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# The Sectoral Origins of Post-Pandemic Inflation

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# Abstract

This paper quantifies the contribution of sector-specific supply and demand shocks to personal consumption expenditure (PCE) inflation. It derives identification restrictions that are consistent with a large class of dynamic stochastic general equilibrium models with production networks. It then imposes these restrictions in structural factor augmented vector autoregressive models with sectoral data on PCE inflation and consumption growth. The identification scheme allows the study to remain agnostic on theoretical modeling assumptions yet still gain structural empirical results: sectoral shocks cannot explain the initial inflation increases that followed the COVID-19 pandemic. This changed from the end of 2021 onward when shocks originating in non-services sectors became a major source of the post-pandemic inflation surge.

*Topics: Business fluctuations and cycles; Econometric and statistical methods; Inflation and prices*
*JEL codes: C50, E31, E32*



# Résumé

Dans cette étude, nous quantifions la contribution des chocs sectoriels d'offre et de demande à l'inflation mesurée par l'indice de prix relatif aux dépenses de consommation des ménages (indice PCE) aux États-Unis. Nous déduisons des restrictions d'identification qui cadrent avec une grande classe de modèles d'équilibre général dynamiques et stochastiques dotés de réseaux de production. Nous appliquons ensuite ces restrictions dans des modèles autorégressifs vectoriels enrichis de facteurs intégrant des données sectorielles sur l'inflation mesurée par l'indice PCE et la croissance de la consommation. Notre système d'identification nous permet de garder une posture agnostique face aux hypothèses de modélisation théorique et d'obtenir tout de même des résultats empiriques structurels. Ces résultats montrent que les chocs sectoriels ne peuvent pas expliquer les premières hausses d'inflation qui ont suivi la pandémie de COVID-19. Ils indiquent toutefois qu'à partir de la fin de 2021, les chocs provenant de secteurs hors services sont devenus un important facteur derrière la poussée d'inflation postpandémique.

*Sujets : Cycles et fluctuations économiques; Méthodes économétriques et statistiques; Inflation et prix*
*Codes JEL : C50, E31, E32*

# 1 Introduction

Like many other countries, the U.S. experienced a rapid surge in inflation following the COVID-19 pandemic. Annual headline inflation rose from below 2 percent in March 2020 to over 7 percent by June 2022. Many explanations for this surge point to sector-specific factors, such as *supply chain disruptions* or the *rebound in consumer demand*, which affected some sectors more than others. However, attributing these shocks to specific sectors does not diminish their broader economic impact. On the contrary, shocks originating in one part of the economy can spill over to other sectors, generating effects of macroeconomic relevance. This also raises a key question in the ongoing policy debate: was the post-pandemic inflation surge driven primarily by supply shocks or demand shocks? Given that both played a role, analyzing inflation at a sectoral level is crucial for distinguishing their relative contributions. This distinction is essential for designing an effective monetary policy response.

Well before the onset of the COVID-19 pandemic, a growing interest emerged in embedding production networks into macroeconomic models. These models allow economists to analyze the origin and intricate transmission patterns of economic shocks, including spillovers from sector-specific shocks. However, most macroeconomic multi-sector studies focus on either how *sector-specific* shocks affect real aggregate activity or how *aggregate* shocks propagate through the production network and influence aggregate activity and inflation. A smaller and more recent subset of the literature studies the effect of *sector-specific* shocks on inflation. Moreover, quantifications of sectoral shocks typically rely on theoretical modeling choices and calibration. Few papers provide empirical evidence that does not rely on these modeling specifics, limiting empirical conclusions due to the risk of theoretical misspecification.

The paper makes two main contributions. First, I address how to obtain robust empirical quantifications of sectoral supply and demand shocks, thereby limiting the effects from theoretical misspecification. To that end, I develop an identification scheme that is consistent with a wide array of canonical dynamic stochastic general equilibrium (DSGE) models with production networks. The method further ensures that identified sectoral shocks are not conflated with aggregate shocks. Second, I use this scheme to identify sector-specific supply and demand shocks in a structural time-series model and gauge their aggregate consequences for inflation, with a focus on recent years.

The intuition behind the identification scheme is the following. Different model specifications deliver solutions on how economic shocks propagate through the network and affect prices and quantities. These solutions reveal very different *quantitative* effects of sectoral shocks and their contributions to inflation. However, I show that for a given sector-specific shock, the solutions are, in many cases, similar with regard to how sectors are *relatively* affected by sectoral shocks. For instance, the quantitative implications of a negative supply shock in a specific manufacturing sector may be very different between a model with fully flexible prices and one with sectoral heterogeneity in price stickiness. Nevertheless, my theoretical results suggest that both models exhibit a similar *ranking* of sectoral price and quantity responses to the supply shock.[1] I exploit this robustness in relative responses across models as identification restrictions. This

[1] In other words, different types of models imply cardinal differences in sectoral responses to shocks. These responses however do not change ordinal ranks across models.

therefore allows me to remain agnostic on the myriad of potential choices for structural modeling assumptions yet still gain structural empirical results.

My identification strategy delivers novel empirical evidence on the sectoral origins of inflation. In most years, sectoral supply and demand shocks exhibit limited contributions to personal consumption expenditure (PCE) inflation. The two last high-inflation periods, the Great Inflation from the 1970s to the mid-1980s and the period following the COVID-19 pandemic, are both notable exceptions. I find that supply shocks originating in non-services sectors were a major source of post-pandemic increases in inflation. In fact, shocks to non-services sectors have never had such strong contributions to inflation in recent U.S. history. The nature of these contributions does not stem from one sector-specific shock alone, but from many non-services sector shocks with varying degrees of importance and different dynamics. Aggregating all identified sectoral shocks—both sectoral demand and supply shocks from services and non-services sectors—reveals that their contribution to recent inflation was high, though lower than during the Great Inflation. This is because sectoral demand shocks had only a limited positive effect while sectoral supply shocks in the services sector had a significant negative impact on post-pandemic inflation. On the flip side, all types of sectoral supply shocks contributed to low inflation prior to the pandemic.

Focusing on the importance of sectoral shocks in recent years, I determine four distinct sub-periods with different sources of inflation. Initially, between March 2020 and February 2021, with headline inflation still below 2 percent, negative sectoral supply-side shocks had small, negligible negative effects on aggregate prices. At the same time, sectoral demand shocks exhibited substantial negative contributions to inflation. In the second sub-period, from March 2021 to September 2021, most strikingly, sectoral shocks do not explain the surge in inflation to levels well above 2 percent. In the third sub-period, commencing October 2021, the importance of negative supply shocks originating in non-services sectors increased sharply, contributing by more than 2.5 percentage points to PCE inflation by April 2022 and lasting until around January 2023. Sectoral demand shocks also started to develop increasing demand-pull contributions in this period. Finally, the fourth sub-period, from February 2023 until the end of my sample in March 2024, is characterized by a steady decline in the importance of sectoral shocks, as inflation continued its downturn and began to normalize. It is important to note that there is still a large scope for potential *aggregate* positive demand contributions as a source of inflation, especially in the second and third sub-periods.

To derive these findings, my analysis proceeds in three steps. First, I analyze the propagation patterns of sectoral shocks within a range of popular DSGE model specifications with production networks. Given the multitude of theoretical models on production networks, I derive my identification of sector-specific supply and demand shocks from five different specifications of popular DSGE models. I build in particular on Pastén, Schoenle, and Weber (2024) and map their model setup to PCE data by distinguishing between intermediate and final goods producers, similarly to Smets, Tielens, and Van Hove (2019). This paves the way to combine input-output (I-O) data, based on the North American Industry Classification System (NAICS), with PCE time series on prices and quantities. The resulting variations of theoretical specifications, combined with different calibrations, allow me to summarize the network propagation of sectoral supply and demand shocks in a wide array of theoretical settings. I focus on differences in sectoral price rigidity that range from a model with fully flexible prices to one with heterogeneity in price stickiness and labor market segmentation. Unlike most of the existing literature, which calibrates models using only one year of I-O data, I calibrate each of the five models using annual data over a 26-year period. This ensures that my results are robust to changes in the production network over time, which has previously been evidenced by Foerster and Choi (2017).

In contrast to sectoral supply shocks, sectoral demand shocks are modeled as changes to the weights in a household's consumption basket. For instance, a positive shock to *motor vehicles and parts* implies a larger weight for this particular category of consumer goods and a proportional decrease for all other types of consumer goods. Identification of sectoral demand shocks requires more a-priori theory than identification of sectoral supply shocks. Within the resulting narrower set of theoretical models, I show that identification of sectoral demand shocks is still robust to differing calibrations.

In a second step, I show the central insight behind the identification strategy: for many sectoral shocks, these propagation patterns are robust across models. All model solutions deliver quantitative responses of prices and quantities in response to sector-specific shocks. For a given sectoral shock and model, I rank these shock responses across sectors and group them into clusters that range from highly to weakly responsive. It turns out that for a given sectoral shock there exist cluster compositions that are consistent across many, sometimes all, of the different model solutions. This allows identification of the shock without relying on a specific theoretical model or calibration.

Exploiting this robustness of sector clusters in a third and final step, I identify structural sectoral supply and demand shocks within Bayesian factor-augmented vector autoregressive (FAVAR) models. First, I extract factors from sectoral and aggregate monthly PCE inflation and consumption growth rates, and then I express them in vector autoregressive (VAR) form. The FAVAR structure and estimation are based on Bernanke, Boivin, and Eliasz (2005); Boivin, Giannoni, and Mihov (2009) and Stock and Watson (2016).[2] I then estimate structural VAR shocks via *heterogeneity restrictions*, i.e., for each sector-specific shock, I rank sectoral impulse responses so that they comply with the respective cluster composition. I implement structural identification using standard algorithms from the VAR sign restriction literature, in particular from Rubio-Ramírez, Waggoner, and Zha (2010). The identification method and findings in this paper relate to various strands of the literature, but they contribute primarily to the still limited empirical research on how sectoral shocks propagate through the production network and have an impact on inflation.

The literature has seen a myriad of recent contributions on the supply- and demand-side causes of post-pandemic inflation for different countries. Most of the empirical work however focuses on the role of aggregate supply and demand shocks (see e.g., Bernanke and Blanchard

[2]Other empirical papers using factor or FAVAR methods with a focus on sectoral prices are Maćkowiak, Moench, and Wiederholt (2009); Kaufmann and Lein (2013); Dixon, Franklin, and Millard (2014); De Graeve and Walentin (2015); Andrade and Zachariadis (2016); Auer, Levchenko, and Sauré (2019); Bańbura, Bobeica, and Martínez Hernández (2023) and Ha et al. (2024). These contributions, however, do not solve the fundamental identification problem of disentangling aggregate shocks from sectoral shocks with aggregate consequences.

2024; Giannone and Primiceri 2024) or selective sector-specific shocks, such as energy shocks (see e.g., Bańbura, Bobeica, and Martínez Hernández 2023). These papers do not uncover supply- or demand-side shocks originating within a disaggregated set of economic sectors.[3] In general, no consensus exists on the most important inflation drivers of recent years: e.g., Ascari, Bonam, and Smadu (2024); Bańbura, Bobeica, and Martínez Hernández (2023) and de Santis (2024) highlight the effect of supply shocks, whereas e.g. Giannone and Primiceri (2024); Ascari et al. (2024) and Bergholt et al. (2024) stress more the importance of demand-side shocks.[4] My results show that on the sectoral level most inflationary pressure originated in goods-producing sectors. While I do not explicitly identify aggregate shocks, such as those identified in the recent literature, my approach allows room for their influence.

On the theory side, most papers on production-networks written before the pandemic focused on how sectoral shocks affect real fluctuations.[5] Recently, more theory-dependent work has shed light on how sectoral-shock propagation affects aggregate inflation (see e.g., Pastén, Schoenle, and Weber 2024; Rubbo 2024; Ruge-Murcia and Wolman 2024; Bouakez, Höynck, and Rachedi 2024; Comin and Jones 2024; Di Giovanni et al. 2024; Baqaee and Farhi 2022; Guerrieri et al. 2022; Carvalho, Lee, and Park 2021; Smets, Tielens, and Van Hove 2019). These contributions provide quantitative empirical results on the effect of sectoral shocks on prices, but they do this by relying on their respective theoretical model. This paper provides empirical estimates on the effects of sectoral shocks that do not rely on a specific theoretical model.

Identification using heterogeneity restrictions, as introduced by De Graeve and Karas (2014), has recently been further developed by Amir-Ahmadi and Drautzburg (2021) and Matthes and Schwartzman (2025) to improve identification of aggregate shocks. De Graeve and Schneider (2023) impose heterogeneity restrictions to identify sectoral shocks and their impact on industrial production growth. My identification scheme to gain structural sectoral shocks builds on the novel econometric framework developed in this previous work, but it differs along two major dimensions: first, De Graeve and Schneider (ibid.) derive heterogeneity restrictions directly from I-O data using common network measures, such as Leontief inverses. In the current paper, I motivate and show the robustness of my restrictions across a range of theoretical DSGE models. Second, identification in this paper is not exclusively based on quantities, but I include a *price* dimension in the time series model and identification framework. This allows me not only to explicitly study sector-specific shocks in a New Keynesian setting where prices are sticky, but also to exploit for identification that sectors exhibit *heterogeneity* in price rigidity. Moreover, identification with quantities and prices delivers a better separation of supply and demand shocks.

[3] Brinca, Duarte, and Faria-e-Castro (2021) and Cesa-Bianchi and Ferrero (2021) are also recent empirical approaches but they do not explicitly disentangle sectoral from aggregate shocks.

[4] A range of open-economy approaches have also been investigating the effect of mostly aggregate shocks on the global inflation surge (see e.g., de Soyres et al. 2024; Dao et al. 2024; Ha et al. 2024; Jordà and Nechio 2023).

[5] Earlier models are Horvath (1998, 2000) and Dupor (1999) and date back to Long and Plosser's (1983) seminal contributions. There have been many expositions, theoretical and empirical, on how sector-specific shocks affect real activity; these include Shea (2002); Foerster, Sarte, and Watson (2011); Gabaix (2011); Acemoglu et al. (2012); Carvalho and Gabaix (2013); Acemoglu, Akcigit, and Kerr (2016); Barrot and Sauvagnat (2016); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017); Atalay (2017); Baqaee (2018); Baqaee and Farhi (2019); Boehm, Flaaen, and Pandalai-Nayar (2019); Carvalho, Lee, and Park (2021); vom Lehn and Winberry (2021); Arata and Miyakawa (2022) and Foerster et al. (2022).

A frequently adopted approach in a structural VAR setting is to separate supply from demand shocks by imposing sign restrictions. The conventional economic wisdom underlying this identification approach is reminiscent of a simple supply-and-demand analysis: supply shocks induce quantity and price changes in opposite directions; and, in contrast, demand shocks move quantity and prices in the same direction. In recent work, Shapiro (2024) classifies PCE categories as supply- or demand-driven using sign restrictions on individual PCE prices and quantities. I contribute to this recent empirical strand of the literature by providing an identification scheme that further allows us to pinpoint the origins of the shocks. A simple sign restriction approach cannot disentangle the different sources that cause sectoral price and quantity responses. In my framework, I can determine whether the supply or demand shock originated in the sector itself or spilled over from another sector.[6]

While the focus of this paper is on PCE inflation, my empirical model also delivers contributions of sectoral shocks on aggregate PCE consumption growth. My results suggest that business cycle fluctuations of consumption are somewhat better explained by sectoral shocks throughout my sample. This paper is therefore also largely in line with the production network literature on the importance of sectoral shocks in explaining real fluctuations, including De Graeve and Schneider (2023).

The remainder of the paper is structured as follows. Section 2 sketches the theoretical model setup and derives analytical solutions thereto. A detailed description of the theoretical model framework is deferred to the appendix. In Section 3, I cluster these analytical solutions and motivate how sector clusters can serve as identification restrictions. Section 4 outlines the FAVAR model and implementation of structural identification. Empirical results on the sectoral origins of inflation and consumption growth are shown in Section 5. Section 6 concludes.

## 2 Theoretical models

The identification of sectoral shocks in the empirical model draws on insights from established multi-sector DSGE frameworks. In this section, I first sketch the key features of the model framework and then outline analytical solutions for different specifications that serve as the foundation for my empirical identification strategy. The detailed modelling setup is provided in Appendix A.

My theoretical framework closely resembles Pastén, Schoenle, and Weber (2024), but I introduce two key modifications. First, I establish a mapping between network I-O data for NAICS industries and PCE time series data on consumption expenditures. This approach enables identification of sectoral supply shocks at the producer level without requiring time series data on producer prices and quantities. Following Smets, Tielens, and Van Hove (2019), I structure production into two distinct layers: intermediate goods producers (corresponding to NAICS industries) and final goods producers (assembling PCE consumer goods). Intermediate goods producers utilize labor and inputs from other sectors to create one of $J$ intermediate goods. Final goods producers transform these intermediate goods into one of $Z$ consumption categories

[6] In principle, I am also able to identify whether sectoral price and quantity responses are the result of an aggregate shock, but the focus in this paper is on contributions from sectoral shocks.

for household consumption. In both production layers, each sector comprises a continuum of firms producing an intermediate good, $j$, or a consumption good, $z$, respectively.

Second, I incorporate two types of sectoral shocks: sector-specific technology shocks affecting intermediate goods producers similar to Pastén, Schoenle, and Weber (2024), and consumer-demand shocks that alter the composition of the consumption basket. For instance, a positive shock to *motor vehicles and parts* implies a larger weight for this particular category of consumer goods and a proportional decrease for all other types of consumer goods.

The model features three sources of heterogeneity in production: (i) intermediate goods producers differ in their input-output linkages; (ii) both intermediate and final goods producers vary in size; and (iii) both types of producers exhibit different degrees of nominal price rigidity. My framework explicitly models price pass-through from NAICS-level intermediate goods producers to final goods producers, while allowing for divergences between consumer and producer price dynamics.

Building on this modeling framework, I compile five distinct specifications/calibrations that reflect common approaches in the literature to model production networks.[7] Specifically, I derive analytical solutions for sectoral price and quantity responses to sectoral shocks, which underpin the empirical identification strategy employed later on in the paper. To obtain closed-form solutions, I adopt Pastén, Schoenle, and Weber's (ibid.) methodological approach by implementing several key simplifying assumptions. Variables represented in lowercase notation correspond to log-linear deviations from the model's steady state equilibrium.

For instance, sectoral prices for intermediate goods producers (at NAICS industry level) in response to sectoral supply shocks solve:

$$\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,, \tag{1}$$

where $\mathbf{a}_t$ is a $J \times 1$ vector of sectoral productivity shocks affecting intermediate goods producers, $\mathbf{p}_t^{im}$ is a $J \times 1$ vector of intermediate goods prices, and the multiplier matrix, $\widehat{\mathbf{X}}^{im}$, captures how productivity shocks propagate through the production network. This matrix varies across the five model specifications, and depends on input-output linkages, price rigidities, and additional model-specific characteristics.

The first three of the five model specifications assume that the inverse-Frisch elasticity, which captures the elasticity of labor supply with respect to wages, is zero, $\varphi = 0$. This shuts down network propagation of shocks through sectoral segmentation of labor markets. The very first model specification also fully shuts down any form of price stickiness, assuming that all prices are fully flexible. Next, I include a model with homogeneous price stickiness, i.e., all producer prices, $\mathbf{p}_t^{im}$, and all consumer prices, $\mathbf{p}_t^{pce}$, exhibit the same degree of price stickiness.

In a third specification, I assume heterogeneity in price stickiness for producer and consumer prices using estimates on average price durations from Nakamura and Steinsson (2008) and Pastén, Schoenle, and Weber (2020).[8] Finally, the fourth and fifth model specifications assume heterogeneity in price stickiness and also allow for a positive inverse-Frisch elasticity. This

[7] In principle, nothing speaks against adding other types of models and specifications to this suite and testing whether solutions thereto comply with the common network propagation patterns that I exploit for identification in my empirical model later on.

[8] More information on sectoral price durations is included in Section 3.3.

activates an additional network propagation channel via upstream effects through wages.

While in all five specifications sectoral productivity shocks have effects on sectoral prices, sectoral demand shocks require that the inverse-Frisch elasticity is positive, $\varphi > 0$. The reason is that with $\varphi = 0$, sectoral demand shocks have no downstream effects on prices. This is a well-known result in multi-sector models with constant returns to scale in production and without heterogeneity in sectoral wages. In these types of models, prices are independent from the demand side.[9] By allowing wages to respond to labor demand, via $\varphi > 0$, sectoral demand shocks can affect sectoral prices. A positive inverse-Frisch elasticity also allows for sectoral supply shocks to generate additional upstream effects to their otherwise downstream propagation through the network.

Departing from log-linearized first-order conditions around the stochastic steady state, I impose simplifying assumptions to generate analytical solutions for prices, consumption, and wages. I present these solutions separately for supply and demand shocks.

## 2.1 Analytical solutions in simplified models: sectoral supply shocks

Abstracting from sectoral demand shocks, this subsection derives analytical solutions in the presence of sectoral supply shocks, $a_{jt}$, with $j = 1, \ldots, J$. The full set of simplifying assumptions is the following:

(i) First, the inverse-Frisch elasticity, $\varphi$, is set to zero, which implies that there is no sectoral segmentation of labor markets in response to shocks. This assumption is lifted later on.

(ii) Monetary policy fully stabilizes nominal GDP growth:

$$p_t^{pce} + c_t = 0\,, \tag{2}$$

with $p_t^{pce}$ referring to aggregate PCE prices and $c_t$ to aggrgegate consumption.

(iii) A simple information friction models price rigidity. This applies to both intermediate and final goods producers:

$$P_{jt} = \begin{cases} \mathbb{E}_{t-1}\left[P_{jt}^*\right] & \text{with probability } \lambda_j\,, \\ P_{jt}^* & \text{with probability } 1 - \lambda_j\,, \end{cases} \tag{3}$$

where $P_{jt}$ is the price for intermediate goods in sector $j$ and $P_{jt}^*$ is the respective optimal price, with $\lambda_j$ representing the probability that a firm must set its price before observing the shocks. Similarly, for final goods producers:

$$P_{zt} = \begin{cases} \mathbb{E}_{t-1}\left[P_{zt}^*\right] & \text{with probability } \lambda_z\,, \\ P_{zt}^* & \text{with probability } 1 - \lambda_z\,. \end{cases} \tag{4}$$

These probabilities are calibrated using estimates on sectors' average price durations.

[9] See Acemoglu, Akcigit, and Kerr (2016) for a proof on why sectoral demand shocks—in their case, sectoral government spending shocks—do not generate effects on prices in such a model.

In addition, I assume that households have log utility: $\sigma = 1$, where $\sigma$ represents the coefficient of relative risk aversion.

### 2.1.1 All simplifying assumptions applied

Assumption (i) implies that the first-order condition for the labor-supply decision simplifies to:

$$w_{jt} = p_t^{pce} + c_t \,. \tag{5}$$

where $w_{jt}$ are sector-specific wages. Monetary policy described in (ii) implies that there is a simple relationship between aggregate consumption and aggregate PCE prices:

$$c_t = -p_t^{pce} \,. \tag{6}$$

Finally, the information friction assumed under (iii) leads to the following relationships of prices and marginal costs for both intermediate and final goods producers:

$$p_{jt} = (1 - \lambda_j) mc_{jt} \,, \tag{7}$$

$$p_{zt} = (1 - \lambda_z) mc_{zt} \,. \tag{8}$$

where $mc_{jt}$ and $mc_{zt}$ represent the marginal costs for intermediate and final goods producers, respectively.

In Appendix D, I show how these assumptions, together with the log-linearized first-order conditions, allow the following closed-form solutions for sectoral and aggregate prices. Sectoral prices for intermediate goods producers solve:

$$\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im} \mathbf{a}_t \,, \tag{9}$$

with

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im}) \,. \tag{10}$$

The multiplier matrix, $\widehat{\mathbf{X}}^{im}$, which maps productivity shocks to intermediate goods prices, takes the form of a price-rigidity-adjusted Leontief inverse. It augments the I-O matrix, $\mathbf{\Omega}$, with matrix $\mathbf{\Lambda}^{im}$, which is a diagonal matrix including all price-rigidity probabilities, $\lambda_j$. Parameter $\delta$ represents the share of intermediate inputs in the production function of intermediate goods producers, and $\mathbf{I}$ is the identity matrix. Furthermore, sectoral PCE prices are downstream to producer prices and hence solve:

$$\mathbf{p}_t^{pce} = -(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} \mathbf{a}_t \,, \tag{11}$$

while sectoral consumption expenditures are given by:

$$\mathbf{c}_t = \left[\eta \mathbf{I} + (1 - \eta)\iota \mathbf{\Omega}_c'\right] (\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} \mathbf{a}_t \,. \tag{12}$$

Diagonal matrix $\mathbf{\Lambda}^{pce}$ is the final-good equivalent to matrix $\mathbf{\Lambda}^{im}$, column-vector $\mathbf{\Omega}_c$ captures the $Z$ consumption shares, and $\iota$ is a column vector of ones of the appropriate dimension. The bridge matrix, $\mathbf{K} \in \mathbb{R}^{Z,J}$, with elements $k_{zj}$ maps the $J$ intermediate goods and prices into $Z$ consumption equivalents. Parameter $\eta$ represents the elasticity of substitution between different consumption goods. Aggregate PCE prices are then a weighted average of sectoral PCE prices:

$$p_t^{pce} = -\mathbf{\Omega}_c'(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,, \tag{13}$$

from which aggregate consumption directly follows as $p_t^{pce} = -c_t$ under assumption (ii).

### 2.1.2 Allowing for labor market heterogeneity

As in Pastén, Schoenle, and Weber (2024), I next relax the zero assumption on the inverse-Frisch elasticity, $\varphi$, imposed by assumption (i). In Appendix D, I show that the multiplier matrix, $\widehat{\mathbf{X}}^{im}$, then has the form:

$$\widehat{\mathbf{X}}^{im} \equiv \widehat{\mathbf{P}}^{im} \left(\mathbf{I} - \mathbf{\Lambda}^{im}\right) \left[\mathbf{I} + \varphi(1-\delta)\mathbf{\Theta}'^{-1}\right] \,. \tag{14}$$

The composite matrix $\widehat{\mathbf{P}}^{im}$ is defined as:

$$\begin{aligned}\widehat{\mathbf{P}}^{im} \equiv \Big[&\mathbf{I} - \delta\left(\mathbf{I} - \mathbf{\Lambda}^{im}\right)\mathbf{\Omega} \\ &- (1-\delta)\left(\mathbf{I} - \mathbf{\Lambda}^{im}\right)\mathbf{\Theta}'^{-1} \\ &\quad \left(\theta_p^{im} + \theta_p^{pce}\left(\mathbf{I} - \mathbf{\Lambda}^{pce}\right)\mathbf{K} - \theta_c\mathbf{\Omega}_c'\left(\mathbf{I} - \mathbf{\Lambda}^{pce}\right)\mathbf{K}\right)\Big]^{-1} \,,\end{aligned} \tag{15}$$

where

$$\begin{aligned}\mathbf{\Theta}' &\equiv (1+\delta\varphi)\,\mathbf{I} - \psi\,(1+\varphi)\,\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D} \,, \\ \theta_c &\equiv \left[\mathbf{I} - \psi\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\right]\iota + \varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{\Omega}_c \,, \\ \theta_p^{pce} &\equiv \left[\mathbf{I} - \psi\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\right]\iota\mathbf{\Omega}_c' + \varphi\eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\left[\mathbf{\Omega}_c\mathbf{\Omega}_c' - \mathbf{D}_c\right] \,, \\ \theta_p^{im} &\equiv \varphi\left[\psi(\eta-1)\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\mathbf{\Omega} + \eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{D}_c\mathbf{K} - \eta\mathbf{I} + \delta\mathbf{\Omega}\right] \,.\end{aligned}$$

Diagonal matrix $\mathbf{D}_c$ includes all consumption shares, $\omega_{zc}$, whereas diagonal matrix $\mathbf{D}$ captures all gross output shares, $n_j$. Parameter $\psi$ is the share of intermediate use in gross output. While this solution appears somewhat complicated, it is, as before, just a combination of model parameters that relates the exogenous variables—i.e., productivity shocks $a_{jt}$—to sectoral prices, and hence consumption. The solutions for prices and consumption are then the same as in the previous section that just use this version of $\widehat{\mathbf{X}}^{im}$.

### 2.1.3 Collecting model solutions for sectoral supply shocks

Collecting all solutions for multiplier matrix $\widehat{\mathbf{X}}^{im}$, the five model specifications that I use for identification are then given by the following:

$$\widehat{\mathbf{X}}^{im} \equiv \begin{cases} [\mathbf{I} - \delta\boldsymbol{\Omega}]^{-1} & \text{for specification (I)}, \\ \left[\mathbf{I} - \delta(\mathbf{I} - \bar{\boldsymbol{\Lambda}}^{im})\boldsymbol{\Omega}\right]^{-1} (\mathbf{I} - \bar{\boldsymbol{\Lambda}}^{im}) & \text{for specification (II)}, \\ \left[\mathbf{I} - \delta(\mathbf{I} - \boldsymbol{\Lambda}^{im})\boldsymbol{\Omega}\right]^{-1} (\mathbf{I} - \boldsymbol{\Lambda}^{im}) & \text{for specification (III)}, \\ (14) \text{ with } \varphi = 1 & \text{for specification (IV)}, \\ (14) \text{ with } \varphi = 2 & \text{for specification (V)}, \end{cases} \tag{16}$$

where $\bar{\boldsymbol{\Lambda}}^{im}$ in specification (II) corresponds to a calibration with homogeneous price stickiness and hence includes a constant parameter, $\lambda$, on its diagonal. For this case, I also assume that $\bar{\boldsymbol{\Lambda}}^{pce} = \bar{\boldsymbol{\Lambda}}^{im}$. The final solutions for sectoral prices in response to sectoral supply shocks are then given by:

$$\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,, \tag{17}$$

$$\mathbf{p}_t^{pce} = -\widehat{\mathbf{X}}^{pce}\mathbf{a}_t\,. \tag{18}$$

Multiplier matrix $\widehat{\mathbf{X}}^{pce}$ corresponds to the five cases such that:

$$\widehat{\mathbf{X}}^{pce} \equiv \begin{cases} \mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (I)}, \\ (\mathbf{I} - \bar{\boldsymbol{\Lambda}}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (II)}, \\ (\mathbf{I} - \boldsymbol{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (III)}, \\ (\mathbf{I} - \boldsymbol{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (IV)}, \\ (\mathbf{I} - \boldsymbol{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (V)}. \end{cases} \tag{19}$$

Sectoral consumption is then expressed as:

$$\mathbf{c}_t = \widehat{\mathbf{X}}^{c}\mathbf{a}_t\,, \tag{20}$$

with

$$\widehat{\mathbf{X}}^{c} \equiv \left[\eta\mathbf{I} + (1-\eta)\iota\boldsymbol{\Omega}_c'\right]\widehat{\mathbf{X}}^{pce}\,. \tag{21}$$

Finally, aggregate PCE prices and consumption solve:

$$p_t^{pce} = -\mathbf{X}^{pce}\mathbf{a}_t\,, \tag{22}$$

$$c_t = \mathbf{X}^{pce}\mathbf{a}_t\,, \tag{23}$$

where

$$\mathbf{X}^{pce} \equiv \boldsymbol{\Omega}_c'\widehat{\mathbf{X}}^{pce}\,. \tag{24}$$

## 2.2 Analytical solutions in simplified models: sectoral demand shocks

Now, abstracting from sectoral supply shocks (i.e., $a_{jt} = 0$ for all $j = 1, \dots, J$), this subsection derives analytical solutions in presence of sectoral demand shocks, $f_{zt}$, for $z = 1, \dots, Z$. Other than for sectoral supply shocks, sectoral demand shocks rely on propagation through labor markets. I therefore only consider specifications with a positive inverse Frisch-elasticity, i.e., $\varphi > 0$. Under simplifying assumptions (ii) and (iii), as well as assuming log utility, $\sigma = 1$, sectoral intermediate good prices solve:

$$\mathbf{p}_t^{im} = \widehat{\mathbf{F}}^{im}\mathbf{f}_t\,, \tag{25}$$

where the multiplier matrix, $\widehat{\mathbf{F}}^{im}$, is derived in Appendix D.3 and is given by:

$$\widehat{\mathbf{F}}^{im} \equiv \widehat{\mathbf{P}}^{im}\left(\mathbf{I} - \mathbf{\Lambda}^{im}\right)(1-\delta)\mathbf{\Theta}'^{-1}\varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}\mathbf{D}_c\,. \tag{26}$$

The composite matrix $\widehat{\mathbf{P}}^{im}$ is defined as in the previous supply-shock section.

### 2.2.1 Collecting model solutions for sectoral demand shocks

As noted earlier, I consider sectoral demand shocks only under specifications (IV) and (V). I therefore summarize multiplier matrix $\widehat{\mathbf{F}}^{im}$ for the two cases as:

$$\widehat{\mathbf{F}}^{im} \equiv \begin{cases} (26) \text{ with } \varphi = 1 & \text{for specification (IV)}\,, \\ (26) \text{ with } \varphi = 2 & \text{for specification (V)}\,. \end{cases} \tag{27}$$

Similarly to productivity shocks, sectoral prices and consumption solve the following:

$$\mathbf{p}_t^{pce} = \widehat{\mathbf{F}}^{pce}\mathbf{f}_t\,, \tag{28}$$

$$\mathbf{c}_t = \left[(\eta-1)\iota\mathbf{\Omega}_c' - \eta\mathbf{I}\right]\widehat{\mathbf{F}}^{pce}\mathbf{f}_t\,, \tag{29}$$

where

$$\widehat{\mathbf{F}}^{pce} \equiv \begin{cases} (\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{F}}^{im} & \text{for specification (IV)}\,, \\ (\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{F}}^{im} & \text{for specification (V)}\,. \end{cases} \tag{30}$$

Aggregate prices then solve, using the respective multiplier matrix $\widehat{\mathbf{F}}^{pce}$ for the two cases:

$$p_t^{pce} = \mathbf{F}^{pce}\mathbf{f}_t \tag{31}$$

where

$$\mathbf{F}^{pce} \equiv \mathbf{\Omega}_c'\widehat{\mathbf{F}}^{pce}\,. \tag{32}$$

Finally, note that the total change of sectoral consumption is equal to consumption plus the consumption demand shocks, $\mathbf{c}_t + \mathbf{f}_t$, which implies the following multipliers:

$$\mathbf{c}_t + \mathbf{f}_t = \widehat{\mathbf{F}}^{c,f} \mathbf{f}_t \,, \tag{33}$$

where

$$\widehat{\mathbf{F}}^{c} \equiv \left[(\eta - 1)\iota \boldsymbol{\Omega}_c' - \eta \mathbf{I}\right] \widehat{\mathbf{F}}^{pce} \,, \tag{34}$$

$$\widehat{\mathbf{F}}^{c,f} \equiv \mathbf{I} + \widehat{\mathbf{F}}^{c} \,. \tag{35}$$

Aggregate consumption is then equal to:

$$c_t = \boldsymbol{\Omega}_c' \mathbf{c}_t + \boldsymbol{\Omega}_c' \mathbf{f}_t \,, \tag{36}$$

where $\boldsymbol{\Omega}_c' \mathbf{f}_t = 0$.

# 3 Identification

In this section, I introduce a framework to identify sectoral supply and demand shocks. I first motivate the identification strategy using simple, stylized examples and then present the more structural clustering approach and its results that deliver the final set of identification restrictions.

## 3.1 Sector-shock rankings in example economies

Take a generic three-sector economy, described by the following quantities:

$$\boldsymbol{\Omega} = \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.4 & 0.5 & 0.1 \\ 0.2 & 0.7 & 0.1 \end{bmatrix} \quad , \quad \boldsymbol{\Omega}_c' = \begin{bmatrix} 0.2 & 0.3 & 0.5 \end{bmatrix} \,, \tag{37}$$

where $\boldsymbol{\Omega}$ is the I-O coefficient matrix and $\boldsymbol{\Omega}_c$ the vector of consumption shares. I further assume, for sake of simplicity, that the inverse-Frisch elasticity is zero ($\varphi = 0$) and that the bridge matrix, $\mathbf{K}$, is the identity matrix.[10] Moreover, I consider only sectoral supply shocks, $a_{jt}$, in this example. The solution of sectoral intermediate and PCE prices, as implied by the results of the previous section, are then equal to:

$$\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im} \mathbf{a}_t \,, \tag{38}$$

$$\mathbf{p}_t^{pce} = -\widehat{\mathbf{X}}^{pce} \mathbf{a}_t \,, \tag{39}$$

with the multiplier matrices given by:

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \boldsymbol{\Lambda}^{im})\boldsymbol{\Omega}\right]^{-1} (\mathbf{I} - \boldsymbol{\Lambda}^{im}) \,, \tag{40}$$

[10] A bridge matrix, $\mathbf{K}$, that is the identity matrix implies that every final goods firm produces its final (PCE) good using one intermediate good exclusively.

$$\widehat{\mathbf{X}}^{pce} \equiv (\mathbf{I} - \mathbf{\Lambda}^{pce})\widehat{\mathbf{X}}^{im}\,. \tag{41}$$

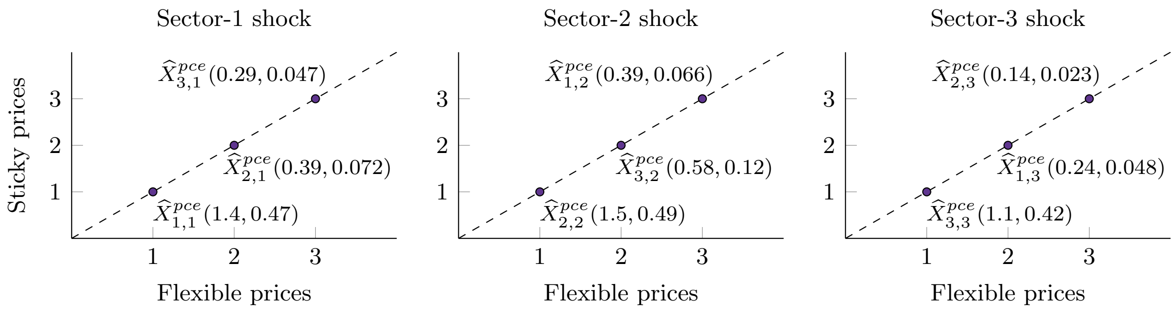
In response to sector-specific shocks, the multiplier matrix, $\widehat{\mathbf{X}}^{pce}$, contains the relevant price responses of PCE categories in the corresponding columns. For instance, a positive sector-2 shock would imply that $a_{2t} > 0$ and $a_{1t} = a_{3t} = 0$. The relevant price responses are then contained in the second column of $\widehat{\mathbf{X}}^{pce}$. Ranking these responses indicates which PCE category responds most strongly to the sector-2 supply shock. In the following, I show that these sector rankings are fairly robust across model specifications.

Figure 1 illustrates the robustness of sector rankings across a few different cases: I compare the values of $\widehat{\mathbf{X}}^{pce}$ under fully flexible prices with three differing calibrations regarding sticky prices. Panel 1a contrasts the economy with flexible prices to one with *homogeneous* PCE and intermediate price rigidity. Fully flexible prices are equivalent to setting $\mathbf{\Lambda}^{pce} = \mathbf{\Lambda}^{im} = \mathbf{0}$, whereas homogeneous PCE and intermediate price rigidity imply that the diagonal elements of $\mathbf{\Lambda}^{pce}$ and $\mathbf{\Lambda}^{im}$ are equal to constants $\lambda^{pce}, \lambda^{im} \in (0, 1)$, respectively. Here, I set the average price duration for all prices equal to one month, which implies frequencies of $\lambda^{pce} = \lambda^{im} = 1 - (1 - \exp(-1/1) = 0.37$. Despite the introduction of price stickiness, all rankings are exactly the same as under flexible prices. The reason is that homogeneous price rigidity scales the multiplier matrices $\widehat{\mathbf{X}}^{im}$ and $\widehat{\mathbf{X}}^{pce}$ by a constant factor but leaves the sector rankings unchanged in this example. The numbers in parentheses in Figure 1 refer to the actual multiplier values for the flexible and sticky price economies, respectively. While rankings stay the same, the introduction of sticky prices leads to overall smaller multipliers. This is consistent with the notion that price stickiness reduces the pass-through of economic shocks.

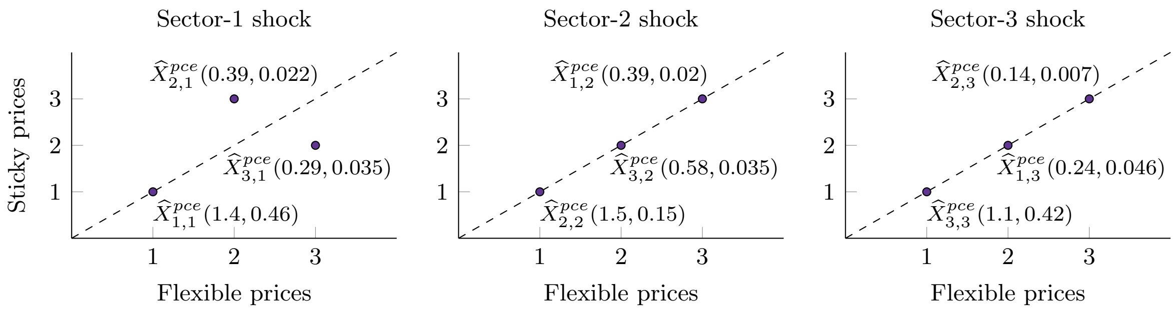
The second calibration, shown in Panel 1b, introduces *heterogeneity* in price stickiness. Here, I assume that the second intermediate good sector has more rigid prices than all other prices by setting the average duration to 4 months, which implies $\lambda_2^{im} = 0.78$. In this case, sectoral rankings change for a sector-1 shock but only at ranks 2 and 3. Increasing the degree of stickiness for sector 2's intermediate prices switches the relative importance of sectors 2 and 3 as downstream customers for sector 1's materials. Under flexible (and homogeneously sticky) prices, sector 2 responds relatively more strongly than sector 3 to supply shocks originating in sector 1. The reason is that sector 1 is a more important direct input supplier for sector 2 than for sector 3, as $\omega_{1,2} > \omega_{1,3}$. This also translates, in absence of heterogeneous price rigidities, to overall larger responses in sector 2 compared to 3, given all direct and indirect network effects. Increasing the frequency of price changes in sector 2 then switches the importance of sectors 2 and 3 as downstream customers of sector 1. Sector 2's prices now change less than those in sector 3, whose prices are more flexible. Even though the ranking of sector 1 changes at ranks 2 and 3, the first rank is not affected. The largest response to a sector-1 shock is observed in sector 1 itself, across both calibrations. Furthermore, note that the remaining rankings for shocks originating in sectors 2 and 3 remain unchanged across the two calibrations.

Finally, Panel 1c introduces an additional layer of heterogeneity by increasing the average price duration for sector 3's PCE prices to 6 months, i.e., $\lambda_3^{pce} = 0.85$. Compared to the previous example, the introduction of additional price rigidity for sector 3's PCE prices balances out the higher rigidity of sector 2's intermediate prices and leads to an overall ranking for sector-1

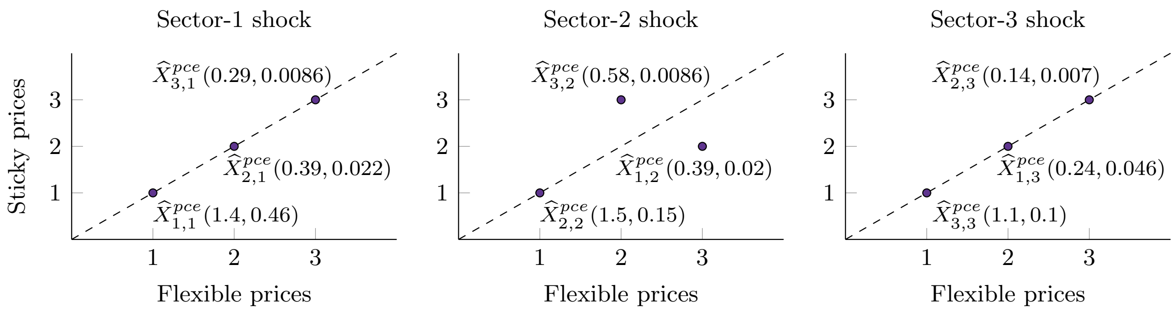
Figure 1: Sectoral supply shocks in example economies — flexible versus sticky prices




(a) Homogeneous price rigidity: $\lambda^{im} = [0.37, 0.37, 0.37]$, $\lambda^{pce} = [0.37, 0.37, 0.37]$




(b) Heterogeneous intermediate price rigidity: $\lambda^{im} = [0.37, \mathbf{0.78}, 0.37]$, $\lambda^{pce} = [0.37, 0.37, 0.37]$




(c) Heterogeneous intermediate & PCE price rigidity: $\lambda^{im} = [0.37, \mathbf{0.78}, 0.37]$, $\lambda^{pce} = [0.37, 0.37, \mathbf{0.85}]$

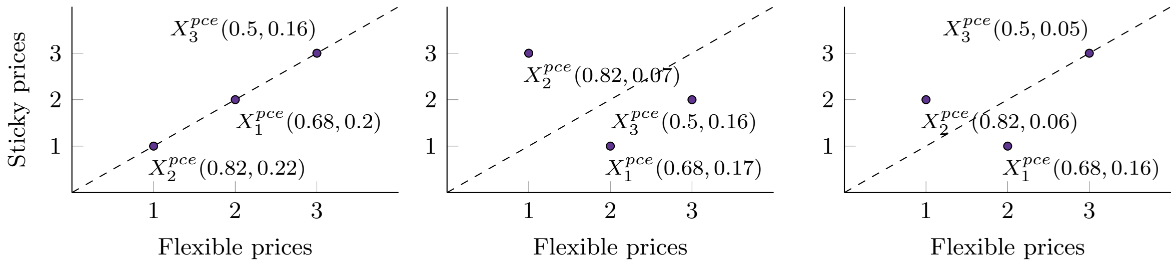
*Notes*: The figure plots sector-shock rankings against two different models. Multiplier matrices are based on the example economy described by equation (37). Numbers in parentheses are the actual values of the multiplier matrix $\widehat{\mathbf{X}}^{pce}$. The first number corresponds to the value for the flexible-price economy and the second to the respective sticky-price economy.

shocks that is the same as for the flexible economy.

However, the ranking for a sector-2 shock changes between calibrations. The newly introduced stickiness of sector 3's prices makes sector 3 respond less to sector-2 shocks than in sector 1, which has more flexible prices than sector 3, even though sector 2 is a larger input provider for sector 3 than sector 1, as $\omega_{3,2} > \omega_{3,1}$. Crucially, the introduction of heterogeneity only affects ranks 2 and 3 and not the highest rank: sector 2 has the largest response to sector-2 shocks for all calibrations.

Figure 2 summarizes the effects of the three calibration exercises on the sectoral contributions to aggregate price responses. The figure ranks the relative importance of the three sectoral shocks for aggregate prices. Similarly to the sector rankings, homogeneous price rigidity, shown in Panel 2a, has the same ranking as an economy with flexible prices. In my example setup,

Figure 2: Aggregate contributions of sectoral supply shocks — flexible versus sticky prices




(a) $\lambda^{im}, \lambda^{pce} = [0.37, 0.37, 0.37]$ (b) $\lambda_2^{im} = \mathbf{0.78}$ (c) $\lambda_2^{im} = \mathbf{0.78}, \lambda_3^{pce} = \mathbf{0.85}$

*Notes*: The figure plots sector-shock rankings against two different models. Multiplier matrices are based on the example economy described by equation (37). Numbers in parentheses are the actual values of the multiplier matrix $\mathbf{X}^{pce}$. The first number corresponds to the value for the flexible-price economy and the second to the respective sticky-price economy.

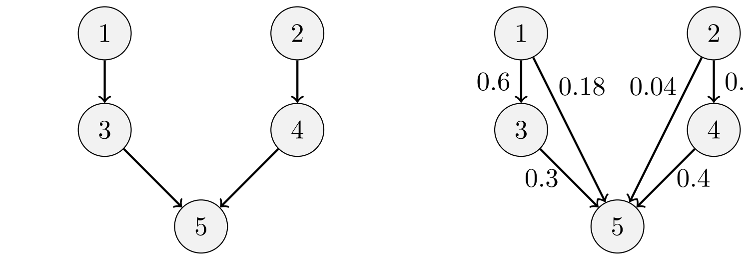
shocks to sector 2 have a larger impact on aggregate prices than sector 1 and sector 3. The introduction of heterogeneity in price rigidity, shown in Panels 2b and 2c, has more severe implications for aggregate contributions than for the sector rankings. In Panel 2b, the now stickier intermediate prices in sector 2 mute the importance of sector-2 shocks on aggregate prices and thereby move sector-2 shock contributions from the first to the last rank. Similarly, in Panel 2c the introduction of stickier PCE prices in sector 3 reduces the contribution of sector-3 shocks and switches the ranking again. This example illustrates that identification of sectoral shocks is robust at sectoral level but not necessarily with regard to the contribution of sectoral shocks to aggregate prices (and quantities equivalently).

## 3.2 Sectoral versus aggregate shocks

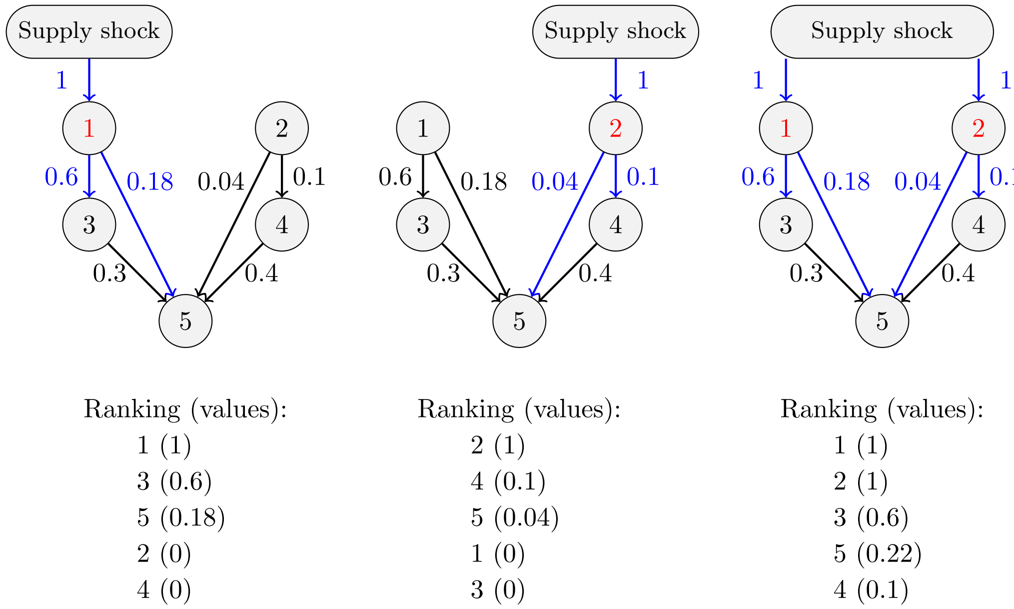
Figure 3 presents a stylized example on how sectoral and aggregate shocks have different propagation patterns. The setup is described in Panel 3a: a generic sector 1 sells to sector 3, sector 2 sells to sector 4, and both sector 3 and 4 sell to sector 5. Panel 3b then illustrates a solution to a model, similar to for instance the one presented in Section 2. Any such solution implies that connections between sectors are weighted and that, due to network effects, there can be indirect connections between sectors that are not directly connected. For instance, the additional edge from sector 1 to 5 captures that sector 1 can have an indirect effect on 5 via its connection to 3 and 3's connection to 5.

Next, let us consider the effects of three supply shocks. The left-side figure of Panel 3c shows a supply shock originating in sector 1. Given the heterogeneous connections between sectors, a sector-1 shock has the largest impact in sector 1. The second-most affected sector is 3, followed by sector 5. In this example, a sector-1 shock has, in absence of any relevant network connections, no effect on sector 2 or 4. The overall cross-sectional propagation pattern is summarized in the ranking below. The middle figure of Panel 3c considers the cross-sectional ranking in response to a sector-2 shock. Comparing this ranking from high to low (2, 4, 5, 1, 3) with that of a sector-1 shock (1, 3, 5, 2, 4) reveals an entirely different propagation pattern. Due to the heterogeneity in network linkages and the implied heterogeneity in cross-sectional rankings, it is possible to separate a sector-1 from a sector-2 shock. Finally, the right-hand

Figure 3: Stylized identification example: 3 shocks, 3 rankings




(a) Example economy (b) Stylized model solution




(c) Different shocks imply different rankings

*Notes*: This is a stylized example illustrating how different shocks, sectoral or aggregate, generally imply different sector rankings. Panel 3a first sketches a network structure of the example economy and Panel 3b sketches a stylized model solution capturing both direct and indirect network effects. The three figures in Panel 3c illustrate three different shocks and their respective cross-sectional rankings of sectoral responses: first, a shock originating in sector 1, second, a shock in sector 2, and third, a combination of sector-1 and sector-2 shocks (as an example for a sort of aggregate shock). All shocks imply different rankings, which illustrates the idea behind the identification strategy in this paper.

figure in Panel 3c illustrates a combination of a sector-1 and sector-2 shock. The underlying idea is that aggregate shocks can be considered as a combination of sectoral shocks. The implied cross-sectional ranking (1, 2, 3, 5, 4) is yet again different to the previous two cases. Intuitively, by mixing shocks 1 and 2, this joint shock generates its own distinct propagation pattern.

In contrast to this stylized example, these differences in rankings are even more pronounced in larger economies with more network connections. In the empirical model later on, I do not explicitly identify aggregate shocks. But my identification, which is based on sector rankings, ensures that sector-specific shocks are not only disentangled from another, but are also not conflated with aggregate shocks. De Graeve and Schneider (2023) show that imposing sector rankings on impulse responses is indeed a powerful identification tool that disentangles sectoral from aggregate shocks.

### 3.3 Theory calibration

Deriving the five supply-side specifications in equation (19) and two demand-side specifications in equation (30) requires calibration with I-O data and other model parameters.

The input-share matrix, $\mathbf{\Omega}$, is derived from make and use tables of the Bureau of Economic Analysis's (BEA) I-O accounts for the United States at NAICS classification. I use annual I-O data for the years 1997 to 2022 to derive $\mathbf{\Omega}$, consumption weight vector, $\mathbf{\Omega}_c$, and NAICS-PCE bridge matrix, $\mathbf{K}$. I compile these matrices for 33 NAICS industries and 72 PCE categories, respectively. Appendix F.1 presents the derivation of the input-share matrix, $\mathbf{\Omega}$, and Appendix F.2 the derivation of the bridge matrix, $\mathbf{K}$.

Estimates for monthly frequencies of producer price changes are based on Pastén, Schoenle, and Weber (2020). Finally, frequencies of price changes for PCE categories are based on estimates by Nakamura and Steinsson (2008). Their original estimates on frequencies and durations of price changes are for 1998–2005 and available for Entry Line Items (ELI). I use the Bureau of Labor Statistics' (BLS) concordance tables to transform ELIs to PCE categories. Appendix F.5 provides more details on the procedure.

The following model parameters appear in equations (19) and (30) and therefore require calibration: I set the elasticity of substitution across sectors/categories, $\eta = 0.5$.[11] As in Pastén, Schoenle, and Weber (2024), the elasticity of substitution within sectors/categories is set to $\theta = 6$. The intermediate input share in production, $\delta$, depends on the respective I-O data used for calibration. For every annual I-O calibration, I derive the share of intermediate use in gross output, $\psi$, which is used in turn to calibrate $\delta = \psi \frac{\theta}{\theta - 1}$.

### 3.4 Clustering

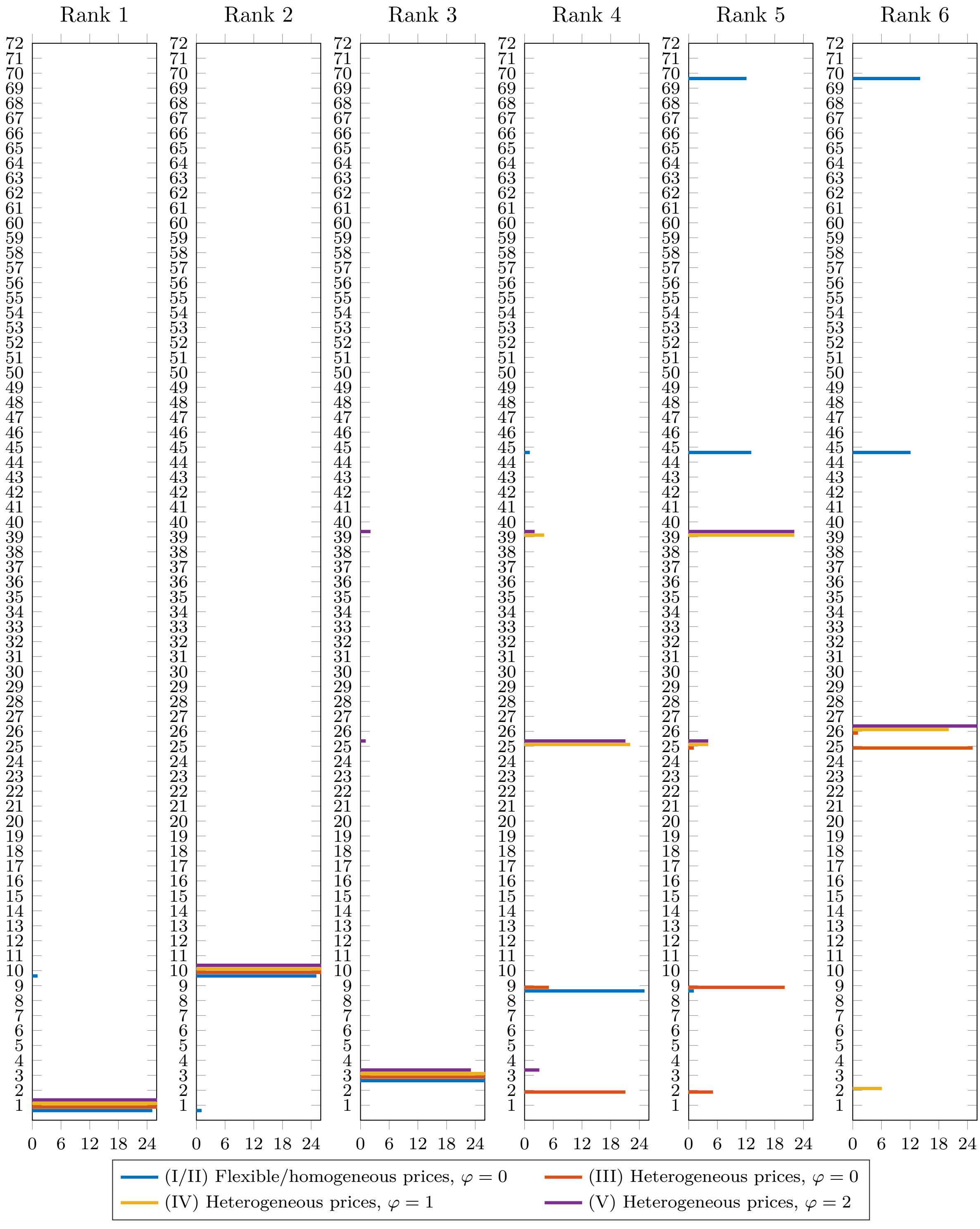
The goal of this section is to derive robust identification restrictions based on the model specifications and calibration presented earlier. As a first step, I remove homogeneous price stickiness models, as motivated by the exercise presented in Figure 1. Homogeneous price stickiness and flexible prices lead to the same sector rankings and therefore imply the same identification assumptions. Considering supply shocks, I hence use the remaining specifications (I, III, IV, V) in a clustering exercise.

I calibrate every specification with annual I-O data from 1997 to 2022. This yields 26 calibrations per specification and hence 104 versions of $\widehat{\mathbf{X}}^{pce}$ in total. Similarly, I use the two specifications (IV, V) for demand shocks, amounting to 52 total versions of $\widehat{\mathbf{F}}^{pce}$. The goal of clustering is to find robust features in $\widehat{\mathbf{X}}^{pce}$ ($\widehat{\mathbf{F}}^{pce}$) across its 104 (52) variations. I define matrices $\widehat{\mathbf{X}}_r^{pce}$ and $\widehat{\mathbf{F}}_r^{pce}$ that rank the columns of multiplier matrices $\widehat{\mathbf{X}}^{pce}$ and $\widehat{\mathbf{F}}^{pce}$, respectively.

The intuition behind clustering is illustrated in Figures 4 and 5. In these, I visualize two examples of sectoral supply shocks and their cross-sectional rankings across all model specifications and I-O calibrations. The bars summarize how often the multipliers for the 72 PCE category appear at rank 1 through 6 across the 26 calibrations of the respective specification. Figure 4 shows rankings for a supply shock originating in *Transportation equipment*. At rank 1, the bar chart indicates that PCE category 1, *New motor vehicles*, is the one with the largest

[11] I use an alternative calibration with $\eta = 1$ that yields almost exactly the same composition of clusters that I use for identification of sectoral shocks. There are only minor differences for a small number of shocks.

Figure 4: Rankings for *Transportation equipment* supply shocks

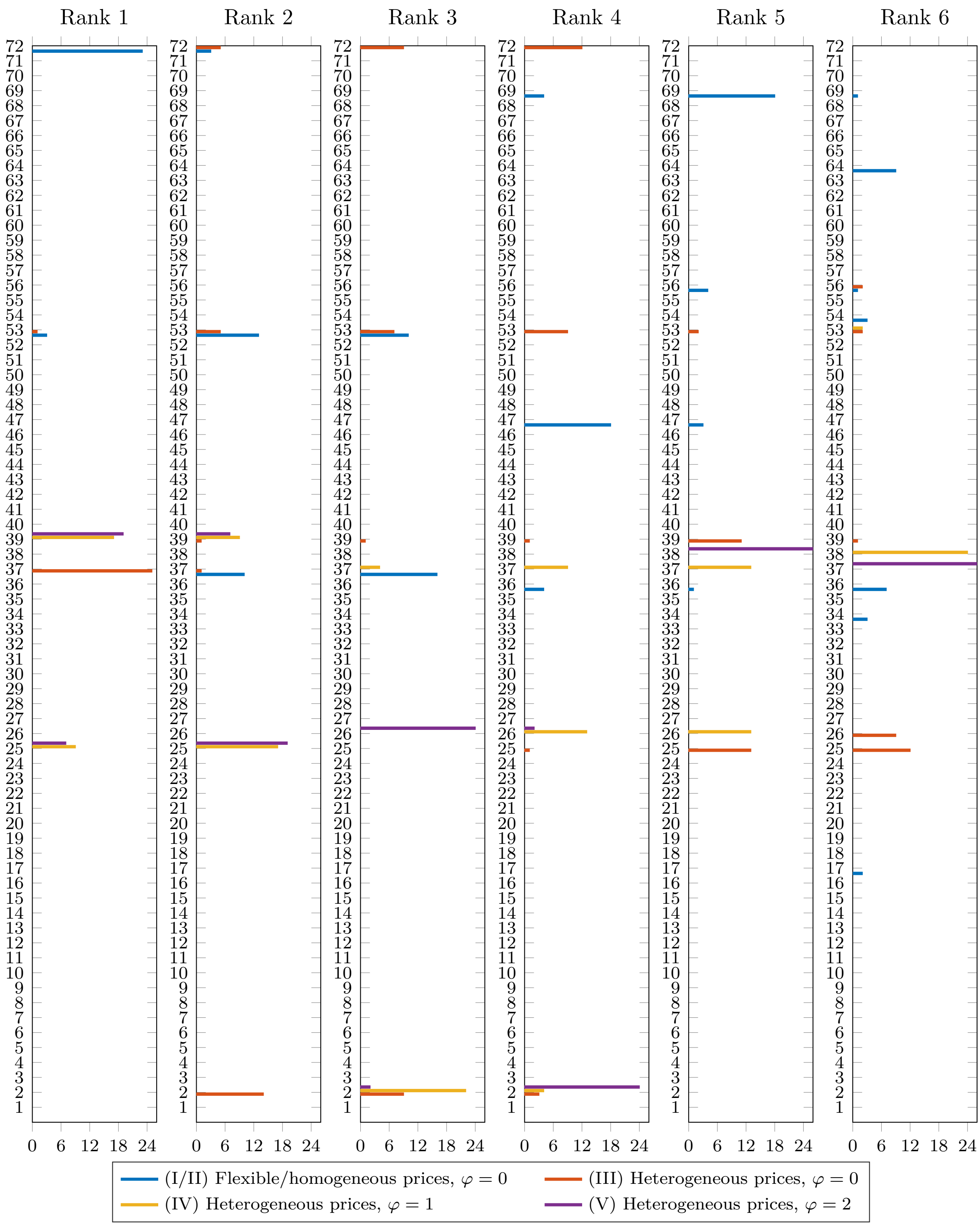



*Notes*: This figure summarizes the first six rankings for the sector-specific supply shock that originates in the given sector. The four models correspond, in this order, to specifications (I/II), (III), (IV), and (V). For every specification, I consider 26 calibrations based on input-output tables for the years 1997 to 2022. The bars summarize for the respective specification how often the multipliers for the 72 personal consumption expenditure category appears at rank 1 through 6 across the 26 calibrations.

price responses across almost all calibrations and specifications.[12] At second rank, and in al-

[12]See Appendix Table A.7 for PCE indices used in this paper and their respective PCE category names.

Figure 5: Rankings for *Management, administrative and waste services* supply shocks




*Notes*: See notes to Figure 4.

most all cases, PCE category 10, *Sports and recreational vehicles*, exhibits the next largest price responses. A sectoral supply shock originating in the *Transportation equipment* sector is hence fairly easy to cluster. A first cluster containing PCE category 1 responds more than a second cluster, composed of PCE category 10, which in turn responds more than a third cluster with all remaining 70 PCE categories. Such a cluster composition is consistent with around 99 percent of all model specifications and calibrations.

Next, Figure 5 illustrates a counter-example to the previous case. Supply shocks originating in *Management, administrative and waste services* do not exhibit a straightforward cluster structure that holds across model specifications and calibrations. Already at ranks 1 and 2, different models favor different PCE categories, which makes it challenging to compile a model-robust cluster composition. I therefore label these types of shocks as *infeasible* and do not identify them in the empirical model henceforth. Shocks with a cluster structure similar to the first two examples are instead labeled as *feasible* shocks.[13]

To determine *feasibility* for all sector shocks, I use a variety of standard clustering algorithms. Every algorithm is initialized to deliver three clusters for the given shock. Recall, to identify a sector-specific shock, the corresponding column of $\widehat{\mathbf{X}}^{pce}$ or $\widehat{\mathbf{F}}^{pce}$ can be ranked to derive the relative price (and similarly consumption) responses to the shock. I apply a range of clustering algorithms, each with numerous calibrations.[14] I then check how often a ranking is consistent with a cluster and select the clustering method with the highest match rate. In other words, I inspect in how many cases the sector ranking is embedded within the cluster. I find 33 potential sector-specific supply shocks and 72 sectoral demand shocks in my sample. Instead of identifying sectoral demand shocks for all 72 individual categories, I aggregate to 15 broader composite categories and consider sectoral-demand shocks for those.

These examples highlight a need for a more formal criterion that sorts sectoral shocks into *feasible* and *infeasible* categories: if a cluster is consistent with more than 70 percent of its underlying model specifications and calibrations, and, crucially, the cluster composition includes a combination of unique PCE categories, I label the identified shock as *feasible* for identification. All 15 demand shocks exceed this 70 percent threshold, while less than half of the sectoral supply shocks do. This is not surprising as the cluster for supply shocks needs to match a fairly wide range of specifications, across (I) to (V). I hence also consider clustering exercises using narrower sets of model specifications. In a second set, I remove specification (I) (and II) and only cluster across specifications (III) to (V), i.e., I only use models with heterogeneity in price stickiness. Similarly, in an even tighter set I only cluster across specifications (IV) and (V), which corresponds to the same set of model specifications used for the identification of demand shocks.

One further concern is that some PCE categories are ranked highly for several sector shocks. These sort of problematic categories include, for instance, *Motor vehicle fuels, lubricants, and fluids* and *Natural gas*. Cluster compositions that consist of any of these categories in their first two clusters exclusively will be conflated with rankings corresponding to other shocks. I therefore check all clusters against these sets of problematic sectors and make sure that the final cluster composition includes other price categories that are unique compared to other shocks' clusters. If a sector cluster includes only problematic categories in the first cluster, I also label the shock as *infeasible*. Table 1 summarizes the final set of clusters that could be imposed as identification restrictions.

[13] Appendix G includes additional illustrations on PCE rankings.

[14] Appendix H presents the cluster evaluation in more detail.

Table 1: Cluster composition of feasible shocks

| Shock ($j$) | Origin sector | PCE categories $z$: Cluster 1 | Cluster 2 | Cluster 3 | Based on sets |
|---|---|---|---|---|---|
| | **Sectoral supply shocks: $\widehat{\mathbf{X}}_r^{pce}$** | | | | |
| (1) | Agriculture, forestry, fishing, and hunting | 20 | 18, 28, 31, 55 | Rest | (I)–(V) |
| (3) | Utilities | 38, 39 | 37 | Rest | (I)–(V) |
| (9) | Computer and electronic products | 8, 17 | Rest | 42 | (III)–(V) |
| (10) | Electrical equipment, appliance, and comp. | 5 | 1, 2, 3, 8, 25, 26, 30, 38, 39 | Rest | (IV)–(V) |
| (11) | Transportation equipment | 1 | 10 | Rest | (I)–(V) |
| (12) | Furniture and related products | 4 | 2, 25, 26, 38, 39 | Rest | (IV)–(V) |
| (13) | Miscellaneous manufacturing | 12 | 2, 9, 13, 14, 25, 26, 28, 38, 39 | Rest | (IV)–(V) |
| (14) | Food and beverage and tobacco products | 31 | 18, 19, 55 | Rest | (III)–(V) |
| (19) | Plastics and rubber products | 3 | 6 | Rest | (III)–(V) |
| (23) | Information | 63 | 15, 51 | Rest | (I)–(V) |
| (24) | Finance and insurance | 62 | 60 | Rest | (I)–(V) |
| (28) | Educational services | 68 | 66 | Rest | (III)–(V) |
| (30) | Arts, entertainment, and recreation | 50 | 25, 39, 52 | Rest | (IV)–(V) |
| (31) | Accommodation and food services | 56 | 36 | Rest | (I)–(V) |
| (32) | Other services, except government | 45 | 25, 39 | Rest | (IV)–(V) |

| Shock ($z$) | Origin (composite) category | PCE categories $z$: Cluster 1 | Cluster 2 | Cluster 3 | Based on sets |
|---|---|---|---|---|---|
| | **Sectoral demand shocks: $\widehat{\mathbf{F}}_r^{pce}$** | | | | |
| (1–3) | Motor vehicles and parts | 1, 2 | Rest | 38, 39 | (IV)–(V) |
| (4–7) | Furnishings and durable household equip. | 2 | Rest | 38, 39, 56 | (IV)–(V) |
| (8–12) | Recreational goods and vehicles | 2 | 1 | Rest | (IV)–(V) |
| (13–17) | Other durable goods | 2 | Rest | 38, 39, 56 | (IV)–(V) |
| (18–20) | Food and beverages purchased for off-premises consumption | 2, 31 | 18, 20, 55 | Rest | (IV)–(V) |
| (21–24) | Clothing and footwear | 2 | Rest | 38, 39, 56 | (IV)–(V) |
| (25, 26) | Gasoline and other energy goods | 25 | 26 | Rest | (IV)–(V) |
| (27–32) | Other nondurable goods | 2 | Rest | 38, 39, 56 | (IV)–(V) |
| (33–39) | Housing and utilities | 39 | 38 | Rest | (IV)–(V) |
| (54–56) | Food services and accommodations | 56 | 36, 54 | Rest | (IV)–(V) |
| (57–62) | Financial services and insurance | 60, 62 | 57, 58, 59, 61 | Rest | (IV)–(V) |

*Notes*: The table shows the final set of *feasible* sectoral supply and demand shocks that could be used for identification. Note that for supply-shock rankings, $\widehat{\mathbf{X}}_r^{pce}$, the *Shock* index refers to sector $j$ of 33; whereas for demand-shock rankings, $\widehat{\mathbf{F}}_r^{pce}$, the index corresponds to the 72 composite personal consumption expenditure (PCE) categories. In the cluster columns, indices always refer to PCE categories, $z$. The last column indicates the largest possible set of model specifications that is robust to the clustering. The algorithm to dertmine feasibilitiy and cluster compositions is further explained in Appendix H.

# 4 Empirical model

Given the set of *feasible* sector clusters, derived in the previous section, this section presents the empirical model I use to identify sectoral supply and demand shocks. I first sketch the reduced-form model and then focus on the implementation of the identification strategy.

## 4.1 The reduced-form factor-augmented VAR

The estimation of sectoral shocks is based on a reduced-form Bayesian FAVAR model that is similar to the one we use in De Graeve and Schneider (2023):

$$x_t = \lambda^x f_t^x + \lambda^y y_t + \epsilon_t \qquad \text{with } \epsilon_t \sim \mathcal{N}(0, R_\epsilon)\,, \tag{42}$$

$$\begin{pmatrix} f_t^x \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \phi_p \begin{pmatrix} f_{t-p}^x \\ y_{t-p} \end{pmatrix} + u_t \qquad \text{with } u_t \sim \mathcal{N}(0, Q_u)\,, \tag{43}$$

where $y_t$ is an $M$-by-1 vector of observable factors.[15]

As in De Graeve and Schneider (ibid.), I estimate a separate model (42)-(43) for every *feasible* sector-specific shock. Across these different estimations, the composition of $y_t$ changes depending on the sector-specific cluster composition, introduced in the previous section. All sectoral PCE consumption growth and sectoral inflation rates that are included in the first cluster are treated as observable factors. For example, if for a given sector-specific supply shock the first cluster is composed of PCE category $z$, then both $c_z$ and $p_z$ are treated as observable factors. Other than for sectoral supply shocks, the identification of sectoral demand shocks does not require that the respective first cluster of consumption and price variables is the same. For demand shocks, I just treat sectoral price variables included in the first cluster as observable factors.[16] The $N_x$-by-1-vector $x_t$ on the left-hand side includes aggregate PCE consumption growth and inflation rates, as well as all sectoral consumption growth and inflation rates other than those sectoral variables used as observable factors. I extract the unobservable factors, $f_t^x$, by means of the first $K$ principle components of $x_t$. Factor loadings, $\lambda^x$ and $\lambda^y$, correspond to those unobservable and observable factors, respectively.

The VAR process described by equation 43 has parameters $\phi_p$ with $P$ numbers of lags. Reduced-form shocks, $u_t$, are associated with the variance-covariance matrix, $Q_u$, and the measurement errors, $\epsilon_t$, with the diagonal variance matrix, $R_\epsilon$. The model (42) and (43) can be expressed more compactly in companion form:

$$X_t = \Lambda F_t + E_t\,, \tag{44}$$

$$F_t = \Phi F_{t-1} + U_t\,, \tag{45}$$

[15] That model is in turn based on Bernanke, Boivin, and Eliasz (2005); Boivin, Giannoni, and Mihov (2009) and Stock and Watson (2016).

[16] Including all consumption growth rates in addition to price variables would lead to a large total number of factors, which may affect the estimation. Appendix Table A.6 provides an overview of the categories included in the relevant clusters of sectoral demand shocks.

where

$$X_t \equiv (x_t', y_t')' \,, \tag{46}$$
$$f_t \equiv (f_t^{x'}, y_t')' \,, \tag{47}$$
$$\lambda \equiv \begin{bmatrix} \lambda^x & \lambda^y \\ \mathbf{0}_{M\times K} & \mathbf{I}_M \end{bmatrix} \,, \tag{48}$$
$$F_t \equiv \left(f_t', f_{t-1}', \ldots, f_{t-P+1}'\right)' \,, \tag{49}$$
$$E_t \equiv \left(\epsilon_t', \mathbf{0}_{M\times 1}'\right)' \,, \tag{50}$$
$$U_t \equiv \left(u_t', \mathbf{0}_{(K+M)(P-1)\times 1}\right)' \,, \tag{51}$$
$$\Phi \equiv \begin{bmatrix} \phi_1 & \cdots & \phi_P \\ \mathbf{I}_{KM(P-1)} & & \mathbf{0}_{KM(P-1)\times KM} \end{bmatrix} \,, \tag{52}$$
$$\Lambda \equiv \left[\lambda \; \mathbf{0}_{(N_x+M)\times(K+M)(P-1)}\right] \,. \tag{53}$$

I estimate the model using the two-step estimation procedure introduced by Bernanke, Boivin, and Eliasz (2005).[17] In the first step, principle components are used to estimate the unobserved factors. I ensure that the unobserved factors do not capture dynamics induced by the observed factor by following Boivin, Giannoni, and Mihov (2009). In the second step, the factors are expressed in a reduced-form VAR with priors on parameters chosen as in Koop and Korobilis (2009).

The identification scheme, presented next, is implemented using the algorithm of Rubio-Ramírez, Waggoner, and Zha (2010).

## 4.2 Structural identification using cross-sectional restrictions

The identification setup builds on De Graeve and Schneider (2023) and extends it with regard to identification based on quantities *and prices*. I implement the sector-shock clusters derived in previous sections as heterogeneity restrictions in the reduced-form FAVAR models to identify structural shocks. Identification is based on comparing contemporaneous impulse responses.[18] These are defined in the following way:

$$r_a^{(f)} = \mathbf{a} \,, \tag{54}$$
$$r_a^{(X)} = \lambda r_a^{(f)} \,, \tag{55}$$

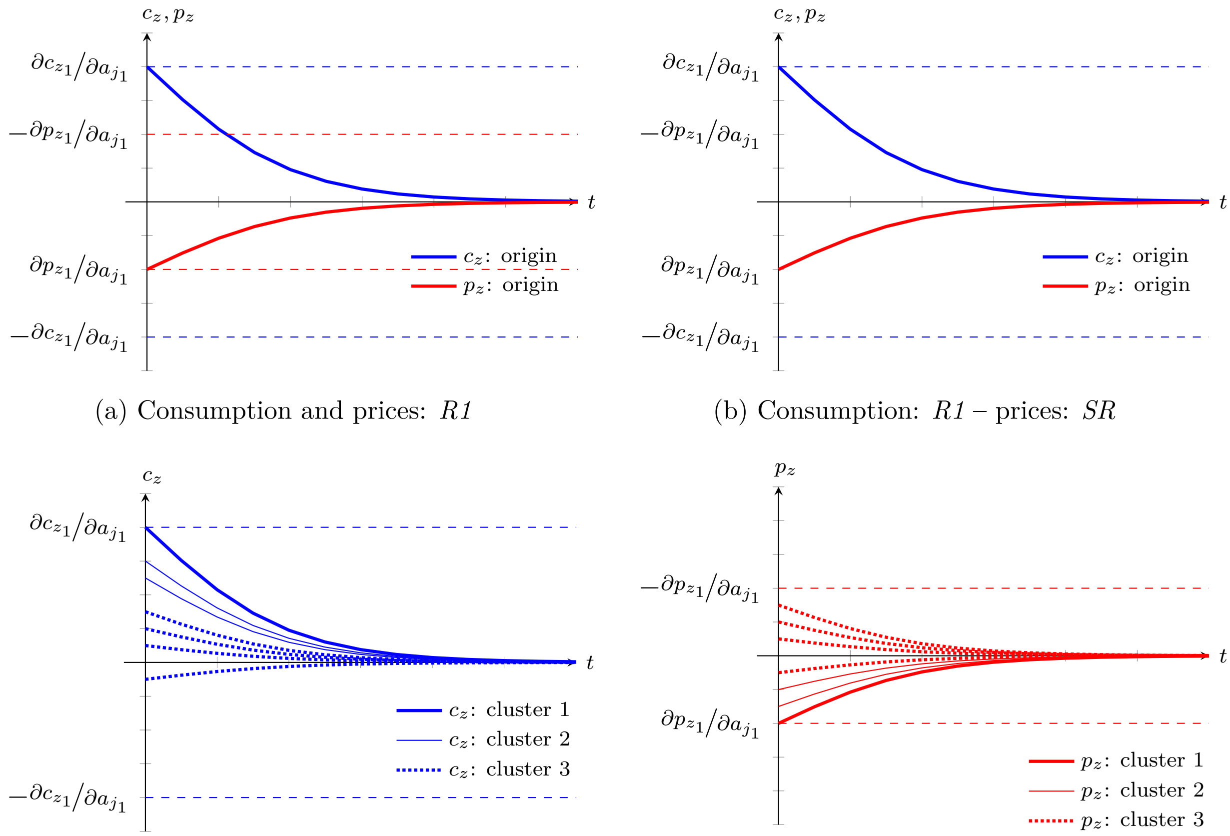
where $\mathbf{a} \in R^{K+M}$ is an impulse vector that I check against the restrictions. Impulse response vector, $r_a^{(X)}$, is derived using the factors' impulse responses, $r_a^{(f)}$. I map the latter to the former via the factor loadings, $\lambda$.

If the resulting impulse response complies with the restrictions, I retain the identified draw. The identification restrictions depend on the type of variable. For instance, to impose restrictions on sectoral prices, I therefore use a subset of impulse vector, $r_a^{(X)}$, that only includes sectoral prices. I denote this subset of impulse response as $\hat{r}_a^{(X)}$, which, depending on the con-

[17] See Appendix I.

[18] I require only that heterogeneity restrictions hold on impact and do not restrict later horizons.

Figure 6: Identification of (positive) sectoral supply shocks




(a) Consumption and prices: *R1*

(b) Consumption: *R1* – prices: *SR*

(c) Consumption: *R2*

(d) Prices: *R2*

*Notes*: This illustration shows stylized sectoral impulse response functions of sectoral inflation and consumption growth rates in response to a positive supply shock originating in a generic sector 1. Panels 6a and 6b present restrictions that relate variables of sectors included in the first cluster against all remaining clusters (*R1* restrictions), whereas Panels 6c and 6d illustrate restrictions that compare adjacent clusters (*R2* restrictions). Here, it is assumed that the first cluster assigned to the shock includes only one PCE category. The dashed lines refer to a corridor imposed by *R1* restrictions. *SR* refers to identification using only sign restrictions.

text, refers to impulse responses of either sectoral inflation or consumption growth rates. For a given vector $\hat{r}_a^{(X)}$, I compare the sector elements against the restrictions, i.e., $\hat{r}_a^{(X)}(i)$, for all $i = 1, \ldots, N$.

For every sector specific shock, $j$, I define a *strict* ranking, $\gamma_j$, as:[19]

$$\gamma_j = (\gamma_{1j}, \gamma_{2j}, \ldots, \gamma_{Nj})' \;, \tag{56}$$

where $\gamma_j$ corresponds to the respective column of ranked multiplier matrices, $\widehat{\mathbf{X}}_r^{pce}$ or $\widehat{\mathbf{F}}_r^{pce}$. In addition, a *cluster* ranking, $\Gamma_j$, is defined as:

$$\Gamma_j \equiv (\Gamma_{1j}, \Gamma_{2j}, \ldots, \Gamma_{Gj})' \;, \tag{57}$$

where $G = 3$ is the total number of imposed clusters. The individual clusters $\Gamma_{gj}$ for shock $j$

[19]Note that in this notation I use index $j$ for a generic shock, which could be either a sectoral supply or a sectoral demand shock.

are composed of the strict rankings $\gamma_j$, such that:

$$\Gamma_{1j} \equiv (\gamma_{1j}, \ldots, \gamma_{l_1,j}) \,,$$
$$\Gamma_{2j} \equiv (\gamma_{2j}, \ldots, \gamma_{l_2,j}) \,,$$
$$\vdots$$
$$\Gamma_{Gj} \equiv \left(\gamma_{(l_{(G-1)}+1),j}, \ldots, \gamma_{l_G,j}\right) \,,$$

where $l_g$ is an index for the last sector included in cluster $g$.

Next, I define a few types of restrictions using strict and cluster rankings. I distinguish here between restrictions that relate variables of sectors included in the first cluster against all remaining clusters (*R1* restrictions) from restrictions that compare adjacent clusters (*R2* restrictions). Consider a sector shock that has multiple PCE categories in its first cluster: an *R1* restriction that requires a positive response of those variables is defined as:

$$min\left\{\hat{r}_a^{(X)}(\Gamma_{1j})\right\} > |\hat{r}_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_1+1, \ldots, N \,, \tag{58}$$

and equivalently for a negative response:[20]

$$max\left\{\hat{r}_a^{(X)}(\Gamma_{1j})\right\} < -|\hat{r}_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_1+1, \ldots, N \,. \tag{59}$$

Cluster restrictions of type *R2* are defined in the following way, for a positive response:

$$min\left\{\hat{r}_a^{(X)}(\Gamma_{gj})\right\} > max\left\{\hat{r}_a^{(X)}(\Gamma_{(g+1),j})\right\}, \quad \forall g = 2, \ldots, (G-1) \,, \tag{60}$$

and a negative response, such that:[21]

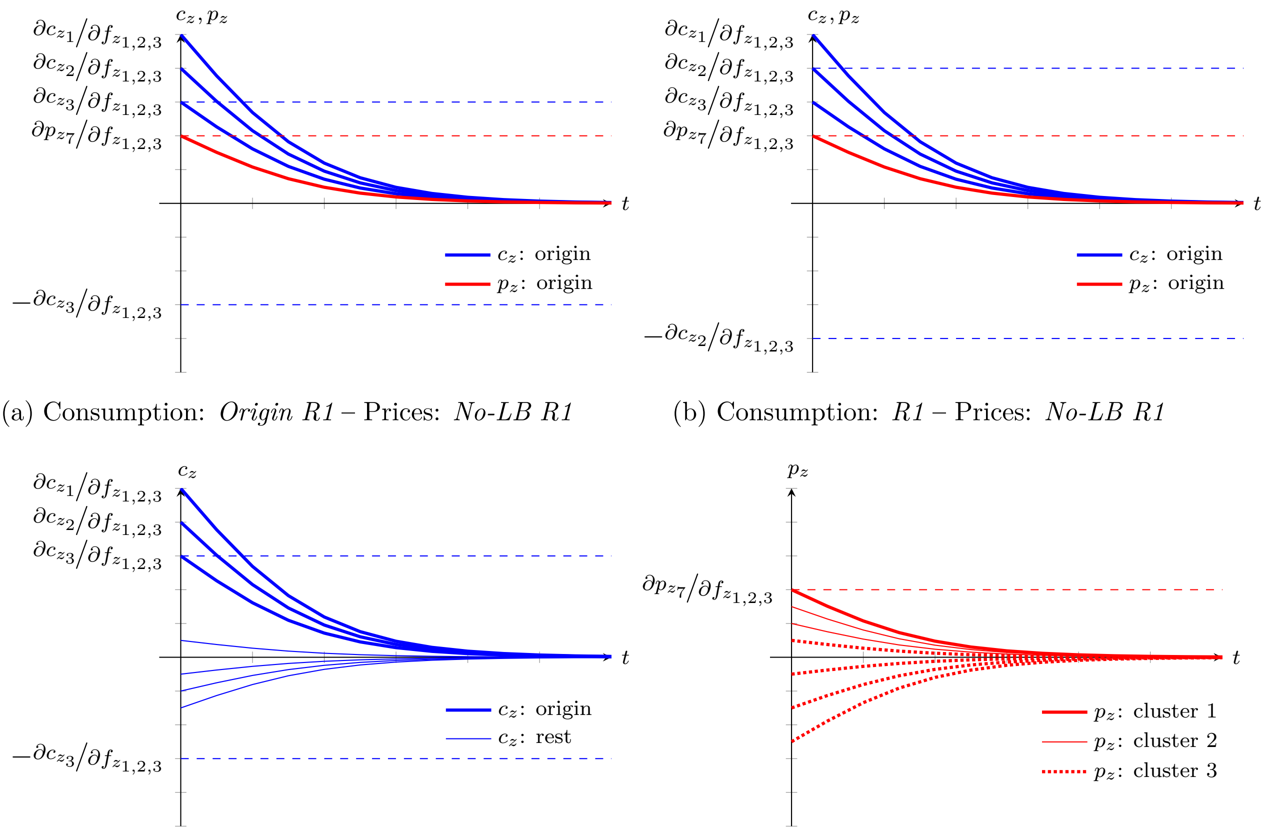
$$max\left\{\hat{r}_a^{(X)}(\Gamma_{gj})\right\} > min\left\{\hat{r}_a^{(X)}(\Gamma_{(g+1),j})\right\}, \quad \forall g = 2, \ldots, (G-1) \,. \tag{61}$$

Combining *R1* and *R2* restrictions for prices and quantities leads to a range of different identification schemes of varying levels of restrictiveness. Figure 6 summarizes those different approaches for a (positive) supply shock originating in a generic sector 1. Note that in these illustrations, I assume that the first cluster includes only one PCE category. Panels 6a and 6b illustrate two variations of *R1*-type restrictions. Panel 6a depicts an *R1* restriction on both price and quantity variables. The restriction requires that price and quantity in the first cluster need to have opposite signs and, furthermore, have the largest response among their respective variable type (in absolute terms). This last requirement is indicated by the two corridors (dashed lines). In Panel 6b, I illustrate a slightly weaker combination of restrictions. Here, it is only the quantity variable that adheres to an *R1* restriction. Price responses are simply using a sign restriction. Panels 6c and 6d illustrate *R2* restrictions for consumption and prices. Note that, as indicated in the lower panels, it is permitted for some sectoral responses to have the

[20] *R1*-restrictions for shocks with just a single PCE category in the first cluster are given by $\hat{r}_a^{(X)}(\gamma_{1j}) > |\hat{r}_a^{(X)}(\gamma_{ij})|$ (positive response) and $\hat{r}_a^{(X)}(\gamma_{1j}) < -|\hat{r}_a^{(X)}(\gamma_{ij})|$ (negative response), for all $i = 2, \ldots, N$.

[21] *R2*-restrictions for strict rankings are simply given by $\hat{r}_a^{(X)}(\gamma_{ij}) > \hat{r}_a^{(X)}(\gamma_{(i+1),j})$ (positive response) and $\hat{r}_a^{(X)}(\gamma_{ij}) < \hat{r}_a^{(X)}(\gamma_{(i+1),j})$ (negative response) for all $i = 2, \ldots, (N-1)$.

Figure 7: Identification of (positive) sectoral demand shocks




(a) Consumption: *Origin R1* – Prices: *No-LB R1*

(b) Consumption: *R1* – Prices: *No-LB R1*

(c) Consumption: *Origin R1* without an *R2*

(d) Prices: *R2* with *No-LB R1*

*Notes*: This illustration depicts different approaches to implement *R1*- and *R2*-type restrictions on sectoral inflation and consumption growth rates in response to a positive sectoral demand shock. The dashed corridors refer to the corridor imposed by *R1* restrictions. *No-LB* refers to *R1* restrictions without imposing a lower bound.

opposite sign compared to the sectoral responses in the first cluster, as long as these responses stay within the corridor set by the respective *R1* restrictions.

Next, I contrast identification of sectoral supply shocks with sectoral demand shocks. Sectoral demand shocks require a modified approach with regards to *R1*- and *R2*-type restrictions. First, I introduce an *origin R1* restriction. In this paper, I do not identify sectoral demand shocks for all 72 PCE categories individually, but for broader categories that are aggregated using a number of PCE categories. For instance, the first indexed sectoral demand shock relates to *Motor vehicles and parts*, which consists of three individual PCE categories (with indices 1, 2, 3). I label these categories as the *origin* categories. In this case, a positive demand shock requires that consumption growth in all three PCE categories increases. Since sectoral demand shocks change the composition of the consumption basket, all other PCE categories are subject to a negative direct demand effect. Depending on the network structure, some consumption responses may turn positive, but the majority of "other" responses stays negative. The *origin R1* captures this by stipulating that the least affected origin sector determines the *R1* corridor. All other quantity responses are restricted to stay within this corridor.

Formally, I define an *origin R1* restriction for a positive response as:

$$min\left\{r_a^{(X)}(\Gamma_j^{ori})\right\} > |r_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_{ori}+1,\ldots,N\,, \tag{62}$$

and for a negative response as:

$$max\left\{r_a^{(X)}(\Gamma_j^{ori})\right\} < -|r_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_{ori}+1,\ldots,N\,, \tag{63}$$

where $l_{ori}$ refers to the index of the last (ranked) origin sector. All ranks of origin sectors are included in $\Gamma_j^{ori}$.

Another modification is the *no-lower-bound R1* (*No-LB R1*) restriction, which is somewhat less restrictive than *origin R1* restrictions. This restriction does not impose a lower bound. In other words, it allows for some sectors that are not part of the first cluster to respond more than sectors in the first cluster in absolute terms. For a positive response, this is defined as:

$$min\left\{r_a^{(X)}(\Gamma_{1j})\right\} > r_a^{(X)}(\gamma_{ij}), \quad \forall i = l_1+1,\ldots,N\,, \tag{64}$$

and for a negative response as:

$$max\left\{r_a^{(X)}(\Gamma_{1j})\right\} < -r_a^{(X)}(\gamma_{ij}), \quad \forall i = l_1+1,\ldots,N\,. \tag{65}$$

Figure 7 illustrates these specific restrictions for sectoral demand shocks. Panel 7a presents an *origin R1* restriction for sectoral consumption, combined with a *no-lower-bound R1* restriction for prices. Panel 7b depicts a case where consumption responses, instead, follow a regular *R1* restriction. This could be useful in the following case. Some sectoral demand shocks include quite a large number of origin sectors. It may therefore be helpful to restrict responses of origin shocks to the most important ones. The consequence is that the *R1* corridor tends to be set wider because it is not defined by the least ranked origin sector. Panel 7c illustrates how an *origin R1* for consumption growth works without imposing an additional *R2*-type restriction. For demand shocks, I distinguish only between two clusters for consumption variables: origin sectors versus the rest. For prices, I still impose an *R2* restriction but in combination with a *no-lower-bound R1*. This is illustrated in Panel 7d.

I impose one final restriction for supply shocks exclusively: a sign restriction on aggregate inflation and consumption growth. This entails that in response to a positive sectoral supply shock, aggregate inflation decreases and aggregate consumption growth increases. This is supported by the analysis underlying the creation of sector rankings in earlier sections.[22] In contrast, I impose no such sign restriction for sectoral demand shocks. The illustrations in Figure 7 show that on the sectoral level, not all price and quantity responses follow the same sign. It is crucial, however, that a classical sign-restriction of supply and demand shocks holds on the sectoral level for origin and/or first-cluster variables: for these specific sectors, prices and consumption move in opposite directions for supply shocks and in the same direction for demand shocks.

[22] Appendix K provides robustness results, derived without imposing aggregate sign restrictions for sectoral supply shocks.

Table 2: Identification restrictions for feasible and successfully retrieved shocks

| Sectoral supply shocks: $\widehat{X}_r^{pce}$ | | | Sectoral demand shocks: $\widehat{F}_r^{pce}$ | | |
|---|---|---|---|---|---|
| $(j)$ | *R1* | *R2* | $(z)$ | *R1* | *R2* |
| (1) | *R1* $c_z$; *R1* $p_z$ | | (1–3) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (2) | Not feasible | | (4–7) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (3) | *R1* $c_z$; *R1* $p_z$ | | (8–12) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (4) | Not feasible | | (13–17) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (5) | Not feasible | | (18–20) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (6) | Not feasible | | (21–24) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (7) | Not feasible | | (25, 26) | *Origin R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (8) | Not feasible | | (27–32) | *R1* $c_z$; *No-LB R1* $p_z$ | *R2* $p_z$ |
| (9) | *R1* $c_z$; *R1* $p_z$ | | (33–39) | Feasible but not successful | |
| (10) | *R1* $c_z$; *R1* $p_z$ | | (40–44) | Not feasible | |
| (11) | *R1* $c_z$; *R1* $p_z$ | *R2* $c_z$; *R2* $p_z$ | (45–49) | Not feasible | |
| (12) | *R1* $c_z$; *R1* $p_z$ | | (50–53) | Not feasible | |
| (13) | *R1* $c_z$; *R1* $p_z$ | | (54–56) | Feasible but not successful | |
| (14) | *R1* $c_z$; *R1* $p_z$ | | (57–62) | Feasible but not successful | |
| (15) | Not feasible | | (63–72) | Not feasible | |
| (16) | Not feasible | | | | |
| (17) | Not feasible | | | | |
| (18) | Not feasible | | | | |
| (19) | *R1* $c_z$; *R1* $p_z$ | *R2* $c_z$; *R2* $p_z$ | | | |
| (20) | Not feasible | | | | |
| (21) | Not feasible | | | | |
| (22) | Not feasible | | | | |
| (23) | *R1* $c_z$; *R1* $p_z$ | | | | |
| (24) | *R1* $c_z$; *R1* $p_z$ | | | | |
| (25) | Not feasible | | | | |
| (26) | Not feasible | | | | |
| (27) | Not feasible | | | | |
| (28) | *R1* $c_z$; *R1* $p_z$ | | | | |
| (29) | Not feasible | | | | |
| (30) | *R1* $c_z$; *R1* $p_z$ | | | | |
| (31) | *R1* $c_z$; *R1* $p_z$ | *R2* $c_z$; *R2* $p_z$ | | | |
| (32) | *R1* $c_z$; *R1* $p_z$ | | | | |
| (33) | Not feasible | | | | |

*Notes*: This table summarizes for all feasible shocks the final mix of *R1* and *R2* restrictions used for identification. If a column does not include a $c_z$ or $p_z$, it implies that this variable type remains unrestricted. Feasible shocks are those that adhere to the feasibility criterion established in Section 3.4. Feasible but not successful, on the other hand, refers to shocks that cannot be empirically retrieved.

In order to determine which of these variations in identification restrictions to apply for a given *feasible* sectoral shock, I follow the following considerations. For some shocks it is empirically much harder to find successful draws that adhere to the most restrictive combination of identification restrictions. Hence, I apply both *R1*- and *R2*-type restrictions when possible but revert to a less restrictive mix, with *R1*-type restrictions only, when necessary. Table 2 summarizes for all feasible shocks the final restrictions I use for identification of the shock.[23]

For many sectoral supply shocks, an *R2*-type restriction is too restrictive and no successful draws were found. But since the category within the first cluster for those sectoral supply shocks is unique compared to all other feasible shocks, I impose no *R2*-type restriction and let the identification rely fully on the *R1* restriction.[24]

Finally, note that I do not explicitly identify shocks other than the feasible set of sectoral shocks. This also implies that no aggregate supply or demand shocks are explicitly identified.

### 4.3 Time series data and FAVAR parameterization

The FAVARs use monthly time series on PCE real quantity and price indices for 72 PCE categories and aggregates from the BEA from 1959 until March 2024. Many of these PCE series are affected by outliers. I therefore check for all individual PCE series whether observations exceed the interquartile range by a factor 5. A value that exceeds this threshold is then adjusted to the positive or negative value of that very threshold.[25]

In the FAVAR, I use first differences of log PCE price indices and log real quantity indices. Following the discussion in De Graeve and Schneider (2023), I impose a total number of factors that is larger than the typical number of factors used in the literature. My benchmark is to have that all factors explain at least 50 percent of sectoral consumption growth and inflation rates. To achieve that, I require 27 unobserved factors, $K$. Additionally, recall that the number of observed factors, $M$, depends on the composition of the first cluster for the respective shocks. Given this number of factors, I determine the number of VAR lags by Akaike and Schwartz criteria, which both suggest that one lag is sufficient.

## 5 Results

This section presents the empirical contributions of sectoral supply and demand shocks to PCE inflation and consumption growth. I identify sectoral shocks via the scheme summarized in Table 2.[26]

My main objects of interest are the sectoral origins that drive business cycle variation of PCE inflation. Figure 8 illustrates the aggregated median contributions of sectoral shocks to inflation: I contrast actual observed year-on-year (y-o-y) PCE inflation (red line) with PCE inflation conditional on only sectoral supply and demand shocks (black line). The differences between the red and black line comprise all other drivers of inflation that I do not explicitly identify.[27] The colored bars provide a further breakdown into median supply and demand contributions to PCE inflation. Note that the black line is the median of the sum of all *feasible and successfully identified* sectoral supply and demand contributions.[28]

[23] Appendix K includes additional robustness results for alternative combinations of *R1*- and *R2*-type restrictions.

[24] See Table 1 for the full set of possible clusters that could be imposed as identification restrictions.

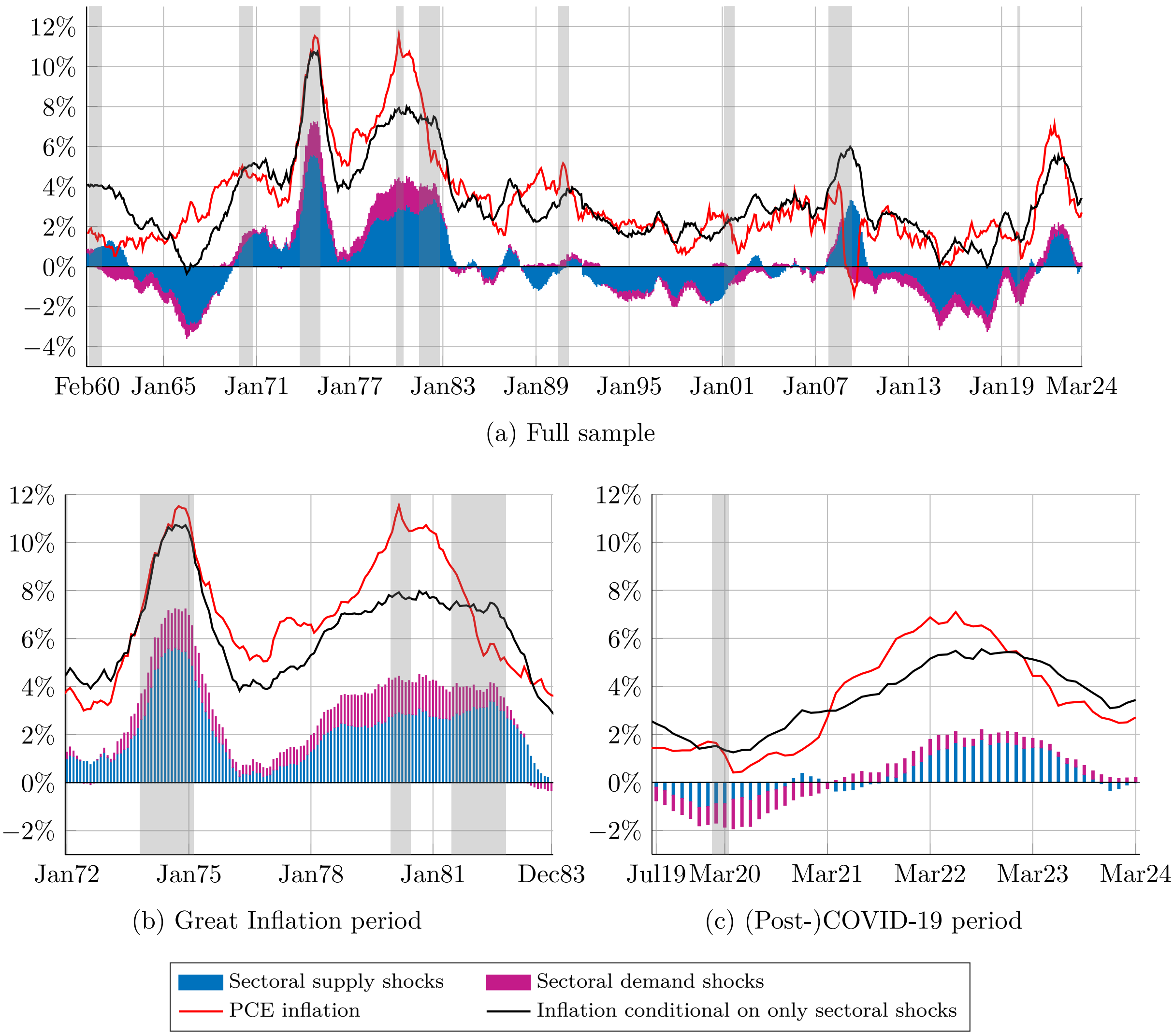
[25] See Appendix F.3 for additional information.

[26] In Appendix K, I show that the sectoral origins of inflation in recent years is qualitatively robust to several variations in identification restrictions.

[27] These drivers could be aggregate shocks, which, in principle, I am able identify but, as illustrated in earlier sections, are not the focus of this paper.

[28] These contributions are in addition to the sample mean of inflation, which captures other exogenous components of inflation. In this paper, I am interested in business cycle fluctuations; exogenous to my model are, for

Figure 8: Inflation and its sectoral origins




(a) Full sample

(b) Great Inflation period

(c) (Post-)COVID-19 period

*Notes*: The figure illustrates the aggregated median contributions of all identified sectoral shocks to inflation. Observed, year-on-year personal consumption expenditure (PCE) inflation is shown in red and contrasted with PCE inflation conditional on only sectoral supply and demand shocks (in black).

At a bird's eye view, sectoral shocks explain a sizable portion of the business cycle but leave ample room for other, non-identified shocks. With regard to a supply-and-demand breakdown, supply shocks are of much larger macroeconomic relevance than sectoral demand shocks. Recall that the types of sectoral demand shocks I identify are shocks to changes in consumer demand composition. Hence, this result by no means rules out that *aggregate* demand shocks, e.g., fiscal or monetary policy shocks, have large contributions to PCE inflation.

A key empirical result of this paper is that sectoral shocks exerted substantial (more than usual) inflationary pressure both during the Great Inflation and in recent years.[29] I find that a major part of PCE inflation originates from sectoral supply sources. However, the importance and sectoral breakdown of sectoral shocks varied throughout both periods. Panels 8b and 8c provide an enlarged picture for these two periods.

instance, any long-term drivers of inflation.

[29] Appendix J includes similar decompositions for sectoral shocks and consumption growth.

### 5.1 Sectoral shocks and post-pandemic inflation

In the wake of lifted COVID-19 lockdowns, the U.S. economy experienced rapid increases of inflation from the first half of 2021 onward. PCE inflation started its decline around mid-2022. Comparing these rapid price increases and decreases in the data with inflation conditional on only sectoral shocks in Panel 8c reveals four distinct sub-periods with changing degrees of sectoral origins that explain inflation.

In a first sub-period from March 2020 until February 2021, I find that sectoral demand shocks have had fairly substantial negative contributions to inflation. This is no surprise, considering the effect the pandemic had on depressing demand in 2020. On the contrary, total sectoral supply contributions have had small, negligible, negative effects on aggregate prices. While inflation has been recovering from its initial drop in early 2020, it stayed below the two-percent objective during this period. I present a more detailed picture on individual sectoral contributions below, but one important inflationary driver at the time were supply shocks originating in the *Electrical equipment, appliance and components* sector. Overall, inflation conditional on sectoral shocks increased to levels somewhat above observed PCE inflation. The residual between the data and conditional series could be explained by negative aggregate demand shocks that further depressed inflation.

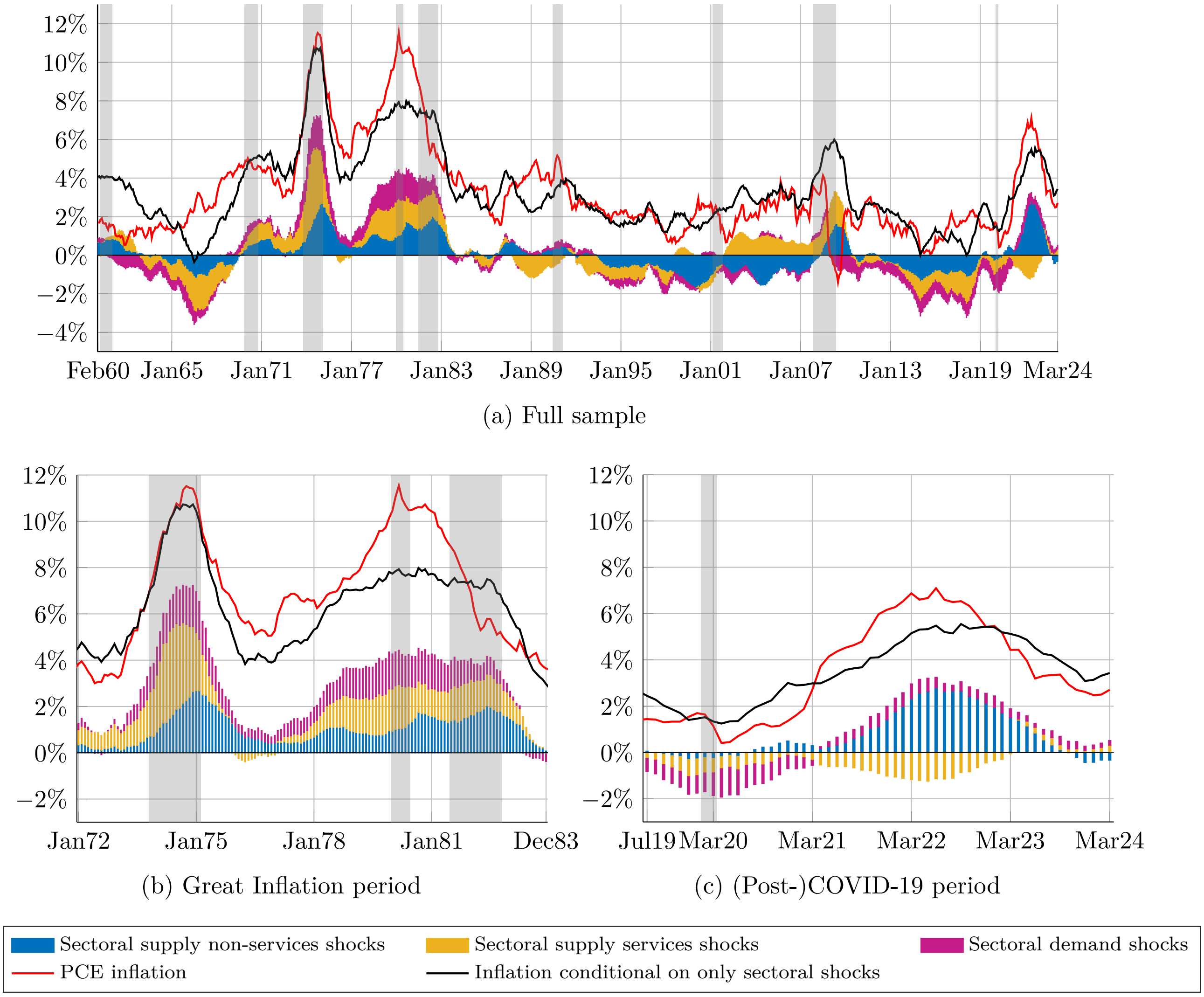
In a second sub-sample that I date from March 2021 until September 2021, negative contributions from sectoral demand shocks receded and turned increasingly positive. Most strikingly, sectoral shocks cannot explain the sharp increase in actual PCE inflation. With the portion of inflation stemming from sectoral shocks being small in this sub-period, other factors have to explain the steep increase in inflation. While my model cannot speak to those factors directly, a likely candidate are additional aggregate demand-pull factors such as COVID-19 relief spending. In the wake of the pandemic, the U.S. government issued three stimulus checks to boost demand: the first check in April 2020, a second in December 2020/January 2021, and a third in March 2021.

The third sub-period commences in October 2021 and lasted until around January 2023, with yet again changing sectoral contributions. Sectoral supply shocks became a major driver during this high inflation period. These supply-shock contributions do not stem from one sectoral source alone but are distributed across numerous sectors with varying degrees of importance. As further decomposed in the next sub-section, the most important shocks originated in goods-producing sectors, for instance in the *Transportation equipment*, *Furniture and related products*, and the *Plastics and rubber products* sector. On the contrary, sectoral demand shocks developed relatively small demand-pull contributions. As in the second sub-period, there remains a large scope for aggregate demand shocks.

Finally, the fourth sub-period from February 2023 until the end of my sample in March 2024 is characterized by a steady decline in contributions from sectoral supply shocks.

Going further back in time, Panel 8a illustrates that such strong inflationary contributions have not occurred since the Great Inflation concluded in the mid-1980s. There is one exception: during the Great Recession negative sectoral supply shocks raised prices substantially. But they did so in anticipation of a dramatic collapse of the overall price level midway through the recession. Apart from this exception, the results show that overall sectoral shocks had no

Figure 9: Inflation and its sectoral origins: goods versus services




*Notes*: The figure contrasts observed, year-on-year personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black lines). Conditional PCE inflation is based on the aggregated median contributions of all identified sectoral shocks. Contributions from supply shocks are further decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which only originate in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

substantial inflationary effects for around four decades. On the contrary, they had mostly negative contributions to inflation during this era. In particular, prior to the COVID-19 pandemic, sectoral shocks contributed to the low inflation environment. Given the path that inflation has taken from the mid-2010s, the inflationary pressure exerted by sectoral supply shocks in recent years appears all the more striking: from 2018 to September 2022, inflation conditional on only sectoral shocks changed from about 0 percent to 5.5 percent.

### 5.2 Decomposing aggregated sectoral shock contributions

The aggregate contributions of sectoral supply and demand shocks, presented so far, already provide a good overview of the overall sectoral sources of heightened inflation at certain points in time. I now provide decompositions of these contributions into smaller subsets.

Figure 9 decomposes the sectoral supply-side drivers of Figure 8 into contributions from services and non-services sectors.[30] Panel 9c shows that in recent years, services sectors were mostly subject to *positive* supply shocks and thereby had negative contributions to inflation. One explanation could be that certain services sectors have benefited predominantly from lifting policies imposed to reign in the COVID-19 pandemic in 2020. Removing social distancing measures and return-to-workplace measures could have had a stronger impact in services-sectors, whereas inflationary supply-chain disruptions are a phenomenon occurring in goods-producing industries. Given the pattern of services sector contributions, supply shocks in goods-producing (and other non-services) sectors had even larger inflationary contributions to aggregate inflation than Figure 8 suggests. When the first lockdowns were imposed in March 2020, both services and non-services sectors were subject to negative supply shocks. One hypothesis for this finding is that many supply and demand shocks related to the pandemic in 2020 were in fact aggregate or other combined shocks. This would be captured by the residual between the conditional (in black) and unconditional inflation series (in red). Lockdowns, stay-at-home orders, and other similar policies affect the whole economy. However, the shocks I identify are specific to the respective origin sector. The sector-specific contributions I identify in March 2020 and later months likely capture supply (and demand) factors from these policies that were specific to the respective origin sectors.

Panel 9b reveals that no such difference between services and non-services supply disturbances occurred during the Great Inflation. Both types were subject to negative supply shocks. Observing this breakdown further in Panel 9a highlights even more so the particular importance of non-services supply shocks during the pandemic.[31] The extent by which these types of supply shocks drive inflation has never been this high in recent U.S. history, just matched during the early stages of the Great Inflation.

Figure 10 shows additional 95-percent and standard-deviation percentile bands for the sectoral supply-demand and goods-services breakdowns. At standard deviation bands and for recent years, the figure confirms the timing considerations illustrated above.[32]

### 5.3 Which sectors were important sources of post-pandemic inflation?

Figure 11 presents a detailed breakdown of some important individual sector contributions to PCE inflation in recent years.[33] The left panel presents four supply shocks originating in *non-services* sectors. These sectors were key drivers in shaping the overall contribution pattern of sectoral supply shocks presented in Figure 9.

In particular, supply shocks in the *Transportation equipment* sector match the overall pat-

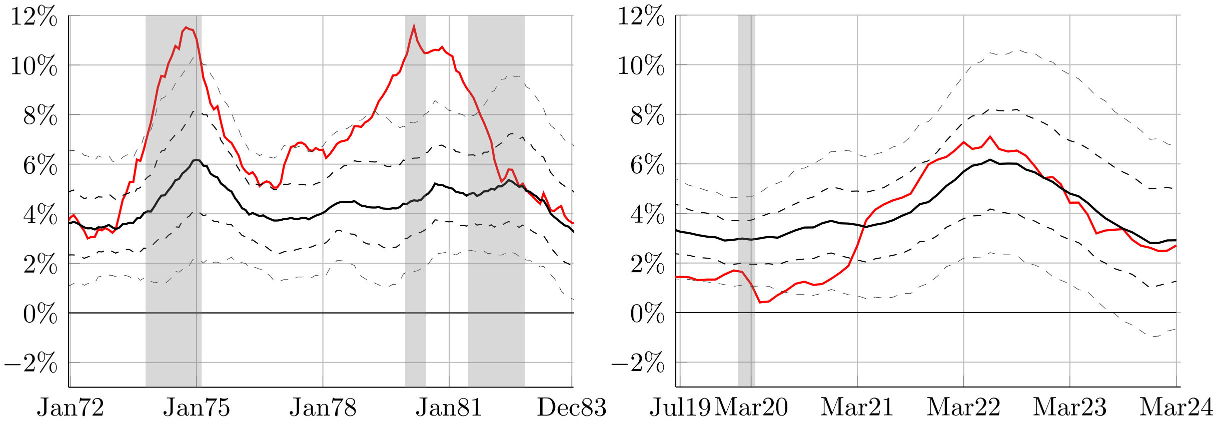
[30]Note that no such decomposition is necessary for sectoral demand contributions. While there are several (potential) sectoral demand shocks for services categories, I cannot uncover any such shocks. The lack of identifiable services-sector shocks may be an interesting result in itself. It may be less common for consumers to change preferences for individual services in contrast to shifting preferences for goods categories.

[31]Figures 8 and 9 show *year-on-year* inflation. Alternatively, Appendix Figure A.6 presents contributions for monthly (annualized) inflation, which provides a better way to date certain contributions.

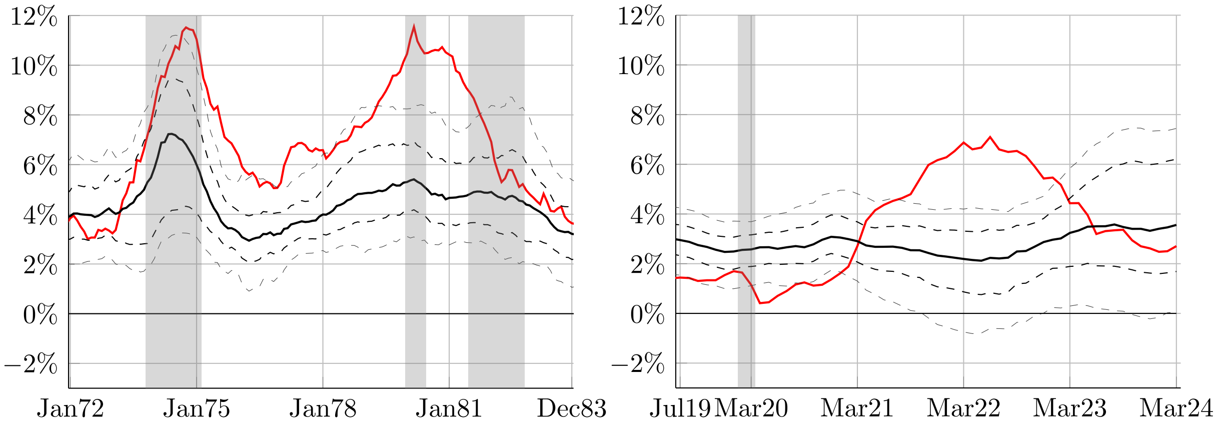
[32]Appendix J includes figures showing the full sample period.

[33]See also Appendix Figures A.9 to A.13 for all individual contributions of *feasible and successfully identified* sectoral shocks.

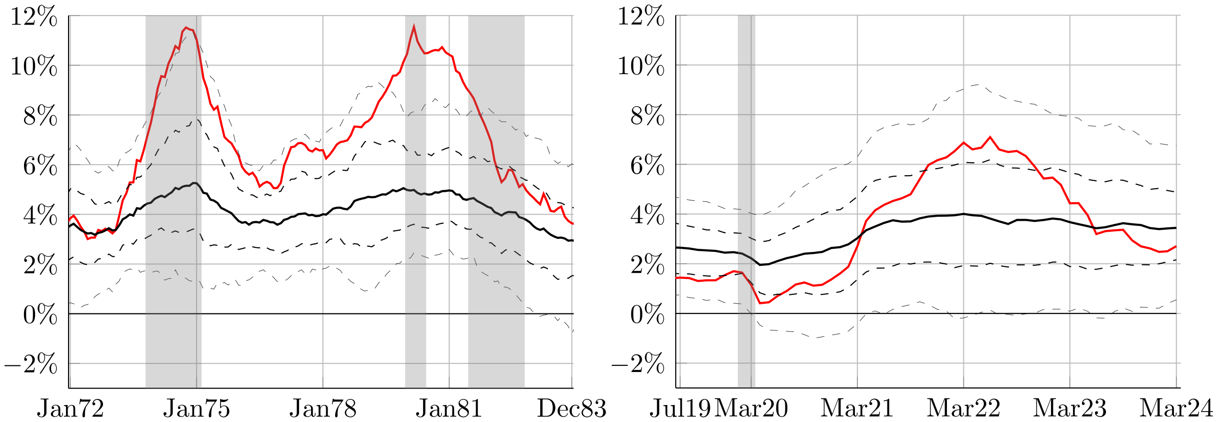
Figure 10: Inflation and its sectoral origins with credible intervals



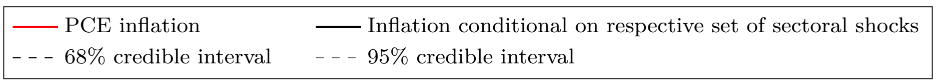

(a) Non-services supply shocks




(b) Services supply shocks




(c) All sectoral demand shocks




*Notes*: The figure contrasts observed, year-on-year personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black lines). These conditional inflation series are based on the aggregated median contributions of the respective set of identified sectoral shocks. Contributions from supply shocks are decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which only originate in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

tern of all identified sectoral shocks. While these types of shocks exerted inflationary pressure throughout early 2023, their overall contributions peaked in 2021. In contrast, contributions from supply shocks in *Electrical equipment, appliance and components* drove up inflation at the very beginning of the pandemic but were of only little importance during 2021 and early 2022. Most recently, a range of positive supply shocks in this sector pushed down aggregate inflation. Supply shocks originating in the *Furniture and related products* sector showed even stronger contributions to inflation, especially during 2021 and 2022. Finally, supply shocks in the *Plastics and rubber products* sector provide yet another type of pattern, illustrating the overall heterogeneity in sectoral shocks and their impact on inflation: shocks from this sector had no meaningful contributions up until end-2021, when negative supply shocks started to contribute substantially to heightened inflation.

The right panel of Figure 11 provides a breakdown of four sectoral supply shocks that explain the major part of the "services"-drag on inflation, illustrated earlier in Figure 9. When inflation started to peak in 2021, sectoral shocks in *Arts, entertainment and recreation*, as well as *Accommodation and food services*, offset some of the increases from non-services sectors. With some delay positive supply shocks in *Educational services* added further downward pressure on inflation starting in mid-2022. With respect to the former two, both sectors are part of a customer-facing services industry which particularly benefited from the reopening of the economy in 2021. While imposing and lifting lockdowns had an effect on large parts of the economy, the identified shocks for these two sectors likely pick up factors that are idiosyncratic to each respective sector, at the given point in time. Finally, supply-shock contributions from *Other services, except government* was subject to a range of negative supply shocks with particularly strong effects towards the end of my sample. This sector includes for instance *Repair and maintenance* or *Personal care services*.

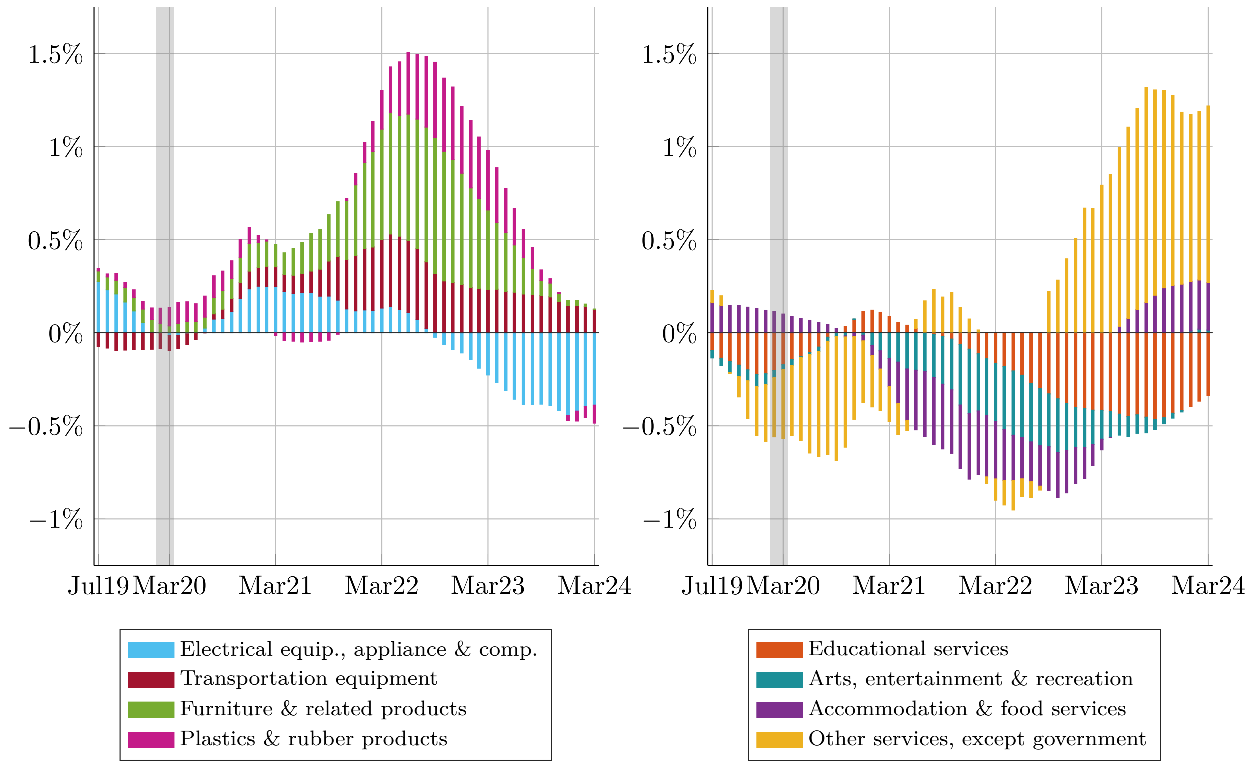
While overall, services shocks had an alleviating effect on inflation, it is important to note that there is still a large scope for *aggregate supply* and *aggregate demand* shocks to explain a significant portion of post-pandemic inflation. For instance, aggregate negative supply shocks such as labor shortages across many sectors or positive fiscal demand shocks likely explain a large share of post-pandemic inflation surges. What is evident, however, is that the role that sector-specific shocks played during this period is more pronounced than during usual times.

### 5.4 Sectoral sources during the Great Inflation

The origins of recently increasing inflation show some resemblance to those of the Great Inflation. My results show that, similarly to the post-pandemic period, a substantial source of inflation is sectoral supply shocks. There are some striking differences, though.

While contributions of sectoral supply shocks originating in non-services sectors are somewhat larger in recent years, the Great Inflation showed larger overall inflationary sectoral contributions. This was also driven by services supply shocks having positive effects and sectoral demand shocks having stronger contributions than they have had in recent years. Inflationary contributions from the supply side are unequivocally stemming from negative sectoral supply shocks; however, the aggregate effects of sectoral demand shocks are ambiguous and differ between consumer-good categories. As illustrated in Section 2, aggregate contributions of demand

Figure 11: Key sectoral supply shocks and their contributions to inflation in recent years




*Notes*: This figure shows eight sectoral supply shocks with substantial contributions to personal consumption expenditure (PCE) inflation in recent years. The left-side chart shows four supply shocks originating in *non-services* sectors and the right-side chart shows four supply shocks originating in *services* sectors. For each sector, the median contributions to year-on-year PCE inflation are shown.

shocks are more dependent on the exact underlying network structure. Sectoral demand shocks change the composition between PCE categories. An exogenous increase in demand for one PCE category also entails a shift away from other PCE categories. In some cases this opposite effect on remaining categories can lead to even larger opposite price effects and overpower price changes occurring within the origin category.

Sectoral shocks explain the bulk of inflation increases compared to the baseline during the first peak of the Great Inflation around 1974. While still having large inflationary contributions, sectoral shocks explain substantially less during the second peak around 1980. Within my model setup, I cannot speak directly to other factors that explain this residual around this second inflation peak. However, the results are compatible with other explanations on the sources of inflation around that time. This includes, for instance, Hazell et al. (2022), who compile novel U.S. state-level price indices for non-tradeable goods between 1978 and 2018 and estimate the slope of the Phillips curve. The authors associate a large share of consumer price inflation increases between 1979 and 1981 to an increase in long-run inflation expectations but also attribute a share to supply shocks. My results leave room for increases of expectations in the build up to the 1980 peak but less so around the first peak around 1974.

## 6 Conclusion

This paper provides empirical evidence on the sectoral origins of inflation using an identification strategy that disentangles sector-specific supply and demand shocks. By deriving identification restrictions from a broad class of DSGE models with production networks, this approach ensures that sectoral shocks are not conflated with aggregate disturbances, allowing this method to determine the origin of a shock and its contributions to inflation.

The findings show that while sectoral shocks were not the leading cause of the initial post-pandemic inflation increase, they became increasingly influential from late-2021 onward. In particular, negative supply shocks from non-services sectors played a dominant role in driving inflationary pressures. Conversely, sectoral demand shocks generally have a more limited impact on inflation, but this does not rule out the role of aggregate demand shocks, especially during the post-pandemic inflation surge.

The methodology introduced here offers a framework for further research into inflation causes and, more generally, into business-cycle determinants. Future work could extend this approach to examine how sectoral shocks interact with monetary policy responses, particularly in terms of transmission mechanisms and policy effectiveness.

## References


Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016). "Networks and the macroeconomy: an empirical exploration". *NBER Macroeconomics Annual 2015* 30, pp. 273–355.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012). "The network origins of aggregate fluctuations". *Econometrica* 80(5), pp. 1977–2016.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2017). "Microeconomic origins of macroeconomic tail risks". *American Economic Review* 107(1), pp. 54–108.

Amir-Ahmadi, Pooyan and Thorsten Drautzburg (2021). "Identification and inference with ranking restrictions". *Quantitative Economics* 12(1), pp. 1–39.

Andrade, Philippe and Marios Zachariadis (2016). "Global versus local shocks in micro price dynamics". *Journal of International Economics* 98, pp. 78–92.

Arata, Yoshiyuki and Daisuke Miyakawa (2022). "Demand shock propagation through an input-output network in Japan". RIETI Discussion Paper Series No. 22-E-027, Mar. 2022.

Ascari, Guido, Dennis Bonam, Lorenzo Mori, and Andra Smadu (2024). "Fiscal policy and inflation in the euro area". Mimeo. Nov. 10, 2024.

Ascari, Guido, Dennis Bonam, and Andra Smadu (2024). "Global supply chain pressures, inflation, and implications for monetary policy". *Journal of International Money and Finance* 142, pp. 1–25.

Atalay, Enghin (2017). "How important are sectoral shocks?" *American Economic Journal: Macroeconomics* 9(4), pp. 254–280.

Auer, Raphael A., Andrei A. Levchenko, and Philip Sauré (2019). "International inflation spillovers through input linkages". *The Review of Economics and Statistics* 101(3), pp. 507–521.

Bańbura, Marta, Elena Bobeica, and Catalina Martínez Hernández (2023). "What drives core inflation? The role of supply shocks". ECB Working Paper No. 2875.

Baqaee, David Rezza (2018). "Cascading Failures in Production Networks". *Econometrica* 86(5), pp. 1819–1838.

Baqaee, David Rezza and Emmanuel Farhi (2019). "The macroeconomic impact of microeconomic shocks: beyond Hulten's theorem". *Econometrica* 87(4), pp. 1155–1203.

— (2022). "Supply and demand in disaggregated Keynesian economies with an application to the COVID-19 crisis". *American Economic Review* 112(5), pp. 1397–1436.

Barrot, Jean-Noël and Julien Sauvagnat (2016). "Input specificity and the propagation of idiosyncratic shocks in production networks". *The Quarterly Journal of Economics* 131(3), pp. 1543–1592.

Bergholt, Drago, Fabio Canova, Francesco Furlanetto, Nicoloò Maffei-Faccioli, and Pal Ulvedal (2024). "What drives the recent surge in inflation? the historical decomposition roller coaster". Norges Bank Working Paper No. 7-2024, Apr. 8, 2024.

Bernanke, Ben and Olivier Blanchard (2024). "An analysis of pandemic-era inflation in 11 economies". Peterson Institute for International Economics Working Paper No. 24-11.

Bernanke, Ben S., Jean Boivin, and Piotr Eliasz (2005). "Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach". *The Quarterly Journal of Economics* 120, pp. 387–422.

Boehm, Christoph E., Aaron Flaaen, and Nitya Pandalai-Nayar (2019). "Input linkages and the transmission of shocks: firm-level evidence from the 2011 Tōhoku earthquake". *The Review of Economics and Statistics* 101(1), pp. 60–75.

Boivin, Jean, Marc P. Giannoni, and Ilian Mihov (2009). "Sticky prices and monetary policy: evidence from disaggregated US data". *American Economic Review* 99(1), pp. 350–384.

Bouakez, Hafedh, Christian Höynck, and Omar Rachedi (2024). "When are technology improvments inflationary?" Mimeo. Oct. 2024.

Brinca, Pedro, Joao B. Duarte, and Miguel Faria-e-Castro (2021). "Measuring labor supply and demand shocks during COVID-19". *European Economic Review* 139, p. 103901.

Carvalho, Carlos, Jae Won Lee, and Woong Yong Park (2021). "Sectoral price facts in a sticky-price model". *American Economic Journal: Macroeconomics* 13(1), pp. 216–256.

Carvalho, Vasco and Xavier Gabaix (2013). "The great diversification and its undoing". *American Economic Review* 103(5), pp. 1697–1727.

Cesa-Bianchi, Ambrogio and Andrea Ferrero (2021). "The transmission of Keynesian supply shocks". Bank of England Working Paper No. 934, Aug. 2021.

Comin, Diego A. and Callum J. Jones (2024). "Supply chain constraints and inflation". NBER Working Paper No. 31179, Aug. 2024.

Dao, Mai Chi, Pierre-Olivier Gourinchas, Daniel Leigh, and Prachi Mishra (2024). "Understanding the international rise and fall of inflation since 2020". *Journal of Monetary Economics* 148.

De Graeve, Ferre and Alexei Karas (2014). "Evaluating theories of bank runs with heterogeneity restrictions". *Journal of the European Economic Association* 12(4), pp. 969–996.

De Graeve, Ferre and Jan David Schneider (2023). “Identifying sectoral shocks and their role in business cycles”. *Journal of Monetary Economics* 140, pp. 124–141.

De Graeve, Ferre and Karl Walentin (2015). “Refining stylized facts from factor models of inflation”. *Journal of Applied Econometrics* 30(7), pp. 1192–1209.

De Santis, Roberto A. (2024). “Supply chain disruption and energy supply shocks: impact on euro area output and prices”. ECB Working Paper No. 2884.

De Soyres, François, Alexandre Gaillard, Ana Maria Santacreu, and Dylan Moore (2024). “Supply disruptions and fiscal stimulus: transmission through global value chains”. In: AEA Papers and Proceedings. Vol. 114. American Economic Association, pp. 112–117.

Di Giovanni, Julian, Șebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yildirim (2024). “Pandemic-era inflation drivers and global spillovers”. NBER Working Paper No. 31887, July 2024.

Dixon, Huw, Jeremy Franklin, and Stephen Millard (2014). “Sectoral shocks and monetary policy in the United Kingdom”. Bank of England Working Paper No. 499, Apr. 2014.

Dupor, Bill (1999). “Aggregation and irrelevance in multi-sector models”. *Journal of Monetary Economics* 43(2), pp. 391–409.

Foerster, Andrew and Jason Choi (2017). “The changing input-output network structure of the U.S. economy”. Federal Reserve Bank of Kansas City Economic Review No. 80(5).

Foerster, Andrew, Andreas Hornstein, Pierre-Daniel Sarte, and Mark Watson (2022). “Aggregate implications of changing sectoral trends”. *Journal of Political Economy* 130(12), pp. 3286–3333.

Foerster, Andrew T., Pierre-Daniel G. Sarte, and Mark W. Watson (2011). “Sectoral versus aggregate shocks: a structural factor analysis of industrial production”. *Journal of Political Economy* 119(1), pp. 1–38.

Gabaix, Xavier (2011). “The granular origins of aggregate fluctuations”. *Econometrica* 79(3) (May 2011), pp. 733–772.

Giannone, Domenico and Giorgio Primiceri (2024). “The drivers of post-pandemic inflation”. NBER Working Paper No. 32859, Aug. 2024.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning (2022). “Macroeconomic implications of COVID-19: can negative supply shocks cause demand shortages?” *American Economic Review* 112(5), pp. 1437–1474.

Ha, Jongrim, M. Ayhan Kose, Franziska Ohnsorge, and Hakan Yilmazkuday (2024). “What explains global inflation”. *IMF Economic Review*, pp. 1–34.

Hazell, Jonathon, Juan Herreño, Emi Nakamura, and Jón Steinsson (2022). “The slope of the Phillips curve: evidence from U.S. states”. *The Quarterly Journal of Economics* 137(3), pp. 1299–1344.

Horvath, Michael (1998). “Cyclicality and sectoral linkages: aggregate fluctuations from independent sectoral shocks”. *Review of Economic Dynamics* 1(4), pp. 781–808.

— (2000). “Sectoral shocks and aggregate fluctuations”. *Journal of Monetary Economics* 45(1), pp. 69–106.

Jordà, Òscar and Fernanda Nechio (2023). “Inflation and wage growth since the pandemic”. *European Economic Review* 156, pp. 1–16.

Kaufmann, Daniel and Sarah M. Lein (2013). “Sticky prices or rational inattention — what can we learn from sectoral price data?” *European Economic Review* 64, pp. 384–394.

Koop, Gary and Dimitris Korobilis (2009). “Bayesian Multivariate Time Series Methods for Empirical Macroeconomics”. *Foundations and Trends in Econometrics* 3(4), pp. 267–358.

Long, John B., Jr. and Charles I. Plosser (1983). “Real business cycles”. *Journal of Political Economy* 91(1), pp. 39–69.

Maćkowiak, Bartosz, Emanuel Moench, and Mirko Wiederholt (2009). “Sectoral price data and models of price setting”. *Journal of Monetary Economics* 56, S78–S99.

Matthes, Christian and Felipe Schwartzman (2025). “The consumption origins of business cycles: lessons from sectoral dynamics”. *American Economic Journal: Macroeconomics* Forthcoming.

Nakamura, Emi and Jón Steinsson (2008). “Five facts about prices: a reevaluation of menu cost models”. *The Quarterly Journal of Economics* 123(4), pp. 1415–1464.

Pastén, Ernesto, Raphael Schoenle, and Michael Weber (2020). “The propagation of monetary policy shocks in a heterogeneous production economy”. *Journal of Monetary Economics* 116, pp. 1–22.

— (2024). “Sectoral heterogeneity in nominal price rigidity and the origin of aggregate fluctuations”. *American Economic Journal: Macroeconomics* 16(2), pp. 318–352.

Rubbo, Elisa (2024). “What drives inflation? lessons from disaggregated price data”. NBER Working Paper No. 32194.

Rubio-Ramírez, Juan F., Daniel F. Waggoner, and Tao Zha (2010). “Structural vector autoregressions: theory of identification and algorithms for inference”. *Review of Economic Studies* 77(2), pp. 665–696.

Ruge-Murcia, Francisco and Alexander L. Wolman (2024). “Relative price shocks and inflation”. Mimeo. Mar. 2024.

Shapiro, Adam Hale (2024). “Decomposing supply- and demand-driven inflation”. *Journal of Money, Credit and Banking.*

Shea, John (2002). “Complementarities and comovements”. *Journal of Money, Credit and Banking* 34(2), pp. 412–433.

Smets, Frank, Joris Tielens, and Jan Van Hove (2019). “Pipeline pressures and sectoral inflation dynamics”. Mimeo. June 2019.

Stock, James H. and Mark W. Watson (2016). “Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics”. In: *Handbook of Macroeconomics*. Vol. 2A, pp. 415–525.

Vom Lehn, Christian and Thomas Winberry (2021). “The investment network, sectoral comovement, and the changing U.S. business cycle”. *The Quarterly Journal of Economics* 137(1), pp. 1–47.

# Appendices

# A Theoretical models

This appendix provides a detailed description of the theoretical modelling framework that underlies the analysis in the main text. I extend Pastén, Schoenle, and Weber's (2024) multi-sector model, which encompasses several variants popular in the literature.

As described in the main text, the model features a two-layer production structure with intermediate goods producers (corresponding to NAICS industries) and final goods producers (assembling PCE consumer goods). The framework incorporates both sector-specific technology shocks and consumer demand shocks that alter the composition of the consumption basket. The model includes three key types of heterogeneities: (i) intermediate goods producers differ in their input-output linkages; (ii) both intermediate and final goods producers vary in size; and (iii) both types of producers exhibit different degrees of nominal price rigidity.

## A.1 Households

A representative household maximizes utility of consumption and disutility from hours worked:

$$\max_{\{C_t, L_{jt}\}_{t=0}^{\infty}} \quad \mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t \left( \frac{C_t^{1-\sigma} - 1}{1-\sigma} - \sum_{j=1}^{J} g_j \frac{L_{jt}^{1+\varphi}}{1-\varphi} \right) , \tag{A.1}$$

subject to

$$\sum_{j=1}^{J} W_{jt} L_{jt} + \sum_{j=1}^{J} \Pi_{jt} + \sum_{z=1}^{Z} \Pi_{zt} + I_{t-1} B_{t-1} - B_t = P_t^{pce} C_t \, , \tag{A.2}$$

$$\sum_{j=1}^{J} L_{jt} \leq 1 \, , \tag{A.3}$$

where $W_{jt}$ are sector-specific wages paid for labor $L_{jt}$ employed in intermediate goods sector $j = 1, \ldots, J$. Households receive profits, $\Pi_{j,t-1}$, from intermediate-goods-producing firms and profits, $\Pi_{z,t-1}$, from final-goods-producing firms, $\Pi_{j,t-1}$. A term with bonds, $B_{t-1}$, paying gross interest rate, $I_{t-1}$, completes the left-hand side of the budget constraint. In absence of government spending, capital formation, and international trade, aggregate consumption, $C_t$, coincides with gross domestic product (GDP) and the consumer price index, $P_t^{pce}$, with the GDP deflator. The aggregate consumption bundle is composed of $Z$ consumption categories:

$$C_t \equiv \left[ \sum_{z=1}^{Z} \omega_{cz}^{\frac{1}{\eta}} e^{\frac{\eta-1}{\eta} f_{zt}} C_{zt}^{1-\frac{1}{\eta}} \right]^{\frac{\eta}{\eta-1}} . \tag{A.4}$$

Sectoral consumption, $C_{zt}$, corresponds to consumption of goods within PCE category, $z$. PCE sectors differ in terms of sector size, which is captured by vector $\boldsymbol{\Omega}_c \equiv [\omega_{c1}, \ldots, \omega_{cZ}]'$, where $\sum_{z=1}^{Z} \omega_{cz} = 1$. Sectoral consumption weights, $\omega_{cz}$, are subject to consumer demand shocks, $f_{zt}$, that change the composition of demand. This implies that $\sum_{z=1}^{Z} f_{zt} = 0$. Consumption weights correspond to the steady-state ratio of sectoral to aggregate consumption, i.e., $\omega_{cz} \equiv \frac{C_z}{C}$. Sectoral demand, $C_{zt}$, is standard and equal to:

$$C_{zt} \equiv \omega_{cz} \left(\frac{P_{zt}}{P_t^{pce}}\right)^{-\eta} C_t \,. \tag{A.5}$$

On the supply side, aggregating sectoral consumption is done in the following way:

$$C_{zt} = \left[n_z^{-\frac{1}{\theta}} \int_{\Im_z} C_{zt}(q)^{1-\frac{1}{\theta}} dq\right]^{\frac{\theta}{\theta-1}} , \tag{A.6}$$

where $C_{zt}(q)$ is consumption of a product of firm $q$ from PCE category $z$. There is a continuum of consumption goods produced, where every good is indexed by $q \in [0,1]$ and sorts into one of the PCE categories, $z$. More formally, there are $Z$ subsets, $\{\widetilde{\Im}_z\}_{z=1}^{Z}$, that correspond to the PCE sector size measure, $\{\omega_z\}_{z=1}^{Z}$. Note that the elasticity of substitution within sectors/categories, $\theta$, can differ from the elasticity of substitution across sectors/categories, $\eta$.

The aggregate PCE price index is defined as:

$$P_t^{pce} \equiv \left[\sum_{z=1}^{Z} \omega_{cz} P_{zt}^{1-\eta}\right]^{\frac{1}{1-\eta}} , \tag{A.7}$$

where $P_{zt}$ is the PCE price index of category $z$. The first-order condition of the household maximization problem is then equal to:

$$\frac{W_{jt}}{P_t^{pce}} = g_j L_{jt}^{\varphi} C_t^{\sigma} \,, \tag{A.8}$$

$$1 = \mathbb{E}_t \left[\beta \left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} I_t \frac{P_t^{pce}}{P_{t+1}^{pce}}\right] . \tag{A.9}$$

As in Pastén, Schoenle, and Weber (2024), labor markets are sector-specific and allow for different wages. Parameters $\{g_j\}_{j=1}^{J}$ are calibrated to ensure a symmetric steady state.

## A.2 Intermediate goods producers

Intermediate goods firms use labor and inputs from other sectors to produce a good $j$. The production function for a firm $r \in j$ with sector-specific technology, $a_{jt}$, is the following:

$$Y_{jt}(r) = e^{a_{jt}} L_{jt}^{1-\delta}(r) M_{jt}^{\delta}(r) \,, \tag{A.10}$$

where $\delta$ is the intermediate input share in production. Intermediate inputs used by firm $r$ of sector $j$, $M_{jt}(r)$ are:

$$M_{jt}(r) = \left[\sum_{j'=1}^{J} \omega_{jj'}^{\frac{1}{\eta}} M_{jj't}^{\frac{\eta-1}{\eta}}(r)\right]^{\frac{\eta}{\eta-1}} . \tag{A.11}$$

The aggregator weights, $\{\omega_{jj'}\}_{j,j'}$, govern the I-O relationship between intermediate goods firms. These weights are included in the symmetric I-O coefficient matrix $\mathbf{\Omega} \in \mathbb{R}^{J,J}$, where each row of the matrix sums to one. An element $\omega_{jj'}$ is the steady-state share for goods from sector $j'$ in the intermediate input use of sector $j$. Again more formally, there are $J$ subsets, $\{\Im_j\}_{j=1}^J$, that correspond to the size measure for intermediate goods producers, $\{n_j\}_{j=1}^J$, where $\sum_{j=1}^J n_j = 1$. Input use of firm $r \in j$ can be further decomposed into input use from a specific sector $j'$:

$$M_{jj't}(r) = \left[ n_{j'}^{-\frac{1}{\theta}} \int_{\Im_{j'}} M_{jj't}(r, r')^{1-\frac{1}{\theta}} dr' \right]^{\frac{\theta}{\theta-1}}, \tag{A.12}$$

which aggregates input uses for firm $r$ of sector $j$ from all firms $r'$ of sector $j'$.

Optimal demand from a firm $r$ in sector $j$ for inputs $j'$, and more granularly for inputs from firm $r'$ in sector $j'$, is such that:

$$M_{jj't}(r) = \omega_{jj'} \left( \frac{P_{j't}}{P_{j't}^m} \right)^{-\eta} M_{jt}(r)\,, \tag{A.13}$$

$$M_{jj't}(r, r') = \frac{1}{n_{j'}} \left( \frac{P_{j't}(r')}{P_{j't}} \right)^{-\theta} M_{jj't}(r)\,. \tag{A.14}$$

For a sector $j$, the price index of the intermediate input bundle, $P_{jt}^m$, is equal to:

$$P_{jt}^m = \left[ \sum_{j'=1}^J \omega_{jj'} P_{j't}^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{A.15}$$

where the price for sector $j$ goods is given by:

$$P_{jt} = \left[ \frac{1}{n_j} \int_{\Im_j} P_{jt}^{1-\theta}(r) dj \right]^{\frac{1}{1-\theta}}. \tag{A.16}$$

As in Pastén, Schoenle, and Weber (2024), I use a simple information friction to model sectoral price rigidity, which is introduced in the main text. Alternatively, a model description of a Calvo pricing problem can be found in Appendix E.

### A.3 Final goods producers

The production function for a final goods producer $q \in z$ is simply given by:

$$Y_{zt}(q) = M_{zt}(q)\,, \tag{A.17}$$

where the bundle of intermediate goods used by firm $q$ is:

$$M_{zt}(q) = \left[ \sum_{j=1}^J k_{zj}^{\frac{1}{\eta}} M_{zjt}(q)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}. \tag{A.18}$$

The bridge matrix, $\mathbf{K} \in \mathbb{R}^{Z,J}$, with elements $k_{zj}$ maps the $J$ intermediate goods and prices into $Z$ consumption equivalents. Similarly to intermediate goods producers, the quantity a firm

$q \in z$ buys from intermediate goods sector $j$ is equal to:

$$M_{zjt}(q) = \left[ n_z^{-\frac{1}{\theta}} \int_{\Im_z} M_{zjt}(q,r)^{1-\frac{1}{\theta}} dr \right]^{\frac{\theta}{\theta-1}} , \tag{A.19}$$

with $M_{zjt}(q,r)$ being the amount of goods firm $q \in z$ buys from a firm $r \in j$. I assume that the cross-sector and within-sector elasticities of substitution, $\eta$ and $\theta$, are the same as for households. The input price for final goods producers, $P^m_{zt}$, is then given by:

$$P^m_{zt} = \left[ \sum_{j=1}^{J} k_{zj} P_{jt}^{1-\eta} \right]^{\frac{1}{1-\eta}} . \tag{A.20}$$

The pricing problem is analogous to intermediate goods sectors.

## A.4 Market clearing

Clearing of the bond market implies that $B_t = 0$. Market clearing of final-goods markets entails that:

$$\int_{\Im_z} Y_{zt}(q) dq = \int_{\Im_z} C_{zt}(q) dq \, , \tag{A.21}$$

$$M_{zjt} = k_{zj} Y_{zt} \, , \tag{A.22}$$

$$Y_{zt} = M_{zt} = e^r_{zt} C_{zt} \, . \tag{A.23}$$

Given that labor and intermediate goods markets also clear, supply and demand for firm $r \in j$ lead to:

$$Y_{jt}(r) = \sum_{j'=1}^{J} \int_{\Im_{j'}} M_{j'jt}(r', r) dr' + \sum_{z=1}^{Z} \int_{\Im_z} M_{zjt}(q,r) dq \, , \tag{A.24}$$

and on the sectoral level to:

$$Y_{jt} = \sum_{j'=1}^{J} M_{j'jt} + \sum_{z=1}^{Z} M_{zjt} \, . \tag{A.25}$$

## B Steady state

I provide a selective summary of the models symmetric steady state. Across firms, the steady state implies:

$$W_j = W\,, \tag{A.26}$$
$$Y_j(f) = Y\,, \tag{A.27}$$
$$L_j(f) = L\,, \tag{A.28}$$
$$M_j(f) = M^{im}\,, \tag{A.29}$$
$$M_z(q) = M^{pce}\,. \tag{A.30}$$

The symmetry yields that all prices are equal: $P_t^{pce} = P_{zt} = P_{zt}^m = P_{jt} = P_{jt}^m = P$. Consumption is equal to:

$$C_z = \omega_{cz} C\,, \tag{A.31}$$
$$C_z(f) = \omega_{cz} C\,. \tag{A.32}$$

Steady-state gross output and intermediate goods sector shares are given by:

$$Y_j(f) = \sum_{j'=1}^{J} \int_{\Im_{j'}} M_{j'j}(f', f) df' + \sum_{z=1}^{Z} \int_{\Im_z} M_{zj}(q, f) dq\,, \tag{A.33}$$
$$Y_j = \sum_{j'=1}^{J} M_{j'j} + \sum_{z=1}^{Z} M_{zj}\,, \tag{A.34}$$
$$Y = M^{im} + M^{pce}\,. \tag{A.35}$$

Steady-state gross output shares, $n_j$, are given by:

$$n_j = \psi \sum_{j'=1}^{J} n_{j'} \omega_{j'j} + (1-\psi) \sum_{z=1}^{Z} \omega_{cz} k_{zj}\,, \tag{A.36}$$
$$\mathbf{N} = (1-\psi) \left[\mathbf{I} - \psi \boldsymbol{\Omega}'\right]^{-1} \mathbf{K}' \boldsymbol{\Omega}_\mathbf{c}\,, \tag{A.37}$$

where $\psi = \frac{M^{im}}{Y}$. Note that $\sum_{z=1}^{Z} \omega_{cz} k_{zj} = \omega_{cj}$ (or $\mathbf{K}'\boldsymbol{\Omega}_\mathbf{c} = \boldsymbol{\Omega}_\mathbf{c}^\mathbf{im}$), which leads to

$$n_j = \psi \sum_{j'=1}^{J} n_{j'} \omega_{j'j} + (1-\psi) \omega_{cj}\,, \tag{A.38}$$
$$\mathbf{N} = (1-\psi) \left[\mathbf{I} - \psi \boldsymbol{\Omega}'\right]^{-1} \boldsymbol{\Omega}_\mathbf{c}^\mathbf{im}\,, \tag{A.39}$$

where $\mathbf{N} \equiv [n_1, \ldots, n_J]'$. The share of intermediate use in gross output solves $\psi = \delta \frac{\theta - 1}{\theta}$. The remaining steady-state solutions are not directly relevant for the closed-form model solutions and are hence not further illustrated here.

# C Log-linearized deviations from steady state

This section summarizes the log-linearized first-order conditions around the steady state.[34]

## C.1 Aggregation

Consumption and production of final goods is given by:

$$c_t = \sum_{z=1}^{Z} \omega_{cz} \left( c_{zt} + f_{zt} \right) = m_t^{pce} \, , \tag{A.40}$$

$$c_{zt} + f_{zt} = m_{zt} \, , \tag{A.41}$$

$$m_t^{pce} = \sum_{z=1}^{Z} \omega_{cz} m_{zt} \, , \tag{A.42}$$

$$m_{zt} = \frac{1}{\omega_{cz}} \int_{\Im_z} m_{zt}(q) dq \, . \tag{A.43}$$

Intermediate production is equal to:

$$m_t^{im} = \sum_{j=1}^{J} n_j m_{jt} \, , \tag{A.44}$$

$$m_{jt} = \frac{1}{n_j} \int_{\Im_j} m_{jt}(f) df \, , \tag{A.45}$$

$$m_{jt}(f) = \sum_{j'=1}^{J} \omega_{jj'} m_{jj't}(f) \, , \tag{A.46}$$

$$m_{jj't}(f) = \frac{1}{n_{j'}} \int_{\Im_{j'}} m_{jj't}(f, f') df' \, . \tag{A.47}$$

Final goods prices are:

$$p_t^{pce} = \sum_{z=1}^{Z} \omega_{cz} p_{zt} = \mathbf{\Omega}_c' \mathbf{p}_t^{pce} \, , \tag{A.48}$$

$$p_{zt}^{m} = \sum_{j=1}^{J} k_{zj} p_{jt} \, , \tag{A.49}$$

$$\mathbf{p}_t^{m,pce} = \mathbf{K} \mathbf{p}_t^{im} \, , \tag{A.50}$$

where $\mathbf{p}_t^{pce}$ is a column vector with elements $p_{zt}$, and similarly $\mathbf{p}_t^{m,pce}$ has elements $p_{zt}^{m}$. Intermediate goods prices are given by:

$$p_{jt}^{m} = \sum_{j'=1}^{J} \omega_{jj'} p_{j't} \, , \tag{A.51}$$

$$\mathbf{p}_t^{m,im} = \mathbf{\Omega} \mathbf{p}_t^{im} \, , \tag{A.52}$$

[34] As noted in the main text, this appendix assumes full Calvo pricing for both intermediate and final goods producers.

$$p_{jt} = \int_{\Im_j} p_{jt}(f)dj\,, \tag{A.53}$$

where $\mathbf{p}_t^{im}$ is a column vector with elements $p_{jt}$, and similarly $\mathbf{p}_t^{m,im}$ has elements $p_{jt}^m$.

Aggregate and sectoral labor is given by:

$$l_t = \sum_{j=1}^{J} l_{jt}\,, \tag{A.54}$$

$$l_{jt} = \frac{1}{n_j}\int_{\Im_j} l_{jt}(f)df\,. \tag{A.55}$$

## C.2 Demand

Demand for consumption goods is equal to:

$$c_{zt} - c_t = \eta(p_t^{pce} - p_{zt})\,, \tag{A.56}$$

$$c_{zt}(q) - c_{zt} = \theta(p_{zt} - p_{zt}(q))\,. \tag{A.57}$$

Demand for intermediate goods by final goods producers is given by:

$$m_{zjt} - m_{zt} = \eta(p_{zt}^m - p_{jt})\,, \tag{A.58}$$

$$m_{zjt}(q) - m_{zt}(q) = \eta(p_{zt}^m - p_{jt})\,. \tag{A.59}$$

Demand for intermediate goods by intermediate goods producers is instead given by:

$$m_{jj't} - m_{jt} = \eta(p_{jt}^m - p_{j't})\,, \tag{A.60}$$

$$m_{jj't}(f) - m_{jt}(f) = \eta(p_{jt}^m - p_{j't})\,, \tag{A.61}$$

$$m_{jj't}(f,f') - m_{jj't}(f) = \theta(p_{j't} - p_{j't}(f'))\,. \tag{A.62}$$

Market clearing conditions at sectoral and aggregate level are expressed as:

$$n_j y_{jt} = \psi \sum_{j'=1}^{J} \omega_{j'j} n_{j'} m_{j'jt} + (1-\psi)\sum_{z=1}^{Z} k_{zj}\omega_{cz} m_{zjt}\,, \tag{A.63}$$

$$y_t = \psi m_t^{im} + (1-\psi) m_t^{pce} = \psi m_t^{im} + (1-\psi)c_t\,. \tag{A.64}$$

## C.3 Euler equation and labor supply

The Euler equation is expressed as:

$$c_t = \mathbb{E}_t\left[c_{t+1}\right] - \sigma^{-1}\left\{i_t - \left(\mathbb{E}_t\left[p_{t+1}^{pce}\right] - p_t^{pce}\right)\right\}\,, \tag{A.65}$$

and labor supply is given by:

$$w_{jt} - p_t^{pce} = \varphi l_{jt} + \sigma c_t\,. \tag{A.66}$$

### C.4 Firms

Intermediate goods firms have the following log-linearized production function:

$$y_{jt}(f) = a_{jt} + (1-\delta)l_{jt}(f) + \delta m_{jt}(f)\,. \tag{A.67}$$

Aggregating this to the sectoral level yields:

$$y_{jt} = a_{jt} + (1-\delta)l_{jt} + \delta m_{jt}\,. \tag{A.68}$$

Final goods firms and sectors have the following production functions, respectively:

$$y_{zt}(q) = m_{zt}(q)\,, \tag{A.69}$$

$$y_{zt}(q) = m_{zt}\,. \tag{A.70}$$

The efficiency condition at firm and sectoral level are given by:

$$w_{jt} - p^m_{jt} = m_{jt}(f) - l_{jt}(f)\,, \tag{A.71}$$

$$w_{jt} - p^m_{jt} = m_{jt} - l_{jt}\,. \tag{A.72}$$

Marginal costs for final and intermediate goods sectors are, respectively:

$$mc_{zt} = p^m_{zt}\,, \tag{A.73}$$

$$mc_{jt} = (1-\delta)w_{jt} + \delta p^m_{jt} - a_{jt}\,. \tag{A.74}$$

Under Calvo pricing, both types of producers set their respective optimal price as:

$$p^*_{zt} = (1-\alpha_z\beta)mc_{zt} + \alpha_z\beta\mathbb{E}_t\left[p^*_{zt+1}\right]\,, \tag{A.75}$$

$$p^*_{jt} = (1-\alpha_j\beta)mc_{jt} + \alpha_z\beta\mathbb{E}_t\left[p^*_{jt+1}\right]\,, \tag{A.76}$$

where sectoral prices are given by:

$$p_{zt} = (1-\alpha_z)p^*_{zt} + \alpha_z p_{zt-1}\,, \tag{A.77}$$

$$p_{jt} = (1-\alpha_j)p^*_{jt} + \alpha_j p_{jt-1}\,. \tag{A.78}$$

### C.5 Monetary policy

While the model is solved using a non-essential, simplifying assumption on a monetary policy rule, the model can also be solved using a standard Taylor rule (see e.g., Pastén, Schoenle, and Weber 2020)

# D Derivations for analytical model solution

In this appendix, I derive solutions to the three model multipliers used in the main text that are key in generating my sector rankings. The solutions are similar to Pastén, Schoenle, and Weber's (2024) but include the two extensions of the main text, i.e., distinguishing between intermediate and final goods producers, as well as the inclusion of sectoral demand shocks.

## D.1 Sectoral supply shocks: all simplifying assumptions applied

I first show a detailed derivation of equation (10). Applying all simplifying assumptions (i) to (iii) of the main text, I weight prices and marginal costs by the sectors' respective level of price stickiness. I set sectoral demand shocks to zero, i.e., $f_{zt} = 0$ for $z = 1, \ldots, Z$). For intermediate goods producers, prices are given by:

$$p_{jt} = (1 - \lambda_j) mc_{jt} \,, \tag{A.79}$$
$$= (1 - \lambda_j)\delta p^m_{jt} - (1 - \lambda_j) a_{jt} \,, \tag{A.80}$$

which in matrix form can be written as:

$$\mathbf{p}^{im}_t = -\left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{a}_t \,. \tag{A.81}$$

Equation (10) is then defined as:

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im}) \,, \tag{A.82}$$

such that:

$$\mathbf{p}^{im}_t = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.83}$$

For final goods producers, sectoral prices and multipliers are derived from:

$$p_{zt} = (1 - \lambda_z) mc_{zt} \,, \tag{A.84}$$
$$= (1 - \lambda_z) p^m_{zt} \,, \tag{A.85}$$

which implies:

$$\mathbf{p}^{pce}_t = (\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\mathbf{p}^{im}_t \,, \tag{A.86}$$
$$= -(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.87}$$

Aggregate prices are then:

$$p^{pce}_t = -\mathbf{\Omega}'_c(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.88}$$

Because of the monetary-policy assumption, $c_t = -p^{pce}_t$, aggregate consumption follows immediately from aggregate prices but can alternatively be expressed as a weighted average of sectoral consumption, $\mathbf{c}_t$:

$$c_t = \mathbf{\Omega}'_c(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.89}$$

Finally, I derive sectoral consumption from the first-order condition on sectoral consumption demand (using again that $c_t = -p_t^{pce}$):

$$c_{zt} + p_t^{pce} = \eta(p_t^{pce} - p_{zt}) \,.$$

In matrix form and substituting for prices, this gives the following solution for sectoral consumption:

$$\mathbf{c}_t = \left[\eta\mathbf{I} + (1-\eta)\iota\mathbf{\Omega}_c'\right](\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.90}$$

## D.2 Sectoral supply shocks: allowing for labor market heterogeneity

In this part, I derive the solutions to key equation (14) of the main text. Allowing a positive inverse-Frisch elasticity, $\varphi > 0$, implies that the labor-supply condition is now given by:

$$w_{jt} = c_t - p_t^{pce} + \varphi l_{jt} \,. \tag{A.91}$$

In order to solve for sectoral prices as a function of only sectoral productivity shocks and parameters, we need to solve for wages as a function of consumption, prices, and technology shocks first.

### D.2.1 Sectoral supply shocks: solution for sectoral wages

I use the first-order conditions for Walras' law, demand relations at sectoral level, and the steady-state solution for gross output shares:

$$\begin{aligned}
n_j y_{jt} &= \psi \sum_{j'=1}^{J} \omega_{j'j} n_{j'} m_{j'jt} + (1-\psi) \sum_{z=1}^{Z} k_{zj}\omega_{cz} m_{zjt} \,, \\
m_{j'jt} &= m_{j't} - \eta(p_{jt} - p_{j't}^m) \,, \\
m_{zjt} &= m_{zt} - \eta(p_{jt} - p_{zt}^m) \,, \\
c_{zt} &= c_t - \eta(p_{zt} - p_t^{pce}) \,, \\
n_j &= \psi \sum_{j'=1}^{J} n_{j'}\omega_{j'j} + (1-\psi)\omega_{cj} \,.
\end{aligned}$$

Recall the following definitions of prices and consumption:

$$\begin{aligned}
p_{jt}^m &= \sum_{j'=1}^{J} \omega_{jj'} p_{j't} \,, \\
\mathbf{p}_t^{m,im} &= \mathbf{\Omega}\mathbf{p}_t^{im} \,, \\
p_{zt}^m &= \sum_{j=1}^{J} k_{zj} p_{jt} \,, \\
\mathbf{p}_t^{m,pce} &= \mathbf{K}\mathbf{p}_t^{im} \,,
\end{aligned}$$

$$p_t^{pce} = \sum_{z=1}^{Z} \omega_{cz} p_{zt} = \mathbf{\Omega}_c' \mathbf{p}_t^{pce} \,,$$
$$c_{zt} = m_{zt} + f_{zt} = m_{zt} \,.$$

Combining all equations and substituting into Walras' law implies the following expression (in matrix form) for sectoral gross output, $\mathbf{y}_t$:

$$\begin{aligned}\mathbf{y}_t = \psi \mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\mathbf{m}_t^{im} + (1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{\Omega}_c\mathbf{c}_t \\ + \eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\left[\mathbf{\Omega}_c\mathbf{\Omega}_c' - \mathbf{D}_c\right]\mathbf{p}_t^{pce} \\ + \left[\psi\eta\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\mathbf{\Omega} - \eta\mathbf{I} + \eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{D}_c\mathbf{K}\right]\mathbf{p}_t^{im} \,.\end{aligned}$$

I then use efficiency and labor supply conditions,

$$w_{jt} - p_{jt}^{m} = m_{jt} - l_{jt} \,,$$
$$w_{jt} - p_t^{pce} = \varphi l_{jt} + \sigma c_t \,,$$

to find expression for $m_{jt}$, which in matrix form is given by:

$$\mathbf{m}_t^{im} = \left(1 + \frac{1}{\varphi}\right)\mathbf{w}_t - \mathbf{\Omega}\mathbf{p}_t^{im} - \frac{1}{\varphi}\iota c_t - \frac{1}{\varphi}\iota\mathbf{\Omega}_c'\mathbf{p}_t^{pce} \,.$$

Using production function and labor supply condition,

$$y_{jt} = a_{jt} + (1-\delta) l_{jt} + \delta m_{jt} \,,$$
$$w_{jt} - p_t^{pce} = \varphi l_{jt} + \sigma c_t \,,$$

as well as the expression for $\mathbf{m}_t^{im}$, I get an expression for gross output $y_{jt}$, which in matrix form is equal to:

$$\mathbf{y}_t = \left(\frac{1}{\varphi} + \delta\right)\mathbf{w}_t - \frac{1}{\varphi}\iota c_t - \frac{1}{\varphi}\iota\mathbf{\Omega}_c'\mathbf{p}_t^{pce} - \delta\mathbf{\Omega}\mathbf{p}_t^{im} + \mathbf{a}_t \,.$$

The derivations above allow for an expression of sectoral wages, $\mathbf{w}_t$, that is dependent only on sectoral prices, aggregate consumption, and supply shocks:

$$\mathbf{\Theta}'\mathbf{w}_t = \theta_c c_t + \theta_p^{pce}\mathbf{p}_t^{pce} + \theta_p^{im}\mathbf{p}_t^{im} - \varphi\mathbf{a}_t \,,$$

which uses the following composite parameters:

$$\begin{aligned}\mathbf{\Theta}' &\equiv (1+\delta\varphi)\,\mathbf{I} - \psi\,(1+\varphi)\,\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D} \,, \\ \theta_c &\equiv \left[\mathbf{I} - \psi\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\right]\iota + \varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{\Omega}_c \,, \\ \theta_p^{pce} &\equiv \left[\mathbf{I} - \psi\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\right]\iota\mathbf{\Omega}_c' + \varphi\eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\left[\mathbf{\Omega}_c\mathbf{\Omega}_c' - \mathbf{D}_c\right] \,, \\ \theta_p^{im} &\equiv \varphi\left[\psi(\eta-1)\mathbf{D}^{-1}\mathbf{\Omega}'\mathbf{D}\mathbf{\Omega} + \eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{D}_c\mathbf{K} - \eta\mathbf{I} + \delta\mathbf{\Omega}\right] \,.\end{aligned}$$

### D.2.2 Sectoral supply shocks: solving for sectoral prices

Given the solution for sectoral wages, we can now solve for sectoral prices: Using the first-order conditions for marginal costs:

$$\begin{aligned} mc_{jt} &= (1-\delta)w_{jt} + \delta p^m_{jt} - a_{jt}\,, \\ mc_{zt} &= p^m_{zt}\,, \end{aligned}$$

and the information friction given by simplifying assumptions (iii):

$$\begin{aligned} p_{jt} &= (1-\lambda_j)mc_{jt}\,, \\ p_{zt} &= (1-\lambda_z)mc_{zt}\,, \end{aligned}$$

delivers the following expressions for sectoral producer and consumer prices:

$$\begin{aligned} p_{jt} &= (1-\lambda_j)(1-\delta)w_{jt} + (1-\lambda_j)\delta p^m_{jt} - (1-\lambda_j)a_{jt}\,, \\ p_{zt} &= (1-\lambda_z)p^m_{zt}\,, \end{aligned}$$

or in matrix form:

$$\begin{aligned} \mathbf{p}^{im}_t &= (1-\delta)(\mathbf{I}-\mathbf{\Lambda}^{im})\mathbf{w}_t + \delta(\mathbf{I}-\mathbf{\Lambda}^{im})\mathbf{\Omega}\mathbf{p}^{im}_t - (\mathbf{I}-\mathbf{\Lambda}^{im})\mathbf{a}_j\,, \\ \mathbf{p}^{pce}_t &= (\mathbf{I}-\mathbf{\Lambda}^{pce})\mathbf{K}\mathbf{p}^{im}_t\,. \end{aligned}$$

Then, using the expression for wages, I get the following expression:

$$\begin{aligned} &\Big[\mathbf{I} - \delta\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Omega} - (1-\delta)\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Theta}'^{-1} \\ &\qquad \left(\theta^{im}_p + \theta^{pce}_p\left(\mathbf{I}-\mathbf{\Lambda}^{pce}\right)\mathbf{K} - \theta_c\mathbf{\Omega}'_c\left(\mathbf{I}-\mathbf{\Lambda}^{pce}\right)\mathbf{K}\right)\Big]\mathbf{p}^{im}_t\,, \\ &\quad = -\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\left[\mathbf{I}+\varphi(1-\delta)\mathbf{\Theta}'^{-1}\right]\mathbf{a}_t + (1-\delta)\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Theta}'^{-1}\left[c_t + p^{pce}_t\right]\,. \end{aligned}$$

Applying simplifying assumption (ii), i.e., $c_t = -p^{pce}_t$, the last term in the expression above disappears, which yields the final expression for sectoral prices:

$$\mathbf{p}^{im}_t = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,,$$

where $\widehat{\mathbf{X}}^{im}$ in key equation (14) is given by:

$$\begin{aligned} \widehat{\mathbf{X}}^{im} \equiv &\Big[\mathbf{I} - \delta\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Omega} \\ &\quad - (1-\delta)\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Theta}'^{-1} \\ &\quad \left(\theta^{im}_p + \theta^{pce}_p\left(\mathbf{I}-\mathbf{\Lambda}^{pce}\right)\mathbf{K} - \theta_c\mathbf{\Omega}'_c\left(\mathbf{I}-\mathbf{\Lambda}^{pce}\right)\mathbf{K}\right)\Big]^{-1} \\ &\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\left[\mathbf{I}+\varphi(1-\delta)\mathbf{\Theta}'^{-1}\right]\,. \end{aligned} \tag{A.92}$$

The solution for sectoral PCE prices and consumption, as well as aggregate PCE prices and consumption is then the same as under the model using all simplifying assumptions.

### D.2.3 Sectoral supply shocks: verification

If I set $\varphi = 0$, then the composite parameters used for key equation (14) are given by:

$$\begin{aligned}
\boldsymbol{\Theta}' &= \left[\mathbf{I} - \psi \mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D}\right] , \\
\theta_c &= \left[\mathbf{I} - \psi \mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D}\right] \iota , \\
\theta_p^{pce} &= \left[\mathbf{I} - \psi \mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D}\right] \iota \boldsymbol{\Omega}_c' , \\
\theta_p^{im} &= 0 ,
\end{aligned}$$

and hence

$$\mathbf{w}_t = \iota c_t + \iota p_t^{pce} , \tag{A.93}$$

which implies that $\widehat{\mathbf{X}}^{im}$ is given by key equation (10).

## D.3 Sectoral demand shocks

The derivation of key equation (26) for sectoral demand shocks follows a similar procedure as for sectoral supply shocks, with a few modifications. Setting sectoral supply shocks to zero (i.e., $a_{jt} = 0$ for $= 1, \ldots, J$), and applying simplifying assumptions (ii) and (iii) of the main text, it can be shown that sectoral wages solve the following expression:

$$\boldsymbol{\Theta}'\mathbf{w}_t = \theta_c c_t + \theta_p^{pce}\mathbf{p}_t^{pce} + \theta_p^{im}\mathbf{p}_t^{im} + \varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}\mathbf{D}_c\mathbf{f}_t ,$$

where

$$\begin{aligned}
\boldsymbol{\Theta}' &\equiv (1+\delta\varphi)\,\mathbf{I} - \psi\,(1+\varphi)\,\mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D} , \\
\theta_c &\equiv \left[\mathbf{I} - \psi \mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D}\right] \iota + \varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\boldsymbol{\Omega}_c , \\
\theta_p^{pce} &\equiv \left[\mathbf{I} - \psi \mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D}\right] \iota\boldsymbol{\Omega}_c' + \varphi\eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\left[\boldsymbol{\Omega}_c\boldsymbol{\Omega}_c' - \mathbf{D}_c\right] , \\
\theta_p^{im} &\equiv \varphi\left[\psi(\eta-1)\mathbf{D}^{-1}\boldsymbol{\Omega}'\mathbf{D}\boldsymbol{\Omega} + \eta(1-\psi)\mathbf{D}^{-1}\mathbf{K}'\mathbf{D}_c\mathbf{K} - \eta\mathbf{I} + \delta\boldsymbol{\Omega}\right] .
\end{aligned}$$

Given this expression and other respective derivations similar to those for sectoral supply shocks, I derive the final expression for key equation (26):

$$\widehat{\mathbf{F}}^{im} \equiv \widehat{\mathbf{P}}^{im}\left(\mathbf{I} - \boldsymbol{\Lambda}^{im}\right)(1-\delta)\boldsymbol{\Theta}'^{-1}\varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}\mathbf{D}_c , \tag{A.94}$$

with composite matrix $\widehat{\mathbf{P}}^{im}$ defined as:

$$\begin{aligned}
\widehat{\mathbf{P}}^{im} \equiv \Big[ & \mathbf{I} - \delta\left(\mathbf{I} - \boldsymbol{\Lambda}^{im}\right)\boldsymbol{\Omega} \\
& - (1-\delta)\left(\mathbf{I} - \boldsymbol{\Lambda}^{im}\right)\boldsymbol{\Theta}'^{-1} \\
& \left(\theta_p^{im} + \theta_p^{pce}\left(\mathbf{I} - \boldsymbol{\Lambda}^{pce}\right)\mathbf{K} - \theta_c\boldsymbol{\Omega}_c'\left(\mathbf{I} - \boldsymbol{\Lambda}^{pce}\right)\mathbf{K}\right)\Big]^{-1} .
\end{aligned} \tag{A.95}$$

# E Alternative DSGE specifications: Calvo pricing

For the identification setup in the main text, I use a simpler information friction that allows for closed-form derivation of sectoral multipliers. This appendix describes the alternative Calvo pricing problem. Firm $r \in j$ solves the following standard problem:

$$\max_{P_{jt}(r)} \mathbf{E}_t \sum_{s=0}^{\infty} Q_{t,t+s} \alpha_j^s \left[ P_{jt}(r) Y_{jt+s}(r) - MC_{jt+s}(r) Y_{jt+s}(r) \right] , \tag{A.96}$$

subject to the market clearing condition, production function, demand schedules, and staggered price setting:

$$Y_{jt}(r) = \sum_{j'=1}^{J} \int_{\Im_{j'}} M_{j'jt}(r', r) dr' + \sum_{z=1}^{Z} \int_{\Im_z} M_{zjt}(q, r) dq \, , \tag{A.97}$$

$$Y_{jt}(r) = e^{a_{jt}} L_{jt}^{1-\delta}(r) M_{jt}^{\delta}(r) \, , \tag{A.98}$$

$$Y_{jt}(r) = \left( \frac{P_{jt}(f)}{P_{jt}} \right)^{-\theta} \left( \int_0^1 Y_{jt}(r') dr' \right) \, , \tag{A.99}$$

$$P_{jt} = \left[ (1-\alpha_j) P_{jt}^{*1-\theta} + \alpha_j P_{jt-1}^{1-\theta} \right]^{\frac{1}{1-\theta}} \, . \tag{A.100}$$

A Calvo pricing problem for final goods producers follows, analogously.

For full details of the theoretical model setup, including households, intermediate goods producers, final goods producers, and market clearing conditions, see Appendix A.

# F Data sources

This appendix summarizes cross-sectional input-output accounts as well as time series data used in the empirical model.

## F.1 Input-output data

I use NAICS input-output tables for the years 1997 to 2022 from the make-use framework of the Bureau of Economic Analysis (BEA). The specification in the main text includes a breakdown of 33 intermediate goods sectors. For all years, I calibrate the input-output weights matrix, $\mathbf{\Omega}$, in the same way as Pastén, Schoenle, and Weber (2024) (see their Appendix for more details):

For a year $\tau$, the make table, $MAKE_\tau$, and the commodity-by-industry use table, $USE_\tau$, are transformed such that:

$$SHARE_\tau = MAKE_\tau \oslash (\mathbf{I} \times MAKE_\tau) \; , \tag{A.101}$$

$$REVSHARE_\tau = SHARE_\tau \times USE_\tau \, , \tag{A.102}$$

$$SUPPSHARE_\tau = [REVSHARE_\tau \oslash (\mathbf{I} \times USE_\tau)]' \; , \tag{A.103}$$

where $\oslash$ is the Hadamard division, $SHARE_\tau$ is the market share matrix, $REVSHARE_\tau$ the revenue share matrix, and $SUPPSHARE_\tau$ the industry-by-industry input-share matrix. Matrix $\mathbf{\Omega}$ in the main text is then calibrated for every year $\tau$ as $SUPPSHARE_\tau$.

## F.2 Bridge table

There are 76 PCE categories included in BEA bridge tables. All items can be identified by a line number. I remove four of those categories. These include national income and product accounts (NIPA) line item 46 (*Net expenditures abroad by U.S. residents*), which does not map to an intermediate goods producer. I also remove line items 109 (*Foreign travel by U.S. residents*), 110 (*Less: Expenditures in the United States by nonresidents*), and 111 (*Final consumption expenditures of nonprofit institutions serving households (NPISHs)*).

## F.3 PCE time series data

I match the 72 PCE categories of the NAICS-PCE bridge matrix with time series data on PCE prices and real quantity indices. As described in the previous section, no individual time series for line items 46, 109, 110, 111 are used. Aggregate price and quantity time series, however, still include these items.

Many of the PCE series are affected by outliers. I therefore check for all individual PCE series whether observations exceed the interquartile range by a factor 5. A value that exceeds this threshold is then adjusted to the positive or negative value of that very threshold. Appendix Figures A.1 and A.2 show some sectors with substantial outlier adjustments.

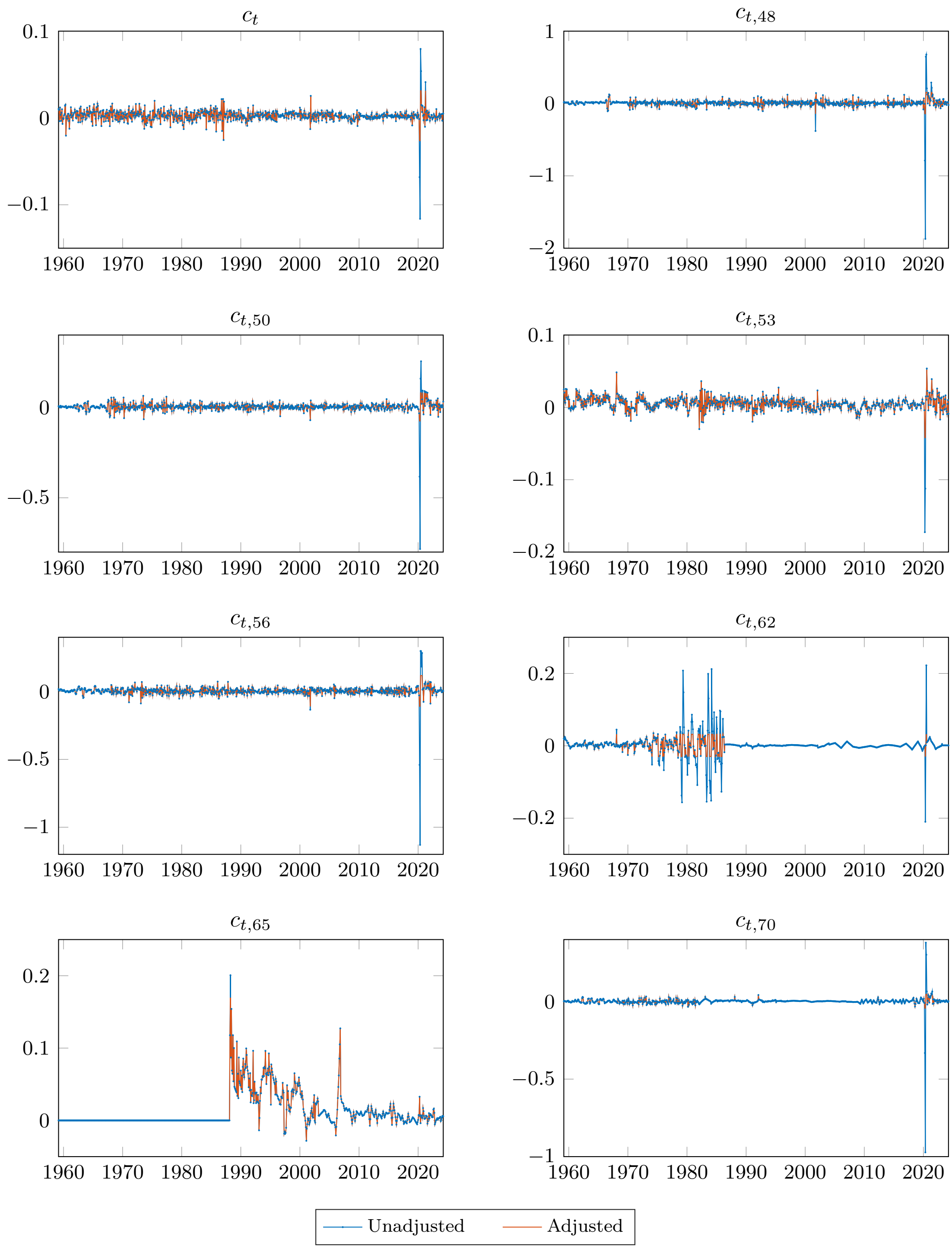
### F.4 Frequencies of NAICS sector price changes

Estimates for monthly frequencies of producer price changes are taken from Pastén, Schoenle, and Weber (2020). Based on the authors' calculations for a breakdown of 58 NAICS sectors, I further aggregate these frequencies to match the 33-sector-level aggregation used in the main text.

### F.5 Durations of PCE price categories

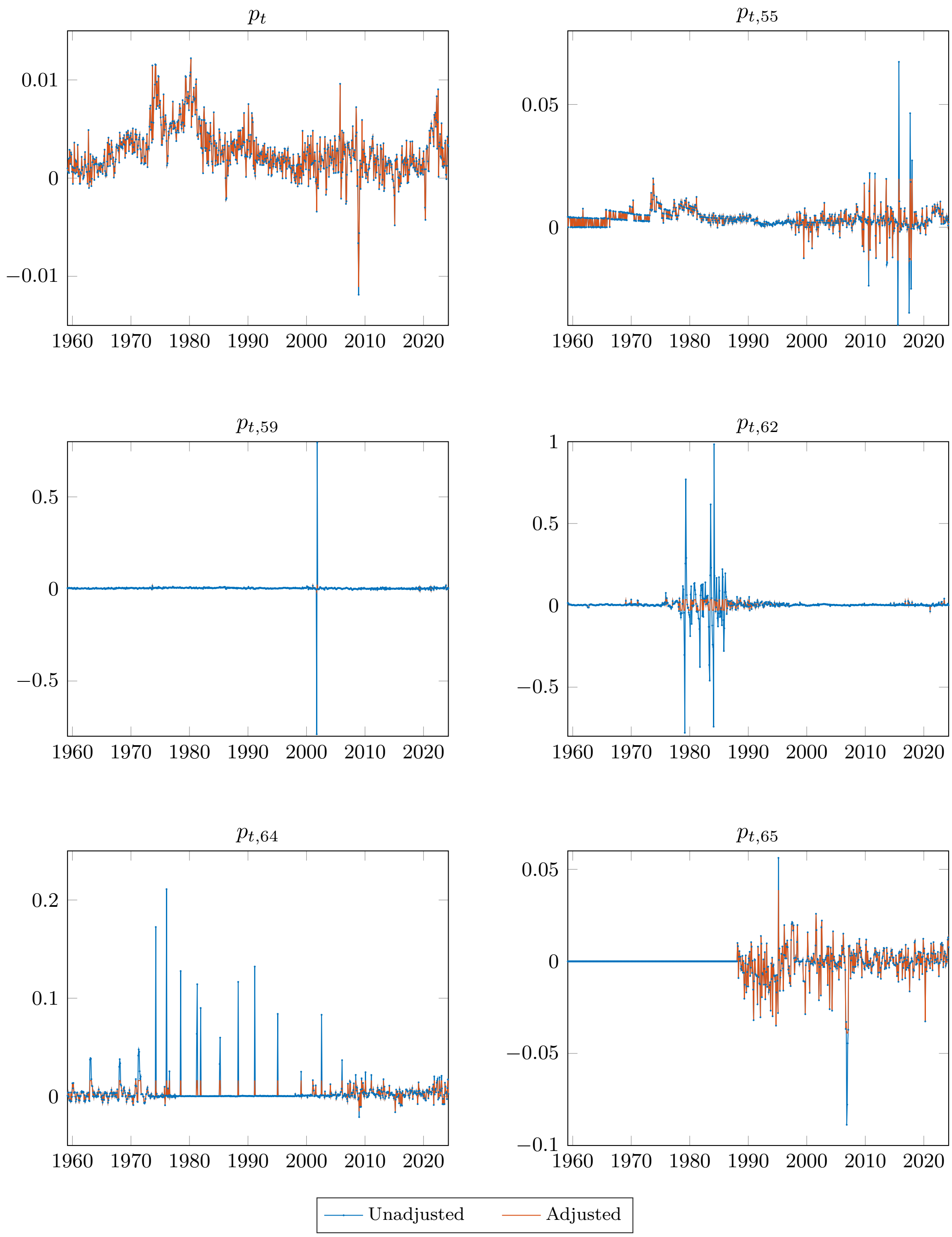
I use median price adjustment durations from Nakamura and Steinsson (2008). To transform these durations to PCE categories requires several conversions. Nakamura and Steinsson's (ibid.) estimates are available for Entry Line Items (ELI), which I first map to the Bureau of Labor Statistics' (BLS) Consumer Expenditure Survey items, i.e., to universal classification codes (UCC). I then use a second BLS concordance table to map UCC items to the BEA's PCE categories. The final durations for PCE categories are weighted averages of the original ELIs. For PCE sectors where no matching data is available, I set the price duration to the average duration of available data.

Figure A.1: Outlier adjustment for some selected consumption growth series




*Notes*: This figure contrasts outlier adjusted data with unadjusted data (in month-on-month growth rates). Many of these personal consumption expenditure (PCE) series are affected by outliers. I therefore check for all individual PCE series whether observations exceed the interquartile range by a factor 5. A value that exceeds this threshold is then adjusted to the positive or negative value of that very threshold.

Figure A.2: Outlier adjustment for some selected inflation series



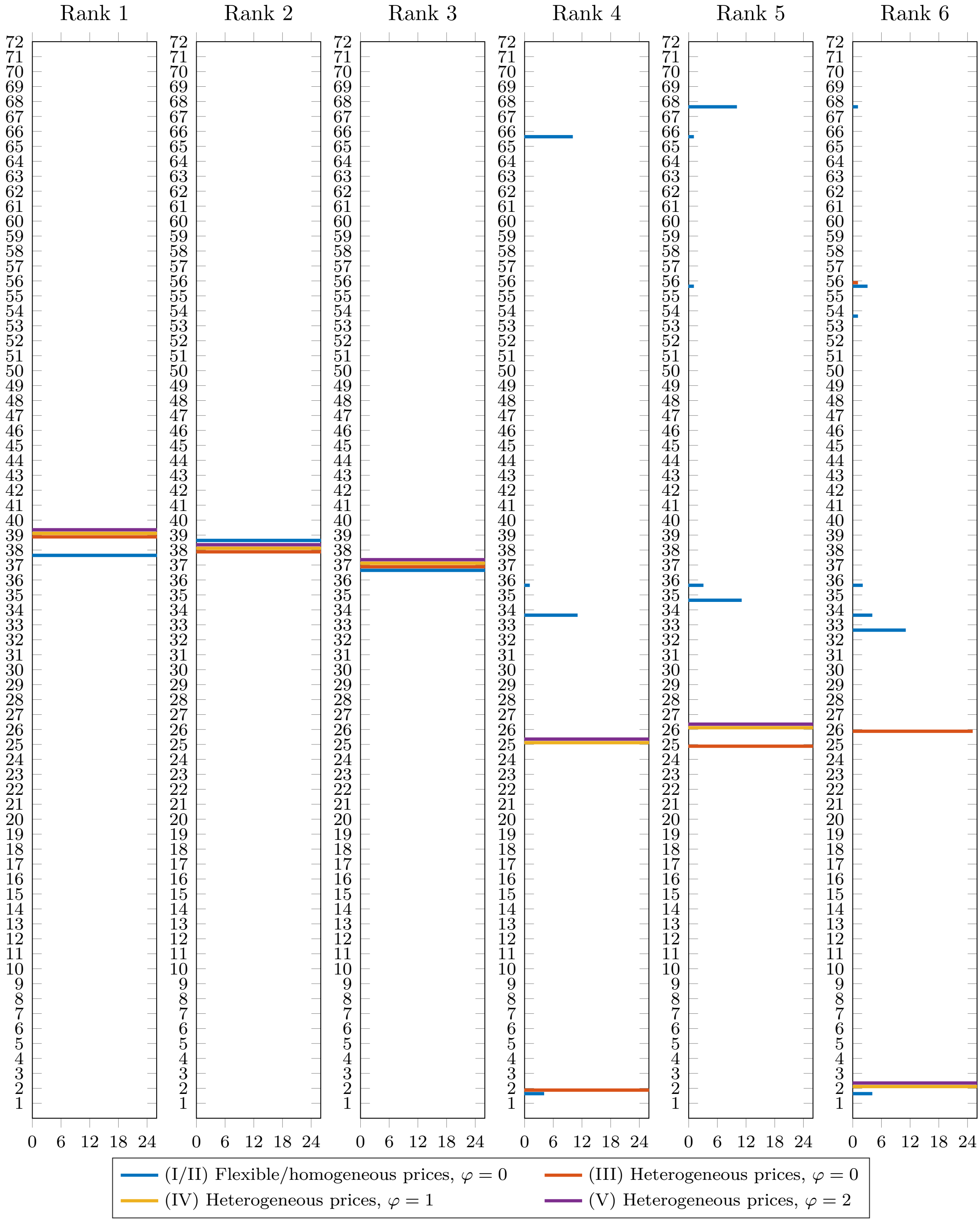

*Notes*: See notes to Figure A.1.

# G Additional clustering illustrations

Figure A.3 summarizes rankings for another supply shock, one that originates in the *Utilities* sector. Inspecting the cross-sectional rankings at ranks 1 and 2 reveals more variation than in the example in Figure 4 of the main text. However, this sectoral shock still allows for fairly straightforward clustering: a first cluster with categories 38, *Electricity*, and 39, *Natural gas*; a second cluster with category 37, *Water supply and sanitation*; and a third cluster including the remaining 69 PCE categories.

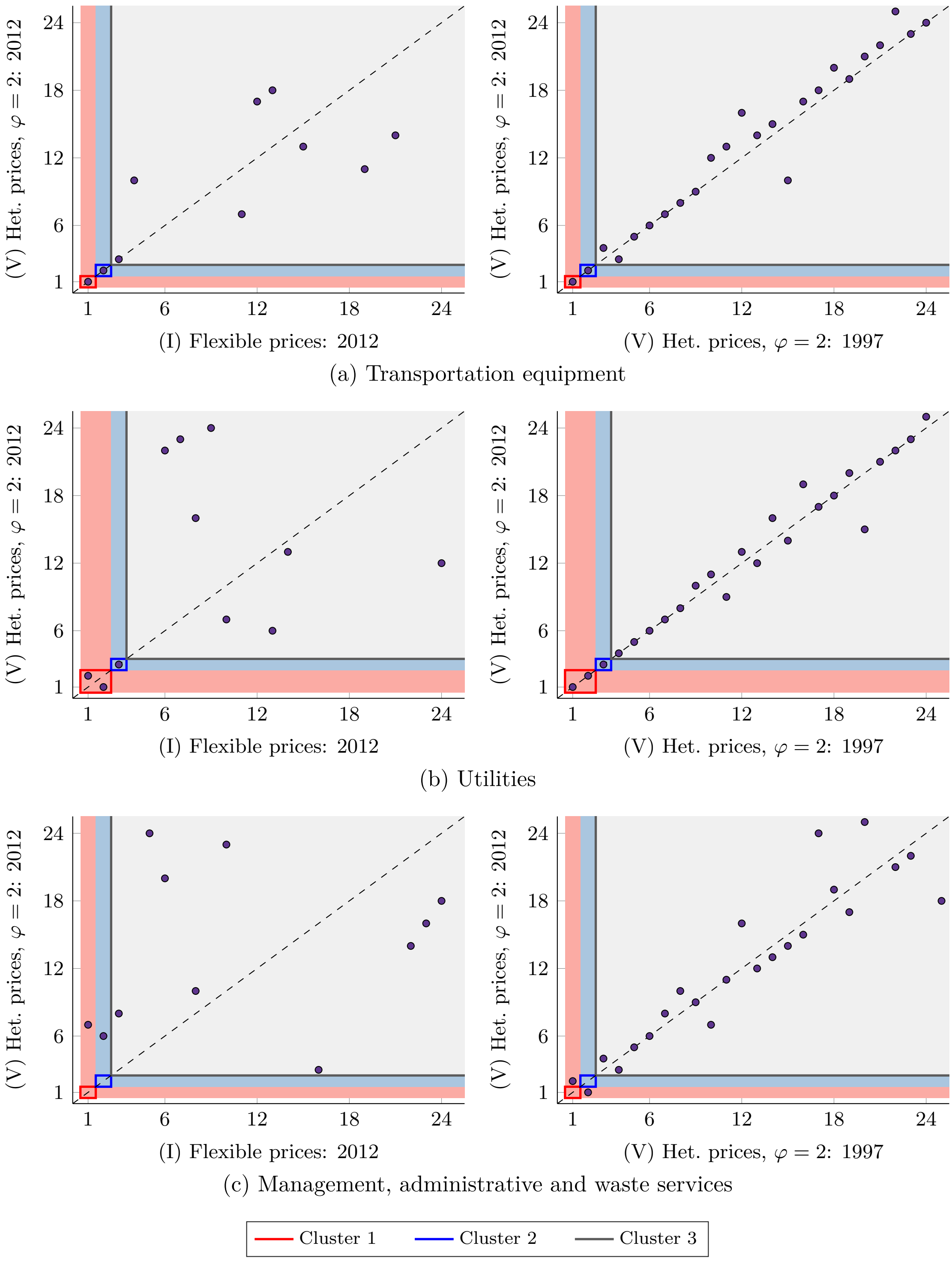
In Figure A.4, I revisit the three earlier examples of sector-specific supply shocks and present the results of the final clustering exercise. The charts in the left column compare a flexible price ranking (specification I) with that of heterogeneous price stickiness and labor market segmentation using $\varphi = 2$ (specification V). The scatter plot contrasts the rankings across the two specifications. The red, blue, and black frames correspond to the final clusters, derived in the clustering exercise described above. If the scatter dots are within the colored frames, it means that the visualized cluster is consistent with both rankings. Similarly, in the right column, I contrast calibrations to different years (1997 versus 2012) for specification (V). Comparing the charts in the first two rows illustrates that the clusters for the first two sectoral supply shocks are both robust across different model specifications (left column), as well as across calibrations (right column). The bottom row in Figure A.4 revisits the case of an infeasible shock originating in *Management, administrative and waste services*, where no robust cluster can be found.

Figure A.3: Rankings for *Utilities* supply shocks




*Notes*: This figure summarizes the first six rankings for the sector-specific supply shock that originates in the given sector. The four models correspond, in this order, to specifications (I/II), (III), (IV), and (V). For every specification, I consider 26 calibrations based on input-output tables for the years 1997 to 2022. The bars summarize for the respective specification how often the multipliers for the 72 personal consumption expenditure category appears at rank 1 through 6 across the 26 calibrations.

Figure A.4: Ranking comparisons across specifications & calibrations




*Notes*: The figure shows, for three examples, sector-specific supply shocks and their respective cluster. If a scatter dot is not within its respective red, blue, or black box, it implies that the cluster is not consistent across the two depicted specifications/calibrations.

# H Clustering performance

This section provides a more detailed description of the clustering exercise and the number of criteria that determine *feasibility*.

Table A.1 presents clustering performance for sectoral supply shocks across specifications (I) to (V). The last column indicates those methods that deliver the best clustering results. These methods include *k-means* (K-mea), *k-medoids* (K-Med), and *hierarchical clustering* (Hier), as well as a simple decision algorithm that I specify based on ranking counts (Init). Finally, the method *Manu* refers to manual clustering that is based on a visual inspection of rankings, presented as in Figures 4 to 5. The *Match* rate indicates the percentage of the 104 calibrations that match against the best performing cluster. Table A.2 includes analogous results of demand shocks' clustering performance.

I then evaluate each cluster against a set of criteria to determine whether it is suitable for identification or not. For supply shocks, Table A.3 presents clusters across as set with specifications (I) to (V), Table A.4 presents a second set with specifications (III) to (V), and Table A.5 a third set with only specifications (IV) and (V).

The *Shock* column in Tables A.3 to A.5 indicates the respective supply shock. Bold numbers signal that the *Match* rate is larger than 70 percent. Underlined PCE categories in the cluster columns indicate problematic categories that occur in clusters 1 and 2. These sort of problematic categories include, for instance, *Motor vehicle fuels, lubricants, and fluids* and *Natural gas*. Cluster compositions that consist of any of these categories exclusively in their first two clusters are likely to be conflated with rankings corresponding to other shocks. I therefore check all clusters against these sets of problematic sectors and make sure that the final cluster composition includes other price categories that are unique compared to other shocks' clusters. If a sector cluster includes only problematic categories in the first cluster, I also label the shock as *infeasible*. Finally, the last column shows whether the corresponding ranking for sectoral consumption growth rates is the same as the price ranking, $\widehat{\mathbf{X}}_r^{pce}$. If a cluster is not feasible for the given set, either due to problematic sectors or because the match rate is too low, I consider the next smaller set of model specifications and repeat the exercise.

Table A.6 presents the cluster results for sectoral demand shocks. In addition to clustering price rankings, $\widehat{\mathbf{F}}_r^{pce}$, the last column also shows the first cluster of the consumption growth rankings, $\widehat{\mathbf{F}}_r^{c}$. For sectoral demand shocks, price and consumption rankings are generally different.

A final criterion that renders a shock *infeasible* is related to the number of sectoral shocks included in the first cluster of $\widehat{\mathbf{F}}_r^{pce}$. If a cluster includes five or more PCE categories, I label the shock *infeasible* as well. Having too many categories in the first cluster has implications on the number of factors used in the empirical model and makes estimation more challenging.

The final set of clusters for *feasible* sector-specific supply and demand shocks are presented in the main text in Table 1.

Table A.1: Clustering performance of supply shocks

| ($j$) | Origin sector | Match | Best clustering methods |
|---|---|---|---|
| (1) | Agriculture, forestry, fishing, and hunting | **83.7**% | K-Mea, K-Med, Hier |
| (2) | Mining | **99**% | K-Mea, Init |
| (3) | Utilities | **100**% | K-Mea, K-Med, Init |
| (4) | Construction | 52.9% | K-Mea, Hier |
| (5) | Wood products | 45.2% | Init |
| (6) | Nonmetallic mineral products | 21.2% | K-Med |
| (7) | Primary metals and fabricated metal products | 10.6% | Hier |
| (8) | Machinery | 20.2% | Hier |
| (9) | Computer and electronic products | 54.8% | Manu |
| (10) | Electrical equipment, appliance, and comp. | 51% | Hier, Init |
| (11) | Transportation equipment | **99**% | K-Mea, K-Med, Hier, Init |
| (12) | Furniture and related products | 50% | K-Mea, K-Med, Hier |
| (13) | Miscellaneous manufacturing | 55.8% | Init |
| (14) | Food and beverage and tobacco products | **100**% | Init |
| (15) | Textiles, apparel, and leather | 47.1% | Hier |
| (16) | Paper and printing | 32.7% | Init |
| (17) | Petroleum and coal products | **100**% | K-Mea, K-Med, Hier, Init |
| (18) | Chemical products | 25% | K-Mea |
| (19) | Plastics and rubber products | 53.8% | K-Mea, Hier, Init |
| (20) | Wholesale trade | **75**% | K-Mea, Hier |
| (21) | Retail trade | **73.1**% | Hier |
| (22) | Transportation and warehousing | 48.1% | K-Mea |
| (23) | Information | **75**% | K-Mea, Hier, Init |
| (24) | Finance and insurance | **75**% | Init |
| (25) | Real estate and rental and leasing | 30.8% | K-Mea |
| (26) | Professional, scientific, and technical services | 50% | Init |
| (27) | Management, administrative and waste services | 34.6% | Init |
| (28) | Educational services | 56.7% | Init |
| (29) | Health care and social assistance | 42.3% | Init |
| (30) | Arts, entertainment, and recreation | 51% | K-Mea, Hier, Init |
| (31) | Accommodation and food services | **75**% | Init |
| (32) | Other services, except government | 39.4% | K-Mea |
| (33) | Government | 31.7% | Init |

*Notes*: This table shows clustering performance for sectoral supply shocks across specifications (I) to (V). The last column indicates those methods that deliver the best clustering results. These methods include *k-means* (K-mea), *k-medoids* (K-Med), and *hierarchical clustering* (Hier), as well as a simple decision algorithm that I specify based on ranking counts (Init). A manual clustering method (Manu) is based on a simple visual inspection of rankings based on visualizations similar to Figures 4 to 5 of the main text. The *Match* rate indicates the percentage of the 104 calibrations that match against the best performing cluster. *Match* rates higher than the *feasibility* cutoff of 70 percent are indicated in bold.

Table A.2: Clustering performance of demand shocks

| $(z)$ | Origin (composite) category | Match | Best clustering methods |
|---|---|---|---|
| (1–3) | Motor vehicles and parts | **100%** | Hier, Init |
| (4–7) | Furnishings and durable household equip. | **100%** | K-Med, Hier |
| (8–12) | Recreational goods and vehicles | **100%** | K-Mea, K-Med, Hier, Init |
| (13–17) | Other durable goods | **100%** | K-Med, Hier |
| (18–20) | Food and beverages purchased for off-premises consumption | **100%** | K-Mea, K-Med, Hier, Init |
| (21–24) | Clothing and footwear | **100%** | K-Med, Hier |
| (25, 26) | Gasoline and other energy goods | **100%** | K-Mea, K-Med, Hier, Init |
| (27–32) | Other nondurable goods | **100%** | K-Med, Hier |
| (33–39) | Housing and utilities | **100%** | K-Mea, K-Med, Hier, Init |
| (40–44) | Health care | **100%** | K-Mea, K-Med, Hier, Init |
| (45–49) | Transportation services | **88.5%** | Init |
| (50–53) | Recreation services | **100%** | K-Mea, K-Med, Hier, Init |
| (54–56) | Food services and accommodations | **100%** | K-Mea, Init |
| (57–62) | Financial services and insurance | **100%** | K-Mea, K-Med, Hier, Init |
| (63–72) | Other services | **100%** | K-Mea, K-Med, Hier |

*Notes*: This table shows clustering performance for sectoral demand shocks across specifications (III) and (V). The last column indicates those methods that deliver the best clustering results. These methods include *k-means* (K-mea), *k-medoids* (K-Med), and *hierarchical clustering* (Hier), as well as a simple decision algorithm that I specify based on ranking counts (Init). The *Match* rate indicates the percentage of the 52 calibrations that match against the best performing cluster. *Match* rates higher than the *feasibility* cutoff of 70 percent are indicated in bold.

Table A.3: Clustering evaluation of supply shocks (all specifications)

| Shock | PCE categories $z$ | | | |
|---|---|---|---|---|
| ($j$) | Cluster 1 | Cluster 2 (or 3*) | Match | $\widehat{\mathbf{X}}_r^c$ |
| **(1)** | 20 | 18, 28, 31, 55 | **83.7**% | = |
| (2) | 25, 26, 38, 39 | 37 | **99**% | = |
| **(3)** | 38, 39 | 37 | **100**% | = |
| (4) | 39 | 2, 25, 26, 38 | 52.9% | = |
| (5) | 26 | 25 | 45.2% | = |
| (6) | 6, 25, 26, 39 | 1, 2, 3, 4, 7, 31, 38, 69 | 21.2% | = |
| (7) | 6 | 1, 9 | 10.6% | = |
| (8) | 5 | 1, 2, 7, 8, 10, 25, 26, 38, 39 | 20.2% | = |
| (9) | 8, 17 | 42* | 54.8% | = |
| (10) | 5 | 3 | 51% | = |
| **(11)** | 1 | 10 | **99**% | = |
| (12) | 4 | 2, 25, 26, 38, 39 | 50% | = |
| (13) | 12 | 13, 14 | 55.8% | = |
| (14) | 18, 31, 55 | 19 | **100**% | = |
| (15) | 16, 21, 22, 24 | 23 | 47.1% | ≠ |
| (16) | 39 | 25 | 32.7% | = |
| (17) | 25 | 26 | **100**% | = |
| (18) | 25, 26, 27, 30, 39 | 2, 29, 38 | 25% | = |
| (19) | 3 | 6 | 53.8% | = |
| (20) | 25 | 2, 26, 31 | **75**% | = |
| (21) | 2 | 1, 25, 26 | **73.1**% | = |
| (22) | 2, 25, 26, 39, 48, 49 | 38, 47 | 48.1% | = |
| **(23)** | 63 | 15, 51 | **75**% | = |
| **(24)** | 62 | 60 | **75**% | = |
| (25) | 2, 25, 26, 33, 34, 35, 38, 39, 46 | 1, 3, 7, 15, 18, 20, 31, 37, 48, 49, 51, 56, 57–62, 63, 72 | 30.8% | = |
| (26) | 39 | 25 | 50% | = |
| (27) | 39 | 25 | 34.6% | = |
| (28) | 68 | 66 | 56.7% | = |
| (29) | 39 | 25 | 42.3% | ≠ |
| (30) | 50 | 52 | 51% | = |
| **(31)** | 56 | 36 | **75**% | = |
| (32) | 45 | 2, 25, 26, 38, 39, 70 | 39.4% | = |
| (33) | 25 | 39 | 31.7% | = |

*Notes*: This table is used to evaluate the cluster performance of sectoral supply shocks across the specifications indicated in the title. The *Shock* column indicates the respective supply shock. Bold numbers signal that the *Match* rate is larger than 70 percent. Underlined PCE categories in the cluster columns indicate problematic categories that occur in clusters 1 and 2. Finally, the last column shows whether the corresponding ranking for sectoral consumption growth rates is the same as the price ranking, $\widehat{\mathbf{X}}_r^{pce}$.

Table A.4: Clustering evaluation of supply shocks (specifications III to V)

| Shock | PCE categories $z$ | | | |
|---|---|---|---|---|
| $(j)$ | Cluster 1 | Cluster 2 (or 3*) | Match | $\widehat{\mathbf{X}}_r^c$ |
| **(1)** | 20 | 18 | **100%** | = |
| (2) | 25, 26, 39 | 38 | **100%** | = |
| **(3)** | 39 | 38 | **100%** | = |
| (4) | 39 | 2, 25, 26, 38 | **70.5%** | = |
| (5) | 26 | 25 | 60.3% | = |
| (6) | 6, 25, 39 | 26, 38 | 53.8% | = |
| (7) | 25, 39 | 1, 2, 6, 9, 26, 38 | 52.6% | = |
| (8) | 5, 25, 26, 39 | 1, 38 | 34.6% | = |
| **(9)** | 8, 17 | 42* | **73.1%** | = |
| (10) | 5 | 3 | 61.5% | = |
| **(11)** | 1 | 10 | **100%** | = |
| (12) | 4 | 2, 25, 26, 38, 39 | 66.7% | = |
| (13) | 12 | 2, 9, 13, 14, 25, 26, 28, 38, 39 | 66.7% | = |
| **(14)** | 31 | 18, 19, 55 | **100%** | = |
| (15) | 2, 16, 21, 22, 23, 24, 25, 26, 38, 39 | 1, 3, 4, 8, 9, 12, 15, 17, 18, 19, 20, 27, 28, 29, 30, 31, 37, 48, 49, 55, 56, 60, 62 | 34.6% | = |
| (16) | 25, 26, 39 | 2, 23, 29, 38 | 43.6% | = |
| (17) | 25 | 26 | **100%** | = |
| (18) | 25, 26, 27, 39 | 2, 29, 30, 38 | 64.1% | = |
| **(19)** | 3 | 6 | **71.8%** | = |
| (20) | 25 | 2, 26, 31 | **100%** | = |
| (21) | 2 | 1, 25, 26 | **97.4%** | = |
| (22) | 2, 25, 26, 39, 47, 48, 49 | 1, 38, 64 | **70.5%** | ≠ |
| **(23)** | 63 | 15, 51 | **100%** | = |
| **(24)** | 60, 62 | 57, 59 | **100%** | = |
| (25) | 39 | 2, 25, 26, 33, 34, 35, 38, 46 | 59% | = |
| (26) | 25, 39 | 2, 26, 38, 53, 69 | 38.5% | = |
| (27) | 1, 2, 25, 26, 37, 38, 39, 53, 56, 72 | 31 | **78.2%** | = |
| **(28)** | 68 | 66 | **75.6%** | = |
| (29) | 25, 39 | 26, 38 | 52.6% | = |
| (30) | 50 | 52 | 67.9% | = |
| **(31)** | 56 | 36 | **100%** | = |
| (32) | 45 | 25, 39 | 64.1% | = |
| (33) | 25, 26, 37, 39 | 2, 38, 46, 52, 64 | 51.3% | = |

*Notes*: See notes to Table A.3.

Table A.5: Clustering evaluation of supply shocks (specifications IV and V)

| Shock | PCE categories $z$ | | | |
|---|---|---|---|---|
| ($j$) | Cluster 1 | Cluster 2 (or 3*) | Match | $\widehat{\mathbf{X}}_r^c$ |
| **(1)** | 20 | 18 | **100%** | = |
| (2) | 25, 26, 39 | 38 | **100%** | = |
| **(3)** | 39 | 38 | **100%** | = |
| (4) | 25, 39 | 2, 26, 38 | **100%** | = |
| (5) | 26 | 25 | **90.4%** | = |
| (6) | 6, 25, 26, 39 | 38 | **86.5%** | = |
| (7) | 25, 39 | 1, 2, 6, 9, 26, 38 | **78.8%** | = |
| (8) | 25, 39 | 1, 2, 3, 5, 7, 8, 10, 26, 31, 37, 38 | **71.2%** | = |
| (9) | 1, 2, 8, 17, 25, 26, 38, 39 | 13, 31 | **82.7%** | = |
| **(10)** | 5 | 1, 2, 3, 8, 25, 26, 30, 38, 39 | **78.8%** | = |
| **(11)** | 1 | 2, 3, 10, 25, 26, 38, 39 | **100%** | = |
| **(12)** | 4 | 2, 25, 26, 38, 39 | **100%** | = |
| **(13)** | 12 | 2, 9, 13, 14, 25, 26, 28, 38, 39 | **100%** | = |
| **(14)** | 31 | 18, 19, 55 | **100%** | = |
| (15) | 2, 16, 21, 22, 23, 24, 25, 26, 38, 39 | 1, 4, 12, 20, 29, 31 | **84.6%** | = |
| (16) | 25, 39 | 2, 23, 26, 29, 38 | **82.7%** | = |
| (17) | 25 | 26 | **100%** | = |
| (18) | 25, 26, 27, 39 | 2, 29, 30, 38 | **96.2%** | = |
| **(19)** | 3 | 2, 6, 25, 26, 38, 39 | **100%** | = |
| (20) | 25 | 2, 26, 31 | **100%** | = |
| (21) | 2 | 1, 25, 26 | **98.1%** | = |
| (22) | 2, 25, 26, 39, 48, 49 | 38, 47 | **96.2%** | = |
| (23) | 15, 51, 63 | 2, 8, 11, 25, 26, 32, 38, 39, 65 | **100%** | = |
| **(24)** | 60, 62 | 25, 39, 57, 58, 59, 61 | **100%** | = |
| (25) | 39 | 2, 25, 26, 33, 34, 35, 38, 46 | **88.5%** | = |
| (26) | 25, 39 | 2, 26, 38, 53 | **100%** | = |
| (27) | 25, 39 | 2, 26, 37, 38 | **96.2%** | = |
| **(28)** | 68 | 25, 38, 39, 66, 67 | **100%** | = |
| (29) | 25, 39 | 2, 26, 38, 41, 43, 44, 71 | **100%** | = |
| **(30)** | 50 | 25, 39, 52 | **94.2%** | = |
| **(31)** | 56 | 36, 39, 54 | **100%** | = |
| **(32)** | 45 | 25, 39 | **96.2%** | = |
| (33) | 25 | 26, 37, 39 | **100%** | = |

*Notes*: See notes to Table A.3.

Table A.6: Clustering evaluation of demand shocks (specifications IV and V)

| Shock | PCE categories $z$ in $\widehat{\mathbf{F}}_r^{pce}$ | | | PCE categories $z$ in $\widehat{\mathbf{F}}_r^{c}$ |
|---|---|---|---|---|
| $z$ | Cluster 1 | Cluster 2 (or 3*) | Match | Cluster 1 |
| **(1–3)** | 1, 2 | 38*, 39* | **100**% | 3 |
| **(4–7)** | 2 | 38*, 39*, 56* | **100**% | 6, 7 |
| **(8–12)** | 2 | 1 | **100**% | 9, 10, 11, 12 |
| **(13–17)** | 1 | 38*, 39*, 56* | **100**% | 14, 15, 16 |
| **(18–20)** | 2, 31 | 18, 20, 55 | **100**% | 19 |
| **(21–24)** | 55 | 38*, 39*, 56* | **100**% | 23 |
| **(25, 26)** | 55 | 55 | **100**% | 24 |
| **(27–32)** | 55 | 38*, 39*, 56* | **100**% | 32 |
| **(33–39)** | 55 | 38 | **100**% | 33, 34, 35, 36, 37 |
| (40–44) | 40–44, 67, 71 | 2*, 25*, 26*, 38*, 39* | **100**% | 40, 42 |
| (45–49) | Majority | 2*, 31*, 38*, 39* | **88.5**% | 46 |
| (50–53) | 15, 50, 51, 52, 63 | 2*, 25*, 26*, 38*, 39* | **100**% | 53 |
| **(54–56)** | 56 | 36, 54 | **100**% | 54, 55 |
| **(57–62)** | 60, 62 | 57, 58, 59, 61 | **100**% | 58, 61 |
| (63–72) | 15, 45, 51, 63, 66–68 | 2*, 25*, 26*, 38*, 39* | **100**% | 64, 65, 69–72 |

*Notes*: This table is used to evaluate the cluster performance of sectoral demand shocks across specifications (IV) and (V). The *Shock* column indicates the set of personal consumption expenditure (PCE) categories that are subject to the demand shock. Bold numbers signal that the shock is *feasible*. In addition to a *Match* rate that is larger than 70 percent, *feasible* shocks cannot include 5 or more PCE categories in the first cluster. Too many categories in the first cluster has implications on the number of factors used in the empirical model and makes estimation more challenging. PCE categories marked with an asterisk in the third column indicate that instead of the second cluster, the third cluster is shown. The last column shows the first cluster of the consumption growth rankings, $\widehat{\mathbf{F}}_r^{c}$. For sectoral demand shocks, price and consumption rankings are generally different.

# I Empirical model derivations

The setup of the Bayesian FAVAR model follows the two-step estimation in De Graeve and Schneider (2023, see their Appendix A) with some differences regarding data and observable factors. De Graeve and Schneider (ibid.) use only quantity variables and one observable factor. In this paper, I also allow for multiple observed factors, as well as multiple types of sectoral variables, i.e., sectoral quantity *and* price variables. The derivations in De Graeve and Schneider (ibid.) extend naturally to this.

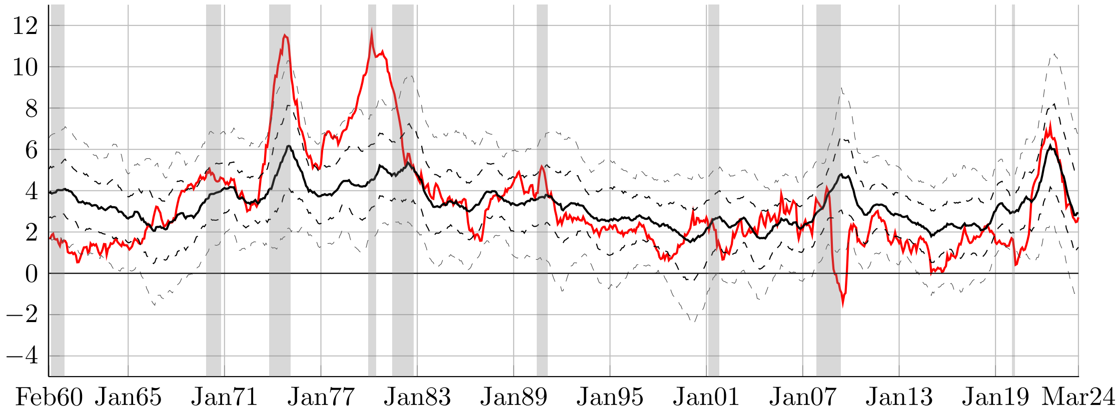
# J Additional findings

This section provides additional figures for the findings presented in the main text.

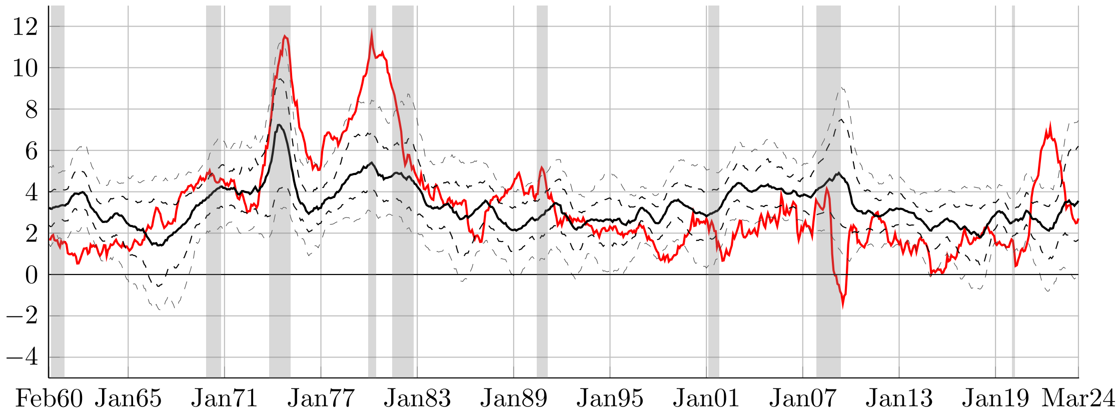
## J.1 Sectoral shocks and consumption growth

While the focus of the main text is on PCE inflation, my model also delivers contributions of sectoral supply and demand shocks to PCE consumption growth. These are summarized in Figure A.7. Panel A.7a shows year-on-year consumption growth and consumption growth conditional on only sectoral shocks. Comparing these contributions with those for PCE inflation, my results suggest that business cycle fluctuations of consumption are somewhat better explained by sector-specific shocks throughout the sample. These results are in line with De Graeve and Schneider (2023), which investigates the sectoral contributions to industrial production (IP) growth from the early 1970s until the onset of the COVID-19 pandemic, and finds that sector-specific shocks, in contrast to aggregate shocks, are the major driver of IP fluctuations. Considering the demand and supply breakdown in Panel A.7b, it is striking that sectoral demand shocks show an overall stronger contribution to consumption growth than inflation.

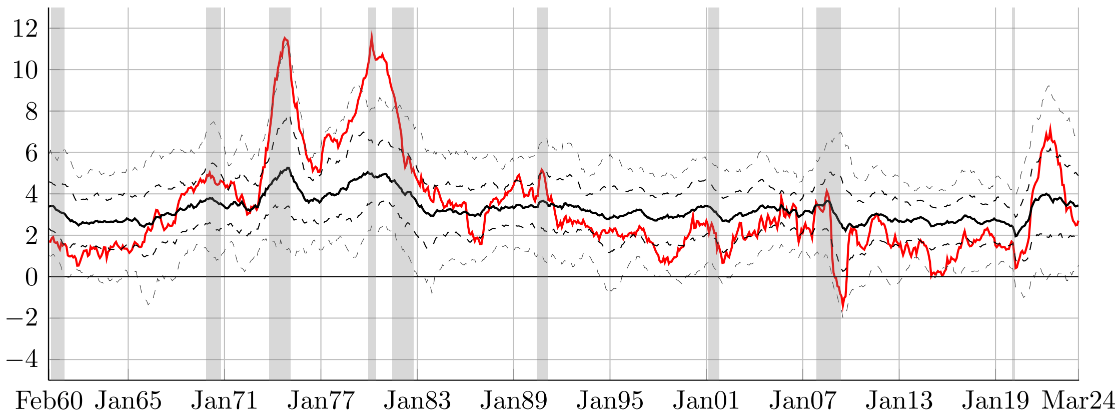
Figure A.5: Inflation and its sectoral origins with credible intervals (full sample)




(a) Non-services supply shocks




(b) Services supply shocks

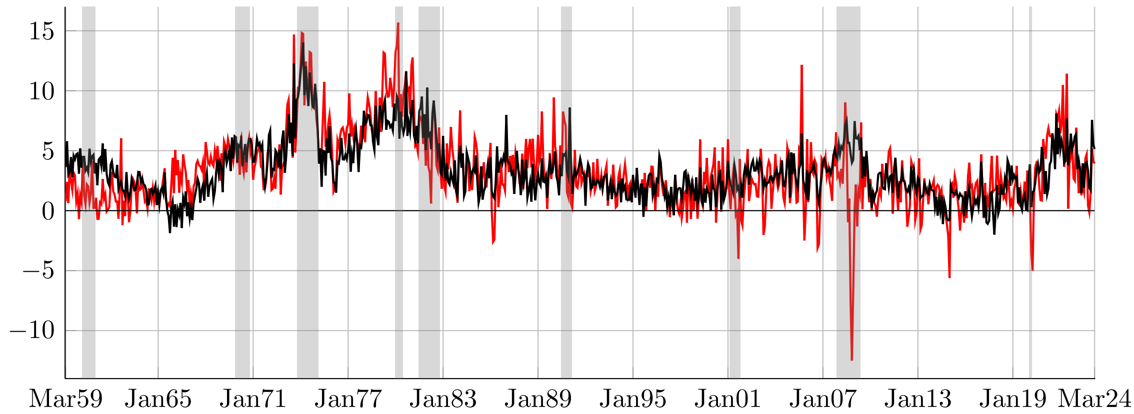



(c) All demand shocks

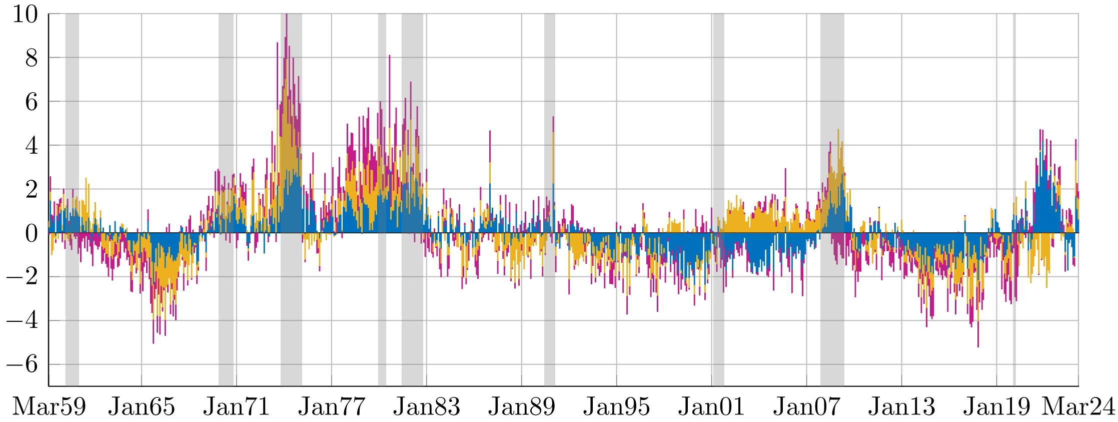
PCE inflation — Inflation conditional on respective set of sectoral shocks
68% credible interval — 95% credible interval

*Notes*: The figure contrasts observed, year-on-year personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black lines). These conditional inflation series are based on the aggregated median contributions of the respective set of identified sectoral shocks. Contributions from supply shocks are decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which originate only in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

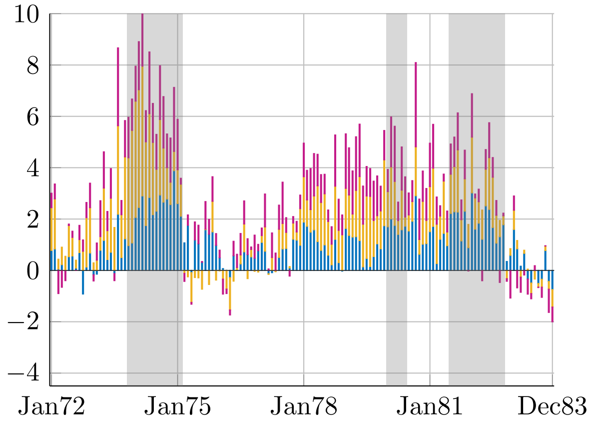
Figure A.6: Inflation (month-on-month, annualized) and its sectoral origins



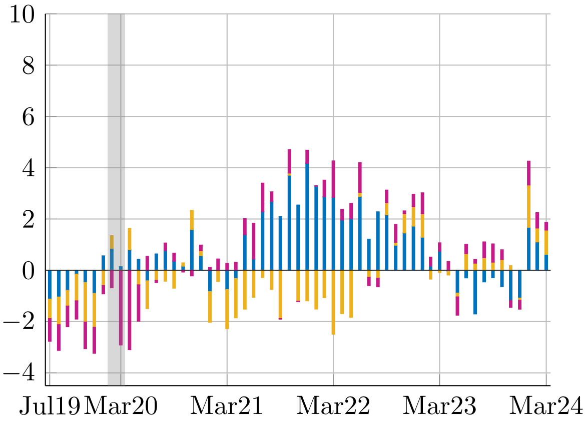

(a) Inflation conditional on only sectoral supply and demand shocks




(b) Contributions of different types of sectoral shocks




(c) Great Inflation period

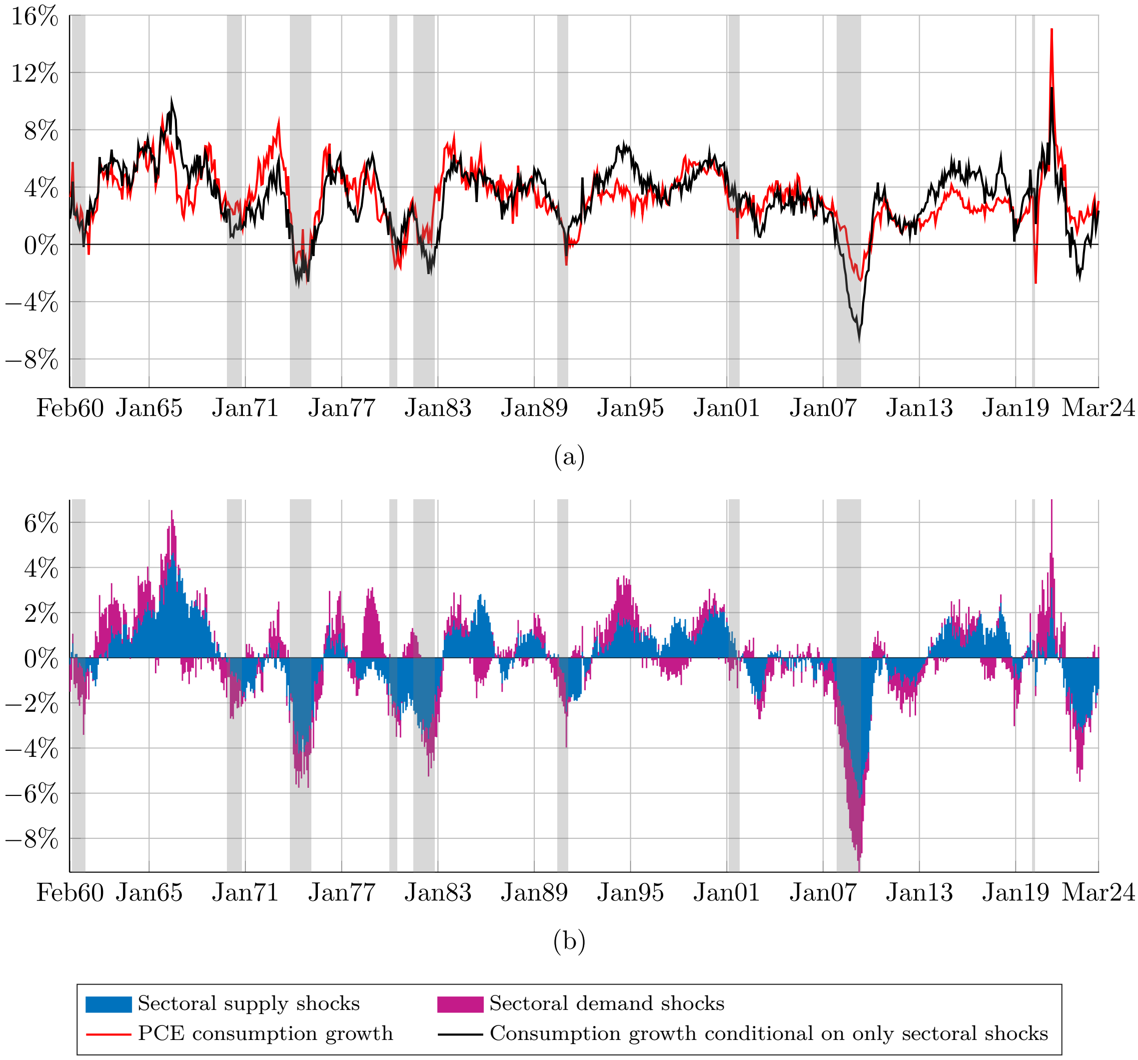



(d) (Post-)COVID-19 period



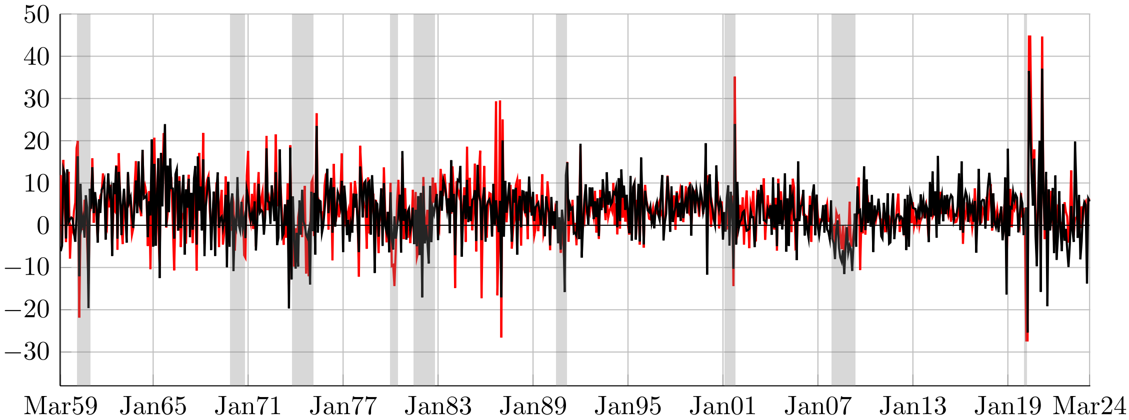
*Notes*: The figure contrasts observed, month-on-month, annualized personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black lines). Conditional PCE inflation is based on the aggregated median contributions of all identified sectoral shocks. Contributions from supply shocks are further decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which only originate in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

Figure A.7: Consumption growth and its sectoral origins

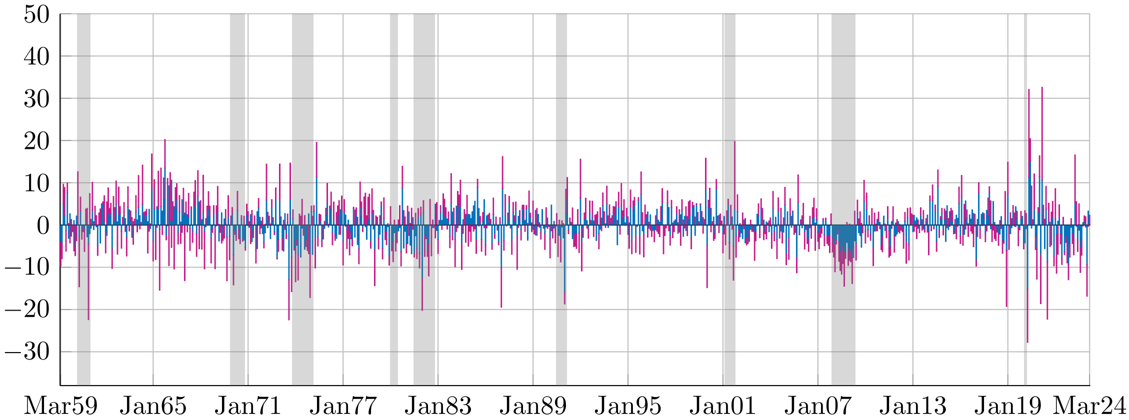



*Notes*: The figure illustrates the aggregated median contributions of all identified sectoral shocks to aggregate consumption growth. Observed, year-on-year personal consumption expenditure (PCE) growth is shown in red and contrasted with consumption growth conditional on only sectoral supply and demand shocks (black line).

Figure A.8: Consumption growth (month-on-month, annualized) and its sectoral origins




(a) Consumption growth conditional on only sectoral shocks

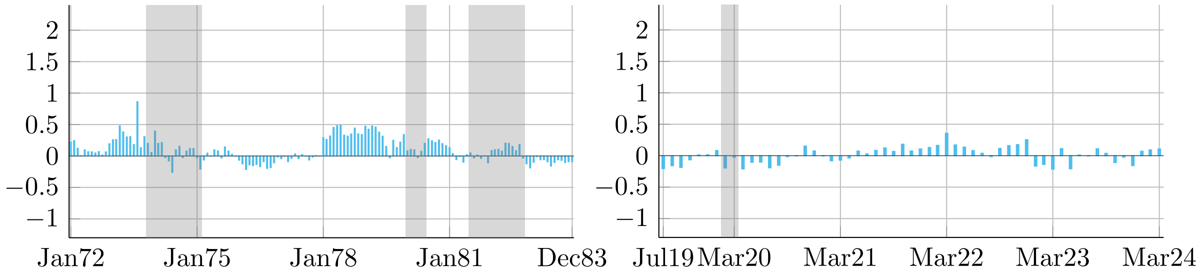



(b) Contributions from sectoral supply and demand shocks



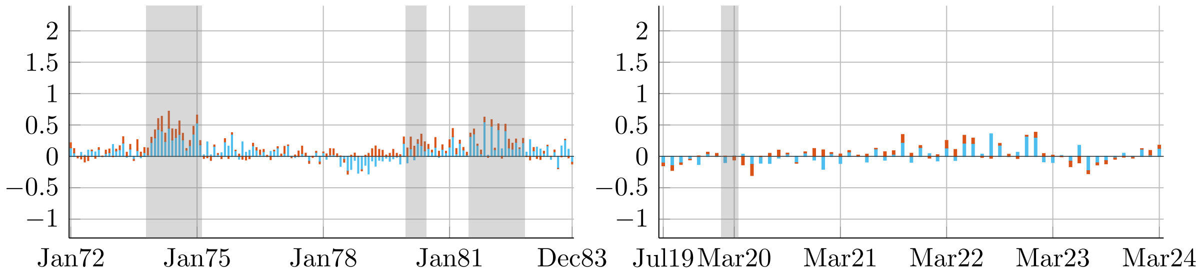
*Notes*: The figure illustrates the aggregated median contributions of all identified sectoral shocks to aggregate consumption growth. Observed, month-on-month, annualized personal consumption expenditure (PCE) growth is shown in red and contrasted with consumption growth conditional on only sectoral supply and demand shocks (black line).

Figure A.9: Individual sectoral contributions to month-on-month, annualized inflation (1/5)



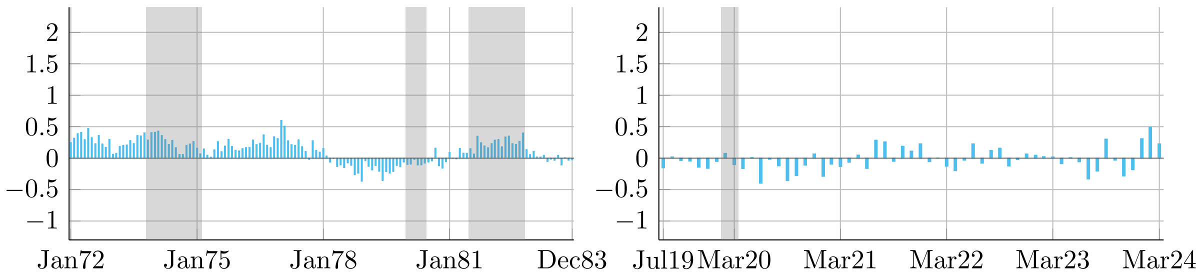

(a) Great Inflation period (b) (Post-)COVID-19 period

Agriculture, forestry, fishing & hunting (supply)



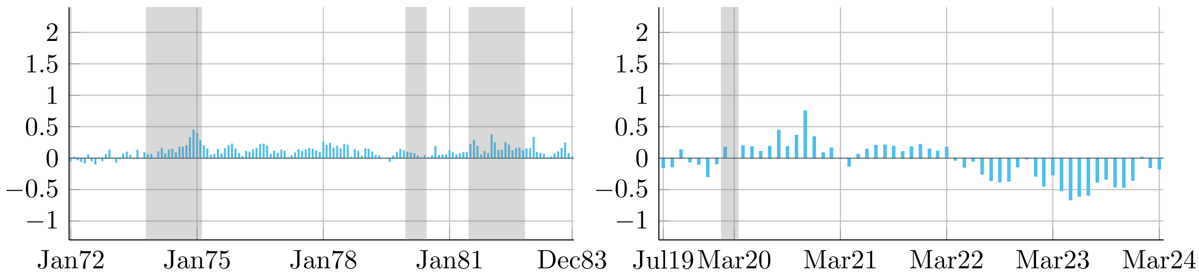

(c) Great Inflation period (d) (Post-)COVID-19 period

Utilities (supply) Housing & utilities (demand)




(e) Great Inflation period (f) (Post-)COVID-19 period

Computer & electronic products (supply)

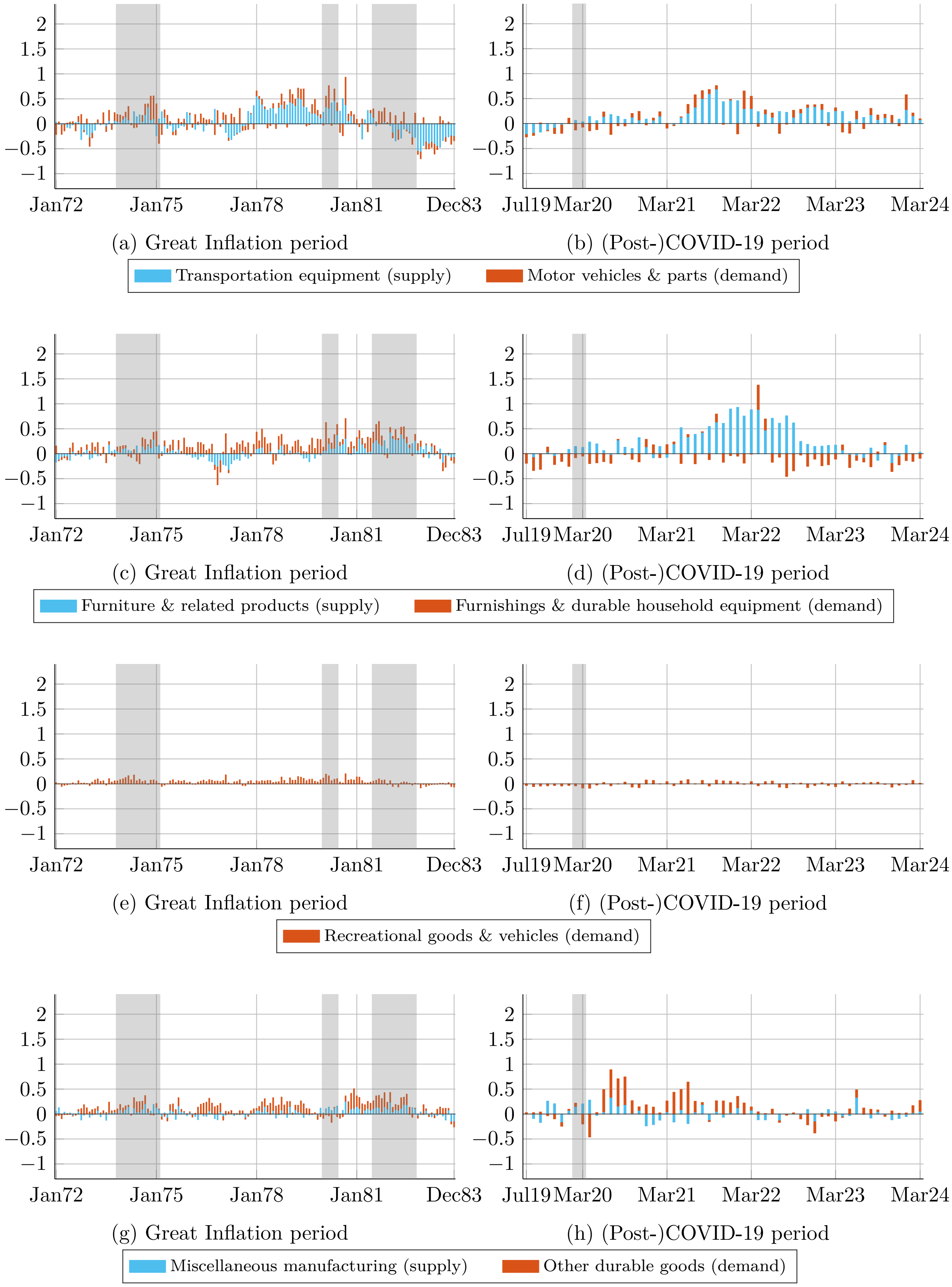



(g) Great Inflation period (h) (Post-)COVID-19 period

Electrical equipment, appliance & components (supply)

*Notes*: This figure shows median historical contributions of individual sectoral shocks to month-on-month, annualized personal consumption expenditure inflation.

Figure A.10: Individual sectoral contributions to month-on-month, annualized inflation (2/5)




(a) Great Inflation period (b) (Post-)COVID-19 period

Transportation equipment (supply) Motor vehicles & parts (demand)

(c) Great Inflation period (d) (Post-)COVID-19 period

Furniture & related products (supply) Furnishings & durable household equipment (demand)

(e) Great Inflation period (f) (Post-)COVID-19 period

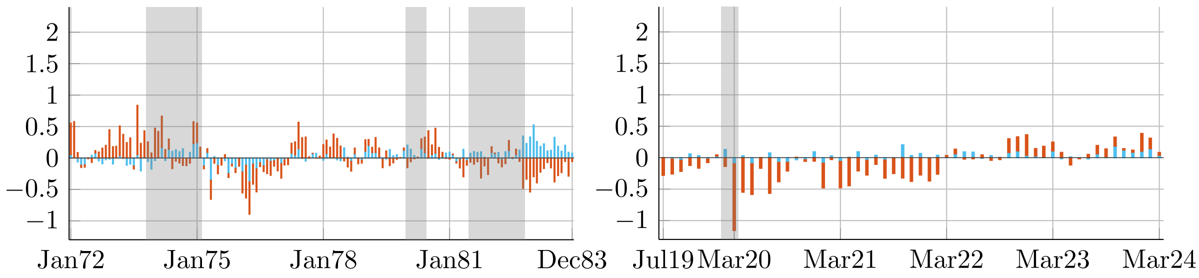
Recreational goods & vehicles (demand)

(g) Great Inflation period (h) (Post-)COVID-19 period

Miscellaneous manufacturing (supply) Other durable goods (demand)

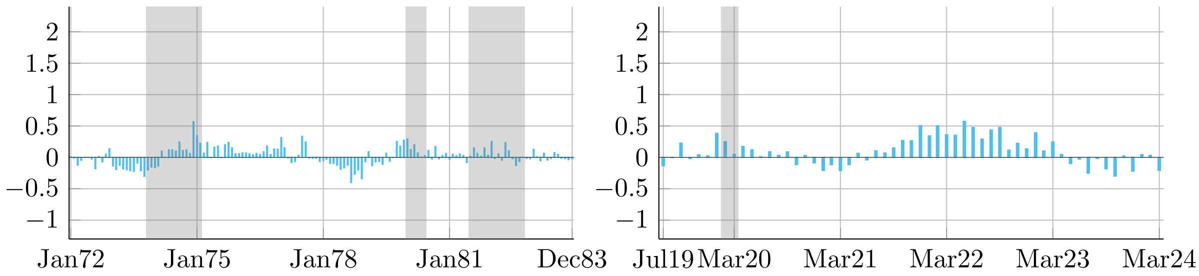
*Notes*: See notes for Figure A.9.

Figure A.11: Individual sectoral contributions to month-on-month, annualized inflation (3/5)



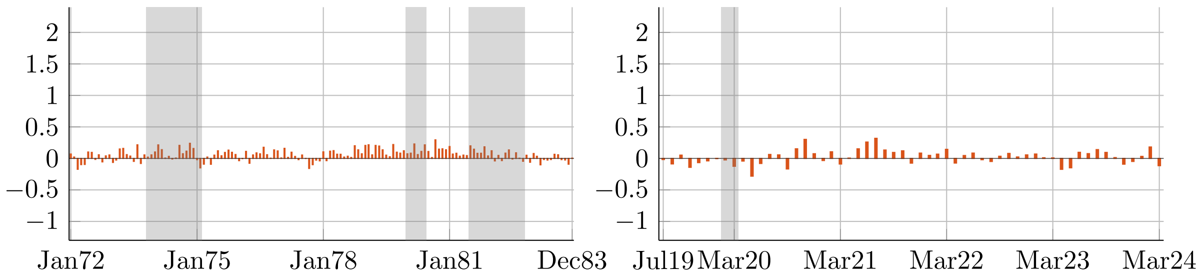

(a) Great Inflation period (b) (Post-)COVID-19 period

Food & beverage & tobacco products (supply) Food & beverages purch. for off-premises consum. (demand)



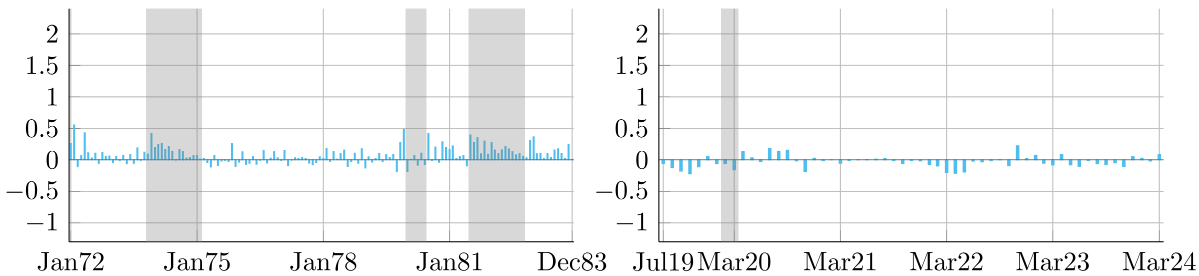

(c) Great Inflation period (d) (Post-)COVID-19 period

Plastics & rubber products (supply)




(e) Great Inflation period (f) (Post-)COVID-19 period

Clothing & footwear (demand)

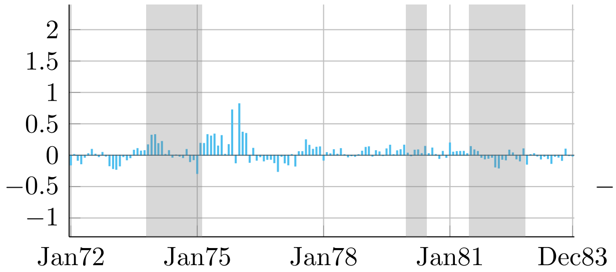



(g) Great Inflation period (h) (Post-)COVID-19 period

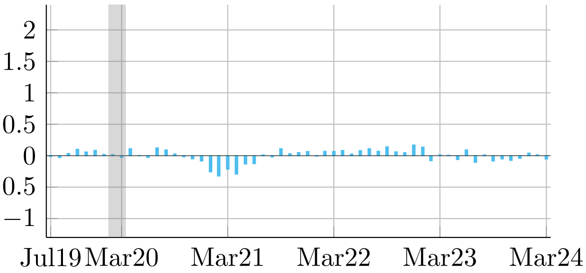
Information (supply)

*Notes*: See notes for Figure A.9.

Figure A.12: Individual sectoral contributions to month-on-month, annualized inflation (4/5)

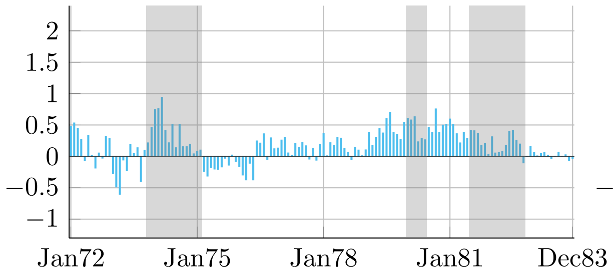



(a) Great Inflation period

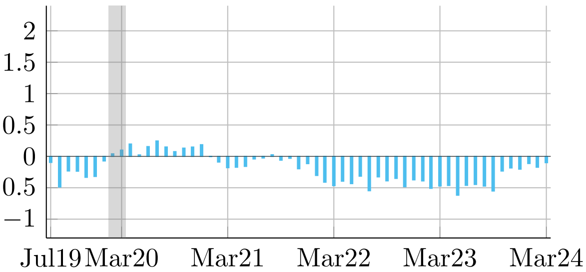



(b) (Post-)COVID-19 period

Finance & insurance (supply)

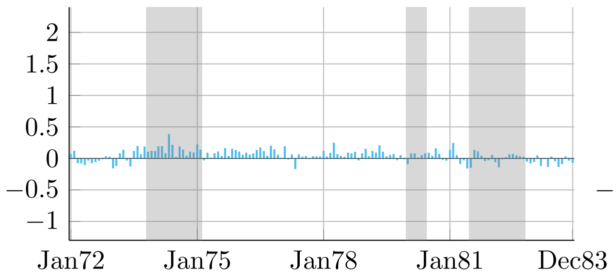



(c) Great Inflation period

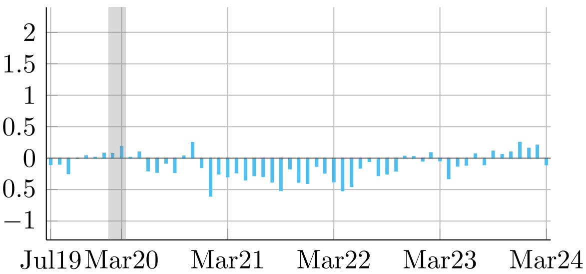



(d) (Post-)COVID-19 period

Educational services (supply)

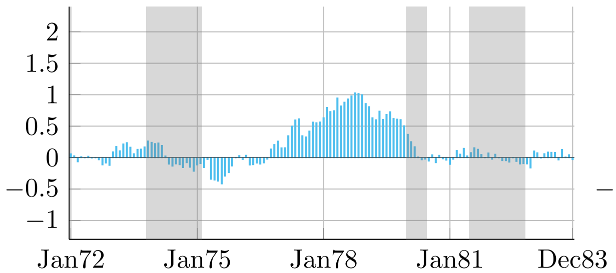



(e) Great Inflation period

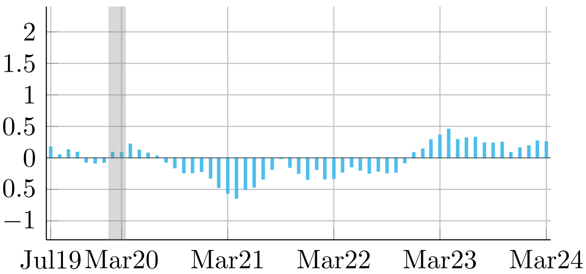



(f) (Post-)COVID-19 period

Arts, entertainment & recreation (supply)




(g) Great Inflation period

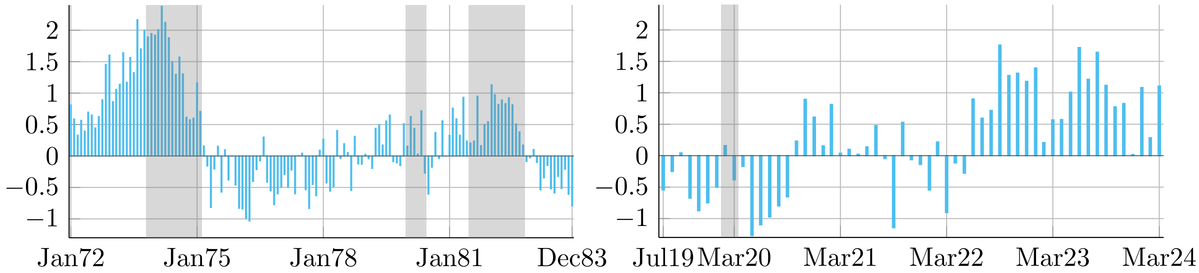



(h) (Post-)COVID-19 period

Accommodation & food services (supply)

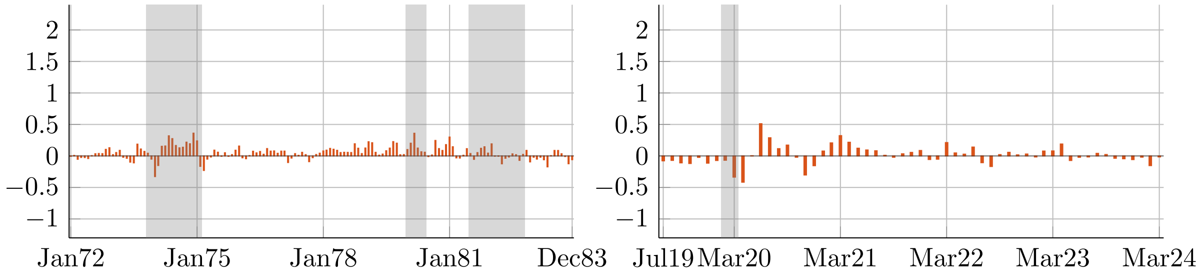
*Notes*: See notes for Figure A.9.

Figure A.13: Individual sectoral contributions to month-on-month, annualized inflation (5/5)




(a) Great Inflation period (b) (Post-)COVID-19 period

Other services, except government (supply)




(c) Great Inflation period (d) (Post-)COVID-19 period

Gasoline & other energy goods (demand)

*Notes*: See notes for Figure A.9.

## K Robustness to alternative identification schemes

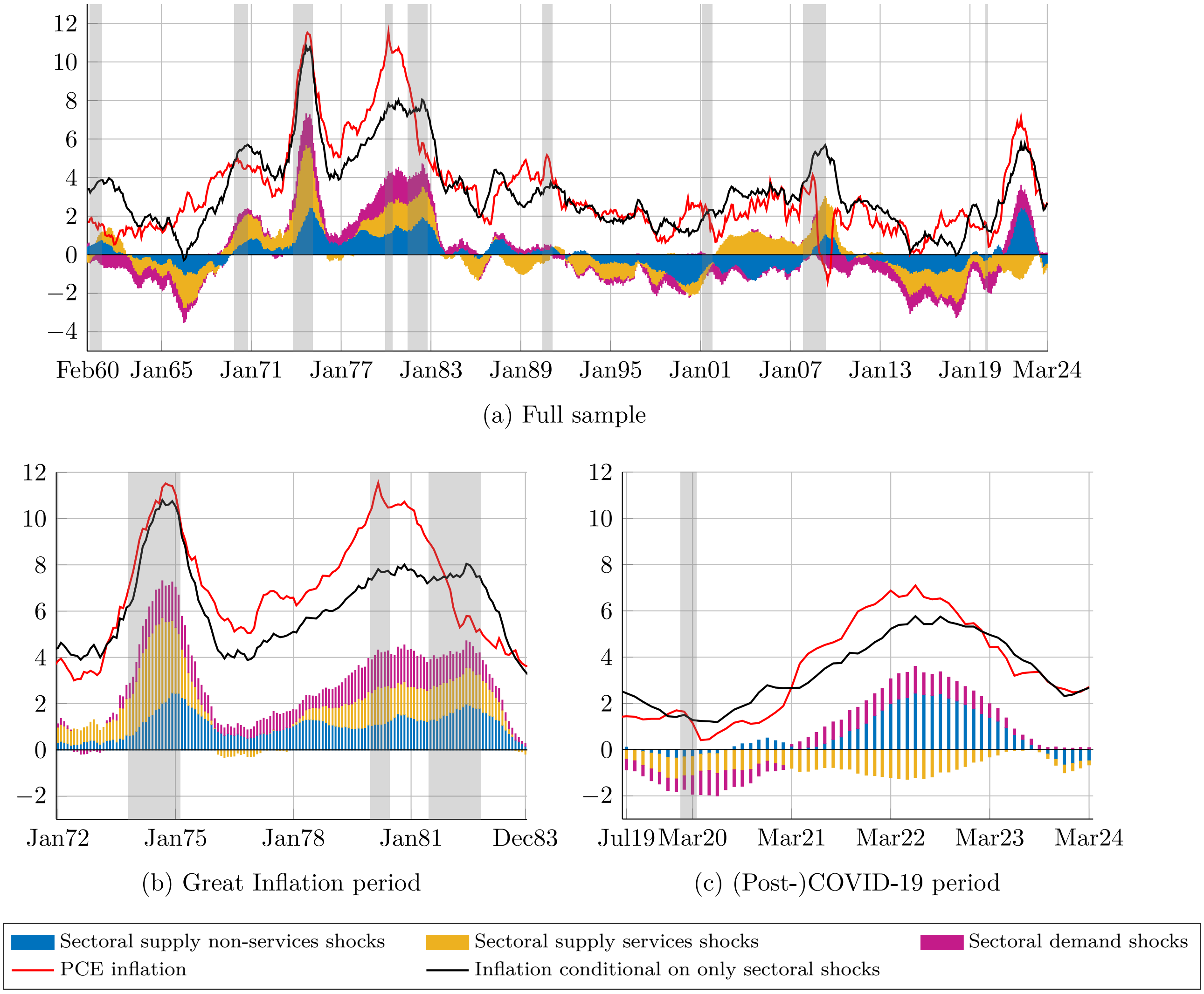
In this appendix, I show that the sectoral origins of inflation in recent years is qualitatively robust to several variations in identification restrictions.

First, Appendix Figure A.14 imposes an alternative combination of restrictions to sectoral shocks. Other than the specification in the main text, where a mix of different identification restrictions is used, Figure A.14 is based on the following consistent scheme. Sectoral supply shocks are exclusively identified by applying *R1* restrictions to $c_z$ and $p_z$. As in the main text, an additional sign restriction is applied to aggregate inflation and consumption growth for sectoral supply shocks. Sectoral demand shocks use an *R1* restriction on $c_z$ and a *no-lower-bound R1* restriction on $p_z$, as well as an *R2* restriction on $p_z$.

Second, Appendix Figure A.15 varies identification of sectoral supply shocks by exclusively imposing *R1* restrictions on $c_z$ and $p_z$, as well as an *R2* restriction on $p_z$. As in the main text, an additional sign restriction is applied to aggregate inflation and consumption growth for sectoral supply shocks. Sectoral demand shocks are retrieved using an *origin R1* restriction on $c_z$ and a *no-lower-bound R1* restriction on $p_z$, as well as an *R2* restriction on $p_z$.

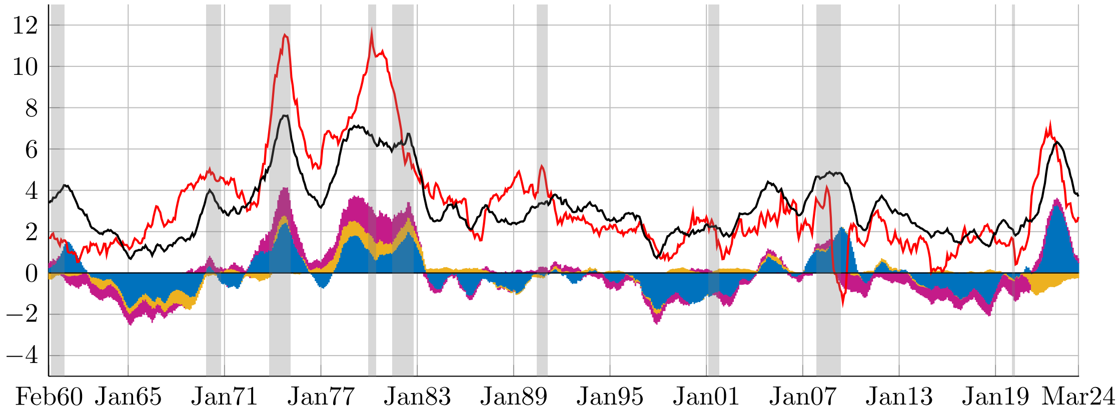
Finally, Appendix Figure A.16 lifts the additional sign restriction to aggregate inflation and consumption growth for sectoral supply shocks.

Figure A.14: Inflation and its sectoral origins: goods versus services with alternative identification 1)

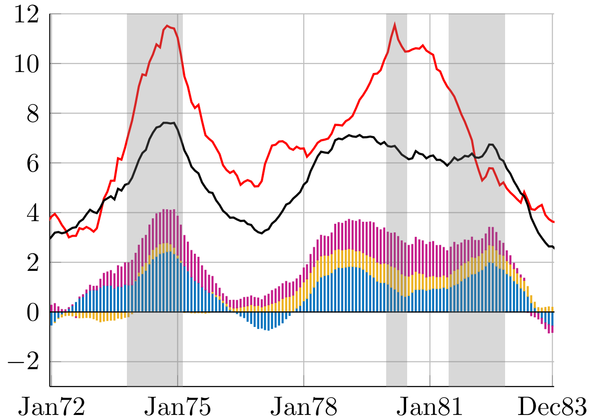



*Notes*: This figure reproduces Figure 9 of the main text but with alternative identification assumptions. Other than the main specification, where a mix of different identification restrictions is used, this figure is based on the following consistent scheme. Sectoral supply shocks are exclusively identified by applying *R1* restrictions to $c_z$ and $p_z$. As in the main text, an additional sign restriction is applied to aggregate inflation and consumption growth for sectoral supply shocks. Sectoral demand shocks are retrieved using an *R1* restriction on $c_z$ and a *no-lower-bound R1* restriction on $p_z$, as well as an *R2* restriction on $p_z$. The figure itself contrasts observed, year-on-year personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black line). Contributions from supply shocks are further decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which only originate in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

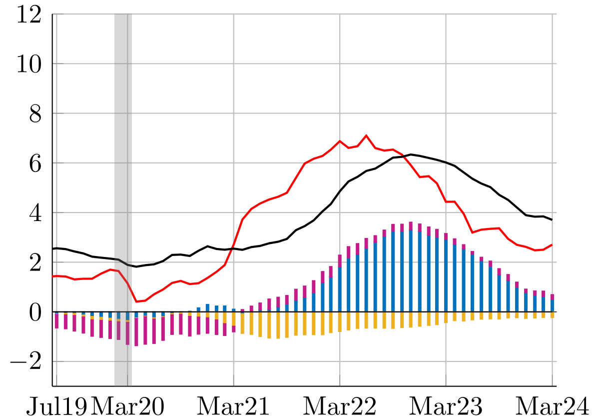
Figure A.15: Inflation and its sectoral origins: goods versus services with alternative identification 2)




(a) Full sample




(b) Great Inflation period

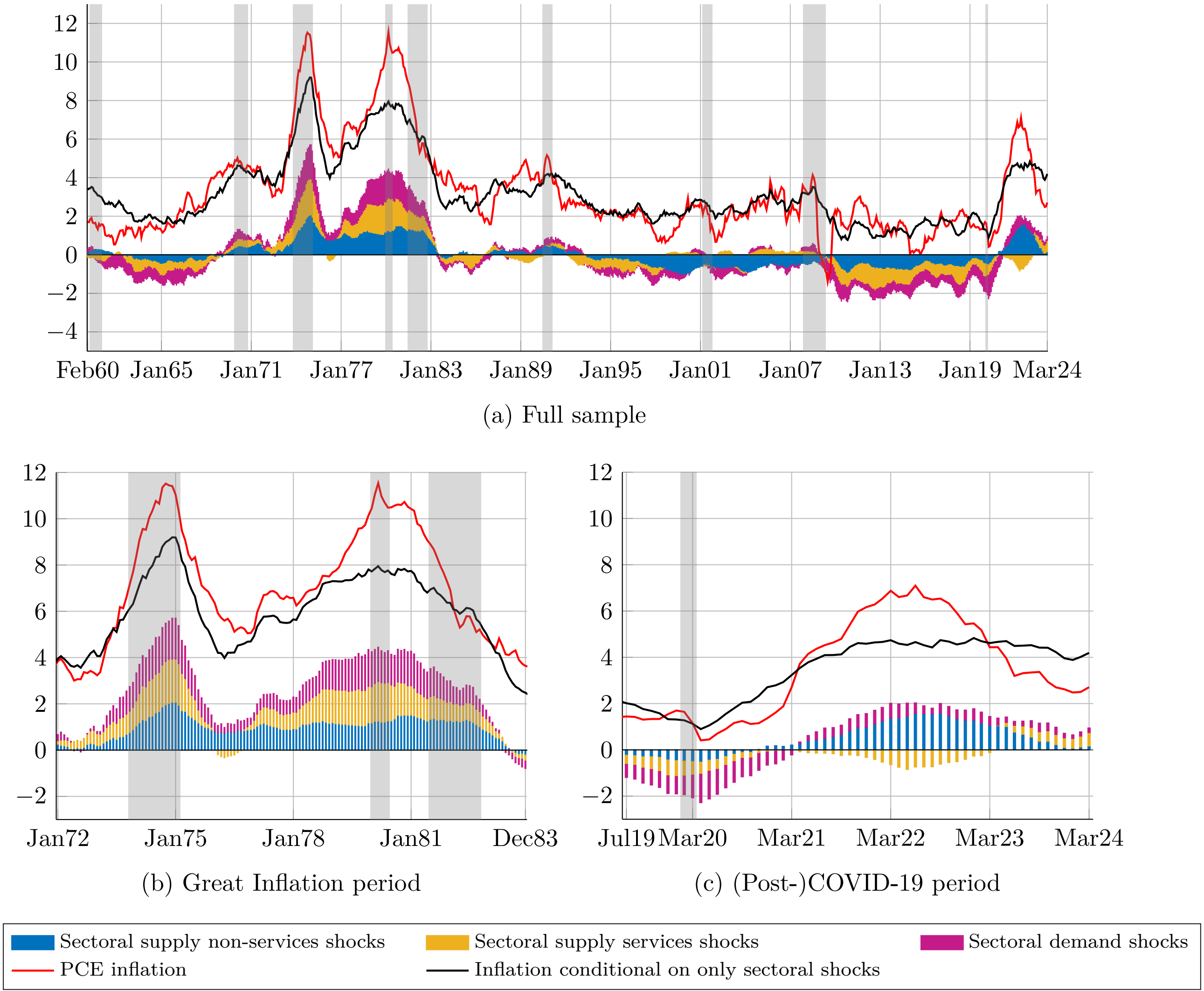



(c) (Post-)COVID-19 period

Sectoral supply non-services shocks | Sectoral supply services shocks | Sectoral demand shocks
PCE inflation | Inflation conditional on only sectoral shocks

*Notes*: This figure reproduces Figure 9 of the main text but with alternative identification assumptions. Other than the main specification, where a mix of different identification restrictions is used, this figure is based on the following consistent scheme. Sectoral supply shocks are exclusively identified by applying *R1* restrictions to $c_z$ and $p_z$, as well as an *R2* restriction to $p_z$. As in the main text, an additional sign restriction is applied to aggregate inflation and consumption growth for sectoral supply shocks. Sectoral demand shocks are retrieved using an *origin R1* restriction on $c_z$ and a *no-lower-bound R1* restriction on $p_z$, as well as an *R2* restriction on $p_z$. The figure itself contrasts observed, year-on-year personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black line). Contributions from supply shocks are further decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which only originate in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

Figure A.16: Inflation and its sectoral origins: goods versus services without aggregate sign restrictions on sectoral supply shocks




(a) Full sample

(b) Great Inflation period

(c) (Post-)COVID-19 period

*Notes*: This figure reproduces Figure 9 of the main text but without imposing an additional sign restriction to aggregate inflation and consumption growth for sectoral supply shocks. The figure itself contrasts observed, year-on-year personal consumption expenditure (PCE) inflation (in red) with PCE inflation conditional on three different types of sectoral shocks (black line). Contributions from supply shocks are further decomposed into those from services and non-services sectors. No such decomposition exists for sectoral demand shocks, which only originate in non-services sectors. This is because demand shocks for services are found to be not empirically relevant.

# L Index table

Table A.7: PCE sector indices and names

| ID | PCE Sector | ID | PCE Sector |
|---|---|---|---|
| 1. | New motor vehicles | 37. | Water supply and sanitation |
| 2. | Net purchases of used motor vehicles | 38. | Electricity |
| 3. | Motor vehicle parts and accessories | 39. | Natural gas |
| 4. | Furniture and furnishings | 40. | Physician services |
| 5. | Household appliances | 41. | Dental services |
| 6. | Glassware, tableware, and household utensils | 42. | Paramedical services |
| 7. | Tools and equipment for house and garden | 43. | Hospitals |
| 8. | Video, audio, photo., info. proc. equip. & media | 44. | Nursing homes |
| 9. | Sporting equipment, supplies, guns, and ammun. | 45. | Motor vehicle maintenance and repair |
| 10. | Sports and recreational vehicles | 46. | Other motor vehicle services |
| 11. | Recreational books | 47. | Ground transportation |
| 12. | Musical instruments | 48. | Air transportation |
| 13. | Jewelry and watches | 49. | Water transportation |
| 14. | Therapeutic appliances and equipment | 50. | Member. clubs, sports cent., parks, theat., mus. |
| 15. | Educational books | 51. | Audio-video, photo., info. proc. equip. services |
| 16. | Luggage and similar personal items | 52. | Gambling |
| 17. | Telephone and related communication equipment | 53. | Other recreational services |
| 18. | Food and nonalc. bever. purch. for off-prem. cons. | 54. | Purchased meals and beverages |
| 19. | Alcoholic beverages purchased for off-prem. cons. | 55. | Food furnished to employees |
| 20. | Food produced and consumed on farms | 56. | Accommodations |
| 21. | Women's and girls' clothing | 57. | Financial services furnished without payment |
| 22. | Men's and boys' clothing | 58. | Financial service charges, fees, and commissions |
| 23. | Children's and infants' clothing | 59. | Life insurance |
| 24. | Other clothing materials and footwear | 60. | Net household insurance |
| 25. | Motor vehicle fuels, lubricants, and fluids | 61. | Net health insurance |
| 26. | Fuel oil and other fuels | 62. | Net motor vehicle and other transportation ins. |
| 27. | Pharmaceutical and other medical products | 63. | Telecommunication services |
| 28. | Recreational items | 64. | Postal and delivery services |
| 29. | Household supplies | 65. | Internet access |
| 30. | Personal care products | 66. | Higher education |
| 31. | Tobacco | 67. | Nursery, elementary, and secondary schools |
| 32. | Magazines, newspapers, and stationery | 68. | Commercial and vocational schools |
| 33. | Rental of tenant-occupied nonfarm housing | 69. | Professional and other services |
| 34. | Imputed rental of owner-occupied nonfarm housing | 70. | Personal care and clothing services |
| 35. | Rental value of farm dwellings | 71. | Social services and religious activities |
| 36. | Group housing | 72. | Household maintenance |

*Notes*: This table serves as a reference for indices of personal consumption expenditure (PCE) categories used in the main text.

## References

De Graeve, Ferre and Jan David Schneider (2023). “Identifying sectoral shocks and their role in business cycles”. *Journal of Monetary Economics* 140, pp. 124–141.

Nakamura, Emi and Jón Steinsson (2008). “Five facts about prices: a reevaluation of menu cost models”. *The Quarterly Journal of Economics* 123(4), pp. 1415–1464.

Pastén, Ernesto, Raphael Schoenle, and Michael Weber (2020). “The propagation of monetary policy shocks in a heterogeneous production economy”. *Journal of Monetary Economics* 116, pp. 1–22.

— (2024). “Sectoral heterogeneity in nominal price rigidity and the origin of aggregate fluctuations”. *American Economic Journal: Macroeconomics* 16(2), pp. 318–352.