analysis. These objects capture the impact response of each sector's quantities and prices to the aggregate demand-like shock, on average over the whole sample. In many instances (about 40% of cases), the sectoral loadings on aggregate demand disturbances imply that the price increases when output falls. This result suggests that some aggregate demand-like shocks are likely to be the consequence of a sectoral supply shock with strong complementarities at play—the Keynesian supply mechanism. Importantly, our sample ends in 2019Q4 and thus the Covid episode does not drive the identification of the sectoral responses. Through the lenses of our analysis, the response to the pandemic has just been an extreme realization of a more general structural feature of the US economy.

In our estimation procedure, none of the thousands draws exhibits loadings with the same sign for output and prices across all sectors. Even more strikingly, in response to a negative demand shock that makes aggregate output and inflation fall, the entire distributions of output and prices loadings fall on the opposite side of zero in about one quarter of the US sectors. In the context of a multi-sector economy, these results suggest a definition of aggregate shocks determined by the "average" sectoral response of quantities and prices. Conversely, the data do not support a "strict" interpretation whereby all sectors respond with the same movement of prices and quantities as implied by the aggregate shock.

These empirical findings speak directly to literature on the sectoral origins of business cycle fluctuations (e.g. Horvath, 2000, and Conley and Dupor, 2003). Closely related to our work, Foerster, Sarte, and Watson (2011) calibrate a multi-sector structural model with input-output linkages to disentangle the relative importance of aggregate and sectoral shocks for the volatility of US industrial production. In a similar vein, the recent literature on production networks, starting with Gabaix (2011), focuses on large firms although most results can also be interpreted in terms of sectors. Gabaix and Koijen (2020) develop a methodology to extract the "granular" (i.e. idiosyncratic) component of common variation, which is orthogonal to aggregate shocks, and therefore can be used as an instrument. With relation to the Covid crisis, Baqaee and Farhi (2020a) emphasize the amplification effect of non-linearities in production networks. Baqaee and Farhi (2020b) extend the model introducing nominal rigidities and financial frictions to endogenize the consequences of the initial supply shock on labor supply and firms exit. These examples suggest that complementarities in production, not only in consumption, also work as a powerful transmission mechanism for Keynesian supply shocks.

In line with these contributions, we validate our empirical results performing a similar estimation exercise on artificial data simulated from a New Keynesian model with a production network, similar to Pasten, Schoenle, and Weber (2020). Differentiated goods enter as complements in production (through an intermediate input bundle) and in consumption. The aggregate VAR picks up aggregate demand shocks even when by construction sectoral productivity shocks are the only source of exogenous variation. The share of sectoral loadings on the "wrong" side of the distribution is comparable to its empirical counterpart. These model-based results provide further support to the idea that complementarities play a key role in the transmission of sectoral supply shocks at the aggregate level. In addition, we show that price rigidities and both upstream and downstream connectedness through the input-output network are important features of the model that determine the strength of Keynesian supply shocks.

Finally, our findings have also important policy implications. In the context of the Covid crisis, understanding the nature of the shock is crucial to shape the policy response.[4] Keynesian supply shocks and their transmission mechanism imply a role for complementarities also in the policy response. As Guerrieri et al. (2020) point out, an interest rate cut can limit the economic consequences of the pandemic by reducing the cost of debt and mitigating liquidity problems. At the same time, targeted fiscal measures, such as profit subsidies or payroll tax cut on employers, also work in supporting the economy by preventing businesses from closing down and laying off workers.[5]

The rest of the paper is organized as follows. Section 2 introduces the empirical model and discusses its identification challenges. Section 3 presents the main empirical results. Section 4 validates the empirical results in the context of a New Keynesian model with input-output linkages. Section 5 concludes.

2. A Multi-Sector Factor-Augmented VAR

In this section, we develop an empirical model to study the impact of aggregate shocks on sectoral quantities and prices. Our approach consists of four key steps. First, we lay out a multi-sector VAR model with a factor structure that captures the sectoral dynamics of the US economy.[6] Second, we aggregate the sectoral models into one economy-wide VAR to separate sectoral idiosyncratic shocks from the common factors. Third, we extract orthogonal innovations from the common factors that we can interpret as aggregate demand and supply shocks following a sign-restriction approach. Finally, we recover the sectoral loadings to

[4] Gourinchas (2020) discusses a number of measures to alleviate the short-run tradeoff between health policy and economic costs. Benmelech and Tzur-Ilan (2020) examine the determinants of the fiscal and monetary policy response across countries.

[5] In a model of endogenous growth, Fornaro and Wolf (2020) highlight a supply-demand loop that may require a combined fiscal and monetary policy response. Woodford (2020) argues that the nature of the Covid crisis may tilt the balance of the response in favor of fiscal policy because of the possibility to target the intervention to the right sectors.

[6] Stock and Watson (2016) survey the literature on factor-augmented VARs. Using a similar framework to ours, Smets, Tielens, and Van Hove (2018) study the contribution of sectoral shocks for inflation persistence and volatility, while Matthes and Schwartzman (2021) focus on the identification of consumption shocks.

the identified aggregate shocks.

In the next two subsections we describe these steps in detail. Before proceeding, however, one qualification is in order. Our approach does not directly solve the identification problem between common shocks and sectoral shocks with aggregate effects described in the introduction. If such sectoral shocks exist, the orthogonal innovations extracted from the common factors are a convolution of "true" aggregate shocks and sectoral shocks with aggregate effects.[7] The key object of interest in our analysis are the sectoral loadings on the common factors, which indirectly allow us to draw conclusions on the relative importance of the two types of shocks.

2.1 Empirical Model

The economy consists of N sectors indexed by $i = 1, 2, ..., N$. We model empirically the joint evolution of sectoral output growth (y_{it}) and inflation (π_{it}) through a VAR(p)

$$x_{it} = \Phi_{i0} + \sum_{j=1}^{p} \Phi_{ij} x_{it-j} + \eta_{it}, \tag{1}$$

where $x_{it} \equiv [y_{it} \; \pi_{it}]'$ is the vector of endogenous variables, η_{it} is a (2×1) vector of sectoral innovations assumed to be serially uncorrelated, Φ_{i0} is a (2×1) vector of constants, and Φ_{ij} are (2×2) matrices of coefficients.

In order to disentangle the dependence of current sectoral variables on aggregate demand and supply shocks, we further assume a factor structure for the reduced-form residuals

$$\eta_{it} \equiv \Gamma_i f_t + u_{it}, \tag{2}$$

where f_t is a (2×1) vector of common factors, Γ_i is a (2×2) matrix of sectoral loadings on the common factors, and u_{it} is a (2×1) vector of idiosyncratic sectoral

[7] Foerster, Sarte, and Watson (2011) show that a factor model like ours may be interpreted as the reduced form of a structural model with explicit sectoral linkages.

innovations. After substituting equation (2) into equation (1), we can rewrite

$$x_{it} = \Phi_{i0} + \sum_{j=1}^{p} \Phi_{ij} x_{it-j} + \Gamma_i f_t + u_{it}. \tag{3}$$

The VAR in equation (3) presents several identification problems. In particular, we need to identify the common factors f_t, the sectoral loadings Γ_i, and the idiosyncratic sectoral innovations u_{it}. All these elements are important for the purpose of isolating the Keynesian supply mechanism. The next section describes the identification process.

2.2 Identification

We achieve identification of the common factors and sectoral loadings *by aggregation*, following the approach in Cesa-Bianchi, Pesaran, and Rebucci (2020). We report the key steps of the identification procedure here and relegate the full derivation to Appendix B. For the sake of clarity, we focus on the case $p = 1$, although all results generalize to $p > 1$.

First, from equation (3), we can solve for x_{it} in terms of current and past values of the aggregate and sectoral shocks

$$x_{it} = \mu_i + \Upsilon_i(L)\Gamma_i f_t + \vartheta_{it}, \tag{4}$$

where $\mu_i \equiv \Upsilon_i(L)\Phi_{i0}$, $\Upsilon_i(L) \equiv (I_2 - \Phi_{i1}L)^{-1} = \sum_{\ell=0}^{\infty} \Phi_{i1}^{\ell}$, I_2 is a (2×2) identity matrix, L is the lag operator, and $\vartheta_{it} \equiv \Upsilon_i(L)u_{it}$.

The second step consists of deriving an aggregate VAR as a weighted average of the sectoral ones. Let $w_i > 0$ be the output share of sector i, such that $\sum_{i=1}^{N} w_i = 1$. We can write aggregate output growth and inflation as

$$\bar{y}_t \equiv \sum_{i=1}^{N} w_i y_{it} \qquad \text{and} \qquad \bar{\pi}_t \equiv \sum_{i=1}^{N} w_i \pi_{it}, \tag{5}$$

where an upperbar denotes cross-sectional averages. As Appendix A shows, these sectoral weighted averages track extremely closely actual aggregate output growth and inflation measured from national accounts. Under the assumption that Φ_{i1} and Γ_i are independently distributed across sectors, we can write

$$\sum_{\ell=0}^{\infty}\sum_{i=0}^{N} w_i \Phi_{i1}^{\ell}\Gamma_i f_{t-\ell} = \Omega(L)\Gamma f_t,$$

where $\Omega(L) = \sum_{\ell=0}^{\infty}\Omega_\ell L^\ell$, $\Omega_\ell = \mathbb{E}(\Phi_{i1}^{\ell})$, $\Gamma = \mathbb{E}(\Gamma_i)$, and $\mathbb{E}(\cdot)$ denotes the population cross-sectional mean operator (see Appendix B for details). Therefore, premultiplying both sides of equation (4) by w_i and summing equation by equation over i, we obtain

$$\bar{x}_t = \bar{\mu} + \Omega(L)\Gamma f_t + \bar{\vartheta}_t, \tag{6}$$

where the vector of endogenous variables is now $\bar{x}_t \equiv [\bar{y}_t\ \bar{\pi}_t]'$, the constant is $\bar{\mu} \equiv \sum_{i=1}^{N} w_i\mu_i$, and the error term is $\bar{\vartheta}_t \equiv \sum_{i=1}^{N} w_i\vartheta_{it}$. Finally, under the assumption that sectoral shocks are weakly correlated in the cross-section and that the sectoral weights are asymptotically small (two common assumptions in the factor models literature), the last term in equation (6) is negligible, that is

$$\bar{\vartheta}_t = O_p\left(N^{-\frac{1}{2}}\right).$$

Given some further regularity conditions on the matrices Φ_{i0}, Φ_{i1}, and Γ_i (also discussed in Appendix B), we can identify the common factors f_t by inverting equation (6)

$$f_t = \theta + \sum_{\ell=0}^{\infty}\Theta_\ell \bar{x}_{t-\ell} + O_p\left(N^{-\frac{1}{2}}\right). \tag{7}$$

where $\theta = -\Gamma^{-1}\Omega^{-1}(1)\bar{\mu}$ and $\Theta_\ell = \Gamma^{-1}\Omega^{-1}(L)$.

Equation (7) defines the common factors in terms of observable variables. In practice, however, we cannot recover the common factors from this equation because of the infinite order lag structure. Chudik and Pesaran (2015) offer a solution to this problem. If the slope heterogeneity is not extreme and $\Omega(L)$ decays exponentially in L, a truncation of order k appropriately approximates the infinite sum in equation (7).[8] Under the maintained assumption $p = 1$, we can therefore rewrite the sectoral VARs in equation (3) as

$$x_{it} = \varphi_{i0} + \Phi_{i1} x_{it-1} + \Xi_{i0} \bar{x}_t + \sum_{\ell=1}^{k} \Xi_{i\ell} \bar{x}_{t-\ell} + u_{it}, \tag{8}$$

where $\varphi_{i0} \equiv \theta + \Phi_{i0}$ and $\Xi_{i\ell} \equiv \Gamma_i \Theta_\ell$.

In equation (8), for convenience, we have isolated the contemporaneous effect of the common factors on the endogenous sectoral variables (the term $\Xi_{i0}\bar{x}_t$, where $\Xi_{i0} \equiv \Gamma_i \Theta_0$), which is the main object of interest for our analysis. The economic interpretation of the factor loadings Ξ_{i0}, however, is not straightforward, as the elements in $\bar{x}_t$ (being a linear combination of the underlying aggregate structural shocks) are correlated.[9]

Our approach to the identification of the common factors, however, offers a solution to this problem. First note that, as in any factor model, the common factors can be identified from the cross-section only up to a rotation matrix. Second, and differently from alternative methodologies that deliver orthogonal factors, we proxy the common factors in terms of aggregate observable variables. We can therefore extract orthogonal innovations from $\bar{x}_t$ by estimating a VAR(k) and applying a standard identification scheme (which we discuss in the next section) to its aggregate reduced form residuals

$$\bar{x}_t = A_0 + \sum_{\ell=1}^{k} A_\ell \bar{x}_{t-\ell} + B e_t, \tag{9}$$

where the covariance matrix of e_t is the identity matrix I_2. In our application, we use basic economic theory to identify B, which in turn allows the innovations to the common factors to have a meaningful economic interpretation.[10] This step

[8] In particular, the lag order k can be estimated using the Akaike or Bayesian Information Criteria, or set to $k = T^{1/3}$, where T is the time dimension of the panel.

[9] This complication is not a feature that is specific of our approach. Alternative methodologies that deliver orthogonal factors (e.g. principal components) lead to similar problems, as the factors themselves have no obvious economic interpretation.

[10] Following a different approach, Cesa-Bianchi, Pesaran, and Rebucci (2020) exploit the patterns of cross-sectional dependence observed in the data to identify B.

yields elements of e_t that are orthogonal and common to all sectors, and can thus be interpreted as aggregate structural shocks. The possibility of recovering innovations to the common factors with a clear economic meaning constitutes an appealing feature of our approach.

Finally, substituting back into the factor model, we can recover the loadings Λ_i on the estimated structural shocks $\hat{e}_t$ for each sector from

$$x_{it} = \Psi_{i0} + \Phi_{i1} x_{it-1} + \Lambda_i \hat{e}_t + \sum_{\ell=1}^{k} \Psi_{i\ell} \bar{x}_{t-\ell} + u_{it}, \tag{10}$$

where $\Psi_{i0} \equiv A_0 + \varphi_{i0}$, $\Lambda_i \equiv \Gamma_i B$, and $\Psi_{i\ell} \equiv A_\ell + \Xi_{i\ell}$. Equation (10), which can be estimated with OLS sector by sector, also allows us to retrieve the sectoral idiosyncratic innovations.[11]

As already stressed at the beginning of this section, our approach cannot directly disentangle "true" aggregate shocks from sectoral shocks that propagate at the aggregate level. In other words, the orthogonal aggregate shocks e_t that we extract from the common factors are a convolution of aggregate shocks and sectoral shocks with aggregate consequences, provided the latter exist. In contrast, the sectoral innovations u_{it} are truly idiosyncratic in the sense that these shocks are weakly correlated across sectors and cannot generate aggregate fluctuations. Separately identifying aggregate shocks and sectoral shocks with aggregate consequences requires imposing further restrictions on the data. For example, Foerster, Sarte, and Watson (2011) employ the structure implied by a calibrated multi-sector real business cycle model to filter out the propagation effects of sectoral shocks induced by production linkages.[12] Our empirical application offers a complementary approach that does not rely on further restrictions.

[11]The factor-augmented sectoral VARs in (3) and a standard Global VAR (GVAR) specification yield the same estimates of the idiosyncratic sectoral innovations. However, our factor model allows for the explicit identification of common shocks whereas the GVAR does not (see the discussion in Chudik, Pesaran, and Mohaddes, 2020). As the identification of structural aggregate shocks is of crucial importance for our analysis, we favor the former modelling approach.

[12]Among others, these restrictions correspond to making assumptions on the degree of complementarity/substitutability in consumption and production. We return to these issues in section 4.

3. Empirical Results

This section presents the main empirical results of the paper in three parts. Subsection 3.1 discusses the identification strategy of demand and supply shocks in the aggregate VAR, the impulse responses of the aggregate variables, and the properties of the shocks. After estimating the sectoral VARs, subsection 3.2 analyzes in more detail the estimated loadings $\hat{\Lambda}_i$, which capture how sectoral output growth and inflation respond to the aggregate structural shocks on average over the whole sample period. Finally, subsection 3.3 reports an extensive set of robustness exercises.

3.1 Aggregate VAR

In this section, we identify the orthogonal innovations to the common factors characterized by the VAR in equation (9), which can be interpreted as aggregate structural shocks. In what follows, we label the aggregate shocks "demand-like" and "supply-like." As discussed above, our hypothesis is that sectoral shocks with aggregate consequences might pollute these aggregate structural shocks.[13]

As anticipated, the vector of endogenous variables $\bar{x}_t$ includes the cross-sectional average of sectoral real gross output ($\bar{y}_t$) and the sectoral output deflator ($\bar{\pi}_t$), both expressed in log differences. We consider all 3-digit sectors except for *Oil and gas extraction* and *Petroleum and coal products*, for a total of 64 sectors. The data come from the Bureau of Economic Analysis at quarterly frequency, from 2005Q1 to 2019Q4. We set the number of lags in the VAR to $k = 1$.[14]

We estimate the VAR parameters and identify the structural shocks in equation (9) following the sign restrictions approach in Uhlig (2005). After specifying a Normal-Wishart prior for the VAR parameters, we draw candidate rotation

[13] Section 3.2 delves into this possibility by looking at the sectoral loadings to the aggregate structural shocks.

[14] A specification with one lag is enough to deliver serially uncorrelated reduced form residuals. Appendix D shows that the results obtained from a specification with four lags are very similar to our baseline.

Table 1: Sign restrictions for the identification of aggregate shocks

	Demand-like	Supply-like
Output Growth	+	+
Inflation	+	-

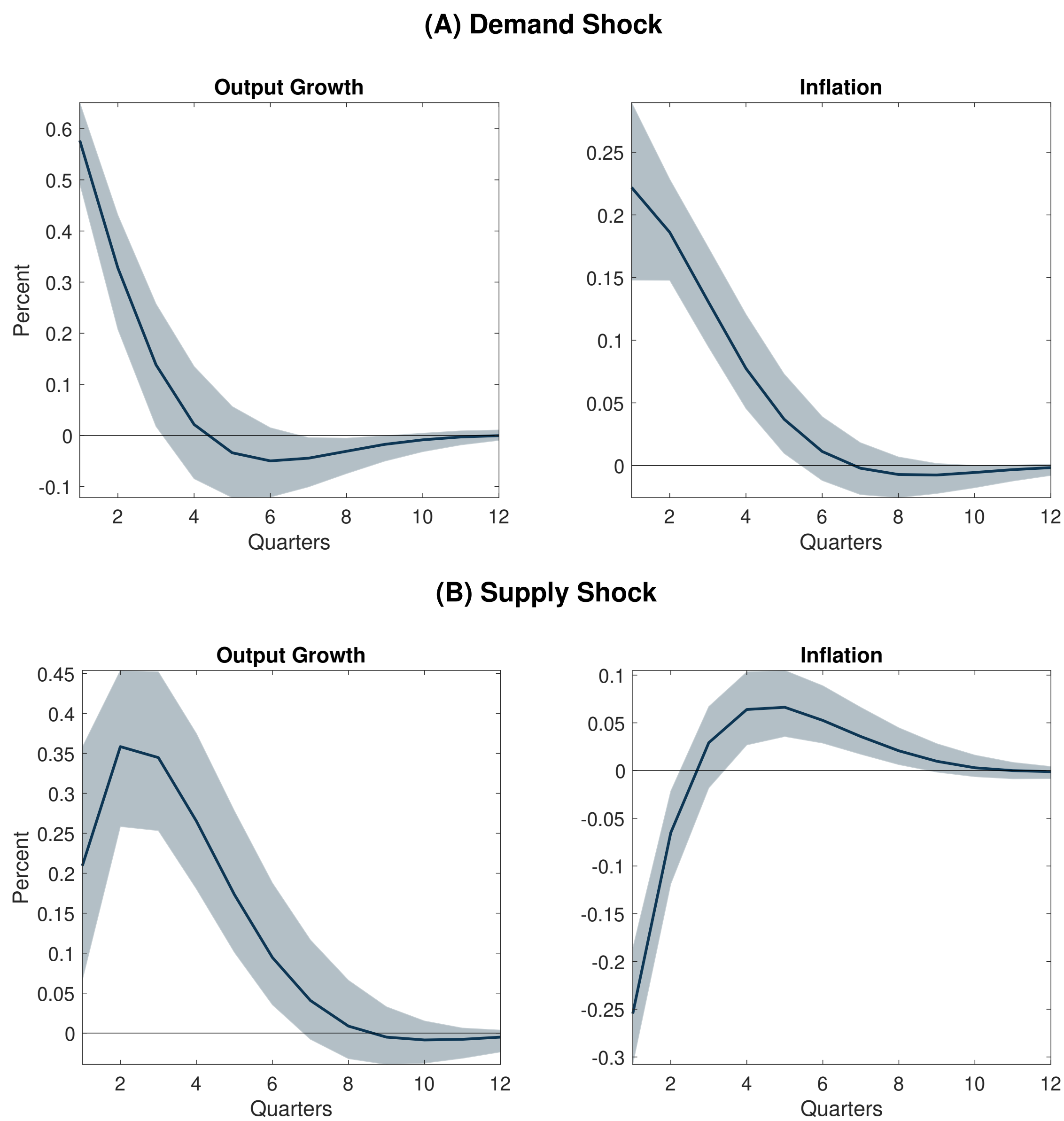
matrices from a uniform (Haar) measure on the space of orthogonal matrices and impose that the sign restrictions reported in table 1 hold for two periods—the quarter when the shock hits and the subsequent one. A positive aggregate demand-like shock pushes up aggregate output and prices. Conversely, a positive aggregate supply-like shock increases aggregate output but makes inflation fall.[15]

Figure 1 displays the median impulse responses (in black), as well as the 68% credible interval (grey shaded area) based on $5,000$ draws of the sign restriction procedure, of aggregate output growth (first column) and aggregate inflation (second column) to an aggregate demand-like (first row) and aggregate supply-like (second row) shock, respectively.

The effect of a positive aggregate demand-like shock on output growth and inflation is significant for three and five quarters, respectively. The median response dies off after slightly more than one year for output growth, while it is more long-lasting for inflation. A positive aggregate supply-like shock causes a persistent and significant (for six quarters) response of output growth and a decline of inflation that lasts significantly for three quarters. At the median, aggregate inflation actually turns positive for the following six quarters before going

[15]Our approach extracts two structural shocks (aggregate demand-like and aggregate supply-like) from two factors (the contemporaneous and lagged values of aggregate quantities and aggregate prices). By construction, these structural shocks explain 100% of the variance of the aggregate variables. This coarse distinction overlooks a more refined view of economic fluctuations, which would include monetary and fiscal policy shocks, financial shocks, different types of technology shocks (total factor productivity, investment-specific), mark-up shocks, and so on. Adding more aggregate variables to the sectoral VARs would introduce more aggregate factors, from which we could extract more aggregate shocks at the expenses of more parameters to estimate and, for our purposes, with no immediate benefit, as shown in robustness analysis reported in subsection 3.3.

Figure 1: Impulse responses from the aggregate VAR



NOTE. Impulse response aggregate output growth (first column) and aggregate inflation (second column) to a demand-like shock (first row) and a supply-like shock (second row) identified with sign restrictions. The shock size is one standard deviation. The black solid lines represent the median impulse response. The shaded area represents the 68% credible interval.

back to zero.

Armed with our estimates of the aggregate structural shocks ($\hat{e}_t$), and for each draw of the sign restriction procedure, we estimate equation (10) to recover the sectoral loadings Λ_i and the sectoral innovations u_{it}. We set the number of lags for the sectoral variables to $p = 1$, i.e. the same number of lags for the aggregate variables ($k = 1$).

The estimation provides evidence in support of the assumption of weak cross-sectional dependence of the sectoral shocks u_{it}, which is key for the identification of the common factors. To measure cross-sectional dependence, we compute the average pair-wise correlation of output growth and inflation for each sector i. Average pairwise correlations measure the average degree of comovement of sector i with all other sectors $j \neq i$. The average pairwise correlation for output growth and inflation in the raw data is 0.16 and 0.17, respectively. In contrast, after controlling for aggregate shocks, the pairwise correlation of the sectoral residuals u_{it} becomes negligible, dropping to 0 for both output growth and inflation. These results are in strong accordance with our identification assumptions.

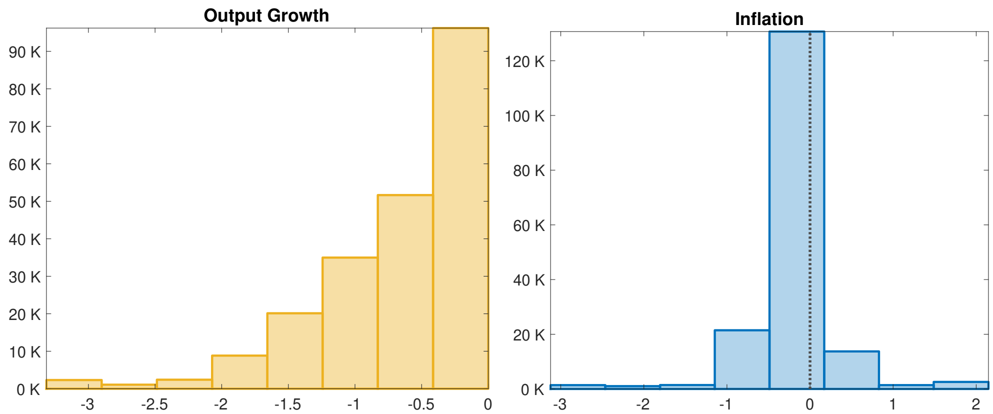
The sectoral loadings, which capture the impact responses of sectoral variables to the structural shocks $\hat{e}_t$, will be the focus of the next section.

3.2 The Sectoral Response to Aggregate Shocks

In this section, we analyze how sectors respond to aggregate demand-like shocks. More precisely, we analyze the impact responses of sectoral output growth and inflation rates to aggregate shocks as captured by the matrix of estimated factor loadings $\hat{\Lambda}_i$ over the whole sample.

We consider the full distribution of the factor loadings across all draws of the sign restriction procedure. For each draw j, we rotate the matrix $B^{(j)}$ to satisfy the sign restrictions in table 1. We then use the series of aggregate shocks $e_t^{(j)}$ associated with a draw to estimate the 64 sectoral VARs defined by equation (10), which allows us to estimate the matrix of loadings $\hat{\Lambda}_i^{(j)}$. The bar charts in figure 2

Figure 2: Distributions of sectoral loadings on aggregate demand-like shocks



NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile.

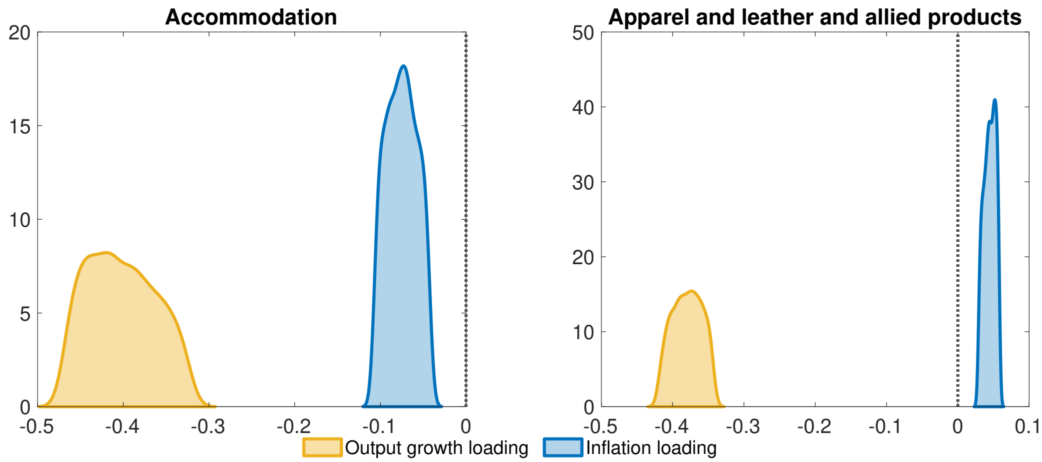
report the distribution of $\hat{\Lambda}_i^{(j)}$ across the $5,000$ draws of the sign restriction procedure and the 64 sectors. To avoid outliers driving the results, we drop all loadings above/below the 16th/84th percentile in each sector.

Figure 2 plots the distribution of the factor loadings of sectoral output growth (left) and inflation rates (right) in response to a negative aggregate demand-like shock. As a few sectors display a positive response of output growth to the shock, we normalize the distribution of output growth responses to be all negative. The object of interest is the distribution of the (normalized) inflation response. Under a "strict" definition of demand shocks, according to which output and inflation co-move in all sectors, we would expect the distribution of the inflation loadings to lie entirely in negative territory.

The figure does not support such a strict view of aggregate demand shocks. As the right panel shows, 40 percent of the draws are associated with positive inflation loadings. In a few sectors of the economy, inflation increases in response to an aggregate demand shock that decreases output.[16]

[16]We obtain a similar result also for aggregate supply-like shocks, although the fraction of the inflation loadings on the "wrong" side is lower (about 33 percent of the draws). See E for more

Figure 3: Distribution of factor loadings for two sectors



NOTE. Distribution of the factor loadings for output growth (yellow) and inflation (blue) in response to an aggregate demand-like shock in the *Accommodation* (left panel) and *Apparel and leather and allied products* (right panel). The distributions are constructed using the $5,000$ draws of the sign restriction procedure and the associated estimated matrix of sectoral loadings Λ_i. The histograms are not normalized. For each sector, we drop all loadings above/below the 16th/84th percentile.

The distributions in figure 2 result from pooling all observations across sectors and draws. Therefore, one possibility is that only a handful of sectors drive a large share of the positive mass of inflation loadings. We address this concern by counting the number of sectors in which output and inflation loadings have opposite signs for at least one draw. We find that 33 out of the 64 sectors in our analysis contribute with at least one observation to the positive mass of inflation loadings in the right panel of figure 2.

Another possibility is that the large share of the positive mass of inflation loadings is due to sectors whose inflation response is not statistically significant from zero. To investigate this possibility, we go one step further and take a closer look at the distributions of the output and inflation loadings sector by sector.

As an example, figure 3 illustrates the nature of this exercise by reporting the results for two sectors. The figure shows the distributions of the factor loadings for output growth (yellow) and inflation (blue) in response to a negative aggre-

results on supply shocks.

gate demand shock. The left panel, which refers to the *Accommodation* sector, shows the example of a sector that responds to the demand shock in line with the restriction imposed at the aggregate level, i.e. with prices and quantities moving in the same direction. However, in many sectors the response of output growth and inflation is inconsistent with such a notion of demand shocks. Figure D.1 in Appendix D presents the full distribution of $\hat{\Lambda}_t^j$ for all 64 sectors. Across all the draws in the sign restriction procedure, we do not find any shock consistent with the sign restrictions that triggers a demand-like response in *all* sectors in the economy. Even more strikingly, the distribution of loadings of output growth and inflation of *Apparel and leather and allied products* (right panel of figure 3) is representative of 16 sectors in the economy (see figure D.8 in Appendix D). In these sectors, prices and quantities move in opposite directions for *all* draws of the sign restriction procedure.

The data, thus, do not support a strict definition of aggregate shocks whereby all sectors behave like the aggregate economy. Conversely, the evidence is consistent with sectors responding like the aggregate economy on average, but with a significant degree of heterogeneity in both the magnitude and, most importantly, the sign of the response to identified aggregate shocks.

Our interpretation of this evidence is that the aggregate VAR confounds true aggregate demand shocks with sectoral supply shocks that have aggregate demand effects, that is, the Keynesian supply shocks discussed in Guerrieri et al. (2020). After confirming that this result is robust to a number of modifications in our empirical approach in the next subsection, we perform a validation exercise of this conjecture in the context of a multi-sector New Keynesian DSGE model with a production network.

3.3 Robustness

This section briefly describes a set of robustness exercises. Appendix D reports the results more extensively.

Value added. Our baseline specification uses data on gross output as a measure of quantity and its deflator as a measure of prices, which have well-defined counterparts in the model that we use in the next section. Our results are unchanged (and, if anything, even stronger) when we use sectoral data on value added and its deflator. Aggregate variables display very similar responses to the structural shocks. Moreover, the share of inflation loadings on the "wrong" side of the distribution increases to 46% from 40% in our baseline (see figure D.2).

Including 2020 data. In our baseline estimation we exclude data for 2020 from the sample to avoid the concern that the Covid crisis might drive the identification. Figure D.3 reports the impact responses of sectoral output growth and inflation rates to the aggregate shocks when we estimate the aggregate and sectoral VARs with data up to 2020Q1.[17] The inclusion of 2020Q1 in the estimation sample does not significantly alter the main conclusions. In this case, the share of inflation loadings on the "wrong" side of the distribution is 42% (see figure D.3).

Additional lags. In our baseline one lag is sufficient to deliver serially uncorrelated residuals both in the aggregate and in the sectoral VARs. The results do not change substantially if we set the number of lags in the VARs to $k = 4$. While slightly less precisely estimated, the impulse responses are very similar to our baseline. Figure D.4 shows that we obtain comparable patterns in the factor loadings, with a share of inflation loadings on the "wrong" side of the distribution equal to 34%.

Levels. In our baseline we specify the aggregate and sectoral VARs in log-differences. The results do not change if we specify the VARs in levels, while setting the number of lags to $k = 4$. Figure D.5 shows that we obtain comparable patterns in the factor loadings, with a share of inflation loadings on the "wrong" side of the distribution of 38%.

Information deficiency. The small scale of the aggregate VAR model used in

[17]We limit the extended sample to 2020Q1 since the large movements of output and prices in some sectors of the economy during subsequent quarters may create additional problems for the estimation (Lenza and Primiceri, 2020).

our baseline might raise concerns about its potential informational deficiency.[18] To address this potential limitation, we include in the specification of the factor model an additional aggregate variable, namely the Excess Bond Premium (EBP) of Gilchrist and Zakrajsek (2012). The EBP has strong predictive power for real activity, and therefore expands the VAR information set. The aggregate VAR has now three variables but we continue to identify the same two shocks (aggregate demand and aggregate supply) as in the baseline case, and leave the third shock unidentified. The impulse response functions obtained from the aggregate VAR are virtually unchanged relative to our baseline. In figure D.6 the share of inflation loadings on the "wrong" side of the distribution is 41%.

In the same spirit, we also repeat the same exercise with a larger aggregate VAR including oil prices. In particular, we use the first difference of the log price of Brent crude. In this case, we combine our sign restriction procedure for aggregate demand and supply shocks with an external instrument (Kanzig, 2021) to also identify oil price shocks, following the methodology in Cesa-Bianchi and Sokol (2017).[19] Also in this case, the results remain substantially unchanged, with a share of inflation loadings on the "wrong" side of the distribution equal to 36% (figure D.7).

4. Model-Based Experiments

In this section we exploit simulated data from a multi-sector DSGE model with a production network to validate our empirical results and their interpretation. We first provide a qualitative description of the model. Second, we apply our em-

[18]An empirical model needs to contain sufficient information to span the space of the structural shock of interest. Otherwise, the history of observed variables may not be enough to recover the correct shocks and impulse response functions (see, for example, Hansen and Sargent, 1991).

[19]Identification of oil news shocks exploits variation in futures prices around OPEC announcements as an instrument. Kanzig (2021) adapts to oil the methodology developed by Stock and Watson (2012) and Mertens and Ravn (2013), and used by Gertler and Karadi (2015) for monetary policy. Specifically, oil price futures instrument the reduced form residuals of the oil price inflation equation. The F-Statistic of this first stage regression is high (equal to 28.85), consistent with the fact that high frequency surprises in oil price futures are a relevant instrument to capture oil price shocks.

pirical strategy to the simulated data under different configuration of the shocks driving the model economy. Third, we investigate which key ingredients of the model are important to deliver our results.

4.1 Model Description

The setup that we use generalizes the one in Guerrieri et al. (2020) to more than two sectors and introduces a potential role for complementarities also on the supply side.

The model is a variant of the textbook New Keynesian framework (Galí, 2015). The key difference is the presence of multiple sectors that differ in the degree of price stickiness, display asymmetric input-output linkages, and feature sector-specific labor markets, as in Pasten, Schoenle, and Weber (2020), Carvalho, Lee, and Park (2021) and Ghassibe (2021). Here we only offer a qualitative description of the model. Appendix C presents the full setup. A representative household maximizes the present discounted value of the utility from consumption and the disutility from hours worked by its members in the various sectors of the economy. In each sector, a continuum of monopolistically competitive firms produce one variety with a constant return to scale technology that combines labor and an intermediate good bundle, and is subject to exogenous sectoral productivity shocks. Varieties enter both the consumption and the intermediate good CES bundles at the sectoral level with an elasticity of substitution greater than one. In turn, the final consumption good and the intermediate input combine sectoral bundles through another CES aggregator with elasticity of substitution that can be greater or smaller than one. Firms set prices on a staggered basis as in Calvo (1983). Labor markets are competitive and clear at the sectoral level. Financial markets are complete.[20] Finally, the central bank sets the nominal interest rate in response of deviations of inflation from target (normalized to zero) and GDP

[20]The assumption of complete financial markets keeps the model tractable but shuts down one channel (imperfect insurance) that magnifies the importance of Keynesian supply shocks in Guerrieri et al. (2020).

growth.

For consistency with the data that we use in the empirical part, one period in the model corresponds to a quarter. We choose the parameters to match salient features of the 64 sectors used in the empirical analysis of section 3. The sectoral data on consumption shares, the input-output coefficients, the input shares in the production function, and the sectoral probabilities of price adjustment are from Pasten, Schoenle, and Weber (2020). Key to the calibration are the elasticities of substitution in consumption and production, which we set to 1 and 0.5, respectively, in line with (Baqaee and Farhi, 2020b) and the references therein. We assume that sectoral total factor productivity is uncorrelated across sectors and follows a stationary autoregressive process of order one with persistence equal to 0.975 and innovations with a standard error of 1%. Appendix C discusses the other parameters, which are standard.

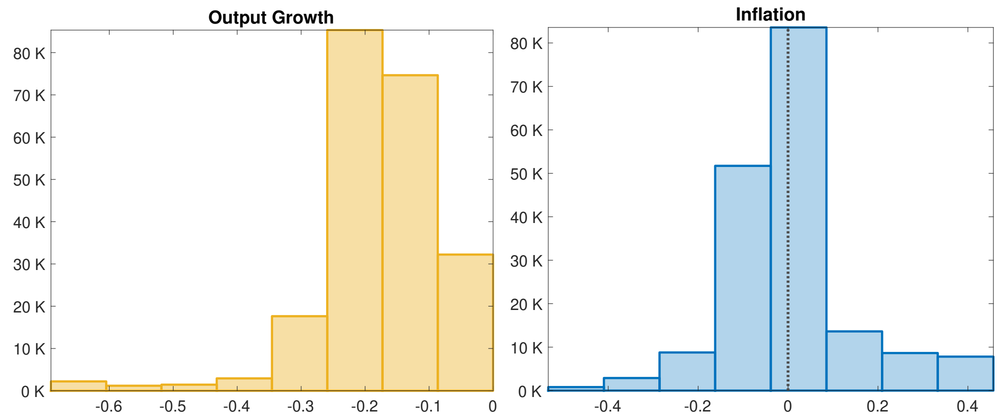
4.2 Estimation of the Factor Loadings with Simulated Data

The first exercise that we perform consists of two steps. First, we simulate the model for 200 periods assuming that sectoral productivity shocks are the only source of exogenous variation. We then discard the first 140 observations as to obtain a time series for gross output and its deflator at the sectoral level of the same length as the data in our sample. Second, we estimate the factor-augmented VAR discussed in section 2 on the simulated data.

Even though sectoral supply shocks are the only source of exogenous variation, the aggregate VAR still identifies an aggregate demand-like shock—i.e. the sign restriction procedure finds a number of rotations consistent with aggregate quantities and prices moving in the same direction. The average share of the variance of output growth explained by demand shocks is 50%, compared to 58% in the data. This result is the first hint that sectoral supply shocks propagate through the network structure of the model in line with the Keynesian supply mechanism.

In the second step, we estimate the sectoral VARs using the simulated data.

Figure 4: Distributions of sectoral loadings on aggregate demand-like shocks (data generating process: sectoral supply shocks only)



NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock generated using artificial data from the model driven by sectoral supply shocks only. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile.

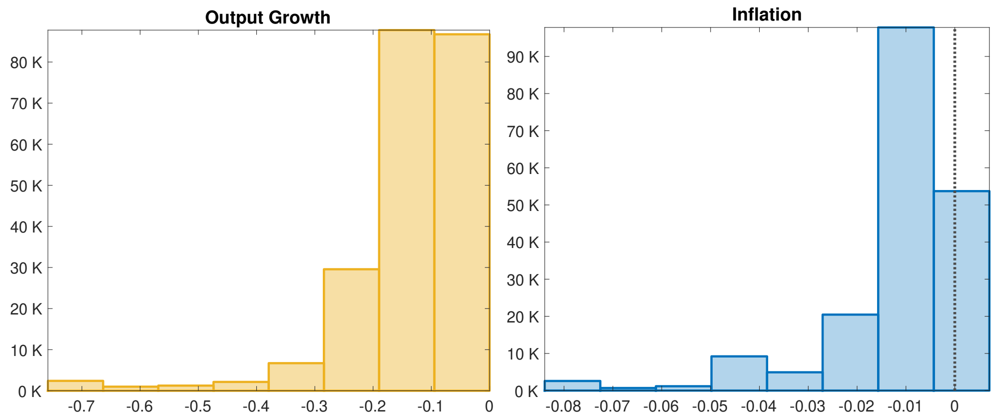
Figure 4 reports the normalized factor loadings in response to the shock that the aggregate VAR has classified as demand-like. Overall, the distribution of the factor loadings for inflation is remarkably similar to the one we obtained in figure 2. The mass of positive inflation responses to a negative aggregate demand-like shock is 38%, compared to 40% in the empirical analysis. Similarly close (in fact, slightly higher) is the number of sectors for which the full distribution of inflation loadings has the opposite sign relative to the output growth loadings (18, compared to 16 in the data).

The bottom line of this exercise is that we can rationalize our empirical findings in a model with input-output linkages and complementarities in production. Next, we ask if other shocks can also lead to similar patterns.

To start, we repeat the same exercise assuming the data generating process is the same model driven by persistent sectoral demand shocks only, modeled as changes of the sectoral weights in the aggregate consumption bundle.[21] At the

[21] Baqaee and Farhi (2020b) argue that these shocks may have played a particularly important

Figure 5: Distributions of sectoral loadings on aggregate demand-like shocks (data generating process: sectoral demand shocks only)



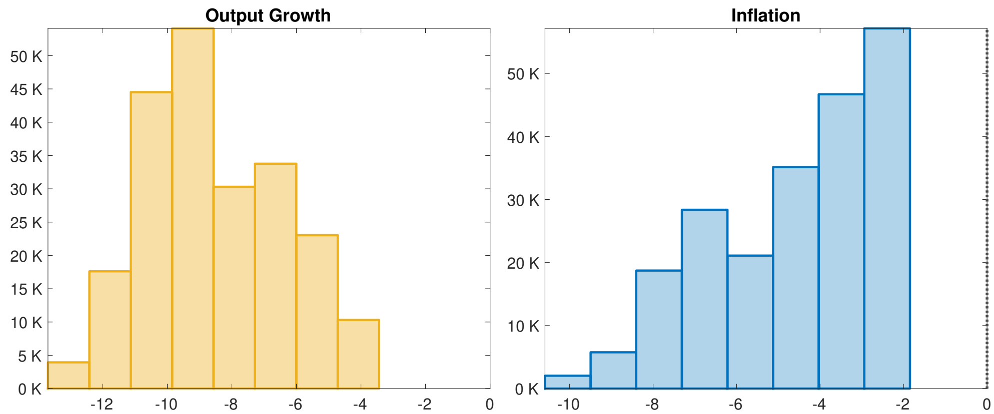
NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock generated using artificial data from the model driven by sectoral demand shocks only. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile.

aggregate level, these shocks give rise to output growth and inflation dynamics in the model that display a high degree of comovement. Perhaps not surprisingly, in this case the aggregate VAR attributes to demand-like shocks a much larger average share of the variance (93%). Yet, the sectoral responses can still be in line with the evidence we discussed in section 3 if preferences shocks induce substitution among some sectors. For example, in response to the pandemic shock, consumers may switch from food away from home to groceries.

Figure 5 shows that indeed some sectors display an increase of inflation in response to a negative aggregate demand-like shock. However, in this case, the share of wrong loadings is only 9%. At a closer inspection, only 4 sectors display a distribution of inflation loadings that fully falls in positive territory. Therefore, we conclude that sectoral demand shocks cannot be the only driver behind our empirical evidence at the sectoral level, and are likely to play a relatively less im-

role in the context of the Covid crisis, as consumers changed the composition of their demand in response to the risk of contagion.

Figure 6: Distributions of sectoral loadings on aggregate demand-like shocks (data generating process: aggregate demand shocks only)



NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock generated using artificial data from the model driven by aggregate demand shocks only. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile.

portant role compared to sectoral supply shocks.

Finally, we simulate data from the model assuming that the only driving force is a persistent aggregate demand shock. In particular, as common in the literature (e.g. Smets and Wouters, 2007), we introduce an intertemporal preference shock that can capture a number of demand disturbances, including reduced-form representations of various financial frictions. The idea, in this case, is to check whether sectoral linkages may propagate a standard demand shock in a way that could be consistent with our empirical evidence.

Once again the sign restriction procedure easily identifies aggregate demand shocks, which account for virtually all of the variation (around 99.7%) in the simulated data. Conversely, aggregate supply shocks are close to noise, accounting for only 0.3% of the average variance of the simulated data.

Figure 6 reports the distribution of sectoral loadings in this case. The response of inflation, which falls in all sectors and for all rotations, is fully consistent with the standard notion of demand shocks. This exercise clarifies that, conditionally on identifying a proper demand shock, the sectoral response of output growth and inflation is theoretically sound. In other words, a strict view of demand shocks would not be unreasonable even in a rich multi-sector model if the only source of exogenous variation were to be true aggregate demand disturbances.

4.3 Inspecting the Mechanism

The previous section demonstrated that input-output linkages can propagate sectoral supply shocks at the aggregate level and give rise to comovement of output and inflation. In this section, we go one step further and investigate which key ingredients of the model are important to deliver the result.

While our simulations have relied on idiosyncratic sectoral supply shocks, in practice these shocks may be correlated among a subset of sectors. The pandemic offers a clear example of this point, whereby the shock hit a group of "social" sectors (Kaplan, Moll, and Violante, 2020). More generally, however, forming priors on the combination of sectors affected by a supply shock is challenging, and trying out all possible combinations quickly leads to an unmanageable number of experiments.

To address this issue without imposing any specific prior and avoiding the curse of dimensionality, we study the aggregate effects of productivity shocks in each sector one by one. In particular, we look at the response of aggregate output growth and aggregate inflation in response to a negative sectoral productivity shock for each sector in the economy. This experiment sets a high bar for Keynesian supply shocks. If a sectoral productivity shock in one sector only leads to a demand-like recession in the aggregate, the likelihood that similar shocks affecting a cluster of sectors can create an aggregate demand-like recession is certainly higher.

We find that 13 out of 64 sectoral TFP shocks imply a demand-like response of output growth and inflation at the aggregate level. As discussed before, shocks hitting two or more of these sectors are even more likely to generate comovement of aggregate output growth and inflation.

In order to gain intuition about the driving forces behind this result, figure 7 plots the impact response of aggregate inflation against the four dimensions of sectoral heterogeneity in the model: (1) the frequency of price adjustment, measured by the probability of being able to reset the price in each period; (2) other sectors' reliance on a sector's intermediate goods (downstreamness), measured as the sum over columns of a row of the input-output table; (3) a sector's reliance on other sectors' intermediate goods (upstreamness), measured as the sum over rows of a column of the input-output table; (4) the share of intermediates in production, measured by exponent of the production function.[22] In the figure, each dot is associated with one of the 64 sectoral supply shocks considered in the experiment, with filled dots denoting sectoral supply shocks that lead to a demand-like response of aggregate output and inflation.

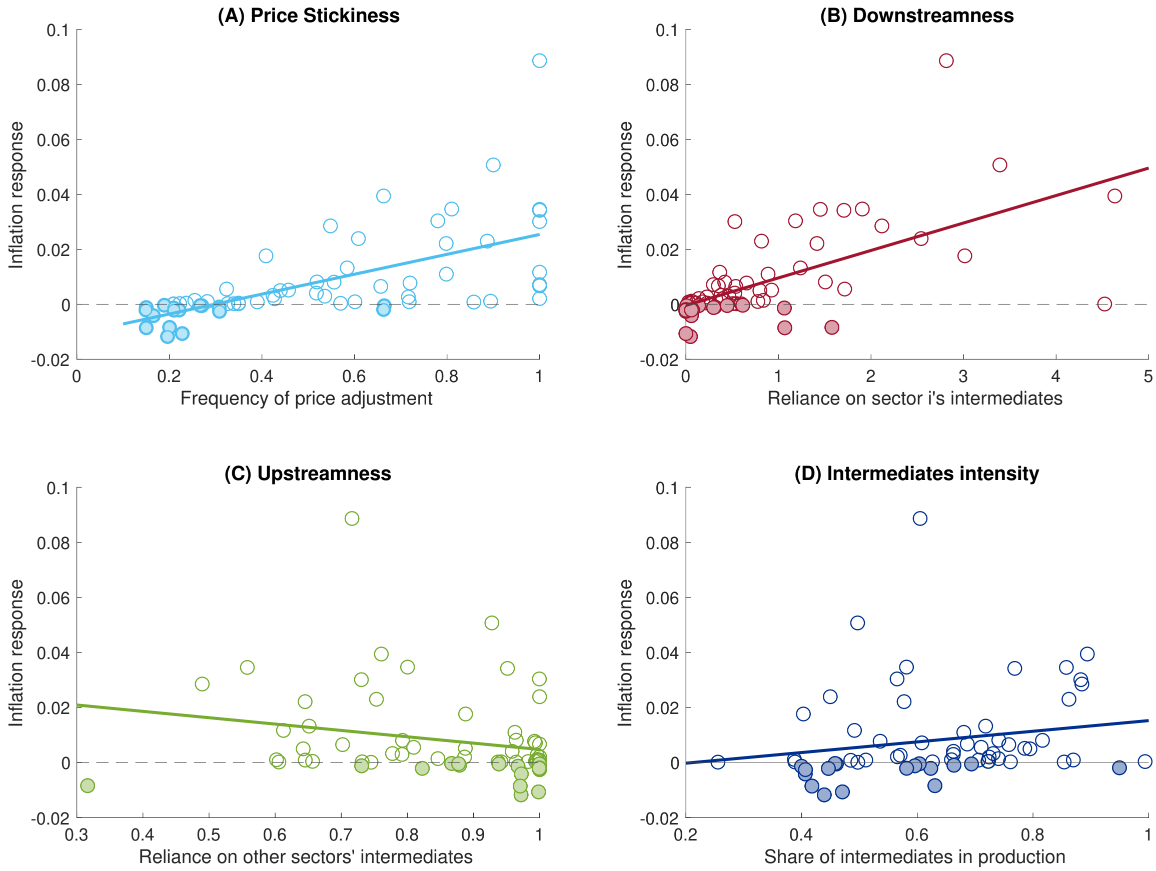
The top-left panel of of figure 7 suggests that price stickiness plays an important role in accounting for the negative response of aggregate inflation to a negative sectoral productivity shock. If prices in the sector hit by the shock are very rigid (low frequency of price adjustment), inflation in that sector will not rise by much in response to the shock while its output falls. But then complementarities in production will lead to a lower demand for inputs from other sectors. Therefore, the other sectors experience a negative demand shock which propagates at the aggregate level.[23]

The top-right panel shows that the aggregate inflation response is increasing in the degree of downstreamness. If the supply shock hits a sector that, in the limit, does not serve as input to any other sector (a low degree of downstreamness), the supply-like response—output and inflation moving in opposite directions—remains confined to that sector alone. However, other sectors are

[22]We follow the definition of downstreamness and upstreamness in La'O and Tahbaz-Salehi (2020), who study optimal monetary policy in production networks.

[23]Price rigidity plays a prominent role for terms of optimal monetary policy stabilization in multi-sector economies, both with (La'O and Tahbaz-Salehi, 2020) and without (Benigno, 2004 and Eusepi, Hobijn, and Tambalotti, 2011) input-output linkages.

Figure 7: Sectoral heterogeneity and the aggregate response of inflation



NOTE. For each panel, each dot corresponds to a sector. On the vertical axis is the impact response of aggregate inflation to a supply shock to that sector. On the horizontal axis are different dimensions of sectoral heterogeneity, namely (A) the frequency of price adjustment, measured by the probability of being able to reset the price in each period; (B) other sectors' reliance on a sector's intermediate goods (downstreamness), measured as the sum over columns of a row of the input-output table; (C) a sector's reliance on other sectors' intermediate goods (upstreamness), measured as the sum over rows of a column of the input-output table; (D) the share of intermediates in production.

still inputs for the one hit by the shock. With complementarities in production, these other sectors will experience a drop in demand, which drives the aggregate response.

The bottom-left panel highlights that the relationship between the impact response of aggregate inflation and upstreamness is instead negative. In this case, if the supply shock hits a sector that, in the limit, does not rely on inputs from any other sector (a low degree of upstreamness), sectoral linkages amplify the positive response of inflation in that sector. The reason is that, while the other sectors will experience a drop in demand for their inputs (leading to a fall in their price), the sector hit by the shock is insulated from this fall in prices, which would have otherwise lowered its marginal cost.

Finally, the bottom-right panel displays little correlation between the share of intermediate goods in production and the response of aggregate inflation. Most negative aggregate inflation responses occur at mid-range levels of intermediate intensity. The reason is that a large share of intermediate goods in production magnifies the effects of both downstreamness and upstreamness (and vice versa). Since these two dimensions have opposite effects on the response of aggregate inflation, high and low shares of intermediate intensity are not associated with a negative response of aggregate inflation.

5. Conclusions

Demand shocks derived from standard identification schemes using aggregate data have widely heterogeneous impacts across sectors, not only in terms of magnitudes but more importantly in terms of sign. While in many sectors output and prices mimic the positive correlation of their aggregate counterparts, the two variables move in opposite directions in about a quarter of 3-digit US sectors.

Therefore, the data are not consistent with a notion of aggregate demand disturbances as shocks that move output and prices in the same direction for all sectors. Instead, our evidence is consistent the idea that identified aggregate demand shocks are the combination of disturbances with true aggregate demand features and sectoral supply disturbances with aggregate demand consequences. The supply-like impact at the sectoral level propagates at the aggregate level as a demand-like response through complementarities in production. Price rigidities and input-output linkages play are crucial in the transmission.

Overall, these Keynesian supply shocks provide a sectoral foundation to demand-driven business cycle fluctuations.

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Appendix

A. Data

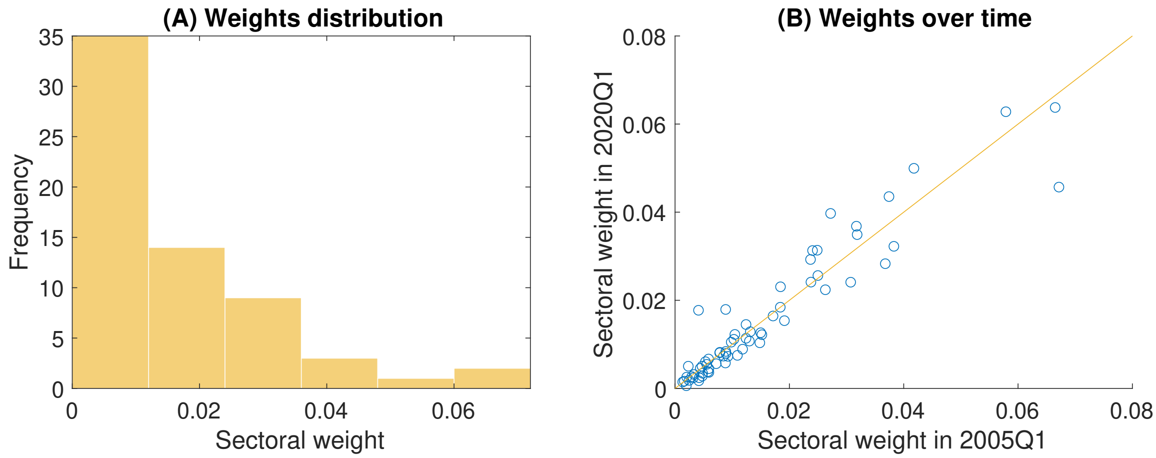
Sectoral data. We obtain data prices and quantities by industry from the Bureau of Economic Analysis (https://www.bea.gov/data/industries). Our measures of output and prices are *Real Gross Output* (in millions of chained 2012 US dollars) and the *Chain-Type Price Indexes for Gross Output* (index 2012=100), respectively. The frequency of the data is quarterly and the available sample covers the 2005Q1–2020Q1 period. Both series are seasonally adjusted. We use the BEA industry-level classification at its most granular level of disaggregation (2 digits for most sectors and 4 digits for *Real Estate*). We exclude *Oil and gas extraction* and *Petroleum and coal products*, which leaves a total of 64 sectors. Table A.1 reports the full list of sectors.

The sectoral weights used for aggregation in equation (5) are based on the share of Real Gross Output in each sector over total Real Gross output. While in principle the weights are time-varying, their actual time variation is minimal. In our empirical application we use the average weights over the 2005Q1–2020Q1 period. Figure A.1 reports the distribution of weights across sectors. Small sectors with an output share of less or equal than 1 percent are prevalent. Moreover, in accordance with our smallness assumptions, the biggest sectors in our sample are still rather small, accounting for less than 7 percent of total output.[24]

Figure A.2 reports the time series behavior of output growth for all sectors (left panel) as well as a comparison between aggregate Real Gross Output and the cross-sectional average of sectoral output series using our aggregation weights (right panel). Figure A.3 reports a similar comparison for the gross output deflator. As noted in the text, the sectoral weighted averages reflect closely actual GDP growth and inflation.

[24] In cross-country analysis weights are considered small in the case of the US or China, which have much larger output shares than those considered here.

Figure A.1: Sectoral weights



NOTE. Panel (A) reports the distribution of sectoral weights, computed as the average over time of the quarterly ratio of the level of gross output in a given sector over total gross output. Panel (B) reports the evolution over time of sectoral weights, by comparing the weight in 2005Q1 to the weight in 2020Q1.

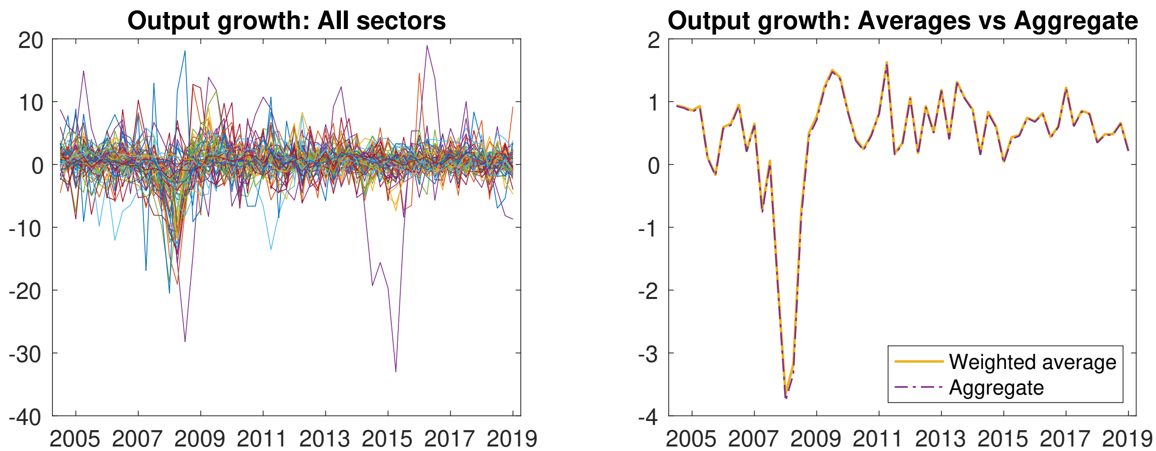
A.1 Data for Robustness Exercises

Oil price data. We obtain the price of oil from FRED (https://fred.stlouisfed.org). We use the global price of Brent Crude (USD per Barrel) at quarterly frequency (average within the quarter).

Oil futures surprises. We obtain the high-frequency surprises from Kanzig (2021), who uses West Texas Intermediate (WTI) crude futures around OPEC announcements

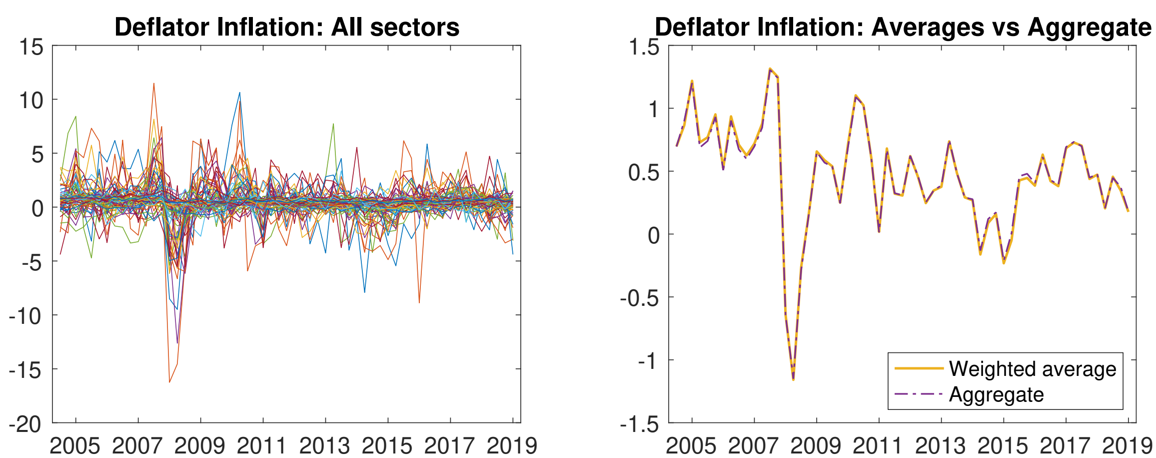
Excess Bond Premium. We obtain the latest series for Gilchrist and Zakrajsek (2012)'s Excess Bond Premium from Favara et al. (2016). We convert the original series to quarterly frequency by taking averages of the monthly data within each quarter.

Figure A.2: Real gross output



NOTE. The left panel reports the time series behavior of gross output growth for all sectors in our sample. The right panel reports the growth rate of aggregate output growth as well as the weighted average of sectoral output growth (both equally weighted and weighted by each sector's size w_i).

Figure A.3: Inflation



NOTE. The left panel reports the time series behavior of the growth rate of the gross output deflator for all sectors in our sample. The right panel reports the inflation rate of gross output, as well as the weighted average of sectoral inflation (both equally weighted and weighted by each sector's size w_i)

Table A.1: List of the 64 industries used in the empirical analysis

Industry name	
Farms	Truck transportation
Forestry, fishing, [..]	Transit and ground passenger transport.
Mining, except oil and gas	Pipeline transportation
Support activities for mining	Other transportation and support activities
Utilities	Warehousing and storage
Construction	Publishing industries, except internet [..]
Wood products	Motion picture and sound recording [..]
Nonmetallic mineral products	Broadcasting and telecommunications
Primary metals	Data processing, internet publishing [..]
Fabricated metal products	Fed banks, credit intermed. [..]
Machinery	Securities, commodity contracts [..]
Computer and electronic products	Insurance carriers [..]
Electrical equipment, appliances [..]	Funds, trusts, and other finan. vehicles
Motor vehicles, bodies and trailers [..]	Housing
Other transportation equipment	Other real estate
Furniture and related products	Rental and leasing services [..]
Miscellaneous manufacturing	Legal services
Food and beverage and tobacco [..]	Computer systems design [..]
Textile mills and textile product mills	Miscellaneous [..] services
Apparel and leather and allied products	Management of companies and enterpr.
Paper products	Administrative and support services
Printing and related support activities	Waste management and remediation [..]
Chemical products	Educational services
Plastics and rubber products	Ambulatory health care services
Wholesale trade	Hospitals
Motor vehicle and parts dealers	Nursing and residential care facilities
Food and beverage stores	Social assistance
General merchandise stores	Performing arts, spectator sports [..]
Other retail	Amusements, gambling, and recreation [..]
Air transportation	Accommodation
Rail transportation	Food services and drinking places
Water transportation	Other services, except government

NOTE. List of 3-digit industries from the BEA classification.

B. Derivation of the Common Factors

The economy consists of N sectors indexed by $i = 1, 2, ..., N$. We model empirically the joint evolution of sectoral output growth (y_{it}) and inflation (π_{it}) through a factor-augmented multisector PVAR(p) (panel VAR of order p). In what follows, to simplify the exposition and without loss of generality, we set the number of lags $p = 1$, so that the model defined by equation (3) becomes

$$x_{it} = \Phi_{i0} + \Phi_{i1} x_{it-1} + \Gamma_i f_t + u_{it}, \tag{B.1}$$

where $x_{it} \equiv [y_{it}\ \pi_{it}]'$ is the vector of endogenous variables, Φ_{i0} is a (2×1) vector of constants, and Φ_{i1} is a (2×2) matrix of coefficients, f_t is a vector of common factors, u_{it} is a vector of sectoral shocks, and Γ_i is a matrix of sectoral loadings.

Following Cesa-Bianchi, Pesaran, and Rebucci (2020), we identify the common factors f_t *by aggregation*. Identification requires a number of assumptions on the common factors (f_t), their loadings (Γ_i), the weights (w_i), the sector-specific innovations (u_{it}), and the VAR coefficients (Φ_{i0} and Φ_{ij}):

Assumption 1 *(Common factors) The common unobservable factors f_t have zero mean and finite variance, are serially uncorrelated, and distributed independently of the sector-specific shocks u_{it} for all i and t.*

Assumption 2 *(Factor loadings) The factor loadings (i.e. the elements of Γ_i) are distributed independently across i and from the common shocks f_t for all i and t. Denoting a generic element of Γ_i by γ_i, we assume that the loadings satisfy*

$$\gamma = \sum_{i=1}^{N} w_i \gamma_i \neq 0 \qquad\qquad \sum_{i=1}^{N} \gamma_i^2 = O_p(N).$$

Furthermore, we assume that $\Gamma \equiv \mathbb{E}(\Gamma_i)$ is invertible, where $\mathbb{E}(\cdot)$ denotes the cross-sectional average operator in the population.

Assumption 3 *(Aggregation weights) The weights w_i are fixed non-zero constants* *such that* $\sum_{i=1}^{N} w_i = 1$ *and satisfy the "smallness" conditions*

$$||w|| = O_p(N^{-1}) \qquad \frac{w_i}{||w||} = O_p(N^{-1/2}),$$

where $w = [w_1\ w_2\ ...\ w_N]$.

Assumption 4 *(Cross-sectional dependence) (a) The sector-specific shocks* u_{it} *have zero mean and finite variance, and are serially uncorrelated, but can be correlated with each other both within and between sectors. (b) Denoting with* $\Sigma_u \equiv Var(u_t)$ *the covariance matrix of the* $N \times 1$ *vector* $u_t = [u_{1t}\ u_{2t}\ ...\ u_{Nt}]'$*, we have*

$$\varrho_{\max}(\Sigma_u) = O_p(1).$$

where $\varrho_{\max}(\Sigma_u)$ *denotes the largest eigenvalue of* Σ_u.

Assumption 5 *(Coefficients) The constants* Φ_{i0} *are bounded, the autoregressive coefficients* Φ_{i1} *are independently distributed for all* i*, the support of* $\varrho(\Phi_{ij})$ *lies strictly inside the unit circle for all* i*, and the inverse of the polynomial* $\Omega(L) = \sum_{\ell=0}^{\infty} \Omega_\ell L^\ell$*, where* $\Omega_\ell = \mathbb{E}\left(\Phi_i^\ell\right)$*, exists and has exponentially decaying coefficients, namely*

$$\|\Omega_\ell\| \leq C_0 \rho^\ell,$$

with $0 < \rho < 1$.

To identify the common factors, we start by solving for x_{it} in terms of current and past values of the aggregate and sectoral shocks from equation (B.1)

$$x_{it} = \mu_i + \Upsilon_i(L)\Gamma_i f_t + \vartheta_{it}, \tag{B.4}$$

where $\mu_i \equiv \Upsilon_i(L)\Phi_{i0}$, $\Upsilon_i(L) \equiv (I_2 - \Phi_{i1}L)^{-1} = \sum_{\ell=0}^{\infty} \Phi_{i1}^\ell$, I_2 is a (2×2) identity matrix, L is the lag operator, and $\vartheta_{it} \equiv \Upsilon_i(L)u_{it}$. Notice that Assumption 5 ensures that the infinite sums converge.

Pre-multiplying both sides of equation (B.4) by the weights w_i and summing over i yields

$$\bar{x}_t = \bar{\mu} + \sum_{\ell=0}^{\infty} \sum_{i=0}^{N} w_i \Phi_i^{\ell} \Gamma_i f_{t-\ell} + \bar{\vartheta}_t. \tag{B.5}$$

In equation (B.5), an upperbar denotes cross-sectional averages, so that the constant is $\bar{\mu} \equiv \sum_{i=1}^{N} w_i \mu_i$, the shock is $\bar{\vartheta}_t \equiv \sum_{i=1}^{N} w_i \vartheta_{it}$, and the vector of endogenous variables is $\bar{x}_t \equiv [\bar{y}_t \; \bar{\pi}_t]$. Recalling that, again because of Assumption 5, Φ_i and Γ_i are distributed independently across i and $\Omega_\ell = \mathbb{E}\left(\Phi_i^{\ell}\right)$ exists and has exponentially decaying coefficients, we can write

$$\sum_{\ell=0}^{\infty} \sum_{i=0}^{N} w_i \Phi_{i1}^{\ell} \Gamma_i f_{t-\ell} = \Omega(L) \Gamma f_t, \tag{B.6}$$

where $\Omega(L) = \sum_{\ell=0}^{\infty} \Omega_\ell L^\ell$, $\Omega_\ell = \mathbb{E}(\Phi_{i1}^{\ell})$, and $\Gamma = \mathbb{E}(\Gamma_i)$. Moreover, because of Assumption 3 and 4, $\bar{\vartheta}_t$ are cross-sectionally weakly correlated and the weights w are small, which implies

$$\bar{\vartheta}_t = O_p(N^{-\frac{1}{2}}). \tag{B.7}$$

Using this results in (B.6) and (B.7), we can rewrite (B.5) as

$$\bar{x}_t = \bar{\mu} + \Omega(L) \Gamma f_t + O_p(N^{-\frac{1}{2}}), \tag{B.8}$$

which corresponds to the result in the main text.

Finally, because Assumptions 4 and 5 guarantee that $\Omega(L)$ and Γ are invertible, we can identify the aggregate shocks f_t by inverting equation (B.8)

$$f_t = \theta + \sum_{\ell=0}^{\infty} \Theta_\ell \bar{x}_{t-\ell} + O_p(N^{-\frac{1}{2}}). \tag{B.9}$$

where $\theta = -\Gamma^{-1}\Omega^{-1}(1)\bar{\mu}$ and $\Theta_\ell = \Gamma^{-1}\Omega^{-1}(L)$.

The formulation of equation (B.9) is in terms of observable variables, but contains infinite lags and thus is not amenable to actual empirical analysis. However, Chudik and Pesaran (2014) show that, if the slope heterogeneity is not extreme (i.e., if the matrices Φ_i do not differ too much across i) and $\Omega(L)$ decays exponentially in L, an appropriate truncation approximates well the infinite order distributed lag functions in $\bar{x}_t$. In the empirical analysis, we use the Bayesian Information Criterion to choose the truncation order.

C. A DSGE Model with a Production Network

A representative household chooses consumption C_t, hours worked N_{kt} in sector $k = 1, ...K$, and a portfolio of state-contingent securities D_{t+1} to maximize the present discounted value of utility

$$\mathbb{V}_t^h = \mathbb{E}_t \left[\sum_{s=0}^{\infty} \beta^s \Delta_{t+s-1} \left(\ln C_{t+s} - \frac{\sum_{k=1}^K N_{kt+s}^{1+\varphi}}{1+\varphi} \right) \right],$$

where $\beta \in (0,1)$ is the individual discount factor, $\varphi > 0$ is the inverse Frisch elasticity of labor supply, and $\delta_t \equiv \ln(\Delta_t/\Delta_{t-1})$ is a preference shock that follows a stationary autoregressive process

$$\delta_t = \rho_\delta \delta_{t-1} + \varepsilon_{\delta t},$$

with $\rho_\delta \in (0,1)$ and $\varepsilon_{\delta t} \sim \mathcal{N}(0, \sigma_\delta^2)$. The budget constraint is

$$P_t C_t + \mathbb{E}_t(Q_{t,t+1} D_{t+1}) = D_t + \sum_{k=1}^K (W_{kt} N_{kt} + \mathcal{P}_{kt}),$$

where P_t is the price of consumption, $Q_{t,t+1}$ is the price of one-period state-contingent securities (the stochastic discount factor), and W_{kt} is the nominal wage and $\mathcal{P}_{kt}$ are profits from ownership of firms in sector k.

The overall consumption index is a CES aggregate of sectoral consumption bundles

$$C_t \equiv \left[\sum_{k=1}^K (e^{m_{kt}} \omega_{ck})^{\frac{1}{\eta_c}} C_{kt}^{\frac{\eta_c - 1}{\eta_c}} \right]^{\frac{\eta_c}{\eta_c - 1}},$$

where $\eta_c > 0$ is the elasticity of substitution in consumption across goods produced in different sectors, the sectoral weights are such that $\sum_{k=1}^{K} \omega_{ck} = 1$, and m_{kt} is a sector-specific demand shock, which follows a stationary autoregressive process

$$m_{kt} = \rho_m m_{kt-1} + \varepsilon_{mt},$$

with $\rho_m \in (0,1)$ and $\varepsilon_{mt} \sim \mathcal{N}(0, \sigma_m^2)$. In turn, each sectoral bundle is a CES aggregator of diversified varieties

$$C_{kt} \equiv \left[f_k^{-\frac{1}{\theta}} \int_0^{f_k} C_{kt}(j)^{\frac{\theta-1}{\theta}} dj \right]^{\frac{\theta}{\theta-1}},$$

where $j \in (0, f_k)$ indexes firms in sector k, $\theta > 1$ is the elasticity of substitution among varieties, f_k is the size of sector k, and $\sum_{k=1}^{K} f_k = 1$.

The technology for firm j in sector k is

$$Y_{kt}(j) = e^{a_{kt}} Z_{kt}(j)^{\alpha_k} N_{kt}(j)^{1-\alpha_k},$$

where $\alpha_k \in (0,1)$ is the sector-specific share of intermediate inputs Z_{kt} in production and a_{kt} is a sector-specific technology shock, which follows a stationary autoregressive process

$$a_{kt} = \rho_a a_{kt-1} + \varepsilon_{kt},$$

with $\rho_a \in (0,1)$ and $\varepsilon_{kt} \sim \mathcal{N}(0, \sigma_a^2)$. Similar to consumers, a firm j in sector k employs a composite intermediate input that combines goods from all sectors of the economy

$$Z_{kt}(j) \equiv \left[\sum_{r=1}^{K} \omega_{kr}^{\frac{1}{\eta_z}} Z_{krt}(j)^{\frac{\eta_z-1}{\eta_z}} \right]^{\frac{\eta_z}{\eta_z-1}},$$

where $\eta_c > 0$ is the elasticity of substitution among intermediate goods produced in different sectors, and the relative input intensities in production are such $\sum_{r=1}^{K} \omega_{kr} = 1,\ \forall k$. In turn, the sectoral intermediate inputs are aggregators of varieties produced by individual firms

$$Z_{krt}(j) \equiv \left[f_r^{-\frac{1}{\theta}} \int_0^{f_r} Z_{krt}(j,\ell)^{\frac{\theta-1}{\theta}} d\ell \right]^{\frac{\theta}{\theta-1}},$$

where $Z_{krt}(j,\ell)$ denotes the total amount of inputs purchased by firm j in sector k from firm ℓ in sector r.

As in Calvo (1983), the probability of not being able to reset the price in any given period for a firm in sector k is $\xi_k \in (0,1)$. A firm that can reset its price at time t solves

$$\mathbb{V}_t^f = \max_{P_{kt}^*(j)} \mathbb{E}_t \left\{ \sum_{s=0}^{\infty} \xi_k^s Q_{t,t+s} \left[P_{kt}^*(j) Y_{kt+s}(j) - W_{t+s} N_{kt+s} - P_{t+s}^k Z_{kt+s}(j) \right] \right\},$$

subject to the demand for its own good, where P_t^k is the price of the intermediate input bundle.

Equilibrium in the labor market for each sector requires

$$N_{kt} = \int_0^{f_k} N_{kt}(j) dj,$$

while goods market clearing implies

$$Y_{kt}(j) = C_{kt}(j) + \sum_{r=1}^{K} \int_0^{f_r} Z_{rkt}(\ell, j) d\ell.$$

Finally, the central bank sets monetary policy following an interest rate feedback rule with inertia that responds to CPI inflation and real GDP growth (which in the model corresponds to consumption)

$$\frac{R_t}{R} = \left(\frac{R_t}{R}\right)^{\rho_i} \left[\left(\frac{P_t}{P_{t-1}}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_{t-1}}\right)^{\phi_y} \right]^{1-\rho_i},$$

where $\phi_\pi > 1$, $\phi_y > 0$, $R_t \equiv 1/\mathbb{E}_t Q_{t,t+1}$ is the gross nominal interest rate, and $Y_t = C_t$ denotes real GDP.

C.1 Calibration

One period corresponds to one quarter. The household parameters are standard. We set $\beta = 0.995$, which corresponds to an annualized net real interest rate of 2%, and the inverse Frisch elasticity of labor supply φ equal to 2.

We follow Pasten, Schoenle, and Weber (2020) for the calibration of the consumption shares ω_{ck}, the input-output coefficients ω_{kr}, the sectoral input shares α_k, and the price rigidity parameter ξ_k (see the paper and supplemental material for details). For consistency with our data, we consider the case of $k = 64$ so as to closely match the 64 sectors in our empirical analysis. The elasticity of substitution among varieties θ equals 6, which implies a steady state markup of 20%, a common value in the literature (Galí, 2015). We follow Baqaee and Farhi (2020b) in setting the elasticity of substitution across sectors in consumption equal to $\eta_c = 1$ and among intermediate goods in production $\eta_z = 0.5$. The interest rate rule inertia ρ_i equals 0.75, the coefficient on inflation ϕ_π is 1.5, and the coefficient on GDP growth ϕ_y is $0.5/4 = 0.125$. Finally, the persistence of the exogenous shocks ρ_i, for $i = \{\delta, a, m\}$, is equal to 0.975, while their standard deviation σ_i is 1%.

D. Additional Results

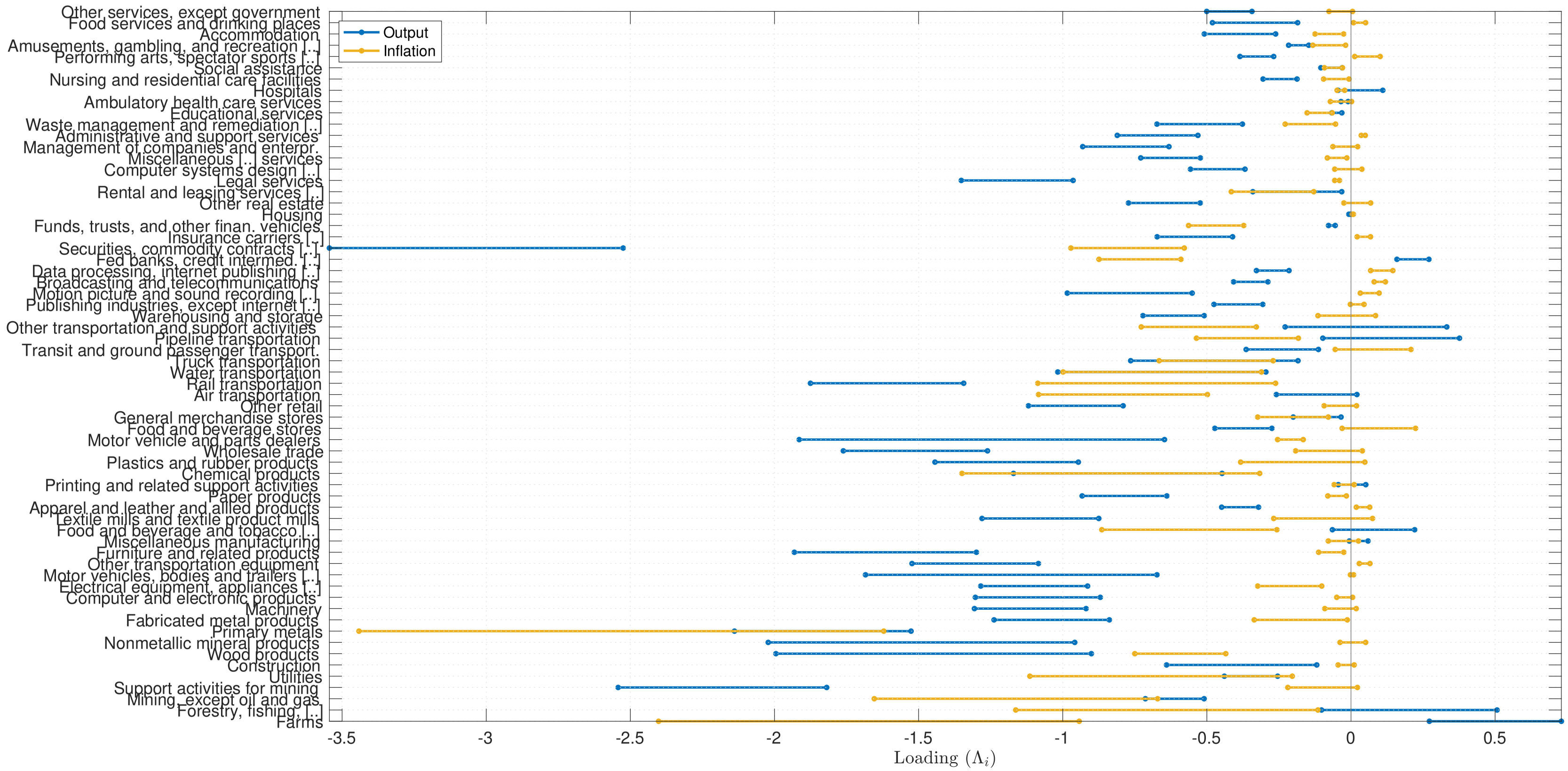
This Appendix reports a few additional results that for brevity are only mentioned in the main text of the paper.

Figure D.1 reports the full distribution of the sectoral loadings of output growth and inflation (across all draws of the sign restriction procedure) for the demand-like shock. The figure is therefore a 1-dimension version of Figure 3, but for each sector rather than for all of them.

Figures D.2 to D.7 report the the full distribution of the factor loadings across all draws of the sign restriction procedure (as in figure 2 in the main text) for the robustness exercises described in section 3.2. Specifically, we report the results based on sectoral data on value added and its deflator in figure D.2; based on data up to 2020Q1 in figure D.3; based on a specification where we set the number of lags in the VARs to $k = 4$ in figure D.4; based on a specification of the the VARs in levels, while setting the number of lags to $k = 4$ in figure D.5; based on a specification that includes the Excess Bond Premium (EBP) in figure D.6; and based on a specification where we separately identify oil shocks in figure D.7. Irrespective of the exercise we consider, we always get a large share of inflation loadings that fall in the positive side of the distribution.

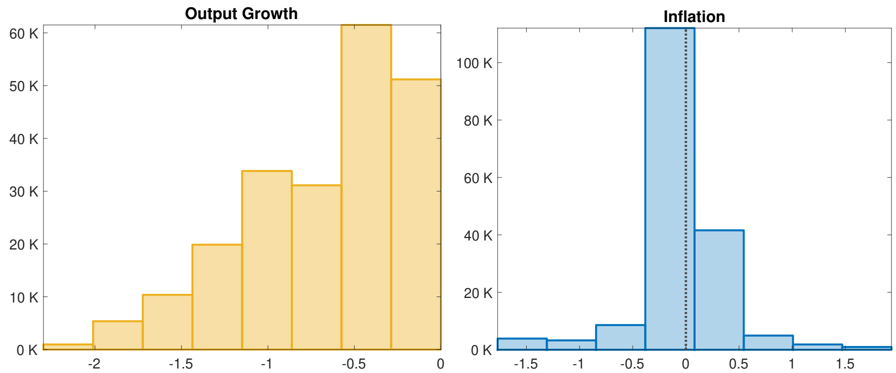
Finally, figure D.8 reports the distribution of the factor loadings for the 16 sectors where prices and quantities move in opposite directions for *all* draws of the sign restriction procedure.

Figure D.1: Distribution of sectoral loadings (demand shock)



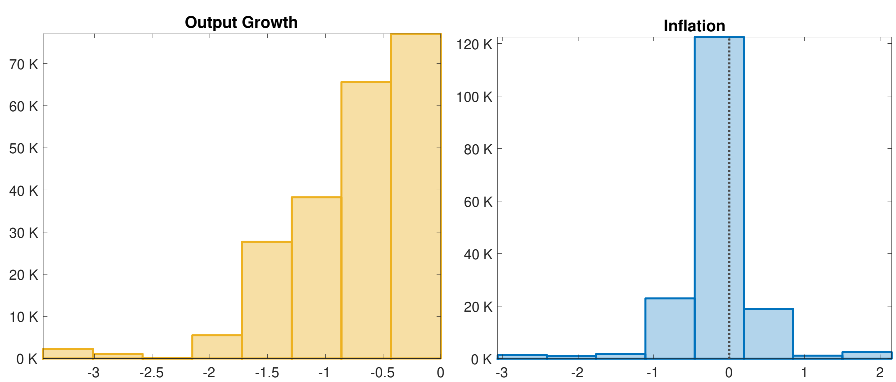
NOTE. Distribution of the sectoral loadings of output growth and inflation to an aggregate demand shock for all sectors across. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. In 16 sectors prices and quantities move in opposite directions for *all* draws of the sign restriction procedure.

Figure D.2: Distributions of sectoral loadings on aggregate demand-like shocks (Value added)



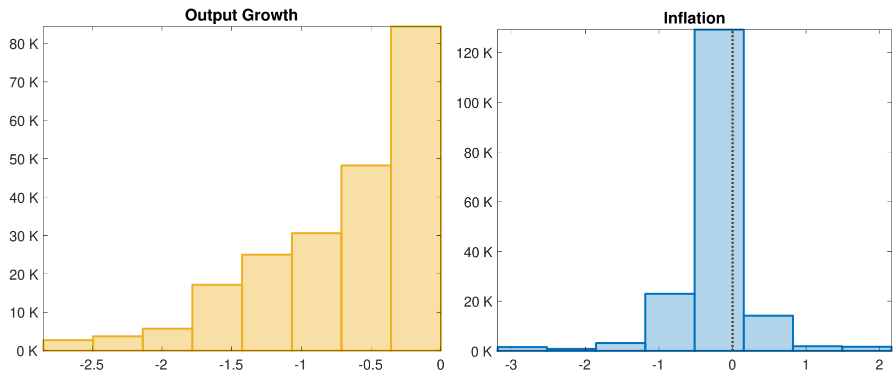
NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. Differently from our baseline, the loadings are estimated using data on value added and its deflator. The share of positive inflation loadings is 46%.

Figure D.3: Distributions of sectoral loadings on aggregate demand-like shocks (2020Q1 sample)



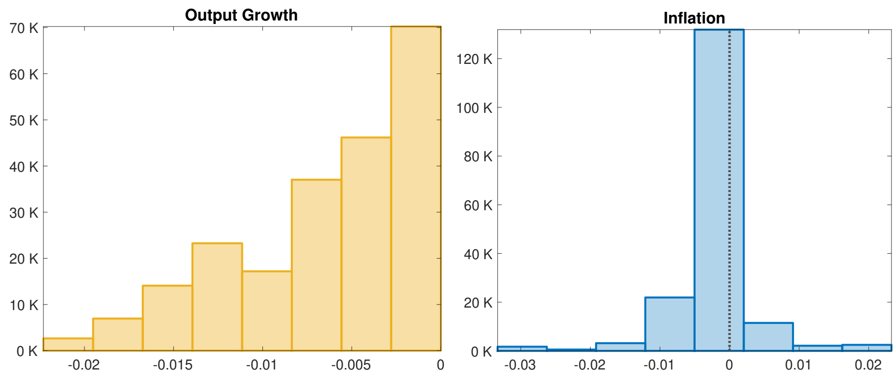
NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. Differently from our baseline, the loadings are estimated using data up to 2019Q4. The share of positive inflation loadings is 42%.

Figure D.4: Distributions of sectoral loadings on aggregate demand-like shocks (4 lags)



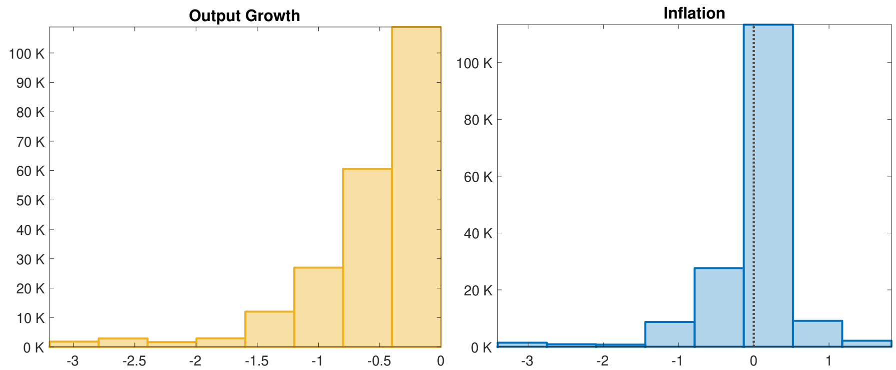
NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. Differently from our baseline, the loadings are estimated with a VAR specification that includes $k = 4$ lags. The share of positive inflation loadings is 34%.

Figure D.5: Distributions of sectoral loadings on aggregate demand-like shocks (levels, 4 lags)



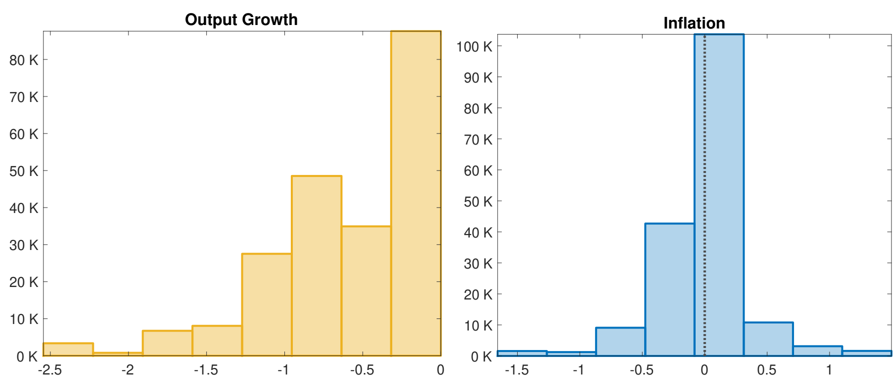
NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. Differently from our baseline, the loadings are estimated with a VAR specification that includes $k = 4$ lags. The share of positive inflation loadings is 38%.

Figure D.6: Distributions of sectoral loadings on aggregate demand-like shocks (EBP)



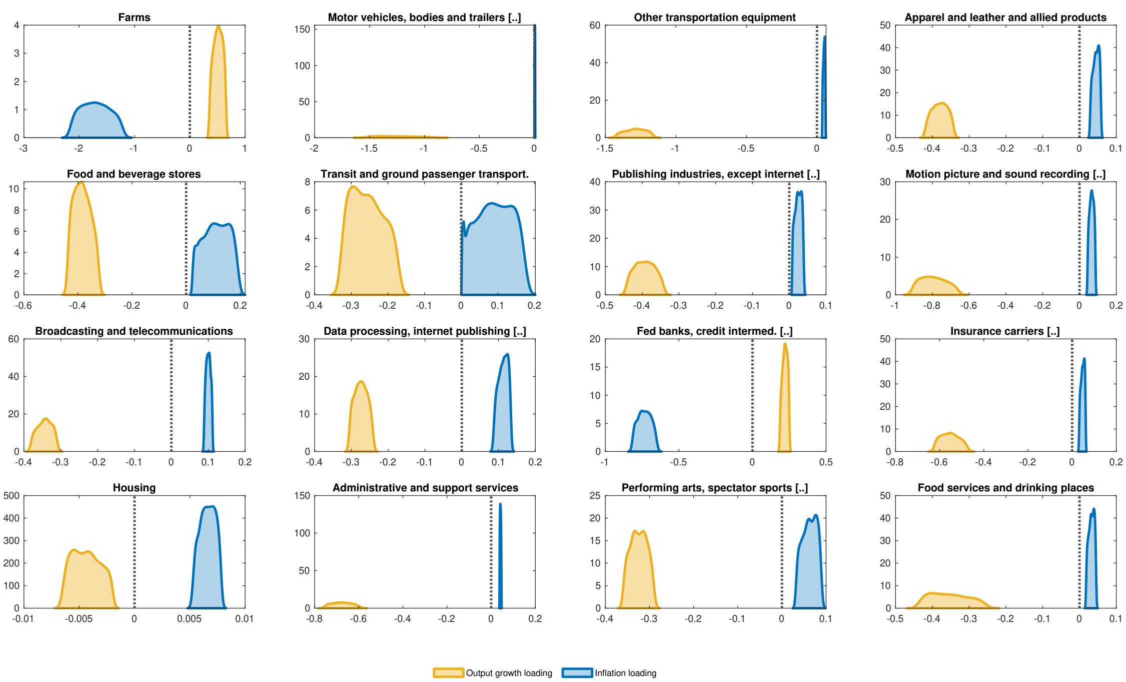
NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. Differently from our baseline, the loadings are estimated with a VAR specification that includes 4 variables, among which the Excess Bond Premium. The share of positive inflation loadings is 41%.

Figure D.7: Distributions of sectoral loadings on aggregate demand-like shocks (Oil shock)



NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate demand-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. Differently from our baseline, the loadings are estimated with a VAR specification that includes the price of Brent crude where we also identify oil price shocks. The share of positive inflation loadings is 36%.

Figure D.8: Distribution of loadings for selected sectors with significant and wrong loadings



NOTE. Distribution of the factor loadings for output growth (yellow) and inflation (blue) in response to an aggregate demand-like shock in all sectors where prices and quantities move in opposite directions for all draws of the sign restriction procedure. The distributions are constructed using the $5,000$ draws of the sign restriction procedure and the associated estimated matrix of sectoral loadings Λ_i. The histograms are not normalized. For each sector, we drop all loadings above/below the 16th/84th percentile.

E. Supply-Like Shocks

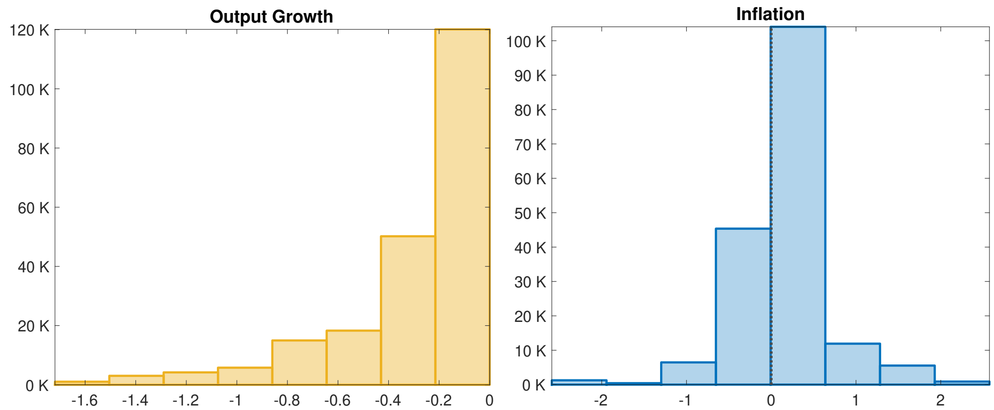
In the aggregate VAR, we identify two orthogonal innovations from data on aggregate output and inflation, namely an aggregate demand shock (which leads to positive comovement between output and prices) and an aggregate supply shock (which leads to negative comovement between output and prices). Our conjecture is that sectoral supply shocks that transmit via a Keyensian supply mechanism might pollute the identified aggregate demand shocks.

The intuition is that, if complementarities are strong enough, the sectoral supply shocks propagate at the aggregate level in a demand-like fashion. With weaker complementarities, prices may not fall at the aggregate level, but the Keynesian supply mechanism may nevertheless exist. A negative supply shock in one sector can still make output and prices fall in other sectors. The propagation, however, may just not be strong enough to generate a decline of the overall price level. In this case, sectoral supply shocks might also pollute aggregate supply-like shocks.

In this section, we analyze how sectors respond to aggregate supply-like shocks. More precisely, we study the impact responses of sectoral output growth and inflation rates to aggregate supply-like shocks as captured by the matrix of estimated factor loadings $\hat{\Lambda}_i$ over the whole sample. As in the main text, we consider the full distribution of the factor loadings across all draws of the sign restriction procedure.

Figure E.1 plots the distribution of the factor loadings of sectoral output growth (left) and inflation rates (right) in response to a negative aggregate supply-like shock. As for demand-like shocks, a few sectors display a positive response of output growth to the shock, so we normalize the distribution of output growth responses to be all negative. The object of interest is the distribution of the (normalized) inflation response. Under a "strict" definition of supply shocks, according to which output and inflation display negative comovement in all sectors, we would expect the distribution of the inflation loadings to lie entirely in posi-

Figure E.1: Distributions of sectoral loadings on aggregate supply-like shocks

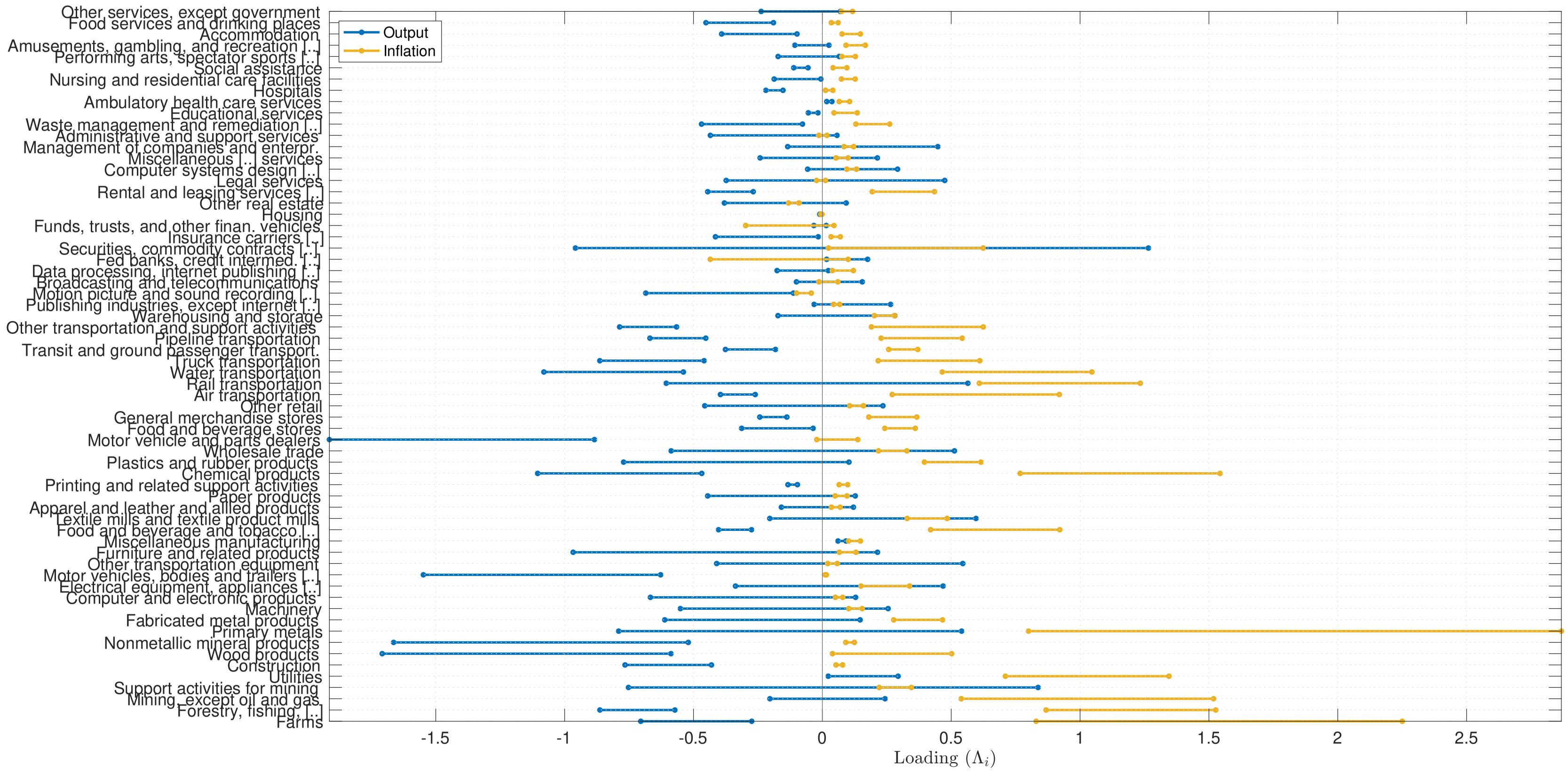


NOTE. Distribution of the normalized loadings of output growth (left panel) and inflation (right panel) in response to a negative aggregate supply-like shock. The loadings are normalized so that all output responses are negative. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. The share of negative inflation loadings is 33%.

tive territory. The figure does not support such a strict view of aggregate supply shocks. As the right panel shows, 33 percent of the draws are associated with negative inflation loadings.

Finally, figure E.2 reports the full distribution of the sectoral loadings of output growth and inflation (across all draws of the sign restriction procedure) for the supply-like shock. The figure shows that there are only 7 sectors where prices and quantities move in the same directions for *all* draws of the sign restriction procedure.

Figure E.2: Distribution of sectoral loadings (supply shock)



NOTE. Distribution of the sectoral loadings of output growth and inflation to an aggregate supply shock for all sectors across. The histograms are based on $5,000$ draws of the sign restriction procedure times the 64 sector. For each sector, we drop all loadings above/below the 16th/84th percentile. In only 7 sectors prices and quantities move in the same direction for *all* draws of the sign restriction procedure.