The sectoral origins of current inflation*

Jan David Schneider[1]

[1]KU Leuven

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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 DSGE models with production networks. It then imposes those restrictions in a structural factor-augmented vector autoregressive model with sectoral data on PCE inflation and consumption growth. The identification scheme allows to remain agnostic on theoretical modeling assumptions, yet still gain structural empirical results: sectoral shocks—while important to understand real fluctuations—did not have substantial inflationary consequences since the Great Inflation in the 1970s and 80s, until now. While the relevance of sector-specific shocks varied during the COVID-19 pandemic, the sources of current inflation are primarily rooted in negative sectoral supply shocks, in particular from end-2021 onward.

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1 Introduction

In the wake of lifted COVID-19 restrictions, the U.S. economy experienced rapid increases in inflation. Annual headline inflation rose from well-below 2 percent back in March 2020 to more than 6 percent in June 2022. Many explanations on the underlying sources of inflation draw on sector-specific narratives: *supply chain disruptions* or *consumer demand recovery* manifest more in certain economic sectors than in others. Assigning these types of shocks to the sectoral level does not downplay their aggregate consequences. On the contrary, shocks originating in certain parts of the economy spill over to other sectors and thereby generate effects of macroeconomic relevance. The two narratives on current sources of inflation also hint at another aspect of the ongoing policy discussion: is elevated inflation driven by supply or demand shocks? Considering that likely both types of shocks play a role, a breakdown of the economy into heterogeneous sectors can further help to disentangle the supply and demand factors leading to inflation.

In recent years—well before the onset of the COVID-19 pandemic—a growing interest emerged in embedding production networks into macroeconomic models. These models allow one to study the origin and detailed transmission patterns of economic shocks, including spillovers from sector-specific (idiosyncratic) shocks. However, the majority of macroeconomic multi-sector studies focuses either on how *sector-specific* shocks affect real aggregate activity or how *aggregate* shocks propagate through the production network and influence aggregate activity and inflation. A much smaller 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 isn't reliant on these modeling specifics, limiting empirical conclusions due to the risk of theoretical misspecification.

In this paper, my contribution is to cater to both the scientific and policy discussions. 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, and their implications for monetary policy.

My analysis proceeds in three steps. First, I infer sector-shock patterns from a range of popular DSGE model specifications with production networks, which are based on Pasten, Schoenle, and Weber (2021). In a second step, I show the central insight behind my identification strategy: for a given sectoral shock, many of these sector-shock patterns are robust across models, which allows identification of the shock without relying on a specific theoretical model or calibration.

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. Comparing these solutions can 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 regards 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 versus one with sectoral heterogeneity in price stickiness. Nevertheless, my theoretical results suggest that both models exhibit a similar (often the same) *ranking* of sectoral price and quantity responses to the supply shock.[1] This robustness in relative responses across models is what I exploit as identification restrictions. It therefore allows me to remain agnostic on the myriad of potential choices for structural modeling assumptions, yet still gain structural empirical results.

In a third step, I impose the restrictions in a structural factor-augmented vector autoregressive (FAVAR) model to identify sector-specific supply and demand shocks. While for a given sectoral shock I exploit the robustness of sectoral responses across models, my strategy requires a sufficient degree of cross-sectional heterogeneity across shocks: different sectoral shocks propagate differently through the production network due to heterogeneity in how sectors are connected to one another. This idea also extends to the identification of aggregate shocks. Aggregate shocks can be considered as a combination of sectoral shocks: combining sectoral shocks results in propagation patterns that are yet again different to those associated with single sector-specific shocks.

My identification strategy delivers novel empirical evidence on the sectoral origins of inflation. While in most years sectoral supply and demand shocks exhibit limited contributions to Personal Consumption Expenditure (PCE) inflation, there are two major periods since the beginning of the 1960s where sectoral supply shocks take center-stage in terms of their total aggregate contributions: the *Great Inflation* from the 1970s through mid-1980s, and the present.

Focusing on the sectoral origins of inflation in recent years, my empirical results show that sectoral supply shocks are the predominant source of current increases in inflation. In March 2020 sectoral shocks had negative effects on inflation with contributions of around -1 percent. These contributions turned positive shortly thereafter and increased to more than 5 percent by June 2022. The nature of these contributions do not stem from one sectoral source alone, but are distributed across numerous sectors with varying degrees of importance. In between the two dates, I determine three subperiods with different sources of inflation.

Initially, between March 2020 and February 2021, with still below-two-percent headline inflation, I find that negative sectoral supply-side shocks developed increasingly negative effects on aggregate prices. At the same time, sectoral demand shocks counterbalanced this with fairly stable negative contributions to inflation. In the second period from March 2021 to September 2021, most strikingly, sectoral shocks do not explain the surge in inflation to levels well-above 2 percent. The composition of sectoral shock contributions changed, however: positive effects from sectoral supply shocks on inflation decreased and the negative impact of sectoral demand shocks receded, keeping overall sectoral contributions to inflation fairly stable. In the final period, starting in October 2021, negative sectoral supply shocks increased their inflationary contributions sharply, being the major source of inflation until the end of my sample in June 2022. Sectoral demand shocks also started to develop increasing demand-pull contributions in this period. Important to note is that there is still a large scope for potential aggregate positive demand contributions as a source of inflation, especially in the second period between March 2021 until September 2021.

[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.

Finally, I show that the trajectory of inflation's sectoral origins in recent years has important implications for how monetary policy should react. Many commentators argued in 2021 that the initial increases in inflation were short-lived. The Fed took a similar stance in 2021, but in November 2021 it started to gradually tighten policy (by reducing asset purchases) and then increased the target range of the Federal Funds Rate in March 2022. I show that these shifts in policy accord well with the rapid increase in inflationary contributions from negative sectoral supply shocks. The flipside of this result is that it was a reasonable assumption up until the second half of 2021 to consider sectoral supply shocks as short-lived. The Fed acknowledged supply-side contributions to inflation, when it started tightening policy.[2] My results show that these supply-side origins are sectoral, i.e. combinations of sector-specific supply shocks with macroeconomic relevance. Given that supply shocks, sectoral or aggregate, are difficult to act upon by monetary policy because hiking interest rates further depresses already reduced real activity, I argue that my results corroborate the Fed's gradual approach.

The identification method and results presented in this paper connect to several strands of the literature but predominantly contribute to the thin empirical literature on propagation of sectoral shocks through production networks and their effects on inflation.

Most production-network papers are interested in how sectoral shocks affect real fluctuations.[3] Few papers explicitly study the impact of sectoral shocks on inflation empirically. Carvalho, Lee, and Park (2021), Pasten, Schoenle, and Weber (2021), and Smets, Tielens, and Van Hove (2019) examine how sectoral shocks affect prices and provide quantitative empirical results but by relying on their respective DSGE models.[4] A paper with a closely related approach to mine is Auer, Levchenko, and Sauré (2019) who empirically investigate spillovers of inflation but through international input-output linkages. In contrast to my analysis on contributions of supply and demand shocks to consumer prices, their analysis considers cost shocks to producer prices.

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 Pasten, Schoenle, and Weber (2021) 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 makes it possible 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 suite of theoretical specifications, combined with different calibrations, allows 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

[2] See for instance a speech by Jerome Powell, Chair of the Fed, on 21 March 2022.

[3] Earlier models are Horvath (1998, 2000) and Dupor (1999) and date back to Long and Plosser's (1983) seminal contributions. There have been many recent 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 et al. (2021), vom Lehn and Winberry (2021), Arata and Miyakawa (2022), and Foerster et al. (2022).

[4] In recent work, using data on U.S. state-level price indices, Hazell et al. (2022) attribute a large share of consumer price inflation between 1979 and 1981 to an increase in long-run inflation expectations and partly to supply shocks. I argue that my results on the Great Inflation leave room for increases of expectations in the build up to the 1980 inflation peak but less so around the first inflation peak in 1974.

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 24 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, identification of sectoral demand shocks requires more a-priori theory. Within the resulting narrower set of theoretical models, I show that identification of sectoral demand shocks is still robust to differing calibrations. Even though I use time series data for PCE prices and quantities, my strategy allows to not only identify sectoral consumer demand shocks but also sectoral supply shocks at producer level, without actually having time series data on producer prices and quantities. By combining network data on industry level (NAICS) with complementary conversion tables to PCE data (bridge tables), I translate network propagation patterns of NAICS industries' supply shocks to PCE data. Such conversion is not trivial and dependent on modeling assumptions. I capture a variety of these assumptions on how to map NAICS I-O data to PCE time series in the different models and calibrations I use to derive my model-agnostic identification restrictions.

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 responses across sectors, and group them into clusters that range from highly to weakly responsive to the shock. It turns out that for a given sectoral shock there exist cluster compositions that are consistent across many, often all, of the different model solutions. Exploiting this robustness of sector clusters, I proceed by identifying structural sectoral supply and demand shocks in a Bayesian FAVAR. First, factors are extracted from sectoral and aggregate monthly PCE inflation and consumption growth rates, and then expressed 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).[5] I then estimate structural VAR shocks via *heterogeneity restrictions*, i.e. I require that for each sector-specific shock, sectoral impulse responses are ranked so that they comply with the respective cluster composition. Structural identification is implemented using standard algorithms from the VAR sign restriction literature, in particular from Rubio-Ramírez, Waggoner, and Zha (2010).

Identification using heterogeneity restrictions, as introduced by De Graeve and Karas (2014), have recently been further developed by Amir-Ahmadi and Drautzburg (2021) and Matthes and Schwartzman (2021) to improve identification of aggregate shocks. In De Graeve and Schneider (2023) we 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 differs along two dimensions: first, in De Graeve and Schneider (ibid.) we derive heterogeneity restrictions directly from I-O data by using common network measures, such as Leontief inverses. In this paper, I motivate and show the robustness of my restrictions across a range of theoretical DSGE models.

[5] Other empirical papers using factor or FAVAR methods with a focus on sectoral prices are Makowiak, Moench, and Wiederholt (2009), Kaufmann and Lein (2013), Dixon, Franklin, and Millard (2014), De Graeve and Walentin (2015), and Andrade and Zachariadis (2016). These contributions however do not solve the fundamental identification problem of disentangling aggregate shocks from sectoral shocks with aggregate consequences.

Second, my 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 not only allows 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 and thereby allows to better assess the relevance of sectoral shocks for monetary policy.

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, on the contrary, demand shocks move quantity and prices in the same direction. In recent work, Shapiro (2022) 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 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]

With regards to other connected literatures, there are recent contributions that investigate the supply-and-demand breakdown of shocks during the initial phases of the COVID-19 pandemic in 2020.[7] The focus of this paper is however on the heightened inflation environment in 2021 and 2022. Finally, there are numerous papers on the interaction of monetary policy and production networks.[8] I connect to this literature by showing that sectoral supply shocks are a major concern for monetary policy in recent years.

In light of my results on the *recent* sectoral origins of inflation, I argue that the production network literature was right to focus on mostly aggregate activity. 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 in line with a large part of 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 Section 3 derives the analytical solutions thereto. In Section 4, I cluster these analytical solutions and motivate how sector clusters can serve as identification restrictions. Section 5 outlines the FAVAR model and implementation of structural identification. Empirical results on the sectoral origins of inflation and consumption growth are shown in Section 6. The

[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.

[7] Guerrieri et al. (2022) and Baqaee and Farhi (2022) stress the occurrence of Keynesian supply shocks during the pandemic. There are also recent empirical papers such as Brinca, Duarte, and Faria-e-Castro (2021) and Cesa-Bianchi and Ferrero (2021) but they do not explicitly disentangle sectoral from aggregate shocks.

[8] See for instance Basu (1995), Bouakez, Cardia, and Ruge-Murcia (2009, 2014), Nakamura and Steinsson (2010), Ozdagli and Weber (2017), Pasten, Schoenle, and Weber (2020, 2021), Ghassibe (2021), Baqaee, Farhi, and Sangani (2022), La'O and Tahbaz-Salehi (2022), Karadi, Schoenle, and Wursten (2022), and Rubbo (2022).

section proceeds by investigating implications for monetary policy. Section 7 concludes.

2 Theoretical model framework

The identification restrictions in my empirical model are derived from various multi-sector DSGE model solutions. To generate these solutions I use Pasten, Schoenle, and Weber's (2021) multi-sector model, which nests several popular variants used in the literature. The theory model I present in this section is therefore quite similar to their model framework but with two noteworthy adjustments, that are the following: first, I provide a mapping from network I-O data for NAICS industries to PCE time series data on consumption expenditures. I use a similar approach to Smets, Tielens, and Van Hove (2019) who split production into intermediate goods producers, corresponding to NAICS industries, and into final goods producers that assemble PCE consumer goods. Intermediate goods producers use labor and intermediate inputs to produce one of J intermediate goods. Final goods producers transform intermediate goods into one of Z consumption categories that are consumed by households. For both types of producers, every sector includes a continuum of firms producing an intermediate good, j, or consumption good, z, respectively.

Second, I focus on two types of shocks: similarly to Pasten, Schoenle, and Weber (2021) I include sector-specific technology shocks. In my setting, these shocks affect intermediate goods producers. Moreover, I include consumer demand shocks that change the composition of the consumption good basket.

Overall, there are three types of heterogeneities in the production sector that, taken together, I exploit for identification in my empirical model: intermediate goods producers are heterogeneous with respect to their I-O linkages. Both intermediate and final goods producers are heterogeneous in size as well as in terms of nominal price rigidity.

2.1 Households

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

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

subject to

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

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

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 GDP and the consumer price index, P_t^{pce}, with the GDP deflator. The aggregate consumption bundle is composed of Z consumption categories:

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

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 $\mathbf{\Omega}_c \equiv [\omega_{c1}, \ldots, \omega_{cZ}]'$, where $\sum_{z=1}^{Z} \omega_{cz} = 1$. Sectoral consumption weights, ω_{cz}, are subject to consumer demand shocks, f_{zt}, that change the composition of demand. This means that $\sum_{z=1}^{Z} f_{zt} = 0$. Consumption weights correspond to 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:

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

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

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

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, θ, can differ to the elasticity of substitution across sectors/categories, η.

The aggregate PCE price index is defined as:

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

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

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

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

As in Pasten, Schoenle, and Weber (2021), labor markets are sector-specific and allow for different wages. Parameters $\{g_j\}_{j=1}^{J}$ are calibrated to ensure a symmetric steady state.

2.2 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:

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

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

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

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':

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

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' are such that:

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

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

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

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

where the price for sector j goods is given by:

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

As in Pasten, Schoenle, and Weber (2021) I use a simple information friction to model sectoral price rigidity which I introduce in the next section. Alternatively, a model description of a Calvo pricing problem can be found in Appendix A.

2.3 Final goods producers

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

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

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

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

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:

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

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, η and θ, are the same as for households. The input price for final goods producers, P_{zt}^{m} is then given by

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

The pricing problem is analogous to intermediate goods sectors.

2.4 Market clearing

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

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

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

$$Y_{zt} = M_{zt} = e_{zt}^{r} C_{zt}\,. \tag{23}$$

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

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

and on sectoral level to:

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

The full set of log-linearized first order conditions as well as steady state are included in the Appendix.[9]

3 Analytical solutions for a suite of theoretical models

Given the model described in the previous section, I set up five different specifications/calibrations that reflect common approaches in the literature to model production networks.[10] To derive analytical solutions to these specifications I closely follow Pasten, Schoenle, and Weber (2021). While my approach is quite similar to theirs, the solutions presented in this paper differ with regards to how producer prices, captured by J-by-1 vector $\mathbf{p}_t^{im}$, map into consumer prices, included in Z-by-1 vector $\mathbf{p}_t^{pce}$. My model allows for different degrees of heterogeneity between consumer and producer prices and explicitly models the pass-through from intermediate goods producers at NAICS level to final goods producer providing PCE consumption goods.

The first three of the five specifications assume that the inverse-Frisch elasticity is zero, $\varphi = 0$, which shuts down network propagation of shocks through labor market segmentation. The first, and simplest, specification assumes 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 Peneva (2011).[11] Finally, the fourth and fifth model specification assumes heterogeneity in price stickiness and also allows for a positive inverse-Frisch elasticity. This activates an additional network propagation channel via upstream effects through wages.

A second difference to the setup in Pasten, Schoenle, and Weber (2021), is the inclusion of sectoral demand shocks. I include sectoral demand shocks that change the composition of the households consumption basket. 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.[12] By allowing wages to respond to labor demand, via $\varphi > 0$, sectoral demand shocks can generate upstream effects and affect prices. A positive inverse-Frisch elasticity also allows for sectoral supply shocks to generate additional upstream

[9]These appendices assume Calvo pricing for intermediate and final goods producers.

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

[11]More information on sectoral price durations are illustrated in Section 4.3.

[12]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.

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.

3.1 Analytical solutions in simplified models: sectoral supply shocks

Abstracting from sectoral demand shocks (i.e. $f_{zt} = 0$ for $z = 1, \ldots, Z$), this subsection derives analytical solutions in the presence of sectoral supply shocks, a_{jt}.

(i) First, the inverse-Frisch elasticity, φ, is set to zero. This assumption is lifted later on.

(ii) Monetary policy fully stabilizes nominal GDP growth:

$$p_t^{pce} + c_t = 0\,. \tag{26}$$

This rule can be generalized to incorporate additional monetary-policy regimes, but its exact specification is not crucial for identification of sectoral shocks.

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

$$P_{jt} = \begin{cases} \mathbb{E}_{t-1}\left[P_{jt}^{*}\right] & \text{with probability } \lambda_j\,, \\ P_{jt}^{*} & \text{with probability } 1 - \lambda_j\,, \end{cases} \tag{27}$$

$$P_{zt} = \begin{cases} \mathbb{E}_{t-1}\left[P_{zt}^{*}\right] & \text{with probability } \lambda_z\,, \\ P_{zt}^{*} & \text{with probability } 1 - \lambda_t\,, \end{cases} \tag{28}$$

where the respective λ_j or λ_z is the probability by which a firm needs to set its price before it can observe the shocks. These probabilities are calibrated using estimates on sectors' average price durations. In addition, I assume that households have log utility: $\sigma = 1$.

3.1.1 All simplifying assumptions applied

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

$$w_{jt} = p_t^{pce} + c_t\,. \tag{29}$$

Monetary policy described in (ii) implies that there is a simple relationship between aggregate consumption and aggregate PCE prices:

$$c_t = -p_t^{pce}\,. \tag{30}$$

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

$$p_{jt} = (1 - \lambda_j)mc_{jt}\,, \tag{31}$$

$$p_{zt} = (1 - \lambda_z)mc_{zt}\,. \tag{32}$$

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:

$$\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,, \tag{33}$$

with

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1}(\mathbf{I} - \mathbf{\Lambda}^{im})\,, \tag{34}$$

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 Λ^{im} that is a diagonal matrix including all price-rigidity probabilities, λ_j. Furthermore, sectoral PCE prices are downstream to producer prices and hence solve:

$$\mathbf{p}_t^{pce} = -(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,, \tag{35}$$

and sectoral consumption expenditures are given by:

$$\mathbf{c}_t = \left[\eta\mathbf{I} + (1-\eta)\iota\mathbf{\Omega}_c'\right](\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,. \tag{36}$$

Diagonal matrix Λ^{pce} is the final-good equivalent to matrix Λ^{im}, column-vector $\mathbf{\Omega}_c$ captures the Z consumption shares, and ι is a column vector of ones of the appropriate dimension. Aggregate PCE prices are then a weighted average of sectoral PCE prices:

$$p_t^{pce} = -\mathbf{\Omega}_c'(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,, \tag{37}$$

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

3.1.2 Allowing for labor market heterogeneity

As in Pasten, Schoenle, and Weber (2021), I next relax the zero assumption on the inverse-Frisch elasticity, φ, imposed by assumption (i). In Appendix D I show that the multiplier matrix, $\widehat{\mathbf{X}}^{im}$, has then the form:

$$
\begin{aligned}
\widehat{\mathbf{X}}^{im} \equiv \Big[& \mathbf{I} - \delta \left(\mathbf{I} - \mathbf{\Lambda}^{im}\right) \mathbf{\Omega} \\
& - (1-\delta) \left(\mathbf{I} - \mathbf{\Lambda}^{im}\right) \mathbf{\Theta}'^{-1} \\
& \left(\theta_p^{im} + \theta_p^{pce} \left(\mathbf{I} - \mathbf{\Lambda}^{pce}\right) \mathbf{K} - \theta_c \mathbf{\Omega}_c' \left(\mathbf{I} - \mathbf{\Lambda}^{pce}\right) \mathbf{K}\right) \Big]^{-1} \\
& \left(\mathbf{I} - \mathbf{\Lambda}^{im}\right) \left[\mathbf{I} + \varphi(1-\delta)\mathbf{\Theta}'^{-1}\right] ,
\end{aligned} \tag{38}
$$

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, ω_{zc}, whereas diagonal matrix $\mathbf{D}$ captures all gross output shares, n_j. Parameter ψ 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 but using this version of $\widehat{\mathbf{X}}^{im}$.

3.1.3 Collecting model solutions for sectoral supply shocks

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

$$
\widehat{\mathbf{X}}^{im} \equiv \begin{cases}
\left[\mathbf{I} - \delta\mathbf{\Omega}\right]^{-1} & \text{for specification (I)}\,, \\
\left[\mathbf{I} - \delta(\mathbf{I} - \bar{\mathbf{\Lambda}}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \bar{\mathbf{\Lambda}}^{im}) & \text{for specification (II)}\,, \\
\left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im}) & \text{for specification (III)}\,, \\
(38) \text{ with } \varphi = 1 & \text{for specification (IV)}\,, \\
(38) \text{ with } \varphi = 2 & \text{for specification (V)}\,,
\end{cases} \tag{39}
$$

where $\bar{\mathbf{\Lambda}}^{im}$ in specification (II) corresponds to a calibration with homogeneous price stickiness and hence includes a constant parameter, λ, on its diagonal. For this case, I also assume that $\bar{\mathbf{\Lambda}}^{pce} = \bar{\mathbf{\Lambda}}^{im}$. Using $\bar{\mathbf{\Lambda}}^{im}$ for the respective specification gives the following solutions for sectoral prices:

$$
\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,, \tag{40}
$$

$$
\mathbf{p}_t^{pce} = -\widehat{\mathbf{X}}^{pce}\mathbf{a}_t \,. \tag{41}
$$

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

$$\widehat{\mathbf{X}}^{pce} \equiv \begin{cases} \mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (I)}, \\ (\mathbf{I}-\bar{\mathbf{\Lambda}}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (II)}, \\ (\mathbf{I}-\mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (III)}, \\ (\mathbf{I}-\mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (IV)}, \\ (\mathbf{I}-\mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im} & \text{for specification (V)}. \end{cases} \tag{42}$$

Sectoral consumption is then expressed as:

$$\mathbf{c}_t = \widehat{\mathbf{X}}^c \mathbf{a}_t \,, \tag{43}$$

with

$$\widehat{\mathbf{X}}^c \equiv \left[\eta \mathbf{I} + (1-\eta)\iota \mathbf{\Omega}_c'\right] \widehat{\mathbf{X}}^{pce} \,. \tag{44}$$

Finally, aggregate PCE prices and consumption solve:

$$p_t^{pce} = -\mathbf{X}^{pce}\mathbf{a}_t \,, \tag{45}$$

$$c_t = \mathbf{X}^{pce}\mathbf{a}_t \,, \tag{46}$$

where

$$\mathbf{X}^{pce} \equiv \mathbf{\Omega}_c' \widehat{\mathbf{X}}^{pce} \,. \tag{47}$$

3.2 Analytical solutions in simplified models: sectoral demand shocks

Now abstracting from sectoral supply shocks (i.e. $a_{jt} = 0$ for all $j = 1, \ldots, J$), this subsection derives analytical solutions in presence of sectoral demand shocks, f_{zt}. As illustrated above, sectoral demand shocks require that they can propagate 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:

$$\mathbf{p}_t^{im} = \widehat{\mathbf{F}}^{im}\mathbf{f}_t \,. \tag{48}$$

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

$$\widehat{\mathbf{F}}^{im} \equiv \widehat{\mathbf{P}}^{im}\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)(1-\delta)\mathbf{\Theta}'^{-1}\varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}\mathbf{D}_c \,. \tag{49}$$

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

$$\begin{aligned}\widehat{\mathbf{P}}^{im} \equiv & \Big[\mathbf{I} - \delta \left(\mathbf{I} - \mathbf{\Lambda}^{im} \right) \mathbf{\Omega} \\ & - (1-\delta) \left(\mathbf{I} - \mathbf{\Lambda}^{im} \right) \mathbf{\Theta}'^{-1} \\ & \left(\theta_p^{im} + \theta_p^{pce} \left(\mathbf{I} - \mathbf{\Lambda}^{pce} \right) \mathbf{K} - \theta_c \mathbf{\Omega}_c' \left(\mathbf{I} - \mathbf{\Lambda}^{pce} \right) \mathbf{K} \right) \Big]^{-1} ,\end{aligned} \tag{50}$$

using, in turn, the same composite parameters specified under supply shocks.

3.2.1 Collecting model solutions for sectoral demand shocks

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

$$\widehat{\mathbf{F}}^{im} \equiv \begin{cases} (49) \text{ with } \varphi = 1 & \text{for specification (IV)} , \\ (49) \text{ with } \varphi = 2 & \text{for specification (V)} . \end{cases} \tag{51}$$

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

$$\mathbf{p}_t^{pce} = \widehat{\mathbf{F}}^{pce} \mathbf{f}_t , \tag{52}$$
$$\mathbf{c}_t = \left[(\eta - 1) \iota \mathbf{\Omega}_c' - \eta \mathbf{I} \right] \widehat{\mathbf{F}}^{pce} \mathbf{f}_t , \tag{53}$$

where

$$\widehat{\mathbf{F}}^{pce} \equiv \begin{cases} (\mathbf{I} - \mathbf{\Lambda}^{pce}) \mathbf{K} \widehat{\mathbf{F}}^{im} & \text{for specification (IV)} , \\ (\mathbf{I} - \mathbf{\Lambda}^{pce}) \mathbf{K} \widehat{\mathbf{F}}^{im} & \text{for specification (V)} . \end{cases} \tag{54}$$

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

$$p_t^{pce} = \mathbf{F}^{pce} \mathbf{f}_t , \tag{55}$$
$$\tag{56}$$

where

$$\mathbf{F}^{pce} \equiv \mathbf{\Omega}_c' \widehat{\mathbf{F}}^{pce} . \tag{57}$$

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:

$$\mathbf{c}_t + \mathbf{f}_t = \widehat{\mathbf{F}}^{c,f} \mathbf{f}_t , \tag{58}$$

where

$$\widehat{\mathbf{F}}^{c} \equiv \left[(\eta - 1) \iota \mathbf{\Omega}_c' - \eta \mathbf{I} \right] \widehat{\mathbf{F}}^{pce} , \tag{59}$$
$$\widehat{\mathbf{F}}^{c,f} \equiv \mathbf{I} + \widehat{\mathbf{F}}^{c} . \tag{60}$$

Aggregate consumption is then equal to

$$c_t = \mathbf{\Omega}_c' \mathbf{c}_t + \mathbf{\Omega}_c' \mathbf{f}_t \,, \tag{61}$$

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

4 Identification

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

4.1 Sector-shock rankings in example economies

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

$$\mathbf{\Omega} = \begin{bmatrix} 0.4 & 0.3 & 0.3 \\ 0.4 & 0.5 & 0.1 \\ 0.2 & 0.7 & 0.1 \end{bmatrix} \quad , \quad \mathbf{\Omega}_c' = \begin{bmatrix} 0.2 & 0.3 & 0.5 \end{bmatrix} \,, \tag{62}$$

where $\mathbf{\Omega}$ is the I-O coefficient matrix, and $\mathbf{\Omega}_c$ 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.[13] Moreover, I only consider sectoral supply shocks, a_{jt}, in this example. The solution of sectoral intermediate and PCE prices are then equal to:

$$\mathbf{p}_t^{im} = -\widehat{\mathbf{X}}^{im} \mathbf{a}_t \,, \tag{63}$$
$$\mathbf{p}_t^{pce} = -\widehat{\mathbf{X}}^{pce} \mathbf{a}_t \,, \tag{64}$$

with the multiplier matrices, as derived in the previous section, given by:

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im}) \,, \tag{65}$$
$$\widehat{\mathbf{X}}^{pce} \equiv (\mathbf{I} - \mathbf{\Lambda}^{pce}) \widehat{\mathbf{X}}^{im} \,. \tag{66}$$

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 the most 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 $\mathbf{\Lambda}^{im} = \mathbf{\Lambda}^{im} = \mathbf{0}$,

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

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.

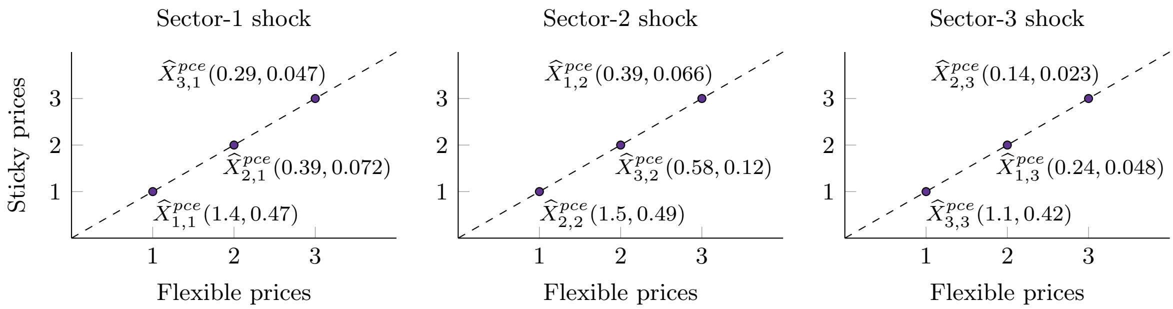
The second calibration, shown in Panel 1b, introduces *heterogeneity* in price stickiness. Here, I assume that the second intermediate good sector has more rigid prices than all other prices by setting the average duration to 4 months, which implies $\lambda_2^{im} = 0.78$. In this case, sectoral rankings change for a sector-1 shock but only at rank 2 and 3. Increasing the degree of stickiness for sector 2's intermediate prices switches the relative importance of sector 2 and 3 as downstream customers for sector 1's materials. Under flexible (and homogeneously sticky) prices, sector 2 responds relatively stronger 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 sector 2 and 3 as downstream customers to sector 1. Sector 2's prices now change less than in sector 3, whose prices are more flexible. Even though sector 1's ranking changes at ranks 2 and 3, crucially 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 sector 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 shocks that is the same as for the flexible economy.

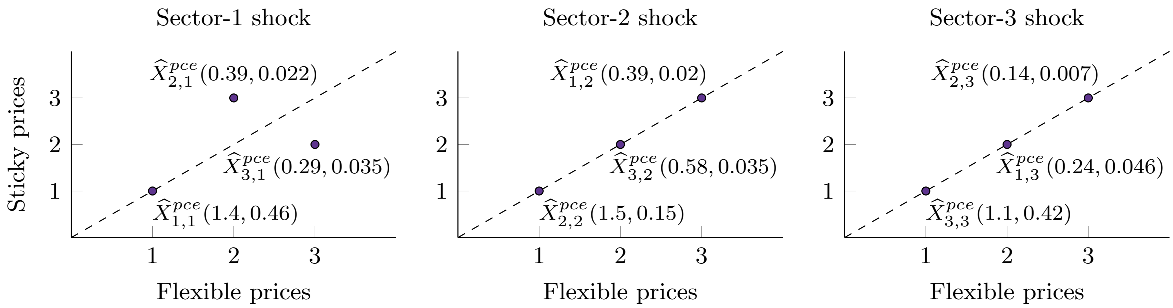
However, the ranking for a sector-2 shock changes between calibrations. The newly introduced stickiness of sector 3's prices makes sector 3 respond less to sector 2 shocks than in sector 1, which has more flexible prices than sector 3, even though sector 2 is a larger input provider for sector 3 than 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, shocks to sector 2 have a larger impact on aggregate prices than sector 1 and sector 3. The

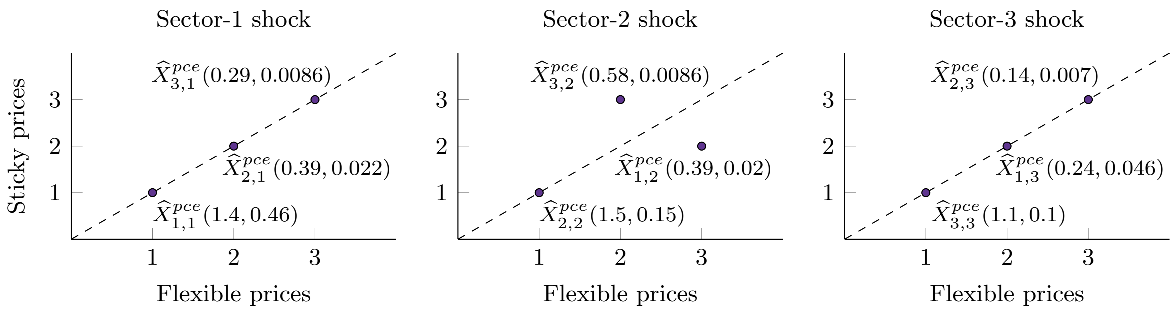
Figure 1: Sectoral shocks in example economies: flexible vs. sticky prices



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



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

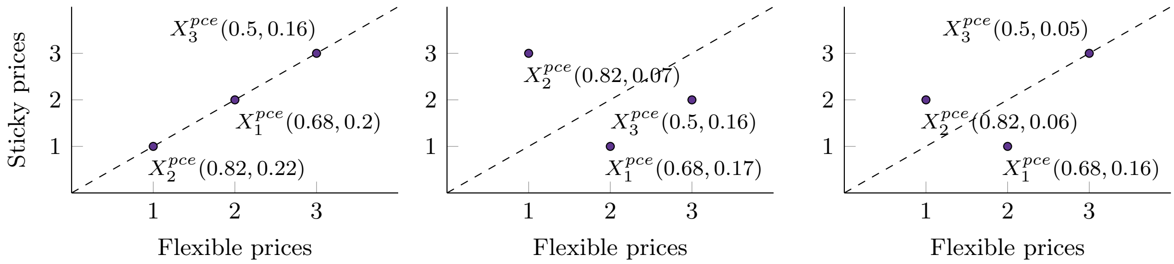


(c) Heterog. intermediate & PCE price rigidity: $\lambda^{im} = [0.37, \mathbf{0.78}, 0.37]$, $\lambda^{pce} = [0.37, 0.37, \mathbf{0.85}]$

Notes: The figure uses the example economy described by equation (62). 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.

introduction of heterogeneity in price rigidity, shown in Panel 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 mutes the importance of sector-2 shocks on aggregate prices and thereby moves 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 switchers the ranking again. This example illustrates that identification of sectoral shocks is robust at sectoral level but not necessarily with regards to the contribution of sectoral shocks to aggregate prices (and quantities equivalently).

Figure 2: Aggregate contributions of sectoral shocks: Flexible vs. 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 uses the example economy described by equation (62). 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.

4.2 Sectoral versus aggregate shocks

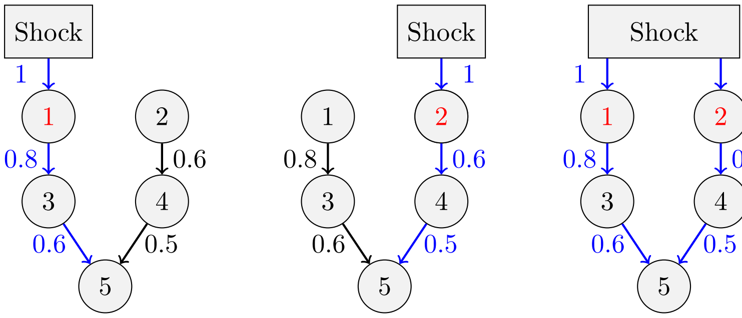
Figure 3 presents a second type of example, which is taken from De Graeve and Schneider (2023). In there, we motivate the differences between sectoral and aggregate shocks with regards to their propagation patterns. In this example, a generic sector 1 sells to sector 3, sector 2 sells to sector 4, and both sector 3 and 4 sell to sector 5. The first panel shows a shock in sector 1. Given the heterogeneous weights on the 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.

In a second graph, the cross-sectional ranking in response to a sector-2 shock is considered. Comparing this ranking from high to low (2, 4, 5, 1, 3) to that of a sector-1 shock (1, 3, 5, 2, 4) reveals that the propagation pattern between the two sectoral shocks is completely different. Due to heterogeneity in network linkages, a sector-1 shock can be identified and separated from a sector-2 shock, based on its ranking in the cross-section.

Finally, the third graph 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 (5, 1, 2, 3, 4) is yet again different to the previous two cases. Intuitively, by mixing shocks 1 and 2, the combined-shock generates its own distinct propagation pattern. In contrast to this stylized example, these ranking differences are even more pronounced in larger economies with more theoretical possibilities to generate heterogeneous network connections. My identification, which is based on such sector rankings, thereby ensures that not only sector-specific shocks are disentangled from another, but also from aggregate shocks.

In De Graeve and Schneider (ibid.) we show that just a quantity variable alone allows to identify sectoral shocks and to explicitly distinguish identification of aggregate shocks. In this paper I also use a price variable for identification. This allows a much better separation of supply and demand shocks.

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



Ranking (value):	Ranking (value):	Ranking (value):
1 (1)	2 (1)	5 (1.1)
3 (0.8)	4 (0.6)	1 (1)
5 (0.6)	5 (0.5)	2 (1)
2 (0)	1 (0)	3 (0.8)
4 (0)	3 (0)	4 (0.6)

Notes: This is a stylized example illustrating how different shocks, sectoral or aggregate, generally imply different sector rankings. We look at three different shocks and rank the magnitude of the responses: first, a shock originating in sector 1, second, a shock in sector 2, and third, a combination of sector 1 and 2 shocks.
Source: De Graeve and Schneider (2023)

4.3 Theory calibration

Deriving the five supply-side specifications in equation (42) and two demand-side specifications in equation (54) requires calibration of the I-O data and model parameters.

The input-share matrix, $\mathbf{\Omega}$, is derived from make and use tables of the BEA's input-output accounts for the United States at NAICS classification. I use annual I-O data for years 1997 to 2020 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 E.1 presents the derivation of the input-share matrix, $\mathbf{\Omega}$, and Appendix E.2 the derivation of the bridge matrix, $\mathbf{K}$.

Estimates for monthly frequencies of producer price changes are taken from Peneva (2011). These estimates are based on 1995–1997 data and are only available for the older Standard Industrial Classification (SIC). In Appendix E.3 I describe the necessary steps and assumptions to convert these SIC estimates to NAICS.

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 E.4 provides more details on the procedure.

The following model parameters appear in equations (42) and (54) and therefore require calibration: I set the elasticity of substitution across sectors/categories $\eta = 0.5$.[14] As in Pasten, Schoenle, and Weber (2021), the elasticity of substitution within sectors/categories is set to

[14] I use an alternative calibration with $\eta = 1$ which 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.

$\theta = 6$. The intermediate input share in production, δ, 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, ψ, which is used in turn to calibrate $\delta = \psi \frac{\theta}{\theta - 1}$.

4.4 Clustering

The goal of this section is to derive my model-robust identification restrictions given the calibration and specifications presented earlier. The first step is to remove homogeneous price stickiness, 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 use the remaining specifications (I, III, IV, V) in a clustering exercise.

I calibrate every specification with annual I-O data from 1997 to 2020. This yields 24 calibrations per specification and hence 96 versions of $\widehat{\mathbf{X}}^{pce}$ in total. Similarly I use the two specifications (IV, V) for demand shocks, amounting to 48 total versions of $\widehat{\mathbf{F}}^{pce}$. My goal is to find robust features in $\widehat{\mathbf{X}}^{pce}$ ($\widehat{\mathbf{F}}^{pce}$) across the 96 (48) versions. I define matrices $\widehat{\mathbf{X}}^{pce}_r$ and $\widehat{\mathbf{F}}^{pce}_r$ 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 to 6. In there I visualize for three supply shocks the cross-sectional rankings across model specifications and input-output calibrations. The bars summarize for the respective specification how often the price for the indicated PCE category appears at ranks 1 to 6 across the 24 input-output calibrations. The examples are chosen to highlight different types of sectoral shocks with regards to their robustness of rankings. Figure 4 shows rankings for the *Electrical equipment, appliance, and components.* At rank 1 the bar chart indicates which PCE category has the highest ranked price response. In response to this specific supply shock the fifth category is the one with largest price responses across all calibrations and specifications.[15] At the second rank, with a large majority, it is PCE category 2 that exhibits the next largest price responses. This example represents a sectoral supply shock that is fairly easy to cluster. Regardless of calibration and specification it turns out that in all cases PCE category 5 responds more than category 3, which responds more than all remaining 70 categories in most cases.

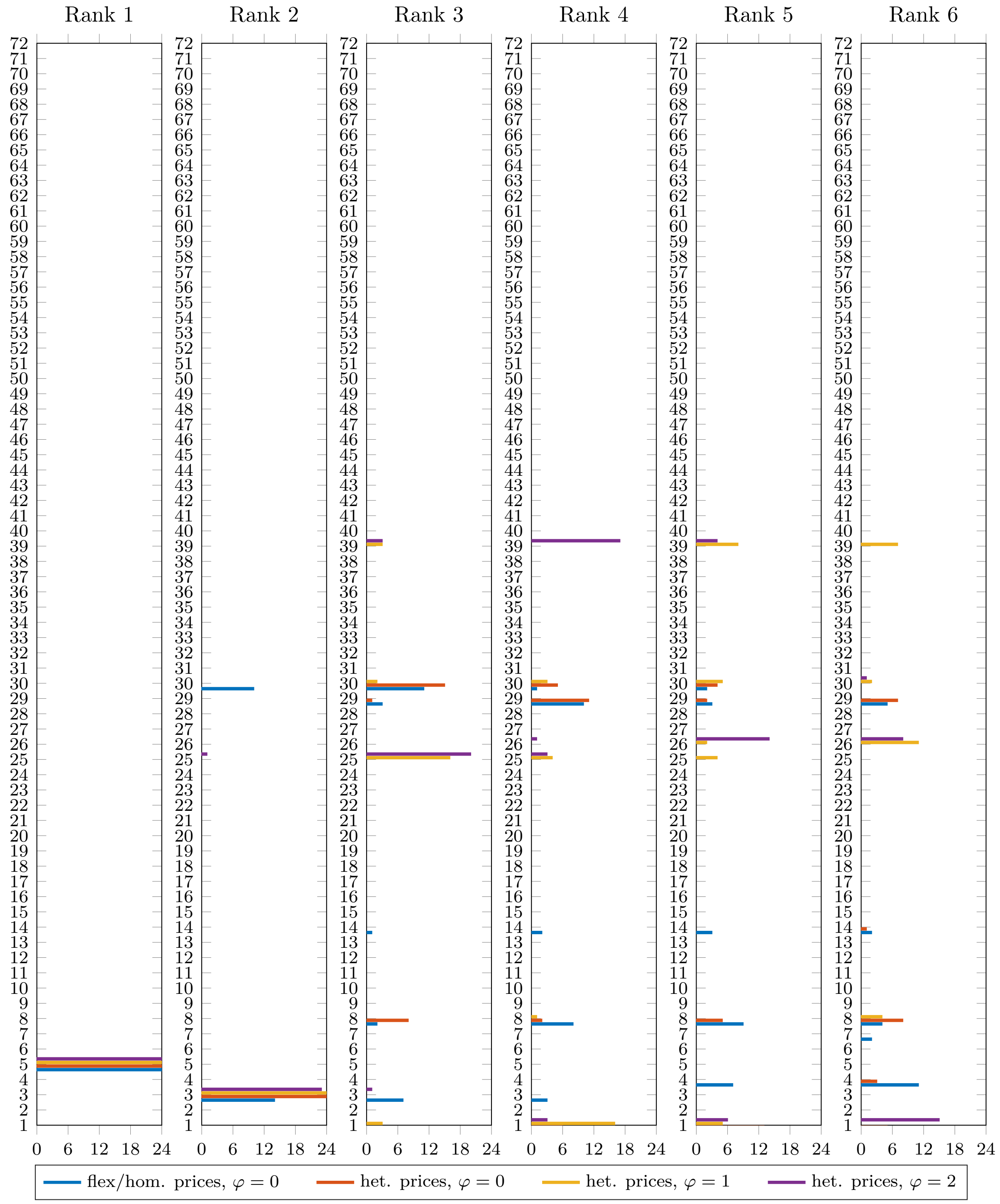
Figure 5 summarizes rankings for supply shocks originating in *Educational services.* Inspecting the cross-sectional rankings reveals more variation than in the previous example, yet still allows for fairly straightforward clustering: a first cluster with categories 68 and 66, a second cluster with category 67, and a third cluster including the remaining PCE categories.

Finally, Figure 6 illustrates a counter-example. Here it is much harder to define a cluster that holds across specifications and calibrations. In fact, the cluster analysis introduced next does not deliver a robust cluster for supply shocks in *Management, administrative and waste services.* I hence label these types of shocks as infeasible and do not identify them in my empirical model.

More specifically on the clustering exercise, I use a variety of standard algorithms to derive a fixed number of three clusters for every shock. Recall that 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

[15] A list that relates PCE indices used in this paper with PCE sector names is provided in Appendix Table A.7.

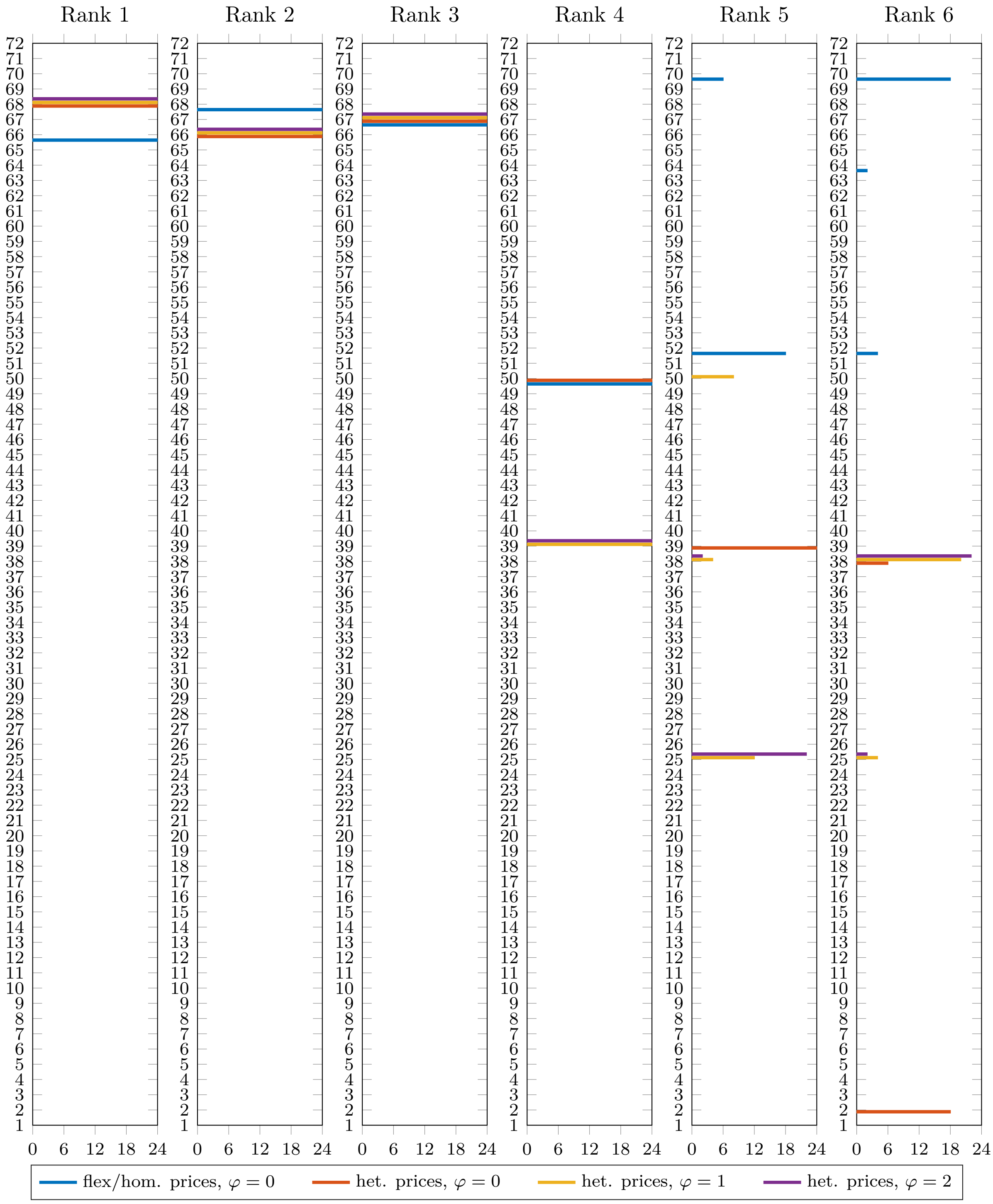
Figure 4: PCE rankings for *Electrical equipment, appliance, and components*



Notes: This figure summarizes the first six rankings for the sector-specific supply shock that originates in the sector indicated in the title. The four models correspond, in this order, to specification (I/II), (III), (IV), and (V). For every specification I consider 24 calibrations based on I-O tables for the years 1997 to 2020. The bars summarize for the respective specification how often the price for the PCE category appears at rank 1 to 6 across the 24 calibrations. A Corresponding figure visualizing rankings for intermediate-goods prices can be found in Appendix I.

similarly consumption) responses to the shock. I apply the following clustering algorithms, each with numerous setups: *k-means*, *k-medoids*, and *hierarchical clustering*, as well as a simple decision algorithm that I specify based on ranking counts. I then compare clustering results

Figure 5: PCE rankings for *Educational services*



Notes: See notes to Figure 4.

Table 1: Feasible shocks

Shocks	Cluster 1	Cluster 2	Cluster 3
		Sectoral supply shocks: $\widehat{\mathbf{X}}_r^{pce}$	
1	20	18, 28, 31, 55	Rest

Table 1 — Continued

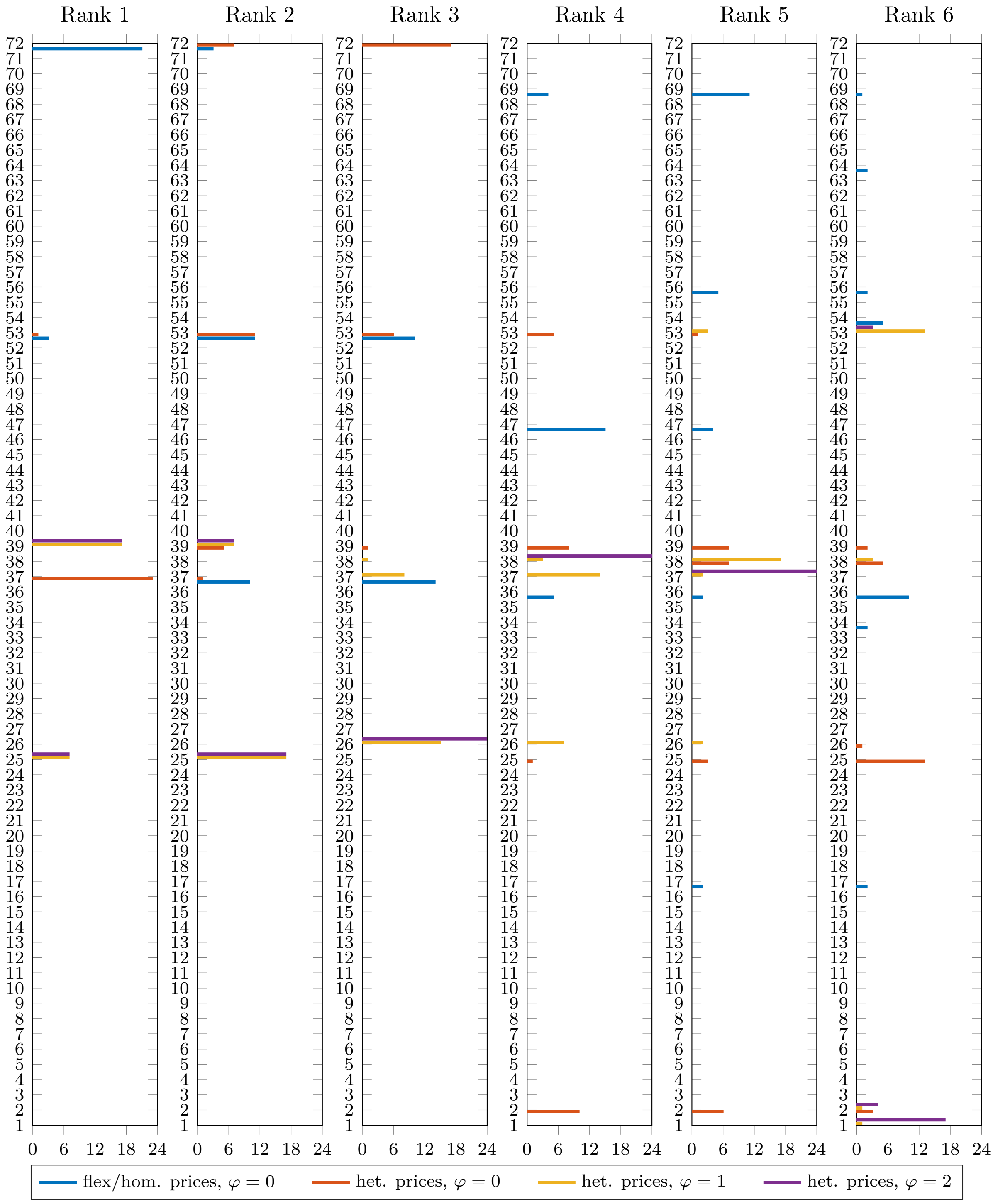
Shocks	Cluster 1	Cluster 2	Cluster 3
3	38, 39	37	Rest
9	17	8	Rest
10	5	3	Rest
11	1	3, 10	Rest
12	4	25, 26, 39	Rest
13	12	9, 13, 14, 25, 26, 28, 39	Rest
14	31	18, 19, 55	Rest
15	22	16, 21, 24	Rest
19	3	6	Rest
21	2	25, 26	Rest
23	63	15, 51	Rest
24	62	60	Rest
28	66, 68	67	Rest
30	50	52	Rest
31	56	25, 26, 36, 38, 39, 54	Rest
32	45	1, 2, 25, 26, 38, 39, 46, 51, 53, 69, 70, 71, 72	Rest
(2, 17)*	25, 26	38, 39	Rest
(20, 21)	2	25, 26	Rest
(20–22)	2	25, 26	Rest
(30, 31)	56	25, 26, 36, 38, 39, 50, 52, 54	Rest
		Sectoral demand shocks: $\widehat{\mathbf{F}}_r^{pce}$	
(1–3)	1	2, 3, 10	Rest
(4–7)	2	3, 4, 5	Rest
(8–12)	1	Rest	25, 26, 38, 39
(13–17)	2	Rest	39
(18–20)	31	2, 18, 19, 20, 55	Rest
(21–24)	2	16, 21, 22, 23, 24	Rest
(25, 26)	25	26	Rest
(27–32)	2	Rest	39
(33–39)	39	38	Rest
(50–53)	50	52	Rest
(54–56)	56	36, 54	Rest
(57–62)	60, 62	57, 58, 59, 61	Rest
(63–72)	68	15, 45, 51, 53, 63, 66, 67, 70	Rest

Notes: The *Shocks* column includes all feasible sectors. The remaining columns indicate the cluster composition. Note that for supply shocks, $\widehat{\mathbf{X}}_r^{pce}$, the shock index refers to the 33 NAICS sectors, whereas for demand shocks, $\widehat{\mathbf{F}}_r^{pce}$, indices correspond to the 72 PCE categories. In the cluster columns, indices always refer to PCE categories. Final clusters for feasible sector-specific supply shocks are determined based on the following specifications: shocks using clusters based on specifications (I) to (V) are 1, 3, 10, 11, 15, 21, 23, 28, 30, (20, 21), and (20-22); clusters based on specifications (III) to (V) are 9, 14, 19, 24, 32; and clusters based on specifications (IV) and (V) are 12, 13, 31, (30-31). The remaining supply shocks are infeasible to be identified. Shock (2, 17), indicated with an asterisk is infeasible but I consider it in one of my exercises nevertheless.

individual categories. Instead, I aggregate individual categories to 15 broader classifications.

In Figure 7 I present three examples for sector-specific supply shocks and their respective cluster. Panels in the left column compare a flexible price ranking (specification I/II) with that

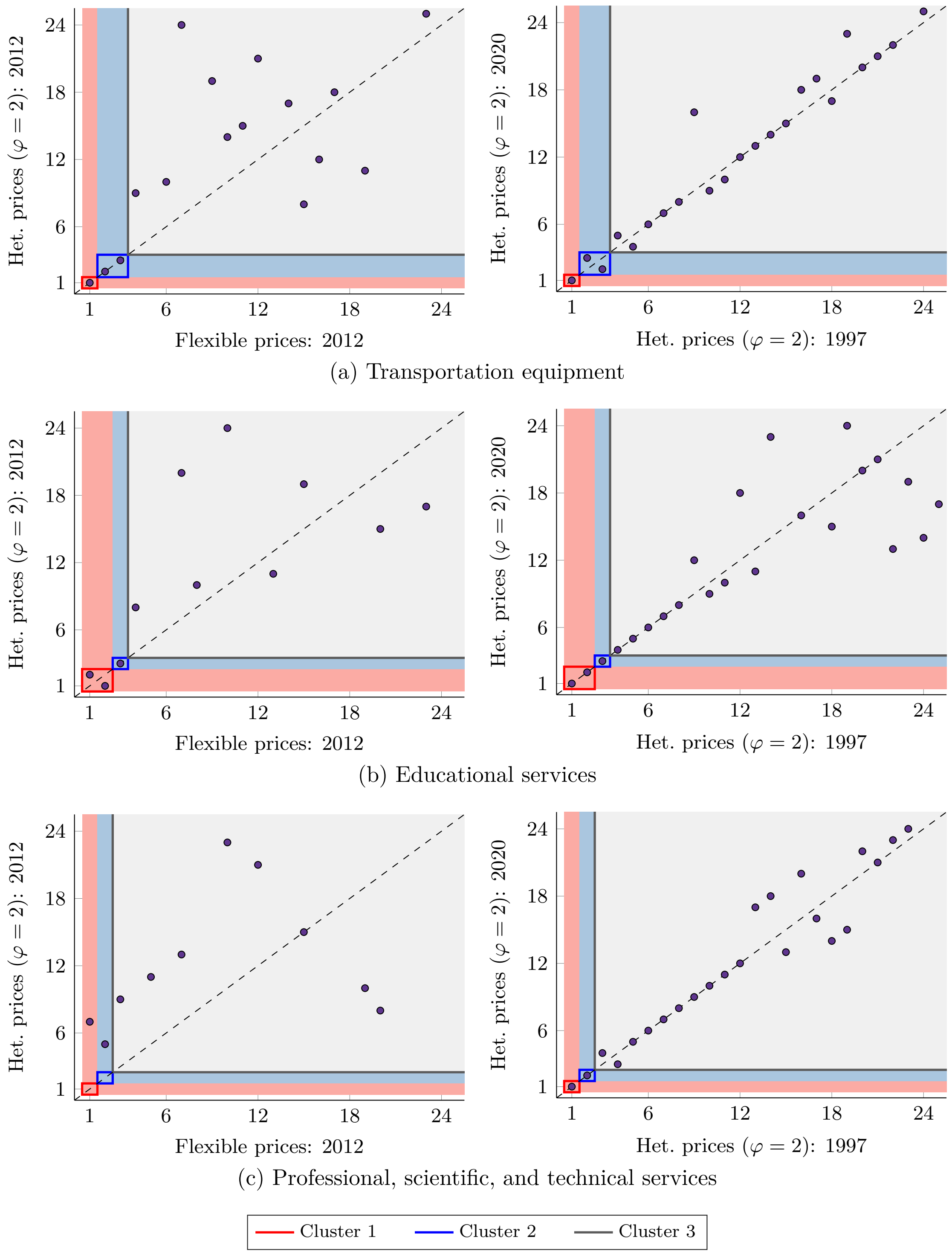
Figure 6: PCE rankings for *Management, administrative and waste services*



Notes: See notes to Figure 4.

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 cluster derived in the 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 vs. 2020) for specification (V). Comparing panels in the left column reveals that the first two sector

Figure 7: 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.

shocks are consistent across rankings, while the last row indicates a counter-example. Shocks originating in this very sector, *Professional, scientific, and technical services*, are therefore harder to identify.

The examples above highlight that not all clusters deliver useful identification assumptions.

I therefore evaluate each cluster against a set of criteria to determine whether it is suitable for identification or not.[16]

If I find that a cluster is consistent with more than 70 percent of the rankings and that the cluster includes unique PCE categories, I label the identified shocks as *feasible* for identification. It turns out, as indicated by Appendix Table A.2 that all 15 demand shocks exceed this threshold, while for sectoral supply shocks less than half the shocks exceed this threshold. This may not be surprising for supply shocks as the cluster needs to match a fairly wide range of specifications, across (I) to (V). I hence also consider clustering exercises using smaller sets of specifications. In a second set I remove specification (I) (and hence II), and only cluster across specifications (III) to (V), i.e. only using models with heterogeneity in price stickiness. Similarly in an even tighter set, I cluster across specifications (IV) and (V), which is the same set used for identification of demand shocks.

One further concern is that some PCE categories are ranked highly in several sector clusters. These sort of problematic categories include for instance *Motor vehicle fuels, lubricants, and fluids* or *Natural gas.* Cluster compositions that have any of these categories in their first two clusters are likely reduced in their ability to identify the corresponding sectoral shocks. I therefore check all clusters against these problematic sectors and make sure that the final cluster composition includes other price categories that are not included in other shocks' clusters. If a sector cluster includes only problematic categories in the first cluster I label the shock as infeasible. Table 1 summarizes the final set of clusters that I impose as identification restrictions.

5 Empirical model

Given the set of sector clusters, 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 my identification strategy. While the setup and estimation of the reduced-form model is fairly standard, the innovation lies in the structural identification setup.

5.1 The reduced-form factor-augmented VAR

I use a similar reduced-form Bayesian FAVAR model as we do in De Graeve and Schneider (2023). This model is in turn based on Bernanke, Boivin, and Eliasz (2005), Boivin, Giannoni, and Mihov (2009), and Stock and Watson (2016):

$$x_t = \lambda^x f_t^x + \lambda^y y_t + \epsilon_t \qquad \text{with } \epsilon_t \sim \mathcal{N}(0, R_\epsilon)\,, \tag{67}$$

$$\begin{pmatrix} f_t^x \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \phi_p \begin{pmatrix} f_{t-p}^x \\ y_{t-p} \end{pmatrix} + u_t \qquad \text{with } u_t \sim \mathcal{N}(0, Q_u)\,, \tag{68}$$

where y_t is an M-by-1 vector of observable factors. The composition of y_t changes depending on the clustering for the sector-specific shock that I intend to identify: I treat all sectoral PCE consumption growth and sectoral inflation rates included in the first cluster as observable factors. Since the clusters for all feasible sectoral supply shocks are the same across consumption and

[16] Appendix F presents the cluster evaluation in more detail.

price variables, the respective price and quantity variables treated as observed factors always stem from the same PCE sectors. For example, if for a given sector-specific shock the first cluster comprises of PCE sector z, then both c_z and p_z are treated as observable factors. My identification of sectoral demand shocks does not require that the first clusters of consumption and price variables are the same. For demand shocks I hence just use sectoral price variables (in the first cluster) as observable factors.[17] The N_x-by-1-vector x_t 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, λ^x and λ^y, correspond to those unobservable and observable factors, respectively.

The VAR process described by the transition equation has parameters ϕ_p with P numbers of lags. Reduced-form shocks, u_t, are associated with variance-covariance matrix Q_u and the measurement errors, ϵ_t with the diagonal variance matrix R_ϵ. The state-space system (67) and (68) can be expressed more compactly in companion form:

$$X_t = \Lambda F_t + E_t\,, \tag{69}$$

$$F_t = \Phi F_{t-1} + U_t\,, \tag{70}$$

where all parameters and variables of the state-space model are stacked as

$$X_t \equiv (x_t', y_t')'\,, \tag{71}$$

$$f_t \equiv (f_t^{x'}, y_t')'\,, \tag{72}$$

$$\lambda \equiv \begin{bmatrix} \lambda^x & \lambda^y \\ \mathbf{0}_{M\times K} & \mathbf{I}_M \end{bmatrix}\,, \tag{73}$$

$$F_t \equiv \left(f_t', f_{t-1}', \ldots, f_{t-P+1}'\right)'\,, \tag{74}$$

$$E_t \equiv \left(\epsilon_t', \mathbf{0}_{M\times 1}'\right)'\,, \tag{75}$$

$$U_t \equiv \left(u_t', \mathbf{0}_{(K+M)(P-1)\times 1}\right)'\,, \tag{76}$$

$$\Phi \equiv \begin{bmatrix} \phi_1 & \cdots & \phi_P \\ \mathbf{I}_{KM(P-1)} & & \mathbf{0}_{KM(P-1)\times KM} \end{bmatrix}\,, \tag{77}$$

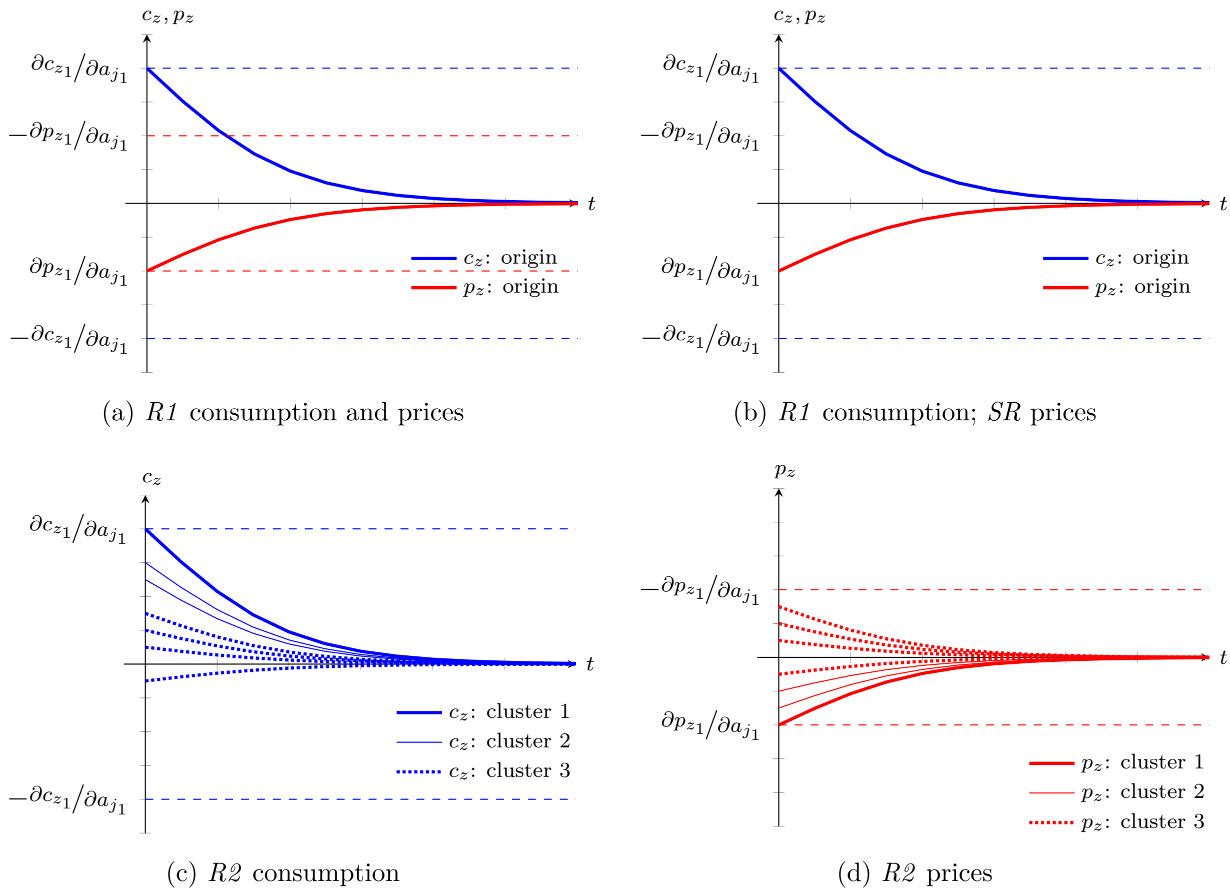
$$\Lambda \equiv \left[\lambda \;\; \mathbf{0}_{(N_x+M)\times(K+M)(P-1)}\right]\,. \tag{78}$$

I estimate the model using the two-step estimation procedure of Bernanke, Boivin, and Eliasz (2005) and Boivin, Giannoni, and Mihov (2009). Appendix G provides a detailed overview on the estimation. In short, the first step uses principle components 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).

As in De Graeve and Schneider (2023), I estimate the model (67)-(68) for every sector-

[17] Including additionally all consumption growth rates for sectoral demand shocks would lead to a large total number of factors which may affect the estimation. Appendix Table A.6 provides an overview over the sectors included in the relevant clusters.

Figure 8: Identification for (positive) sectoral supply shocks



(a) *R1* consumption and prices

(b) *R1* consumption; *SR* prices

(c) *R2* consumption

(d) *R2* prices

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 shock in a generic sector 1. I assume that the first cluster assigned to this shock only includes one PCE category. The dashed corridors refer to the corridor imposed by *R1* restrictions. *SR* refers to identification using sign restrictions.

specific shock separately: for every sector-specific shock, the first cluster comprises a different set of sectors. Including these very sectors' consumption growth and inflation rates explicitly as observed factors allows to capture enough variance to identify the shock; unobserved factors may not be able to achieve that. The partial identification of individual sectoral shocks comes at a cost. Only joint identification can fully ensure that sectoral shocks are orthogonal to one another. However, my identification restrictions should rule out that partially identified sector shocks are not correlated systematically. My identification scheme, presented next, can be implemented using standard sign restriction algorithms as in Uhlig (2005), Rubio-Ramírez, Waggoner, and Zha (2010).[18]

5.2 Structural identification using cross-sectional restrictions

The identification setup builds on De Graeve and Schneider (2023) and extends it with regards to identification based on quantities *and prices*. I implement the sector-shock clusters derived

[18] I apply algorithms from the latter contribution. Amir-Ahmadi and Uhlig (2015) apply these standard sign restriction algorithms in a FAVAR context.

in previous sections as heterogeneity restrictions in the reduced-form FAVAR model to identify structural shocks. Identification is based on comparing contemporaneous impulse responses.[19] These are defined in the following way:

$$r_a^{(f)} = \mathbf{a}\,, \tag{79}$$

$$r_a^{(X)} = \lambda r_a^{(f)}\,, \tag{80}$$

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 λ.

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 $\hat{r}_a^{(X)}$ that depending on the context 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 a given sector specific shock I define a *strict* ranking, γ_j, as:

$$\gamma_j = (\gamma_{1j}, \gamma_{2j}, \ldots, \gamma_{Nj})'\ , \tag{81}$$

where γ_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, Γ_j, is defined as:

$$\Gamma_j \equiv (\Gamma_{1j}, \Gamma_{2j}, \ldots, \Gamma_{Gj})'\ , \tag{82}$$

where G is the total number of imposed clusters. The individual clusters Γ_{gj} for sector j (or PCE category) are composed of the strict rankings γ_j, such that:[20]

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

where l_g is an index for the last sector included in cluster g.[21]

Next, I define a few types of restrictions using strict or cluster rankings. I distinguish here between restrictions that relate variables of sectors included in the first cluster against the rest (*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

[19] I only consider restrictions on impact and not at later horizons.

[20] Note that I use index j for a generic sector-shock, that could both be a sectoral supply or demand shock.

[21] Note that other than in De Graeve and Schneider (2023) Γ_{1j} I allow the first cluster to contain more than one γ_{1j}.

that requires a positive response of those variables is defined as:

$$min\left\{\hat{r}_a^{(X)}(\Gamma_{1j})\right\} > |\hat{r}_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_1+1,\ldots,N\,, \tag{83}$$

and equivalently for a negative response:[22]

$$max\left\{\hat{r}_a^{(X)}(\Gamma_{1j})\right\} < -|\hat{r}_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_1+1,\ldots,N\,. \tag{84}$$

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

$$min\left\{\hat{r}_a^{(X)}(\Gamma_{gj})\right\} > max\left\{\hat{r}_a^{(X)}(\Gamma_{(g+1),j})\right\}, \quad \forall g = 2,\ldots,(G-1)\,, \tag{85}$$

and a negative response, such that:[23]

$$max\left\{\hat{r}_a^{(X)}(\Gamma_{gj})\right\} > min\left\{\hat{r}_a^{(X)}(\Gamma_{(g+1),j})\right\}, \quad \forall g = 2,\ldots,(G-1)\,. \tag{86}$$

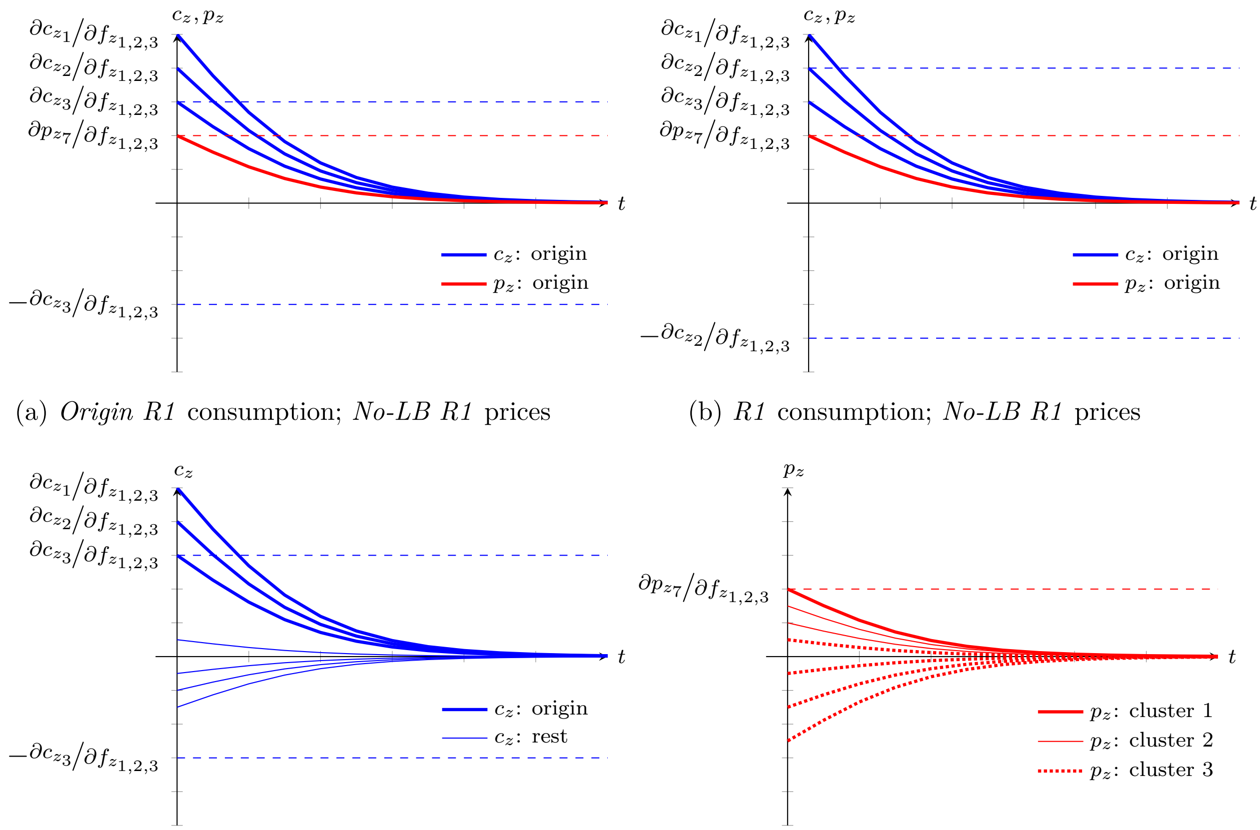
There are multiple ways to identify sectoral shocks. I first illustrate the approach for sectoral supply shocks using sectoral inflation and consumption growth rates. Figure 8 summarizes the different approach for a positive sectoral supply shocks. Note that in this illustrations I assume that the first cluster only includes one PCE category. The first row illustrates two versions for identification using *R1*-type restrictions. Panel 8a 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. In Panel 8b, I illustrate a slightly weaker combination of restrictions. Here it is only the quantity variable that adheres to an *R1*. Price responses are simply using a sign restriction. The bottom rows deal with *R2* restrictions. In Panel 8c, it is illustrated that the impulse responses of consumption growth rates follows the imposed cluster. Note that it is permitted that some PCE prices have responses of the opposite sign than the *R1* categories, as long as they stay within the corridor set by the *R1* restrictions. Similarly, Panel 8d depicts *R2* restrictions for PCE prices, which respond negatively to a positive sectoral supply shock. Again opposite responses, i.e. a positive price response, are permitted for some sectors towards the end of the cluster/ranking.

Next, I contrast identification of sectoral supply shocks with demand shocks. Sectoral demand shocks require a modified approach with regards to *R1* and *R2* type restrictions. First, I introduce the *origin R1*. I do not identify sectoral demand shocks for all 72 PCE categories separately, but for broader categories that include a number of PCE categories. For instance, the first demand shock is for *Motor vehicles and parts*, which consists of three individual PCE categories (with index 1, 2, 3). I label these categories as the *origin* categories. In this case, a positive demand shock requires that consumption in all three PCE categories increases. Since sectoral demand shocks change the composition of the consumption basket, all other PCE cate-

[22] *R1*-restrictions for shocks with just a single PCE category in the first cluster are simple 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 $i = 2,\ldots,N$.

[23] *R2*-restrictions for strict rankings are simple 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 9: Identification for (positive) sectoral demand shocks



(a) *Origin R1* consumption; *No-LB R1* prices

(b) *R1* consumption; *No-LB R1* prices

(c) *Origin R1 without an R2* consumption

(d) *R2* with *No-LB R1* prices

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.

gories 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 the *Origin R1* for a positive response as:

$$min\left\{r_a^{(X)}(\Gamma_j^{ori})\right\} > |r_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_{ori}+1,\ldots,N\,, \tag{87}$$

and for a negative response as:

$$max\left\{r_a^{(X)}(\Gamma_j^{ori})\right\} < -|r_a^{(X)}(\gamma_{ij})|, \quad \forall i = l_{ori}+1,\ldots,N\,, \tag{88}$$

where l_{ori} refers to the index of the last (ranked) origin sector and the ranks of origin sectors are included in Γ_j^{ori}.

Another modification is the *no-lower-bound R1* (*No-LB R1*), which is less restrictive than the original. This restriction does not impose a lower bound. In other words, it allows to have responses that exceed responses of categories in the first cluster in absolute terms. For a positive response, it is defined as:

$$min\left\{r_a^{(X)}(\Gamma_{1j})\right\} > r_a^{(X)}(\gamma_{ij}), \quad \forall i = l_1+1,\ldots,N\,, \tag{89}$$

and for a negative response as:

$$max\left\{r_a^{(X)}(\Gamma_{1j})\right\} < -r_a^{(X)}(\gamma_{ij}), \quad \forall i = l_1+1,\ldots,N\,. \tag{90}$$

Figure 9 illustrates the different restrictions for sectoral demand shocks. Panel 9a presents the origin *R1* for sectoral consumption, combined with a *no-lower-bound R1* for prices. Panel 9b presents a case where consumption responses follow a standard *R1* restriction. For some demand shocks, there are quite a few 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 is set wider because it is not defined by the least ranked origin sector. Panel 9c illustrates how an *origin R1* functions without imposing an additional type-*R2* restriction. For demand shocks, I only distinguish 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*. Panel 9d illustrates this case.

There is one final restriction that I impose for supply shocks exclusively: a sign restriction on aggregate inflation and consumption growth. This entails that in response to a positive sectoral supply shocks I require that aggregate inflation decreases and aggregate consumption growth increases. This is motivated by the theoretical analysis. In contrast, I impose no such sign restriction for sectoral demand shocks as theoretically the response of aggregate variables is more dependent on the individual sectoral demand shock. The analysis above illustrates 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 direction for supply shocks and in the same direction for demand shocks.

Since for some sectors it is much harder to identify shocks than for others, I apply the most restrictive mix of *R1*- and *R2*-type restrictions possible, but revert to a less restrictive mix if necessary. Table 2 summarizes for all feasible shocks the final restrictions I use to identify the shock.

Finally, note that I do not explicitly identify aggregate supply or demand shocks.

5.3 Time series data and FAVAR parameterization

I use monthly time series on PCE real quantity and price indexes for 72 PCE categories and aggregates from the BEA from 1959 until June 2022.[24] 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. Appendix Figures A.1 and A.2 show some sectors with substantial outlier adjustments.

[24] See Appendix E.5 for additional information.

Table 2: Feasible and successful models

	Most restrictive w/ success			Most restrictive w/ success	
Shocks	*R1*	*R2*	Shocks	*R1*	*R2*
Sectoral supply shocks: $\widehat{\mathbf{X}}_r^{pce}$			Sectoral supply shocks: $\widehat{\mathbf{X}}_r^{pce}$ (continued)		
1	*R1* c_z; *SR* p_z	*R2* c_z	(7, 8)	—	—
2	—	—	(2, 17)	—	—
3	*R1* c_z; *SR* p_z	*R2* c_z	(20, 21)*	na	na
4	—	—	(20–22)	*R1* c_z; *R1* p_z	*R2* c_z; *R2* p_z
5	—	—	(24, 25)	—	—
6	—	—	(26, 27)	—	—
7	—	—	(28, 29)	—	—
8	—	—	(30, 31)	*R1* c_z; *SR* p_z	*R2* c_z
9	*R1* c_z; *R1* p_z	*R2* c_z; *R2* p_z			
10	*R1* c_z; *R1* p_z	*R2* p_z	Sectoral demand shocks: $\widehat{\mathbf{F}}_r^{pce}$		
11	*R1* c_z; *R1* p_z	*R2* c_z; *R2* p_z			
12	*R1* c_z; *R1* p_z	*R2* p_z	(1–3)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
13	*R1* c_z; *SR* p_z	*R2* c_z	(4–7)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
14	*R1* c_z; *SR* p_z	*R2* c_z	(8–12)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
15	*R1* c_z; *R1* p_z	*R2* c_z; *R2* p_z	(13–17)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
16	—	—	(18–20)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
17	—	—	(21–24)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
18	—	—	(25, 26)	*Origin R1* c_z; *No-LB R1* p_z	*R2* p_z
19	*R1* c_z; *R1* p_z	*R2* c_z; *R2* p_z	(27–32)	*R1* c_z; *No-LB R1* p_z	*R2* p_z
20	—	—	(33–39)	na	na
21*	na	na	(40–44)	—	—
22	—	—	(45–49)	—	—
23	*R1* c_z; *SR* p_z	*R2* c_z	(50–53)	na	na
24	*R1* c_z; *SR* p_z	*R2* c_z	(54–56)	na	na
25	—	—	(57–62)	na	na
26	—	—	(63–72)	na	na
27	—	—			
28	*R1* c_z; *SR* p_z	*R2* c_z			
29	—	—			
30	*R1* c_z; *SR* p_z	*R2* c_z			
31	*R1* c_z; *SR* p_z	*R2* c_z			
32	*R1* c_z; *SR* p_z	*R2* c_z			
33	—	—			

Notes: This table summarizes for all feasible shocks the final mix of *R1* and *R2* restrictions that I use to identify the shocks. *SR* refers to a sign restriction. If a column does not include a c_z or p_z it implies that this variable type remains unrestricted.

In the FAVAR I use first differences of log PCE price indices and log real log quantity indices. Similarly to De Graeve and Schneider (2023), I impose a total number of factors that is larger than for typical FAVAR models used in the literature. My interest is to identify as many sectoral shocks as possible. Including a small number of factors may not be sufficient to capture the volatility created by all relevant sectoral shocks. My benchmark is to explain at least 50 percent of sectoral consumption growth and inflation rates. To achieve that I require

26 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.

6 Results

This section presents the empirical contributions of sectoral supply and demand shocks to personal consumption expenditure (PCE) inflation and consumption growth. I identify sectoral shocks via the scheme motivated and illustrated in earlier sections.

My main objects of interest are the sectoral origins of PCE inflation. Figure 10 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 comprises all other drivers of inflation that I do not explicitly identify.[25] 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 supply and demand contributions.[26]

At a bird's eye view, sectoral shocks explain a portion of PCE inflation's business cycle but leave ample room for other, non-identified, shocks. In other words, the aggregated contributions of sectoral shocks to inflation hover around its baseline in most periods, sometimes having increasing and in other times decreasing contributions to inflation. With regards 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 does by no means rule out that *aggregate* demand shocks, e.g. fiscal policy shocks, have large contributions to PCE inflation.

A key result of this paper are the two notable time periods where sectoral origins exerted substantial (more than usual) inflationary pressure. During the *Great Inflation* and in recent years, I find that a major part of PCE inflation originates from sectoral supply sources. However, the importance of sectoral shocks varied throughout both periods. Panels 10b and 10c provide an enlarged picture for these two periods.

6.1 Inflation in recent years

In the wake of lifted COVID-19 lockdowns the U.S. economy experienced rapid increases of inflation from the first half of 2021 onward, until the end of my sample in June 2022. Comparing these (unconditional) rapid price increases with my inflation series conditional on sectoral origins

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

[26] 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 instance long-term drivers of inflation.

in Panels 10c reveals three distinct sub-periods with changing degrees of sectoral sources that explain inflation.

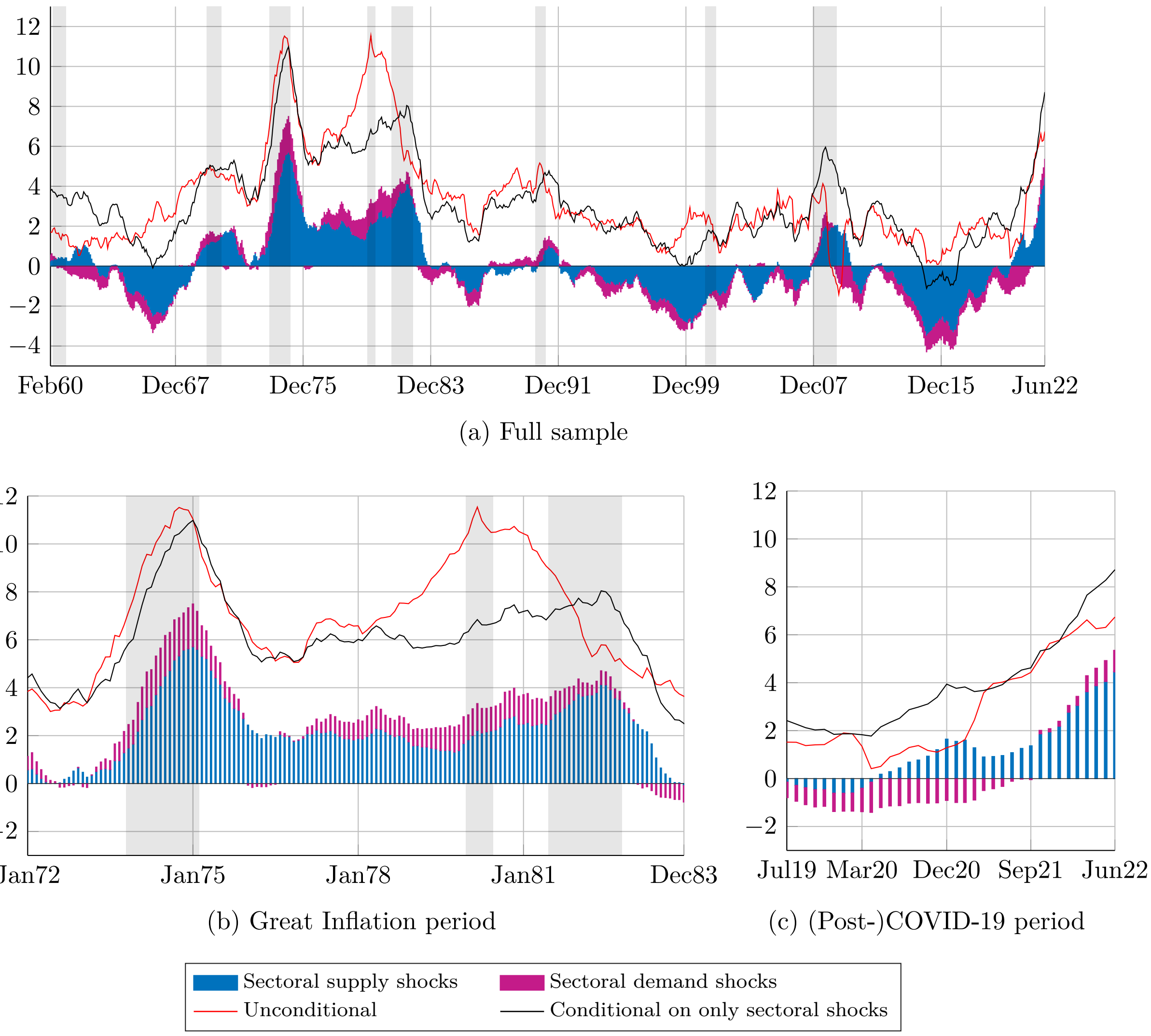
In a first sub-period from March 2020 until February 2021, I find that sectoral demand shocks have had fairly stable negative contributions to inflation. This is no surprise considering the effect the COVID-19 pandemic had on depressing demand in 2020. On the contrary, total sectoral supply contributions have risen steadily until February 2021, increasing their positive effects on aggregate prices. While PCE inflation has been increasing in that period, y-o-y inflation rates essentially recovered to pre-COVID-19 levels and remained consistently below the two-percent objective. I present a more detailed picture on individual sectoral contributions below but one important factor at the time were supply shocks originating in the *Computer and electronic products* sector. Overall, my conditional inflation series increased to levels well above observed PCE inflation and well above the two-percent objective. The residual between the two series could be explained by large aggregate negative demand shocks with negative effects on inflation.

In a second sub-sample that I date from March 2021 until September 2021, I observe an inversion of sectoral contributions. Sectoral demand shocks started to reduce their negative impact on inflation, whereas positive sectoral supply contributions decreased considerably between February and April. At the same time, actual PCE inflation increased sharply. With overall slightly decreasing sectoral contributions in this sub-period, other factors have to explain the rise 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.

Finally, the third sub-period commences in October 2021, with yet again changing sectoral contributions. Sectoral demand shocks developed small demand-pull contributions. More importantly though, sectoral supply shocks increased their inflationary contributions sharply. The nature of these supply shock contributions do not stem from one sectoral source alone but are distributed across numerous sectors with varying degrees of importance. Some of these sectors are, for instance, supply shocks originating in the *Transportation equipment*, *Furniture and related products*, as well as *Computer and electronic products* sectors.

It is in this last sub-period where negative sectoral supply shocks become the major driver of inflation. Going back in time, Panel 10a 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, my results show that overall sectoral shocks had no substantial inflationary effects for around four decades with in fact mostly negative contributions to inflation during that time. When considering the path inflation has taken from the mid-2010s, the inflationary pressure exerted by sectoral supply shocks in recent years appears all the more striking: from 2015 until the end of my sample, my inflation series conditional on only sectoral sources changed from around -1 percent to over 8.5 percent.

Figure 10: PCE inflation and its sectoral origins (y-o-y)

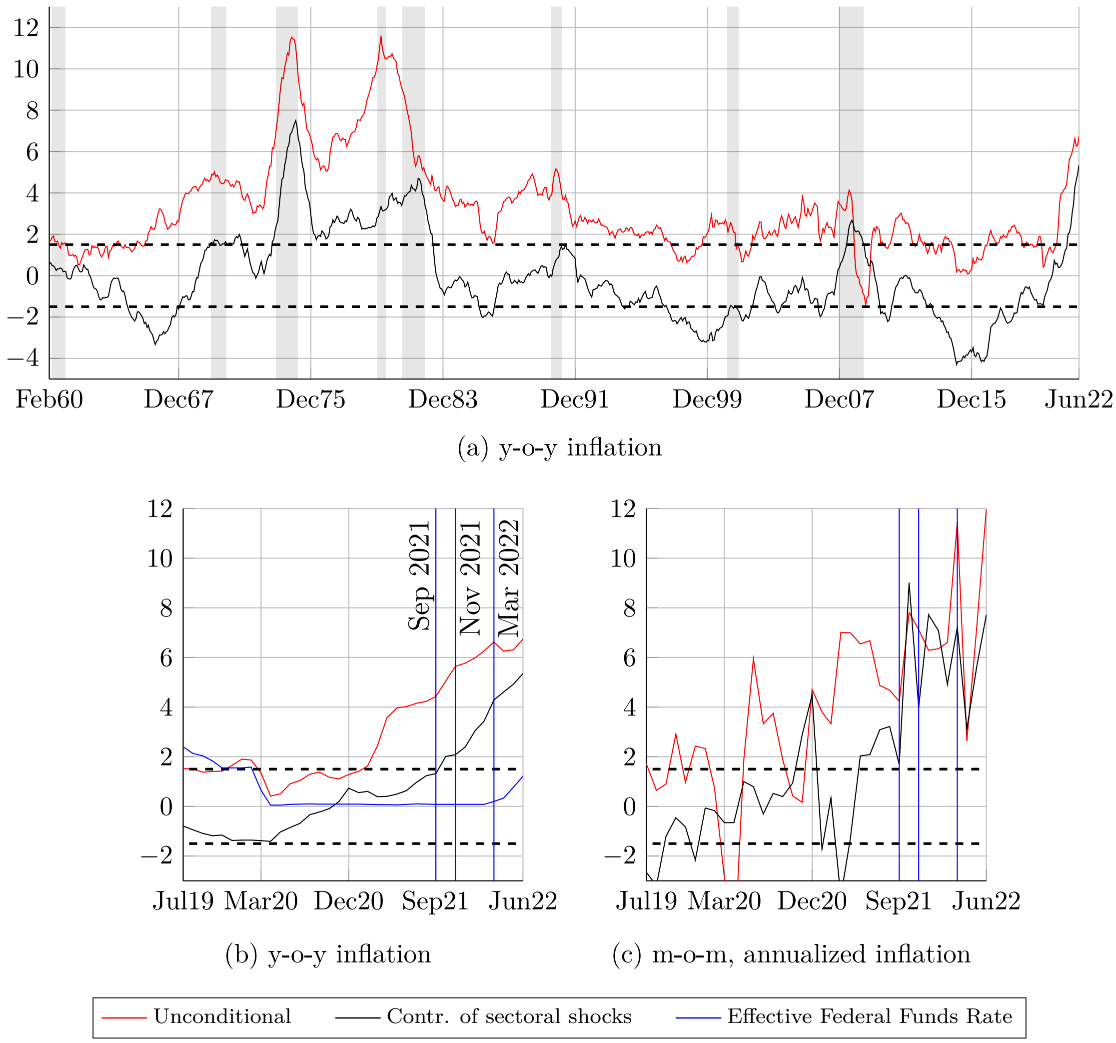


Notes: The figure illustrates the aggregated median contributions of sectoral shocks to inflation: I contrast actual observed year-on-year (y-o-y) PCE inflation with PCE inflation conditional on only sectoral supply and demand shocks (black line).

6.2 Evaluating the Fed's policy stance

After a long spell of below-two-percent annual inflation, the recent price hikes across-the-board have brought the discussion on what drives inflation to the wider policy discussion: "[i]nflation has risen, largely reflecting transitory factors." This was the Federal Open Market Committee's (FOMC) assessment in April 2021a (p. 1). Back then, the nature of heightened inflation was a highly contested topic: Are high inflation levels a short-lived phenomenon or are we entering a *prolonged* period of heightened inflation? The FOMC's April assessment on the short-lived nature of inflation was upheld during its June 2021b and July 2021c meetings. The wording changed slightly to "Inflation is [*elevated*], largely reflecting transitory factors." (both p. 1) and was weakened in the following November 2021d meeting to "Inflation is elevated, largely reflecting factors [*that are expected to be transitory*]." (p. 1). In the next FOMC statement in December 2021c there was no mentioning of "transitory" factors anymore.

Figure 11: PCE inflation and the intensity of sectoral contributions



Notes: Sectoral origins of inflation are displayed as simple median contributions around zero, i.e. without adding the mean of inflation, in contrast to previously depicted series that were *conditional* on sectoral shocks. Dashed lines correspond to a 300-basis-point "relevance" corridor around zero.

In the remainder of this sub-section, I assess the Fed's judgment on these transitory or short-lived factors through the lens of sectoral supply and demand disturbances. In the previous sub-section I argue that, recently, sectoral factors have had exceptionally large contributions to PCE inflation. However, these were of no particular concern up until fall 2021. Figure 11 shows a small transformation of the sectoral contributions presented earlier. Sectoral origins of inflation are now displayed as simple contributions around zero, i.e. without adding the mean of inflation, in contrast to previously depicted series that were *conditional* on sectoral shocks. Additionally, a 300-basis-point "relevance" corridor around zero is plotted.[27] Sectoral contributions have only breached the upper bound of this corridor during the Great Inflation, briefly during the Great Recession, and from end-2021 onward. However, prolonged contributions above this corridor have only occurred during the Great Inflation and recently. In other words, sectoral shocks have had no substantial inflationary effect for about four decades and were therefore of no large

[27]The width of this corridor is arbitrary but it's exact dimension is not important and only matters for illustration purposes.

concern to monetary policy. On the contrary even, sectoral contributions breached the lower bound on a few occasions in that time, suggesting negative contributions to inflation.

Panel 11b enlarges the figure for recent years and allows to better gauge the exact point in time when sectoral shocks began to show exceptionally large contributions. The Panel further marks three key months with regards to changes in the Fed's policy. As noted above, in November 2021 the FOMC started to weaken its language on inflation being *transitory*, and at the following meeting in December it removed the term *transitory* altogether. Furthermore, in November 2021d the FOMC announced for the first time since the outburst of the COVID-19 pandemic in 2020 that it would "[...] begin reducing the monthly pace of its net asset purchases [...]" (p. 2). This suggests that between the September 2021e and November 2021d meetings, the FOMC started to revise it assessment on inflation being driven by *transitory* factors. Between those meetings sectoral contributions increased sharply, breaching the relevance corridor for the first time and increasing up until the end of the sample. In March 2022, the FOMC concluded its quantitative easing program and announced an increase of the target range for the federal funds rate from 0 to 0.25 up to 0.25 to 0.5, for the first time since the COVID-19 pandemic started. My results overall suggest that considering sectoral supply shocks as short-lived phenomena has been a reasonable assumption up until the second half of 2021. The FOMC's shift in policy matches the timing when sectoral supply shocks started becoming macroeconomically relevant.

Panel 11c also shows the month-on-month (m-o-m) contributions. While m-o-m inflation rates are generally more volatile, and therefore breaching the relevance bound more frequently, the timing still matches. Until September 2021 sectoral contributions have not reached levels above the relevance bound. Only starting from October onward have sectoral contributions reached and stayed above this bound.

In a speech on 21 March 2022, Jerome Powell, chair of the Fed, acknowledges the supply-side contributions as a driver of inflation up to this point (p. 4):

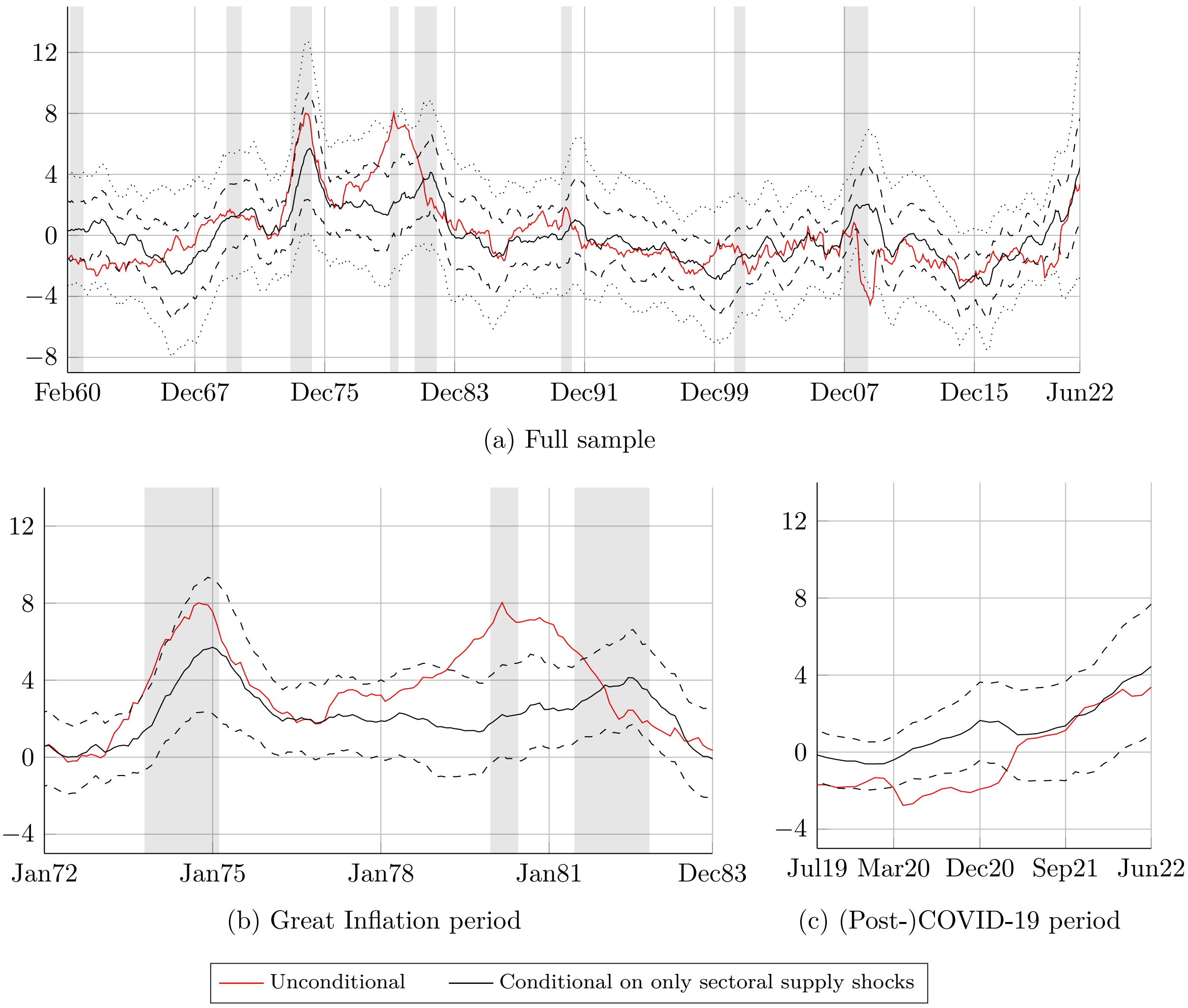
> Why have forecasts been so far off? In my view, an important part of the explanation is that forecasters widely underestimated the severity and persistence of supply-side frictions, which, when combined with strong demand, especially for durable goods, produced surprisingly high inflation.

My results show that these supply-side origins are sectoral, i.e. combinations of sector-specific supply shocks with macroeconomic relevance. In general, supply shocks are difficult to act upon by monetary policy because hiking interest rates further depresses already reduced output growth and likely increases unemployment. The Fed's approach to have gradually tightened monetary policy between November 2021 and March 2022 is therefore compatible with my results.

Further on, in the same speech from 21 March ibid., Jerome Powell states for the time ahead that (p. 5):

> It continues to seem likely that hoped-for supply-side healing will come over time as the world ultimately settles into some new normal, but the timing and scope of that relief are highly uncertain. In the meantime, as we set policy, we will be looking to

Figure 12: PCE inflation and its sectoral supply origins (y-o-y, demeaned)



Notes: The figure shows median contributions of sectoral supply shocks to demeaned inflation. Additionally, 95-percent and standard-deviation confidence bands are plotted.

actual progress on these issues and not assuming significant near-term supply-side relief.

Given the high contributions of sectoral disturbances I find throughout 2022, it remains uncertain whether inflationary sectoral supply and demand factors will decay quickly in the near future.

Finally, Figure 12 shows additional 95-percent and standard-deviation confidence bands for sectoral supply shocks. At standard deviation bands and for recent years, sectoral supply shocks' contributions became significant from March 2022 onward, confirming the timing considerations illustrated above.[28]

[28]The appendix includes a similar figure for demand shocks, whose contributions to PCE inflation are not significant.

6.3 Decomposing aggregated sectoral shock contributions

The aggregate contributions of sectoral supply and demand shocks presented so far already provide a good overview on the overall sectoral sources of heightened inflation at certain points in time. I now provide decompositions of these contributions into smaller subsets as well as highlight individual contributions originating from certain sectors.

Figure 13 decomposes the sectoral supply-side drivers of Figure 10 into contributions from services and non-services sectors.[29] Panel 10c 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 during 2020 to reign in the COVID-19 pandemic. Removing social distancing measures and return to workplace measures could have had a stronger impact in services sectors, whereas 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 10 suggests. Panel 13b reveals that no such difference between services and goods-producing supply disturbances occurred during the *Great Inflation*. Both types of sectors were subject to negative supply shocks.

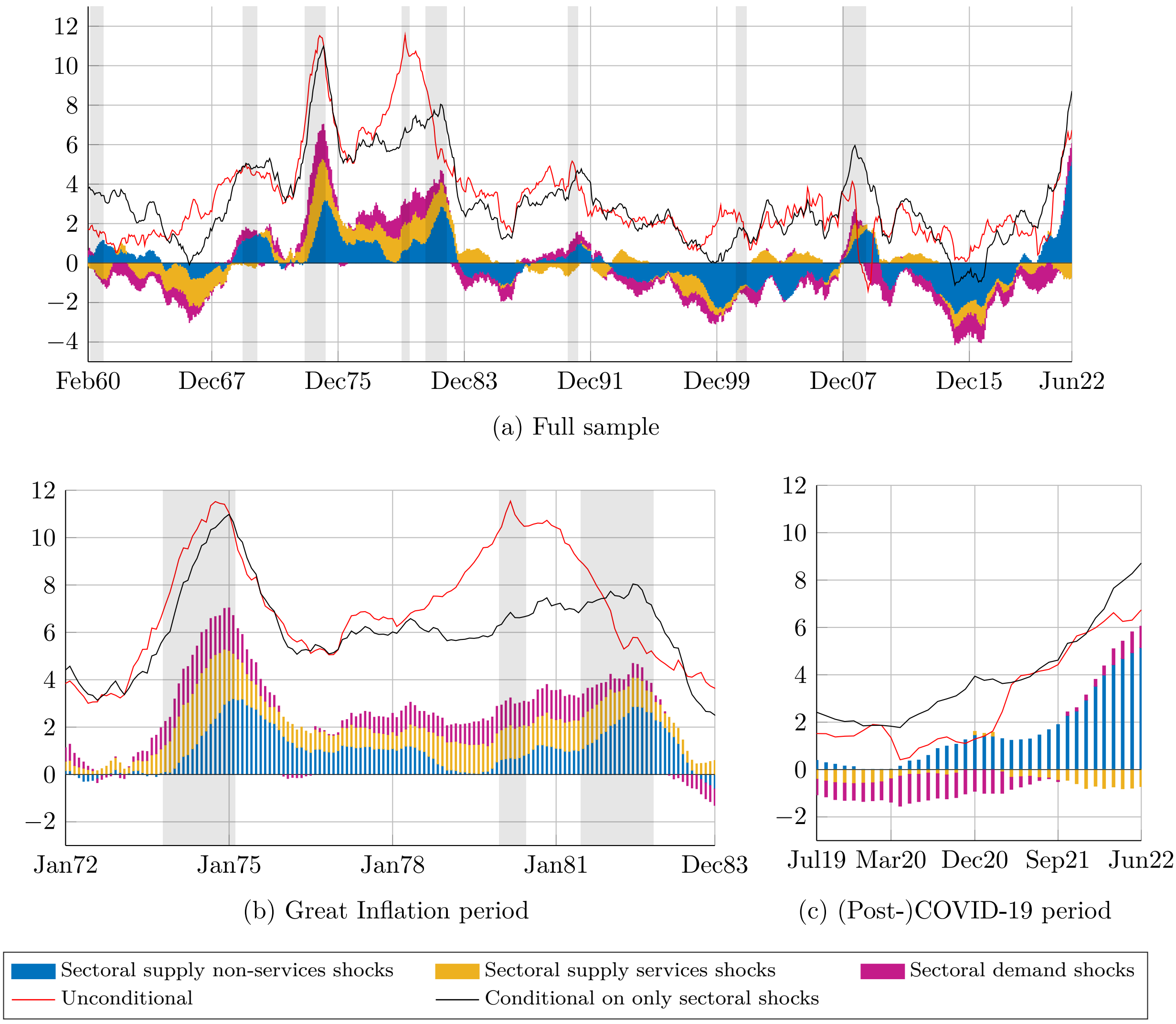
Figures 10 and 13 show conditional and unconditional *year-on-year* inflation. Alternatively, Figure 14 presents contributions for monthly (annualized) inflation, which provides a better way to date certain contributions than using y-o-y inflation. When the first lockdowns were imposed in March 2020, I find that both services and non-services sectors were subject to negative supply shocks. The shocks I identify are specific to the respective origin sector, and then lead to aggregate consequences directly and through spillovers to other sectors. One plausible hypothesis is that many supply and demand shocks related to the pandemic in 2020 were in fact aggregate or other combined shocks. Lockdowns, stay-at-home orders, etc. are economy-wide policies. 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. For instance, as noted above, some services sectors are more affected by these policies.

Figure 15 presents a detailed breakdown of some (important) individual sector contributions to PCE inflation from mid-2019 until mid-2022.[30] The upper left hand corner shows how supply shocks originating in the *Transportation equipment* sector corroborate my previous analysis on the Fed's policy change. While these types of shocks did exert inflationary pressure during 2020, their overall contributions fluctuated up until mid-2021. From July to October 2021 *Transportation equipment's* supply shocks rapidly gained in importance and are therefore some of the contributing factors that led to an increase of overall supply-shock induced inflation. Moving to the upper right-hand panel supply-shock contributions from *Furniture & related products* show an even stronger contribution that increased even further towards the end of

[29] 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 demand shocks. The lack of identifiable services-sector shocks may be an interesting result by itself. It may be less common for consumers to change preferences for individual services in contrast to shifting preferences between goods categories.

[30] See also the Appendix I for more figures on individual contributions as well as the actual sector-shock series.

Figure 13: PCE inflation and its sectoral origins (y-o-y): goods vs. services



(a) Full sample

(b) Great Inflation period

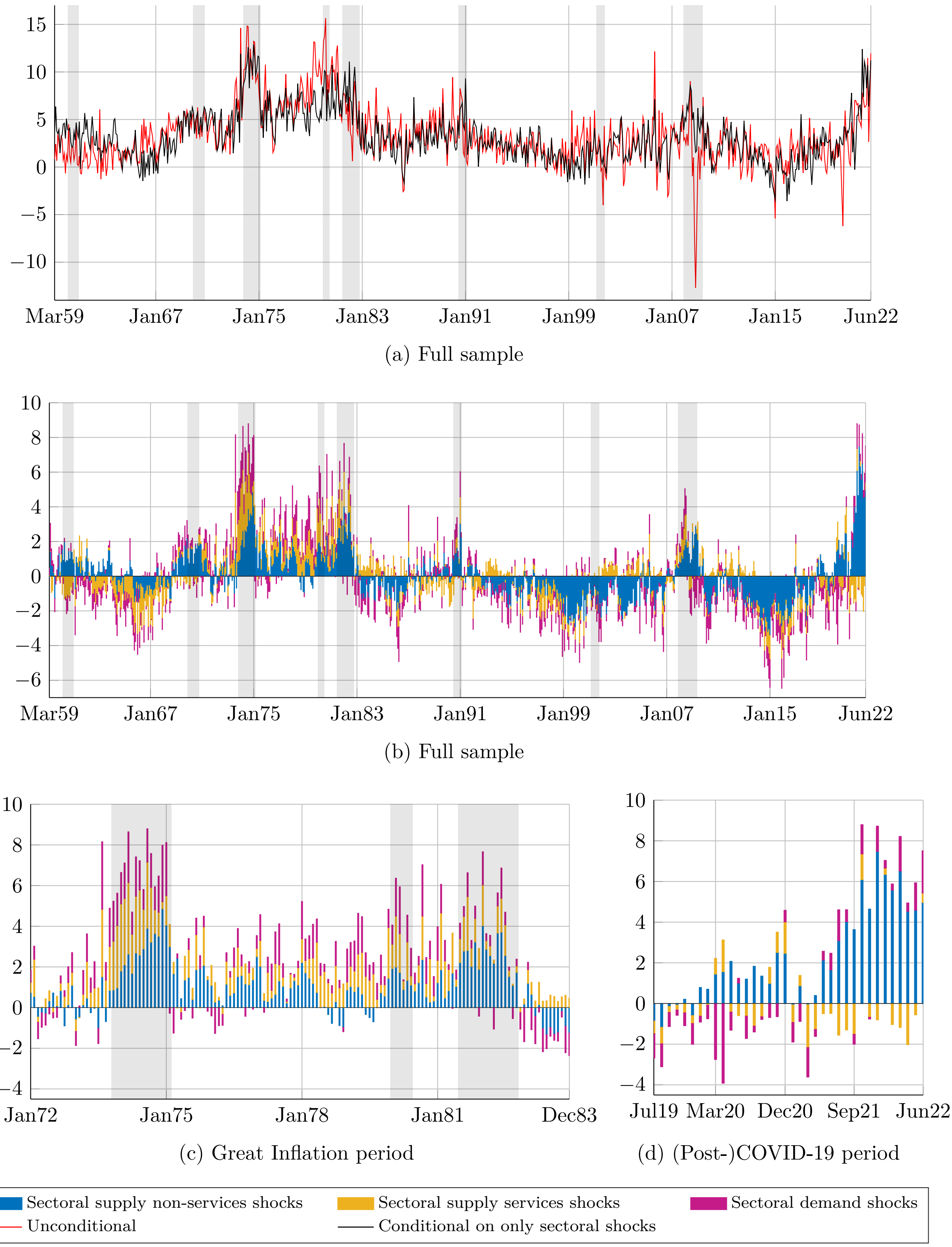
(c) (Post-)COVID-19 period

Notes: See notes to Figure 10.

2021 and early 2022. Interestingly, the closest-matching demand shock contributions for these two supply shocks, also had inflationary effects, albeit smaller compared to their supply-shock counterparts.

The two middle panels of Figure 15 present additional, compatible sector examples. First, *Computer & electronic products* shocks were a source of inflationary supply shocks throughout 2020. Many commentators discussed the semi-conductor shortage recorded shortly after the first COVID-19 lockdowns. These supply shocks however reduced in importance substantially in the first half of 2021, supporting analysis on short-lived cost-push factors at the time. However, my results also show that a resurgence of *Computer & electronic products* shocks occurred, again around September 2021, counteracting views on the short-livedness of inflationary pressure originating in the sector. Second, supply shocks originating in *Plastics & rubber products* provide yet another type of pattern: shocks from this sector had no meaningful contributions up until end-2021, when negative supply shocks started to contribute substantially to heightened inflation.

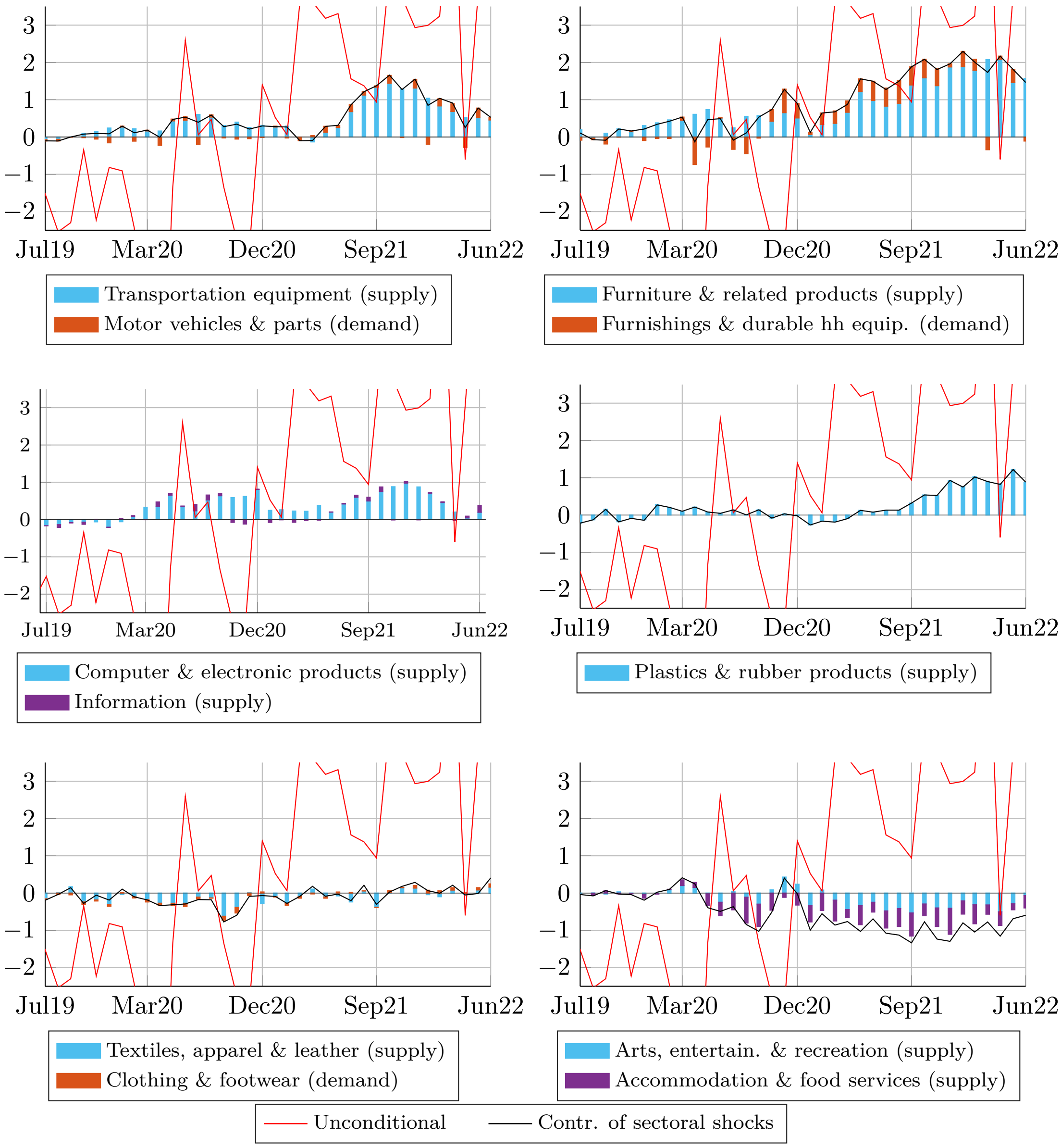
Figure 14: PCE inflation and its sectoral origins (m-o-m, annualized)



Notes: The figure presents contributions for annualized monthly (m-o-m) inflation, which provides a better way to date certain contributions than using year-on-year inflation.

I conclude this sector-by-sector breakdown by presenting two counter examples showing that not every identified shock is also contributing in the same fashion. First, in the lower-left-

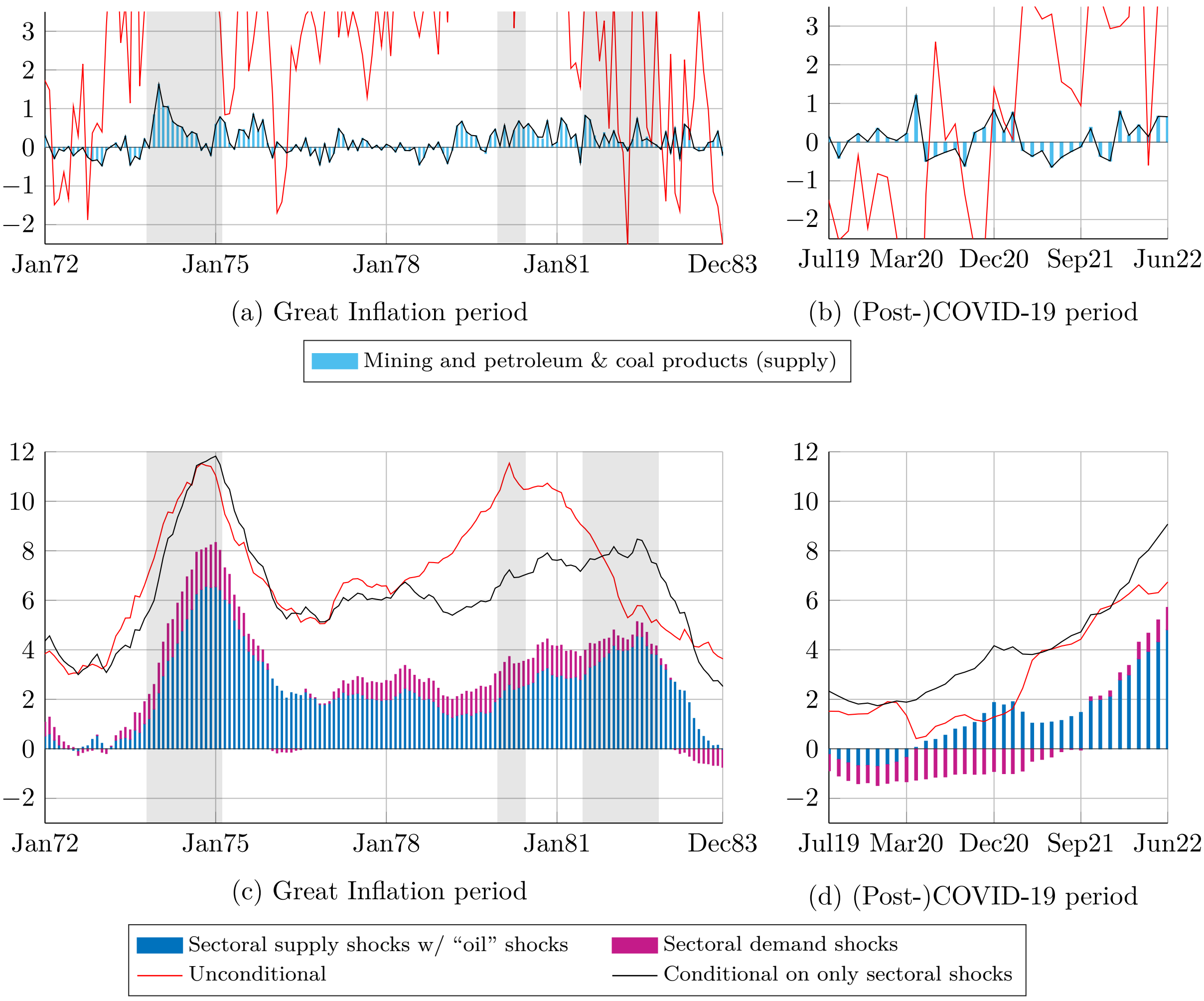
Figure 15: Individual shock contributions to PCE inflation in recent years (m-o-m, annualized)



Notes: This figure shows median contributions of individual sector shocks to demeaned and annualized monthly PCE inflation (m-o-m).

hand panel, contributions from shocks in the textile and related industries had no noteworthy inflationary contributions in recent years. Second, the final panel shows two sectors (*Arts, entertainment & recreation* and *Accommodation & food services*) that mainly experienced positive supply shocks in recent years and thereby alleviated the overall inflationary contributions from sectoral supply shocks. Both sectors are part of customer-facing services industries which particularly benefited from the reopening of the economy. It is noteworthy that my identification picks up shocks that originate in their respective sector. While imposing and lifting lockdowns has an effect on large parts of the economy, the identified shocks may pick up factors from these policies that are idiosyncratic to each of the two sectors.

Figure 16: PCE inflation and “oil”-sector shocks



Notes: The first row of this figure shows median contributions to demeaned and annualized monthly PCE inflation of joint supply shocks to *Mining* and *Petroleum and coal products* (“oil”-sector). The second row shows total sectoral median contributions to year-on-year inflation, including the “oil”-sector shock.

6.4 Sectoral sources during the Great Inflation

The origins of recently increasing inflation show close resemblance to those during the *Great Inflation*. One well-known cost-push factor during the Great Inflation was the oil price. Did this increase in oil prices stem entirely from shocks in oil producing industries or from other sectors? The oil embargo imposed by the OAPEC[31] in October 1973 could certainly be classified as a sectoral supply shock. However, other cost-push factors contributed to the increase in prices. My results show that similarly to the (post-)COVID-19 period a substantial source of inflation are sectoral supply shocks. There are some striking differences, though.

While contributions of sectoral supply shocks are large in both periods, the Great Inflation shows larger inflationary sectoral demand contributions. Inflationary contributions from supply shocks are unequivocally stemming from negative sectoral supply shocks, the aggregate effects of sectoral demand shocks are however ambiguous and differ between consumer-good categories.

[31] Organization of Arab Petroleum Exporting Countries

As illustrated in Section 4, aggregate contributions of demand shocks are more dependent on the exact 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.

As noted in Table 1, my main aggregate sectoral contributions to inflation do not include sector-specific supply shocks originating in oil producing industries. My identification scheme does allow to identify supply shocks from oil producing industries but with some caveats. Intuitively, the reason is that energy prices, due to their volatility, are often among the most affected price categories in many of the sectoral rankings. It is therefore difficult to separate oil-sector supply shocks using my identification from other sectoral shocks that have affects on oil/energy prices. I can identify oil shocks but stay cautious in their interpretation. Second, due to the similarity in rankings the "oil"-shock I identify is in fact a combination of *Mining* and *Petroleum and coal products* supply shocks. It turns out the clusters for both sectoral shocks are identical which does not permit to separate shocks from these two industries. With these caveats in mind, Figure 16 shows the contribution of this shock for the Great Inflation and recent years, both separately and aggregated with all other sectoral shocks. Total sectoral contributions are even larger during the first peak in 1974 and also the second peak in 1981.

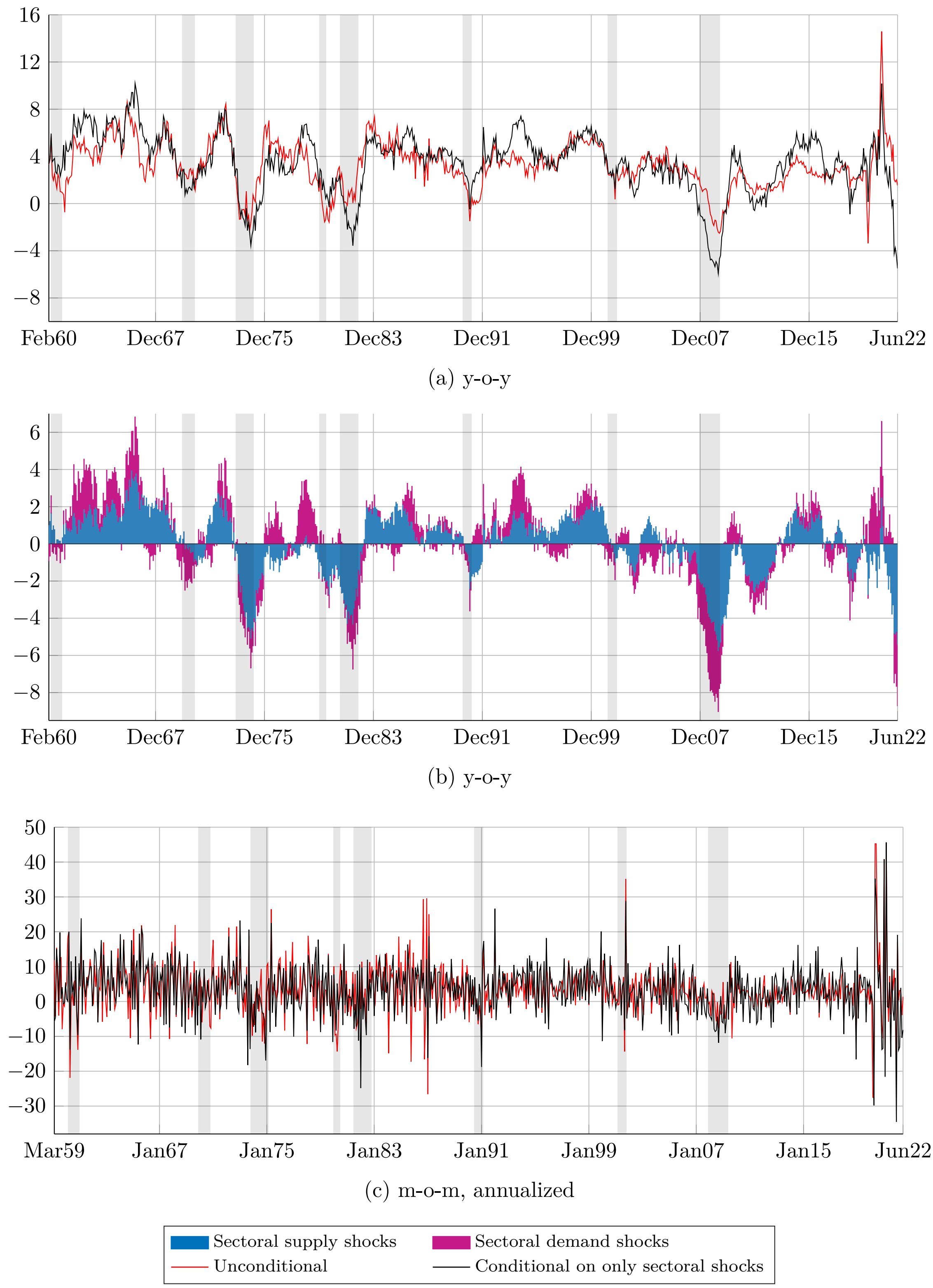
Sectoral shocks, even without oil supply shocks, explain the bulk of inflation increases compared to the baseline during the first peak of the Great inflation around 1974. While still having large inflationary contributions, sectoral shocks explain substantially less during the second peak around 1980. Within my model setup I cannot directly speak to other factors that explain this residual around this second inflation peak. However, my 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 nontradeable 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.

6.5 Sectoral supply and demand shocks and consumption growth

While the focus of this paper is on PCE inflation, my model also delivers contributions of sectoral supply and demand shocks on PCE consumption growth. These are summarized in Figure 17.

Panel 17a shows unconditional and sector-shock-conditional, y-o-y consumption growth. 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 my sample. These results are in line with De Graeve and Schneider (2023). In there we investigate the sectoral contributions to industrial production (IP) from the early 1970s until the onset of the COVID-19 pandemic and find that sector-specific shocks, in contrast to aggregate shocks, are the major driver of IP fluctuations.

Figure 17: Consumption growth and its sectoral origins



Notes: The figure presents median sectoral contributions to aggregate consumption growth.

Considering the demand and supply breakdown in Panel 17b it is striking that sectoral demand shocks show a much stronger contribution to consumption growth than inflation. Appendix Tables A.8 and A.9 show variance decompositions for all identified sectoral shocks for both inflation and consumption growth. While, overall, the sum of median variance decompositions for supply shocks is fairly similar for both variables. Sectoral demand shocks explain more of aggregate consumption growth, making sectoral shocks overall more important for explaining aggregate activity than inflation.

7 Conclusion

This paper provides new estimates on the sectoral origins of PCE inflation. I derive contributions of sector-specific supply and demand shocks to inflation through an identification scheme that harnesses cross-sectional information complementary to sectoral PCE inflation and consumption growth data. At the same time, my identification restrictions are consistent with a wide array of canonical DSGE models and calibrations.

My estimates deliver novel empirical evidence on the importance of sector-specific shocks for explaining high inflation in recent years. I find that sectoral supply shocks were a major source of inflation since the reopening of the U.S. economy in the wake of lifting COVID-19 restrictions. In contrast, sectoral shocks exerted no relevant inflationary pressure within the four decades prior to the COVID-19 pandemic. I then relate the trajectory of sectoral contributions since early-2020 to the policy discussion on whether elevated inflation is only short-lived or a prolonged phenomenon. I find that sector-specific supply shocks became the major inflation driver within the second half of 2021, corroborating an assessment of heightened inflation as a lasting phenomenon from that point forward. The flipside of this is that up until the second half of 2021, it was a reasonable assumption to consider sectoral supply shocks as short-lived. The Fed's gradual tightening commencing end-2021 accords well with the simultaneous rapid increase in inflationary contributions from negative sectoral supply shocks. Looking ahead, it remains uncertain whether sectoral cost-push and demand-pull factors will decay quickly in the near future, given the high contributions of sectoral disturbances I find throughout the first half of 2022.

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A Alternative DSGE specifications

A.1 Calvo pricing

For my identification setup I use a simpler information friction that allows for a better derivation of sectoral multipliers. Here I describe the alternative Calvo pricing problem. Firm $r \in j$ solves the following standard problem:

$$\max_{P_{jt}(r)} \mathbf{E}_t \sum_{s=0}^{\infty} Q_{t,t+s} \alpha_j^s \left[P_{jt}(r) Y_{jt+s}(r) - MC_{jt+s}(r) Y_{jt+s}(r) \right] , \tag{A.1}$$

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

$$Y_{jt}(r) = \sum_{j'=1}^{J} \int_{\Im_{j'}} M_{j'jt}(r', r) dr' + \sum_{z=1}^{Z} \int_{\Im_z} M_{zjt}(q, r) dq \,, \tag{A.2}$$

$$Y_{jt}(r) = e^{a_{jt}} L_{jt}^{1-\delta}(r) M_{jt}^{\delta}(r) \,, \tag{A.3}$$

$$Y_{jt}(r) = \left(\frac{P_{jt}(f)}{P_{jt}} \right)^{-\theta} \left(\int_0^1 Y_{jt}(r') dr' \right) , \tag{A.4}$$

$$P_{jt} = \left[(1 - \alpha_j) P_{jt}^{*1-\theta} + \alpha_j P_{jt-1}^{1-\theta} \right]^{\frac{1}{1-\theta}} . \tag{A.5}$$

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

B Steady state

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

$$W_j = W \,, \tag{A.6}$$
$$Y_j(f) = Y \,, \tag{A.7}$$
$$L_j(f) = L \,, \tag{A.8}$$
$$M_j(f) = M^{im} \,, \tag{A.9}$$
$$M_z(q) = M^{pce} \,. \tag{A.10}$$

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:

$$C_z = \omega_{cz} C \,, \tag{A.11}$$
$$C_z(f) = \omega_{cz} C \,. \tag{A.12}$$

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

$$Y_j(f) = \sum_{j'=1}^{J} \int_{\Im_{j'}} M_{j'j}(f', f) df' + \sum_{z=1}^{Z} \int_{\Im_z} M_{zj}(q, f) dq \,, \tag{A.13}$$
$$Y_j = \sum_{j'=1}^{J} M_{j'j} + \sum_{z=1}^{Z} M_{zj} \,, \tag{A.14}$$
$$Y = M^{im} + M^{pce} \,. \tag{A.15}$$

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

$$n_j = \psi \sum_{j'=1}^{J} n_{j'} \omega_{j'j} + (1-\psi) \sum_{z=1}^{Z} \omega_{cz} k_{zj} \,, \tag{A.16}$$
$$\mathbf{N} = (1-\psi) \left[\mathbf{I} - \psi \mathbf{\Omega'}\right]^{-1} \mathbf{K'} \mathbf{\Omega_c} \,, \tag{A.17}$$

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

$$n_j = \psi \sum_{j'=1}^{J} n_{j'} \omega_{j'j} + (1-\psi) \omega_{cj} \,, \tag{A.18}$$
$$\mathbf{N} = (1-\psi) \left[\mathbf{I} - \psi \mathbf{\Omega'}\right]^{-1} \mathbf{\Omega_c^{im}} \,. \tag{A.19}$$

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 my model solutions and are therefore not included.

C Log-linearized deviations from steady state

This section summarizes the log-linearized first-order conditions around a steady state.[32]

C.1 Aggregation

Consumption and production of final goods is given by:

$$c_t = \sum_{z=1}^{Z} \omega_{cz} \left(c_{zt} + f_{zt} \right) = m_t^{pce} \,, \tag{A.20}$$

$$c_{zt} + f_{zt} = m_{zt} \,, \tag{A.21}$$

$$m_t^{pce} = \sum_{z=1}^{Z} \omega_{cz} m_{zt} \,, \tag{A.22}$$

$$m_{zt} = \frac{1}{\omega_{cz}} \int_{\Im_z} m_{zt}(q) dq \,. \tag{A.23}$$

Intermediate production is equal to:

$$m_t^{im} = \sum_{j=1}^{J} n_j m_{jt} \,, \tag{A.24}$$

$$m_{jt} = \frac{1}{n_j} \int_{\Im_j} m_{jt}(f) df \,, \tag{A.25}$$

$$m_{jt}(f) = \sum_{j'=1}^{J} \omega_{jj'} m_{jj't}(f) \,, \tag{A.26}$$

$$m_{jj't}(f) = \frac{1}{n_{j'}} \int_{\Im_{j'}} m_{jj't}(f, f') df' \,. \tag{A.27}$$

Final-good prices are:

$$p_t^{pce} = \sum_{z=1}^{Z} \omega_{cz} p_{zt} = \mathbf{\Omega}_c' \mathbf{p}_t^{pce} \,, \tag{A.28}$$

$$p_{zt}^{m} = \sum_{j=1}^{J} k_{zj} p_{jt} \,, \tag{A.29}$$

$$\mathbf{p}_t^{m,pce} = \mathbf{K} \mathbf{p}_t^{im} \,, \tag{A.30}$$

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

$$p_{jt}^{m} = \sum_{j'=1}^{J} \omega_{jj'} p_{j't} \,, \tag{A.31}$$

$$\mathbf{p}_t^{m,im} = \mathbf{\Omega} \mathbf{p}_t^{im} \,, \tag{A.32}$$

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

$$p_{jt} = \int_{\Im_j} p_{jt}(f) dj \,. \tag{A.33}$$

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

Aggregate and sectoral labor is given by:

$$l_t = \sum_{j=1}^{J} l_{jt} \,, \tag{A.34}$$

$$l_{jt} = \frac{1}{n_j} \int_{\Im_j} l_{jt}(f) df \,. \tag{A.35}$$

C.2 Demand

Demand for consumption goods is equal to

$$c_{zt} - c_t = \eta(p_t^{pce} - p_{zt}) \,, \tag{A.36}$$

$$c_{zt}(q) - c_{zt} = \theta(p_{zt} - p_{zt}(q)) \,. \tag{A.37}$$

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

$$m_{zjt} - m_{zt} = \eta(p_{zt}^m - p_{jt}) \,, \tag{A.38}$$

$$m_{zjt}(q) - m_{zt}(q) = \eta(p_{zt}^m - p_{jt}) \,. \tag{A.39}$$

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

$$m_{jj't} - m_{jt} = \eta(p_{jt}^m - p_{j't}) \,, \tag{A.40}$$

$$m_{jj't}(f) - m_{jt}(f) = \eta(p_{jt}^m - p_{j't}) \,, \tag{A.41}$$

$$m_{jj't}(f, f') - m_{jj't}(f) = \theta(p_{j't} - p_{j't}(f')) \,. \tag{A.42}$$

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

$$n_j y_{jt} = \psi \sum_{j'=1}^{J} \omega_{j'j} n_{j'} m_{j'jt} + (1-\psi) \sum_{z=1}^{Z} k_{zj} \omega_{cz} m_{zjt} \,, \tag{A.43}$$

$$y_t = \psi m_t^{im} + (1-\psi) m_t^{pce} = \psi m_t^{im} + (1-\psi) c_t \,. \tag{A.44}$$

C.3 Euler equation and labor supply

The Euler equation is expressed as:

$$c_t = \mathbb{E}_t \left[c_{t+1}\right] - \sigma^{-1} \left\{ i_t - \left(\mathbb{E}_t \left[p_{t+1}^{pce}\right] - p_t^{pce}\right) \right\} \,, \tag{A.45}$$

and labor supply is given by:

$$w_{jt} - p_t^{pce} = \varphi l_{jt} + \sigma c_t \,. \tag{A.46}$$

C.4 Firms

Intermediate goods firms have the following log-linearized production function

$$y_{jt}(f) = a_{jt} + (1-\delta)l_{jt}(f) + \delta m_{jt}(f)\,, \tag{A.47}$$

Aggregating this to the sectoral level yields:

$$y_{jt} = a_{jt} + (1-\delta)l_{jt} + \delta m_{jt}\,. \tag{A.48}$$

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

$$y_{zt}(q) = m_{zt}(q)\,, \tag{A.49}$$

$$y_{zt}(q) = m_{zt}\,. \tag{A.50}$$

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

$$w_{jt} - p^m_{jt} = m_{jt}(f) - l_{jt}(f)\,, \tag{A.51}$$

$$w_{jt} - p^m_{jt} = m_{jt} - l_{jt}\,. \tag{A.52}$$

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

$$mc_{zt} = p^m_{zt}\,, \tag{A.53}$$

$$mc_{jt} = (1-\delta)w_{jt} + \delta p^m_{jt} - a_{jt}\,. \tag{A.54}$$

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

$$p^*_{zt} = (1-\alpha_z\beta)mc_{zt} + \alpha_z\beta\mathbb{E}_t\left[p^*_{zt+1}\right]\,, \tag{A.55}$$

$$p^*_{jt} = (1-\alpha_j\beta)mc_{jt} + \alpha_z\beta\mathbb{E}_t\left[p^*_{jt+1}\right]\,, \tag{A.56}$$

where sectoral prices would be given by:

$$p_{zt} = (1-\alpha_z)p^*_{zt} + \alpha_z p_{zt-1}\,, \tag{A.57}$$

$$p_{jt} = (1-\alpha_j)p^*_{jt} + \alpha_j p_{jt-1}\,. \tag{A.58}$$

C.5 Monetary policy

While I solve the model using a non-essential, simplifying assumption on a monetary policy rule, the DSGE model can also be solved by a standard Taylor rule. Pasten, Schoenle, and Weber (2021) for instance specify:

$$i_t = \phi_\pi\left(p^{pce}_t - p^{pce}_{t-1}\right) + \phi_c c_t\,. \tag{A.59}$$

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 Pasten, Schoenle, and Weber (2021) but include my two extensions, i.e. distinguishing between intermediate- and final- good producers, and the inclusion of sectoral demand shocks.

D.1 Sectoral supply shocks: all simplifying assumptions applied

I first show a detailed derivation of equation (34). Applying all simplifying assumptions (i) to (iii) of the main text, prices and marginal costs are weighted by the sectors respective level of prices stickiness. I set sectoral demand shocks to zero, i.e. $f_{zt} = 0$ for $z = 1, \dots, Z$). For intermediate goods producers prices are given by:

$$\begin{aligned} p_{jt} &= (1-\lambda_j) mc_{jt} \,, && \text{(A.60)} \\ &= (1-\lambda_j)\delta p^m_{jt} - (1-\lambda_j) a_{jt} \,, && \text{(A.61)} \end{aligned}$$

which in matrix form can be written as:

$$\mathbf{p}^{im}_t = -\left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{a}_t \,. \tag{A.62}$$

Equation (34) is then defined as:

$$\widehat{\mathbf{X}}^{im} \equiv \left[\mathbf{I} - \delta(\mathbf{I} - \mathbf{\Lambda}^{im})\mathbf{\Omega}\right]^{-1} (\mathbf{I} - \mathbf{\Lambda}^{im}) \,, \tag{A.63}$$

such that:

$$\mathbf{p}^{im}_t = -\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.64}$$

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

$$\begin{aligned} p_{zt} &= (1-\lambda_z) mc_{zt} \,, && \text{(A.65)} \\ &= (1-\lambda_z) p^m_{zt} \,, && \text{(A.66)} \end{aligned}$$

which implies:

$$\begin{aligned} \mathbf{p}^{pce}_t &= (\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\mathbf{p}^{im}_t \,, && \text{(A.67)} \\ &= -(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. && \text{(A.68)} \end{aligned}$$

Aggregate prices are then

$$p^{pce}_t = -\mathbf{\Omega}'_c(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.69}$$

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 $\mathbf{c}_t$:

$$c_t = \mathbf{\Omega}'_c(\mathbf{I} - \mathbf{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t \,. \tag{A.70}$$

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:

$$\mathbf{c}_t = \left[\eta\mathbf{I} + (1-\eta)\iota\boldsymbol{\Omega}_c'\right](\mathbf{I} - \boldsymbol{\Lambda}^{pce})\mathbf{K}\widehat{\mathbf{X}}^{im}\mathbf{a}_t\,. \tag{A.71}$$

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

In this part, I derive the solutions to key equation (38) of the main text. Allowing a positive inverse-Frisch elasticity, $\varphi > 0$, implies that the labor-supply condition is now given by:

$$w_{jt} = c_t - p_t^{pce} + \varphi l_{jt}\,. \tag{A.72}$$

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, as well as 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:

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

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

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

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

I then use efficiency and labor supply conditions,

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

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

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

Using production function and labor supply condition,

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

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:

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

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

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

which uses the following composite parameters:

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

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:

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

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:

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

or in matrix form:

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

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

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

Using assumption on monetary policy in simplifying assumption (ii), i.e. $c_t = -p_t^{pce}$, the last term in the expression above disappears, which yields the final expression for sectoral prices:

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

where $\widehat{\mathbf{X}}^{im}$ in key equation (38) is given by:

$$
\begin{aligned}
\widehat{\mathbf{X}}^{im} \equiv &\Big[\mathbf{I} - \delta\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Omega} \\
&\quad - (1-\delta)\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\mathbf{\Theta}'^{-1} \\
&\quad\ \left(\theta_p^{im} + \theta_p^{pce}\left(\mathbf{I}-\mathbf{\Lambda}^{pce}\right)\mathbf{K} - \theta_c\mathbf{\Omega}_c'\left(\mathbf{I}-\mathbf{\Lambda}^{pce}\right)\mathbf{K}\right)\Big]^{-1} \\
&\left(\mathbf{I}-\mathbf{\Lambda}^{im}\right)\left[\mathbf{I}+\varphi(1-\delta)\mathbf{\Theta}'^{-1}\right]\,.
\end{aligned}
\tag{A.73}
$$

The solution for sectoral PCE prices and consumption as well as aggregate PCE prices and consumption are 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 (38) 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

$$\mathbf{w}_t = \iota c_t + \iota p_t^{pce} . \tag{A.74}$$

which implies that $\widehat{\mathbf{X}}^{im}$ is given by key equation (34).

D.3 Sectoral demand shocks

The derivation of key equation (49) for sectoral demand shocks follows the same 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 (49):

$$\widehat{\mathbf{F}}^{im} \equiv \widehat{\mathbf{P}}^{im}\left(\mathbf{I} - \boldsymbol{\Lambda}^{im}\right)(1-\delta)\boldsymbol{\Theta}'^{-1}\varphi(1-\psi)\mathbf{D}^{-1}\mathbf{K}\mathbf{D}_c , \tag{A.75}$$

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

$$\begin{aligned}
\widehat{\mathbf{P}}^{im} \equiv \Big[& \mathbf{I} - \delta\left(\mathbf{I} - \boldsymbol{\Lambda}^{im}\right)\boldsymbol{\Omega} \\
& - (1-\delta)\left(\mathbf{I} - \boldsymbol{\Lambda}^{im}\right)\boldsymbol{\Theta}'^{-1} \\
& \left(\theta_p^{im} + \theta_p^{pce}\left(\mathbf{I} - \boldsymbol{\Lambda}^{pce}\right)\mathbf{K} - \theta_c\boldsymbol{\Omega}_c'\left(\mathbf{I} - \boldsymbol{\Lambda}^{pce}\right)\mathbf{K}\right)\Big]^{-1} .
\end{aligned} \tag{A.76}$$

E Data sources

E.1 Input-output data

I use BEA's NAICS input-output tables for the United States for years 1997 to 2020 from the make-use framework and include 33 intermediate goods sectors. For all years, I calibrate the input-output weights matrix, $\mathbf{\Omega}$, of the main text in the same way as Pasten, Schoenle, and Weber (2021) (see their Appendix for more details):

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

$$SHARE_\tau = MAKE_\tau \oslash (\mathbf{I} \times MAKE_\tau) \ , \tag{A.77}$$

$$REVSHARE_\tau = SHARE_\tau \times USE_\tau \, , \tag{A.78}$$

$$SUPPSHARE_\tau = [REVSHARE_\tau \oslash (\mathbf{I} \times USE_\tau)]' \ , \tag{A.79}$$

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 τ as $SUPPSHARE_\tau$.

E.2 Bridge table

There are 76 PCE categories available for BEA bridge tables. All items can be identified by a line number. I remove four of those categories. These include 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)*).

E.3 Frequencies of NAICS sector price changes

Estimates for monthly frequencies of producer price changes are taken from Peneva (2011). These estimates are weighted average monthly frequencies for years 1995 to 1997. The 29 available sectors are classified based on the older Standard Industrial Classification (SIC) which requires a conversion to the current NAICS definitions that I use in the main text. I convert SIC to NAICS industries using 1997 gross output conversion weights provided by Yuskavage (2007). There are two major drawbacks to this conversion: First, Peneva's (2011) dataset, which in turn is based on the dataset by Bils and Klenow (2004), does not include estimates for SIC industries *Primary Metals*, *Mining*, and *Construction*. For the latter two SIC industries I set their NAICS equivalent equal to the overall average of monthly frequency of price changes in Peneva (2011), i.e. 26.1 percent. *Primary metals* are aggregated with *Fabricated metal products*, for which SIC estimates are available. The aggregated *Primary metals and fabricated metal products* industry is therefore solely based on estimates for the available SIC *Fabricated metal products* industry.[33]

[33] Consequently, I also ignore any shares of SIC *Primary metals*, *Mining*, and *Construction* that are attributed to NAICS industries other than *Primary metals*, *Mining* and *Construction*. For instance according to the conversion weights, around 6 percent of SIC *Construction* should be attributed to NAICS *Real Estate* but, due to the lack of

Finally, Peneva's (2011) estimates are not available for many individual 2-digit services sectors but only for a *services* aggregate. This leads to very similar price frequency estimates for a number of NAICS industries, which correspond to sectors with indices 26, 27, 28, 29, 30, 31, and 32 of the 33 sectors used in the main text.[34]

E.4 Durations of PCE price categories

I use median price adjustment durations from Nakamura and Steinsson (2008). To transform these durations to PCE categories several conversions need to be made. 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.

E.5 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. This means that no individual time series for line items 46, 109, 110, 111 are used. Aggregate price and quantity time series still include these items.

SIC *Construction* estimates, these are ignored. Rest assured the majority share of NAICS *Real Estate* originates from available SIC estimates.

[34] See for instance Table A.1 for corresponding NAICS sector names.

F Clustering performance

Table A.1 presents clustering performance for sectoral supply shocks across specifications (I) to (V). The last column indicates the methods that deliver the best clustering results. These methods include *k-means*, *k-medoids*, and *hierarchical clustering*, as well as a simple decision algorithm that I specify based on ranking counts. The *Match* rate indicates the percentage of the 96 calibrations that match against the best performing cluster. Similar tables for smaller sets using only specifications (III) to (V) and specifications (IV) and (V) are not presented here. Table A.2 includes clustering performance for demand shocks.

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 for a second set with specifications (III) to (V), and Table A.5 a third set with specifications (IV) and (V).

The *Shocks* column in each table indicates the composition of supply shocks. Bold numbers signal that the *Match* rate is larger than 70 percent. Red indices to PCE categories in the cluster columns indicate problematic sectors that occur in clusters 1 and 2 across several shocks. Finally, the last column shows whether the corresponding ranking for sectoral consumption growth rates is the same to the price ranking, $\widehat{\mathbf{X}}^{pce}$. 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 and repeat the exercise.

Another criterion that renders a shock infeasible is applied in Table A.6 for sectoral demand shocks. I consider sector shock (40-44) as infeasible since it includes 6 sectors in the first cluster. Too many categories in the first cluster has implications on the number of factors used in the empirical model.

Final clusters for feasible sector-specific supply shocks are determined based on the following specifications: shocks using clusters based on specifications (I) to (V) are 1, 3, 10, 11, 15, 21, 23, 28, 30, (20, 21), and (20-22); clusters based on specifications (III) to (V) are 9, 14, 19, 24, 32; and clusters based on specifications (IV) and (V) are 12, 13, 31, (30-31). The remaining supply shocks are infeasible to be identified. Shock (2, 17), which corresponds to a combination of *Mining* and *Petroleum and coal products* supply shocks is infeasible. I consider this shock as a proxy for an "oil" shock. The shock is infeasible due to the occurrence of problematic sectors in clusters 1 and 2. In fact no "non-problematic" price series is included in the first two clusters. I can still identify this "oil" shock but stay cautious in their interpretation, which is why I do not include it in my main results. Finally, out of the 15 demand shocks 13 shocks are feasible.

Table A.1: Clustering performance: supply (all specifications)

Shocks		Match	Best clustering methods
1	Agriculture, forestry, fishing, and hunting	**78.1**%	K-Mea, K-Med, Hier
2	Mining	**92.7**%	K-Mea, Init
3	Utilities	**100**%	K-Mea, K-Med, Init
4	Construction	50%	K-Mea
5	Wood products	39.6%	Init
6	Nonmetallic mineral products	2.1%	K-Mea, K-Med, Hier, Init
7	Primary metals and fabricated metal products	42.7%	K-Mea, K-Med, Hier
8	Machinery	38.5%	Hier
9	Computer and electronic products	68.8%	K-Med, Hier
10	Electrical equipment, appliance, and components	**88.5**%	K-Mea, K-Med, Hier, Init
11	Transportation equipment	**100**%	K-Mea, K-Med, Init
12	Furniture and related products	50%	Hier
13	Miscellaneous manufacturing	64.6%	K-Mea, K-Med, Hier, Init
14	Food and beverage and tobacco products	**100**%	Init
15	Textiles, apparel, and leather	**92.7**%	Init
16	Paper and printing	28.1%	Hier
17	Petroleum and coal products	**99**%	K-Mea, K-Med, Hier, Init
18	Chemical products	18.8%	Hier
19	Plastics and rubber products	58.3%	K-Mea, K-Med, Hier, Init
20	Wholesale trade	**72.9**%	Hier, Init
21	Retail trade	**75**%	Hier
22	Transportation and warehousing	49%	K-Mea
23	Information	**71.9**%	K-Mea, K-Med, Hier, Init
24	Finance and insurance	54.2%	Init
25	Real estate and rental and leasing	25%	K-Med
26	Professional, scientific, and technical services	25%	Hier, Init
27	Management, administrative and waste services	35.4%	Init
28	Educational services	**100**%	Init
29	Health care and social assistance	25%	K-Med
30	Arts, entertainment, and recreation	**75**%	K-Mea, K-Med, Hier, Init
31	Accommodation and food services	50%	Init
32	Other services, except government	66.7%	K-Mea, K-Med, Hier, Init
33	Government	50%	Init
(7, 8)	Metals and machinery	**74**%	K-Med, Init
(2, 17)	Mining and petroleum and coal products	57.3%	Init
(20, 21)	Trade	**75**%	K-Mea, K-Med, Hier, Init
(20–22)	Trade, transportation and warehousing	31.3%	Init
(24, 25)	Finance, insurance, real estate, rental, leasing	50%	K-Mea, Hier, Init
(26, 27)	Professional and business services	46.9%	K-Med
(28, 29)	Educ.services, health care, social assistance	**100**%	K-Mea
(30, 31)	Arts, entertain., recreation, accom., food serv.	**75**%	K-Mea, K-Med, Hier, Init

Notes: This table shows clustering performance for sectoral supply shocks across specifications (I) to (V). The last column indicates the methods that deliver the best clustering results. The 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 96 calibrations that match against the best performing cluster.

Table A.2: Clustering performance: demand

Shocks		Match	Best clustering methods
(1–3)	Motor vehicles and parts	**100%**	K-Mea, K-Med, Hier, Init
(4–7)	Furnishings and durable household equip.	**100%**	K-Mea, Init
(8–12)	Recreational goods and vehicles	**100%**	K-Mea, K-Med, Hier, Init
(13–17)	Other durable goods	**100%**	K-Mea, K-Med, Hier, Init
(18–20)	Food & bever.purch.for off-premises consum.	**100%**	K-Mea, K-Med, Hier
(21–24)	Clothing and footwear	**100%**	K-Mea, Hier, Init
(25, 26)	Gasoline and other energy goods	**100%**	K-Med, Hier
(27–32)	Other nondurable goods	**100%**	Hier
(33–39)	Housing and utilities	**100%**	K-Mea, Hier, Init
(40–44)	Health care	**100%**	K-Mea, Hier, Init
(45–49)	Transportation services	**100%**	K-Mea, K-Med, Hier, Init
(50–53)	Recreation services	**100%**	Hier
(54–56)	Food services and accommodations	**100%**	K-Mea, K-Med, Hier, Init
(57–62)	Financial services and insurance	**100%**	K-Mea, Init
(63–72)	Other services	**97.9%**	Init

Notes: See notes for Table A.1.

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

Shocks	Cluster 1	Cluster 2	Match	$\widehat{\mathbf{X}}_r^c$
1	20	18, 28, 31, 55	**78.1%**	=
2	25	26, 38, 39	**92.7%**	=
3	38, 39	37	**100%**	=
4	25, 26, 38, 39	1, 2	50%	≠
5	26	25	39.6%	=
6	6	1, 25, 26, 38, 39	2.1%	=
7	1	25, 26, 38, 39	42.7%	=
8	7	5	38.5%	=
9	17	8	68.8%	=
10	5	3	**88.5%**	=
11	1	3, 10	**100%**	=
12	4	25, 26, 39	50%	=
13	12	9, 13, 14, 28	64.6%	=
14	18, 31, 55	19	**100%**	=
15	22	16, 21, 24	**92.7%**	=
16	29	23	28.1%	=
17	25	26	**99%**	=
18	27	26	18.8%	=
19	3	6	58.3%	=
20	25	26	**72.9%**	=
21	2	25, 26	**75%**	=
22	2, 25, 26, 39, 48, 49	38, 47	49%	=
23	63	15, 51	**71.9%**	=
24	62	60	54.2%	=

Table A.3 — Continued

Shocks	Cluster 1	Cluster 2	Match	$\widehat{\mathbf{X}}_r^c$
25	33, 46	34, 35	25%	$\neq$
26	53	69	25%	$=$
27	39	25	35.4%	$=$
28	66, 68	67	**100%**	$=$
29	43, 44, 71	40, 41, 42	25%	$\neq$
30	50	52	**75%**	$=$
31	56	39	50%	$\neq$
32	45	70	66.7%	$=$
33	25	26	50%	$=$
(7, 8)	1	5, 7, 25, 26, 38, 39	46.9%	$=$
(2, 17)	25, 26	38, 39	**100%**	$=$
(20, 21)	2	25, 26	**75%**	$=$
(20–22)	2	25, 26	**75%**	$=$
(24, 25)	39	25	46.9%	$=$
(26, 27)	53	37	18.8%	$=$
(28, 29)	68	40–44, 66, 67, 71	25%	$=$
(30, 31)	56	25, 26, 36, 38, 39, 50, 52, 54	50%	$=$

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

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

Shocks	Cluster 1	Cluster 2	Match	$\widehat{\mathbf{X}}_r^c$
1	20	18	**100%**	=
2	25	26, 39	**100%**	=
3	39	38	**100%**	=
4	25, 39	26, 38	**72.2%**	=
5	26	25, 39	66.7%	=
6	1, 6, 25, 26, 38, 39	2–5, 7, 10, 18, 31, 37, 45, 48, 49, 69	52.8%	=
7	1	25, 39	59.7%	=
8	1, 5, 7, 25, 26, 39	2, 3, 8, 10, 38	56.9%	=
9	17	8	**70.8%**	=
10	5	3	**98.6%**	=
11	1	3, 10	**100%**	=
12	4	25, 26, 39	66.7%	=
13	12	9, 13, 14, 25, 26, 28, 39	66.7%	=
14	31	18, 19, 55	**100%**	=
15	22	16, 21, 24	**100%**	=
16	25	39	37.5%	=
17	25	26	**100%**	=
18	25, 26, 39	27	52.8%	=
19	3	6	**76.4%**	=
20	25	26	**97.2%**	=
21	2	25, 26	**100%**	=
22	2, 25, 26, 39, 47, 48, 49	1, 10, 15, 38, 45, 64, 72	65.3%	=
23	63	15, 51	**95.8%**	=
24	62	60	**72.2%**	=
25	25, 26, 33, 34, 35, 38, 39, 46	1, 2, 7, 37, 51	29.2%	=
26	1, 2, 25, 26, 38, 39, 51, 53, 69	37	**100%**	=
27	25, 39	1, 2, 26, 37, 38, 53, 72	66.7%	=
28	68	66, 67	**100%**	=
29	40–44, 67, 71	14	33.3%	=
30	50	52	**100%**	=
31	56	25, 26, 36, 38, 39, 54	66.7%	=
32	45	1, 2, 25, 26, 38, 39, 46, 51, 53, 69–72	**86.1%**	=
33	25	26	66.7%	=
(7, 8)	1	5, 7, 25, 26, 38, 39	62.5%	=
(2, 17)	25	26	**100%**	=
(20, 21)	2	25, 26	**100%**	=
(20–22)	2	25, 26	**100%**	=
(24, 25)	39	25	62.5%	=
(26, 27)	25, 26, 38, 39, 53	1, 2, 37, 51, 69, 72	66.7%	=
(28, 29)	40–44, 66–68, 71	14, 50	33.3%	=
(30, 31)	56	25, 26, 36, 38, 39, 50, 52, 54	66.7%	=

Notes: See notes to Table A.3.

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

Shocks	Cluster 1	Cluster 2	Match	$\widehat{\mathbf{X}}_r^c$
1	20	18	**100%**	=
2	25	26, 39	**100%**	=
3	39	38	**100%**	=
4	25, 39	26, 38	**100%**	=
5	26	25, 39	**100%**	=
6	6, 25, 26, 38, 39	1	**97.9%**	=
7	1, 25, 39	26, 38	**95.8%**	=
8	1, 2, 3, 5, 7, 8, 10, 25, 26, 38, 39	20, 31, 37, 45	**91.7%**	=
9	8, 17	1, 25, 39	**95.8%**	=
10	5	3	**97.9%**	=
11	1	3, 10	**100%**	=
12	4	25, 26, 39	**100%**	=
13	12	9, 13, 14, 25, 26, 28, 39	**100%**	=
14	31	18, 19, 55	**100%**	=
15	22	16, 21, 24	**100%**	=
16	25, 39	26	**70.8%**	=
17	25	26	**100%**	=
18	25, 26, 39	27, 30, 38	**100%**	=
19	3	1, 6, 25, 26, 39	**100%**	=
20	25	1, 2, 26, 31, 38, 39	**100%**	=
21	2	25, 26	**100%**	=
22	2, 25, 26, 39, 48, 49	38, 47	**97.9%**	=
23	15, 51, 63	8, 11, 25, 26, 32, 38, 39, 65	**93.8%**	=
24	25, 26, 38, 39, 57–62	1, 2	**100%**	=
25	39	25, 26, 33, 34, 35, 38, 46	**97.9%**	=
26	39	1, 2, 25, 26, 38, 51, 53, 69	**100%**	=
27	25, 39	1, 2, 26, 37, 38, 53, 72	**100%**	=
28	68	66, 67	**100%**	=
29	25, 26, 38, 39, 41, 43, 44, 71	1, 2, 40, 42, 67	**83.3%**	=
30	50	52	**100%**	=
31	56	25, 26, 36, 38, 39, 54	**100%**	=
32	45	1, 2, 25, 26, 38, 39, 46, 51, 53, 69–72	**100%**	=
33	25	26, 39	**100%**	=
(7, 8)	1, 25, 39	5, 7, 26, 38	**97.9%**	=
(2, 17)	25	26	**100%**	=
(20, 21)	2	25, 26	**100%**	=
(20–22)	2	25, 26, 39	**100%**	=
(24, 25)	39	25, 26, 33, 38, 46, 57, 59, 60, 62	**95.8%**	=
(26, 27)	25, 39	1, 2, 26, 37, 38, 53	**100%**	=
(28, 29)	25, 26, 38, 39, 41, 43, 44, 66–68, 71	1, 2, 40, 42	**87.5%**	=
(30, 31)	56	25, 26, 36, 38, 39, 50, 52, 54	**100%**	=

Notes: See notes to Table A.3.

Table A.6: Clustering evaluation demand: Set 3

	$\widehat{\mathbf{F}}_r^{pce}$			$\widehat{\mathbf{F}}_r^{c}$
Shocks	Cluster 1	Cluster 2 (or 3*)	Match	Cluster 1
(1–3)	1	2, 3, 10	**100%**	2, 3
(4–7)	2	3, 4, 5	**100%**	6, 7
(8–12)	1	25*, 26*, 38*, 39*	**100%**	9, 10, 11, 12
(13–17)	2	39*	**100%**	13, 14, 15, 16, 17
(18–20)	31	2, 18, 19, 20, 55	**100%**	19
(21–24)	2	16, 21, 22, 23, 24	**100%**	23
(25, 26)	25	26	**100%**	26
(27–32)	2	39*	**100%**	32
(33–39)	39	38	**100%**	33, 34, 35, 36, 37
(40–44)	40–44, 71	1*, 2*, 25*, 26*, 38*, 39*	**100%**	40, 42
(45–49)	Majority	38*, 39*	**97.9%**	46, 47
(50–53)	50	52	**100%**	51, 53
(54–56)	56	36, 54	**100%**	54, 55
(57–62)	60, 62	57, 58, 59, 61	**100%**	58, 61
(63–72)	68	15, 45, 51, 53, 63, 66, 67, 70	**100%**	63, 64, 65, 69–72

Notes: The *Shocks* column indicates the composition of demand shocks. Bold numbers indicate that the shock is feasible because its *Match* rate is larger than 70 percent. Red indices to PCE categories in the cluster columns indicate problematic sectors that occur in clusters 1 and 2 across several shocks. Note that I consider sector shock (40-44) as infeasible as it includes 6 sectors in the first cluster. Too many categories in the first cluster has implications on the number of factors used in the empirical model. PCE categories marked with an asterisk indicate that instead of the second cluster the third cluster is shown. Finally the last column indicates the first cluster for multiplier matrix on sectoral consumption. For sectoral demand shocks I allow clusters to differ between sectoral inflation rates and consumption growth.

G Model derivations

The empirical model is similar to De Graeve and Schneider (2023) (see their Appendix B), with slight differences regarding data and observable factors. In De Graeve and Schneider (ibid.) we only use quantity variables and one observable factor. Hence, 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.

H Additional tables

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 reference for indices to PCE categories used in the main text.

Table A.8: Variance decompositions for sectoral supply shocks

	c_t		p_t^{pce}	
Shocks	$VD_{t=0}$	$VD_{t=\text{inf}}$	$VD_{t=0}$	$VD_{t=\text{inf}}$
1	0.577 (0.00146,7.69)	1.28 (0.109,6.86)	2.15 (0.00578,14.6)	2.32 (0.133,12.4)
3	1.17 (0.00232,9.54)	1.75 (0.16,9.01)	1.28 (0.00456,12.5)	1.72 (0.136,10.8)
9	0.615 (0.00235,7.8)	1.18 (0.0988,8.04)	0.83 (0.00112,5.68)	4.17 (0.208,16.1)
10	1.67 (0.0258,6.33)	1.98 (0.585,6.38)	0.282 (0.00521,2.34)	1.31 (0.0608,5.35)
11	4.54 (0.245,26.6)	4.13 (0.843,23.3)	0.639 (0.00162,3.05)	2.44 (0.0838,7.52)
12	1.69 (0.0695,10.1)	1.81 (0.19,8.65)	1.22 (0.0107,6.47)	2.54 (0.118,12)
13	1.88 (0.00939,12.9)	2.24 (0.186,10.9)	0.781 (0.00429,13.3)	1.53 (0.0752,13.9)
14	0.458 (0.00424,4.06)	0.959 (0.116,3.82)	1.6 (0.00953,16.4)	1.99 (0.184,15.6)
15	0.484 (0.0353,14.2)	0.984 (0.433,11.7)	0.639 (0.00051,0.861)	0.874 (0.261,4.16)
19	1.8 (0.0165,9.79)	2.08 (0.237,9.37)	0.893 (0.00575,6.34)	1.97 (0.105,11.3)
21*	na	na	na	na
23	0.761 (0.000806,5.34)	1.26 (0.0626,4.93)	1.01 (0.000938,11.1)	1.65 (0.0956,12.3)
24	0.258 (0.000744,1.97)	0.739 (0.0893,2.47)	0.878 (0.000623,10.8)	1.52 (0.108,12.4)
28	0.399 (0.00322,2.13)	0.779 (0.0762,2.39)	1.64 (0.00527,10.8)	2.17 (0.116,13.1)
30	1.14 (0.00114,8.83)	1.33 (0.107,7.92)	1.19 (0.000404,11)	1.92 (0.12,12.9)
31	1.21 (0.005,7.73)	1.51 (0.106,7.27)	0.848 (0.00979,10.4)	1.6 (0.144,14.3)
32	0.301 (0.00193,3.06)	1.17 (0.157,3.87)	2.05 (0.00749,12.8)	2.41 (0.179,11.8)
(20, 21)*	na	na	na	na
(20–22)	0.383 (0.00141,7.05)	0.8 (0.0595,5.88)	2.69 (0.163,14)	1.84 (0.204,12.4)
(30, 31)	0.863 (0.000572,11)	1.27 (0.189,9.99)	1.16 (0.00224,10.3)	1.78 (0.102,10.5)
Sum	19.34	25.99	20.61	33.98

Notes: This table shows median variance decompositions of aggregate consumption and inflation caused by sectoral supply shocks. In parentheses 95-percent confidence bounds are shown. The sum is for non-overlapping median variance decompositions, i.e. it does not include the variance decomposition for joint (30,31) sector shocks.

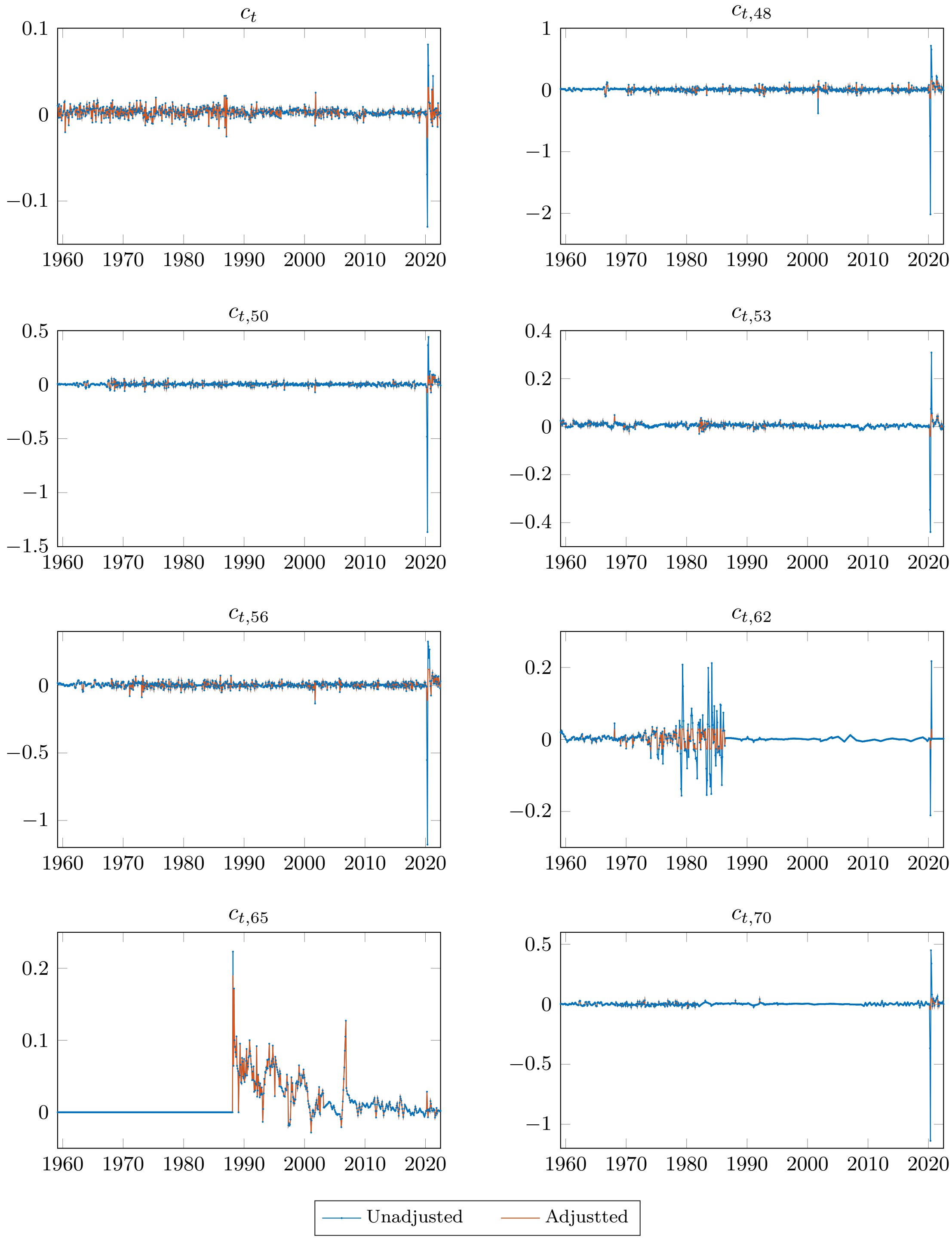
Table A.9: Variance decompositions for sectoral demand shocks

	c_t		p_t^{pce}	
Shocks	$VD_{t=0}$	$VD_{t=\text{inf}}$	$VD_{t=0}$	$VD_{t=\text{inf}}$
(1–3)	6.93 (0.896,21.8)	6.09 (1.29,19)	1.4 (0.00389,11.7)	1.89 (0.123,10.8)
(4–7)	2.65 (2.2,5.87)	3.27 (2.5,5.96)	4.27 (0.108,7.24)	4.46 (0.0658,5.05)
(8–12)	3.57 (0.0558,14.2)	3.88 (0.133,12.1)	1.79 (0.0917,20.4)	1.85 (0.16,20.1)
(13–17)	3.93 (0.195,16.1)	4.09 (0.471,13.9)	1.05 (0.00358,10.4)	1.56 (0.112,11.4)
(18–20)	2.56 (0.339,7.04)	3.98 (1.11,8.77)	1.75 (0.00674,13.2)	2.24 (0.172,13.1)
(21–24)	5.3 (0.572,18.1)	4.87 (0.709,15.7)	0.949 (0.004,9.61)	1.39 (0.0844,10.5)
(25, 26)	1.22 (0.00325,8.23)	1.54 (0.187,7.45)	1.1 (0.00359,10.2)	1.64 (0.116,11.8)
(27–32)	2.12 (0.0146,9.24)	3.58 (0.438,10.2)	0.902 (0.00182,11.2)	1.7 (0.108,12.8)
(33–39)	na	na	na	na
(50–53)	na	na	na	na
(54–56)	na	na	na	na
(57–62)	na	na	na	na
(63–72)	na	na	na	na
Sum	28.28	31.31	13.22	16.73

Notes: This table shows median variance decompositions of aggregate consumption and inflation caused by sectoral demand shocks. In parentheses 95-percent confidence bounds are shown.

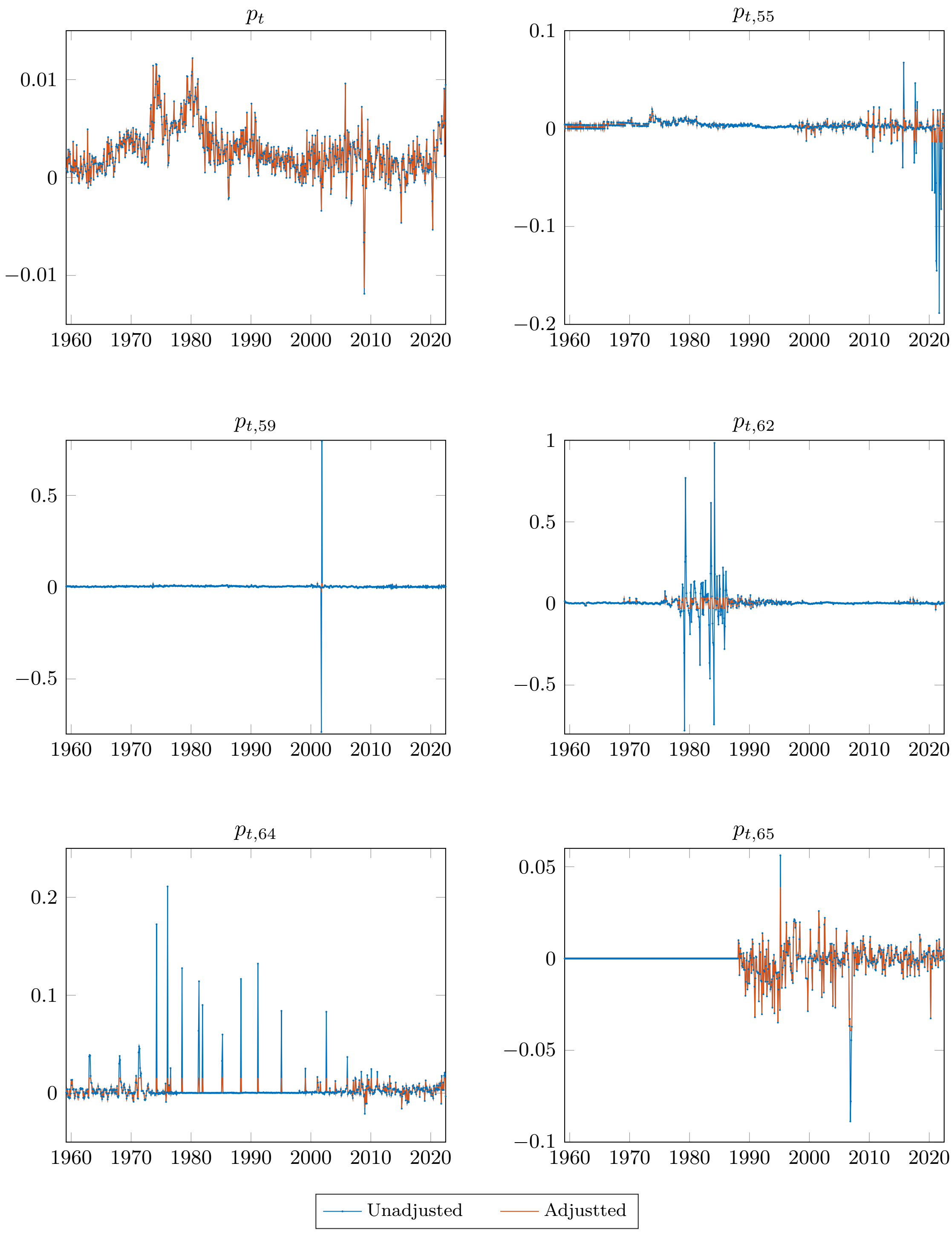
I Additional figures

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



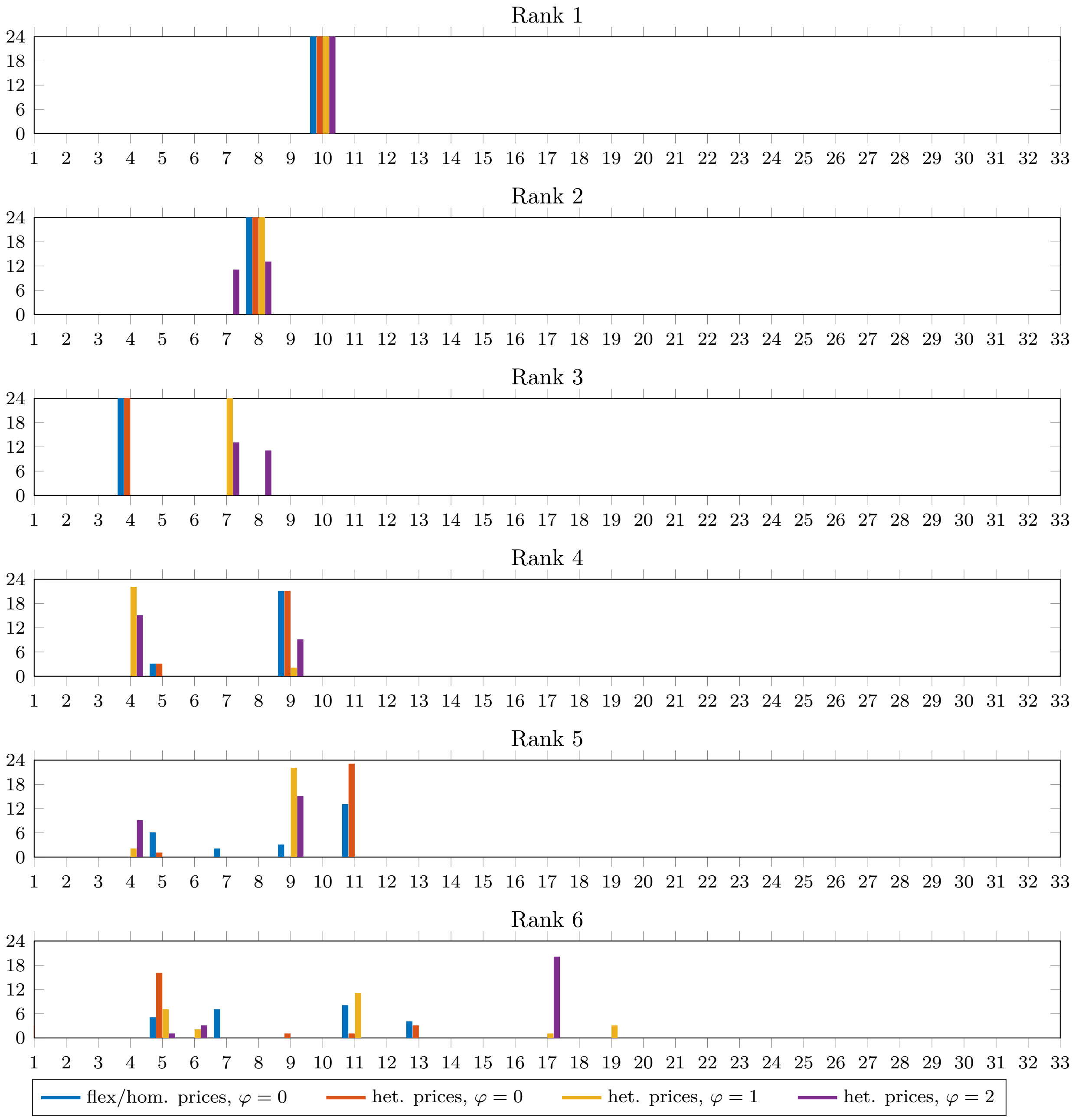
Notes: This figure contrasts outlier adjusted data with unadjusted data. Many of these PCE series are affected by outliers. I therefore check for all individual PCE series whether observations exceed the interquartile range by a factor 5. A value that exceeds this threshold is then adjusted to the positive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

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



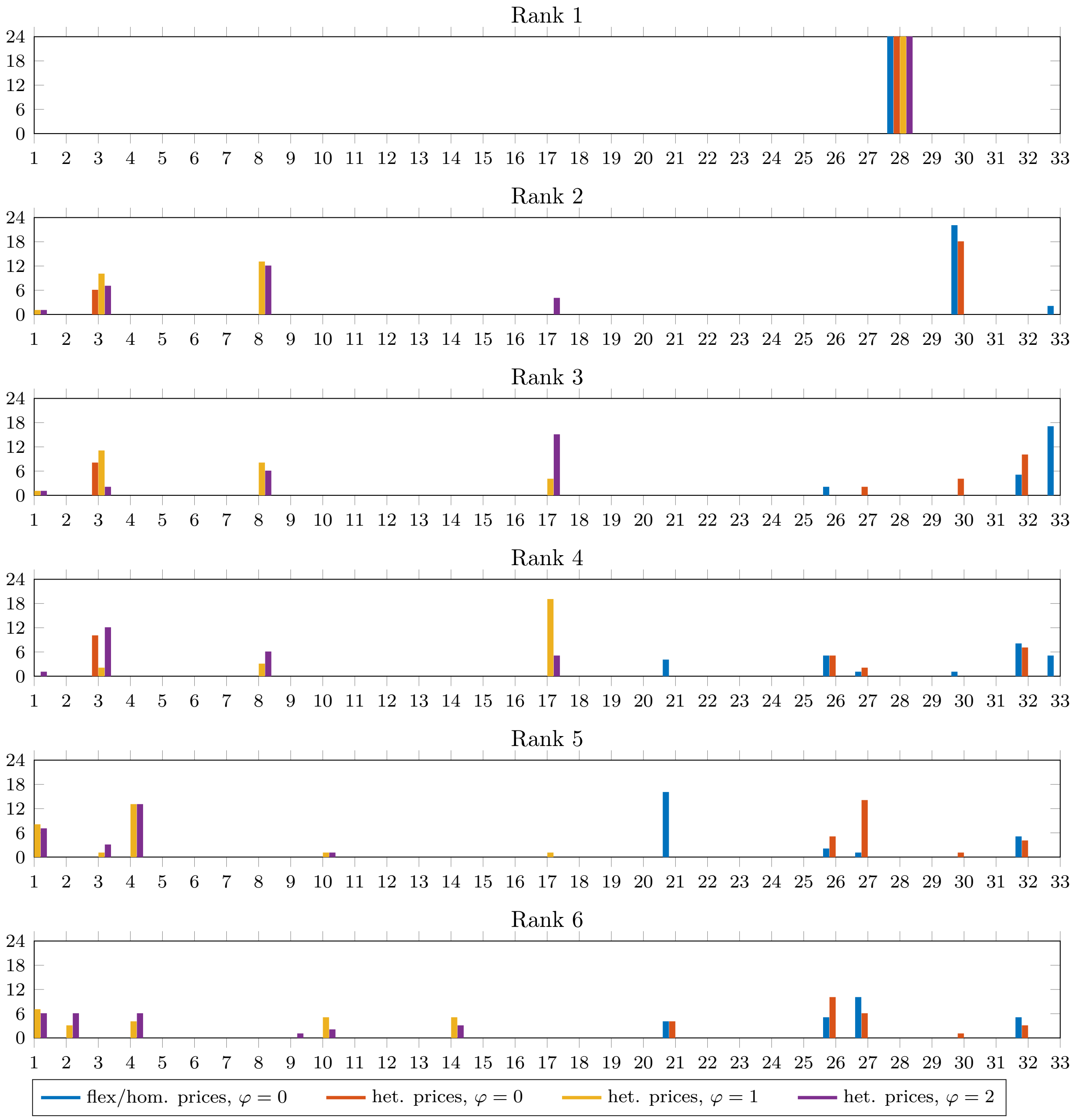
Notes: See notes to Figure A.1.

Figure A.3: PCE rankings for *Electrical equipment, appliance, and components*



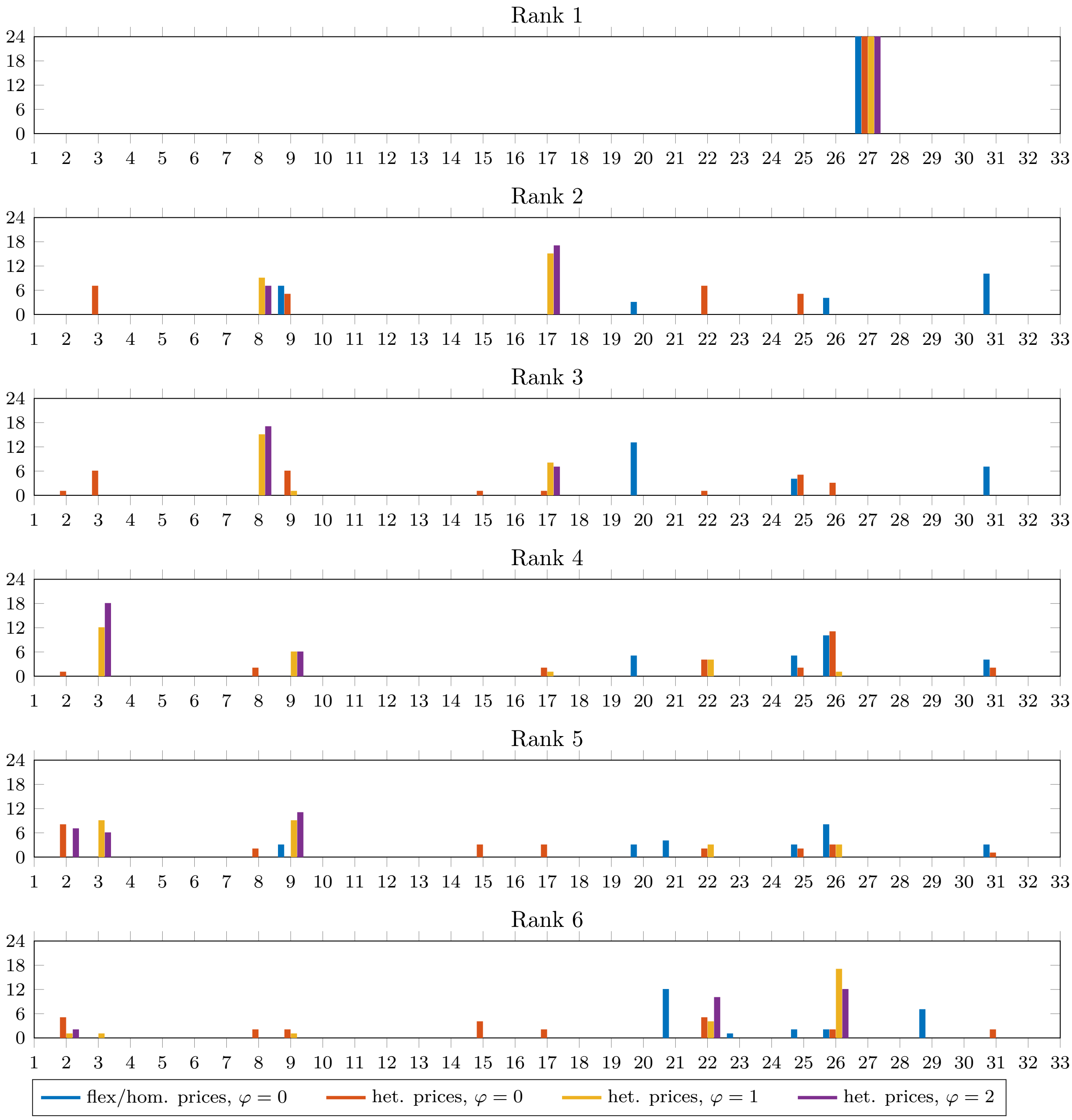
Notes: This figure summarizes the first six rankings for the sector-specific supply shock that originates in the sector indicated in the title. The four models correspond, in this order, to specification (I/II), (III), (IV), and (V) of the main text. For every specification I consider 24 calibrations based on input-output tables for the years 1997 to 2020. The bars summarize for the respective specification how often the price of the intermediate-good sector appears at rank 1 to 6 across the 24 calibrations.

Figure A.4: IM rankings for *Educational services*



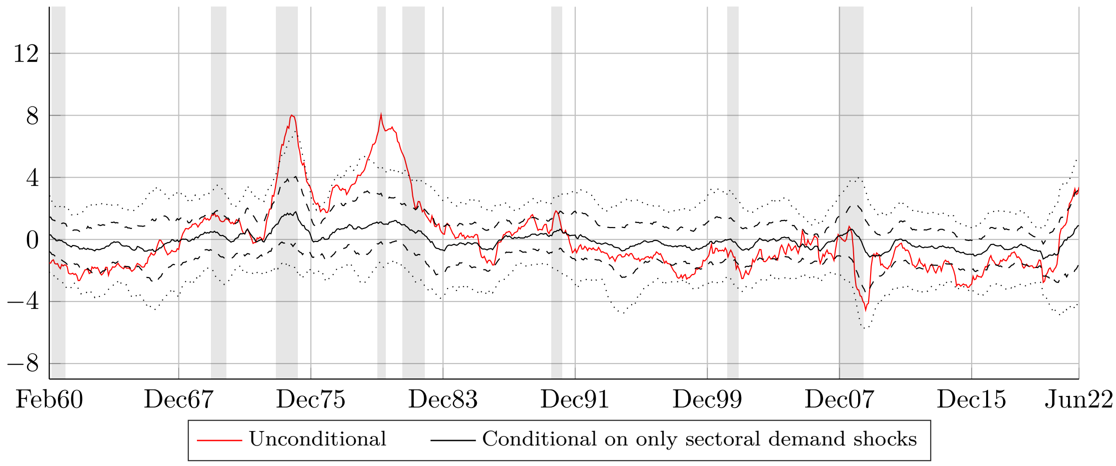
Notes: See notes to Figure A.3.

Figure A.5: IM rankings for *Management, administrative and waste services*



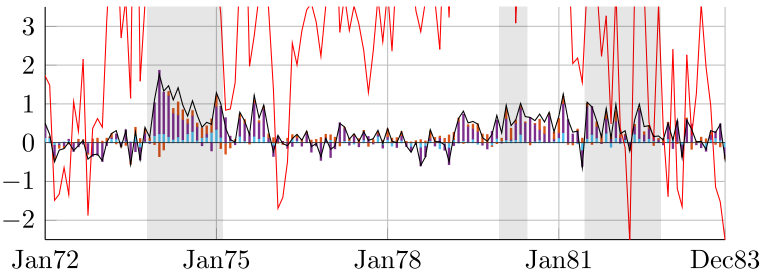
Notes: See notes to Figure A.3.

Figure A.6: PCE inflation and its sectoral demand origins (y-o-y, demeaned)

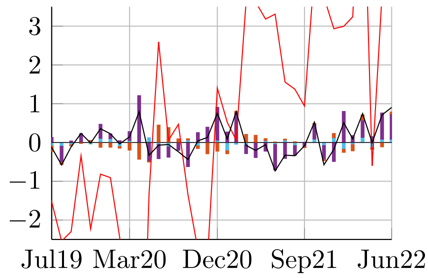


Notes: The figure shows median contributions of sectoral demand shocks to demeaned inflation. Additionally, 95-percent and standard-deviation confidence bands are plotted.

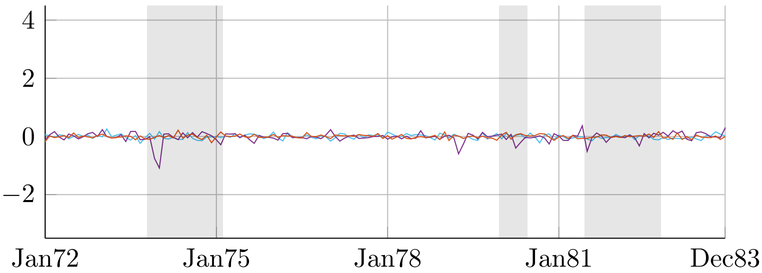
Figure A.7: Individual sector shocks and contributions to PCE inflation (1/5)



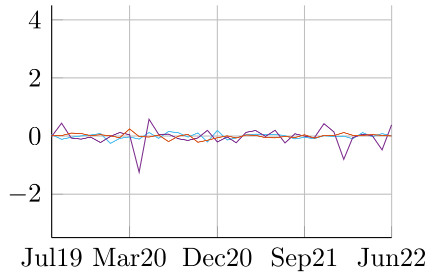
(a) HDs: Great Inflation period



(b) HDs: (Post-)COVID-19 period

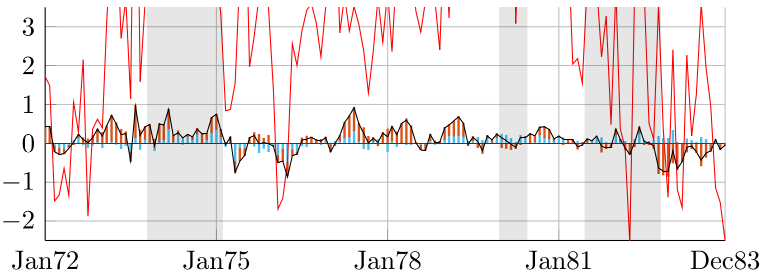


(c) Shocks: Great Inflation period

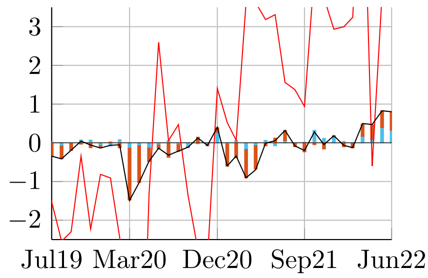


(d) Shocks: (Post-)COVID-19 period

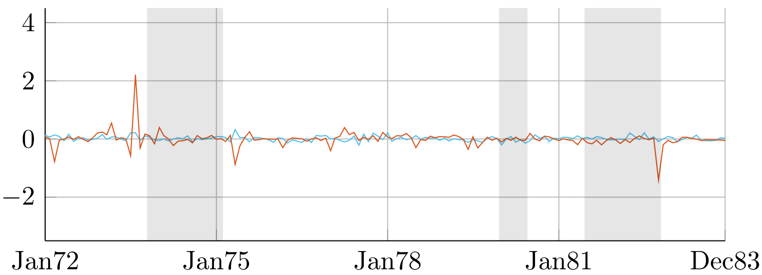
Utilities (supply)
Mining and petroleum & coal products (supply)
Gasoline & other energy goods (demand)
Unconditional
Contr. of 3 sectoral shocks



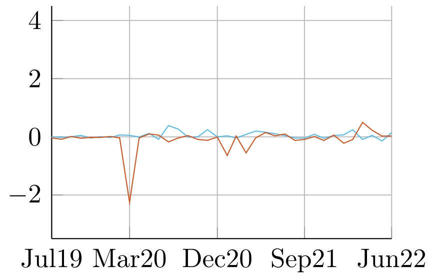
(e) HDs: Great Inflation period



(f) HDs: (Post-)COVID-19 period



(g) Shocks: Great Inflation period

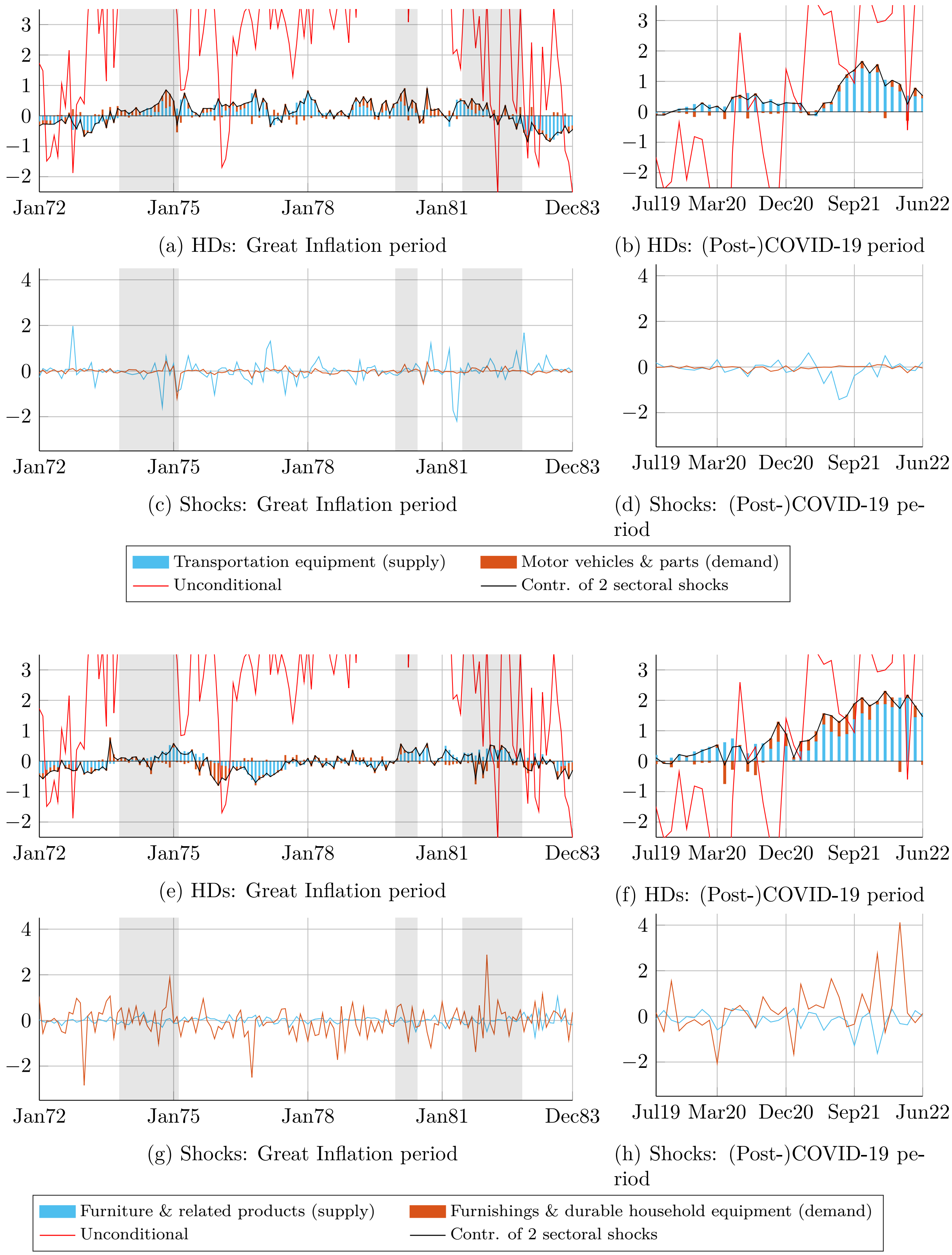


(h) Shocks: (Post-)COVID-19 period

Food & beverage & tobacco products (supply)
Food & beverages purch. for off-premises cons. (demand)
Unconditional
Contr. of 2 sectoral shocks

Notes: This figure shows median contributions of individual sector shocks to demeaned and annualized monthly PCE inflation (m-o-m).

Figure A.8: Individual sector shocks and contributions to PCE inflation (2/5)



(a) HDs: Great Inflation period

(b) HDs: (Post-)COVID-19 period

(c) Shocks: Great Inflation period

(d) Shocks: (Post-)COVID-19 period

(e) HDs: Great Inflation period

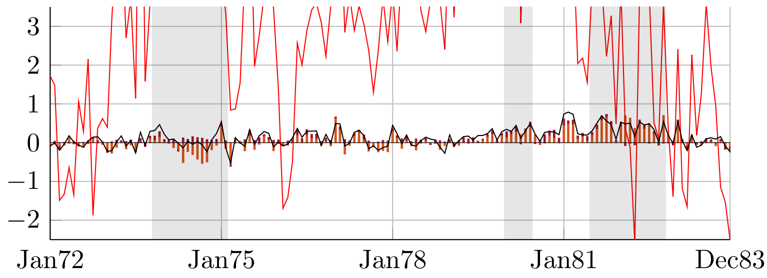
(f) HDs: (Post-)COVID-19 period

(g) Shocks: Great Inflation period

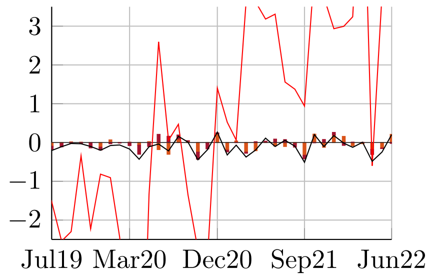
(h) Shocks: (Post-)COVID-19 period

Notes: See notes for Figure A.7.

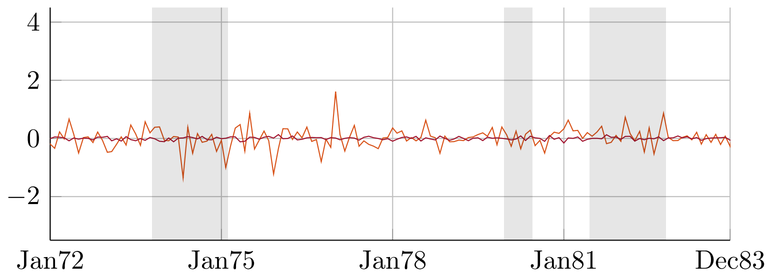
Figure A.9: Individual sector shocks and contributions to PCE inflation (3/5)



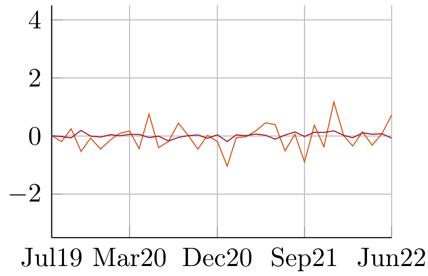
(a) HDs: Great Inflation period



(b) HDs: (Post-)COVID-19 period

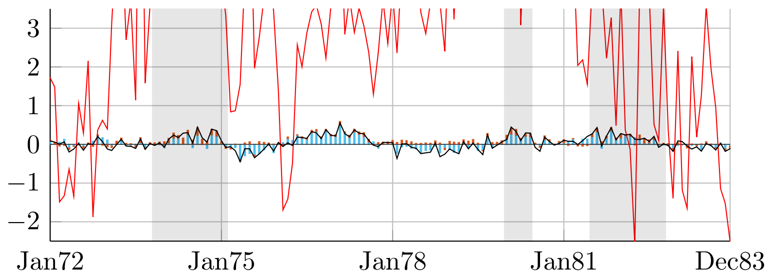


(c) Shocks: Great Inflation period

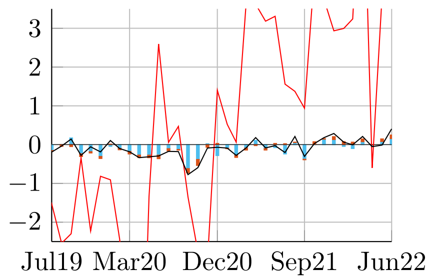


(d) Shocks: (Post-)COVID-19 period

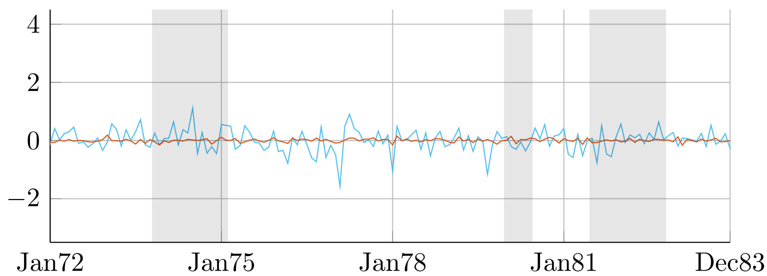
Recreational goods & vehicles (demand) | Other durable goods (demand)
Unconditional | Contr. of 2 sectoral shocks



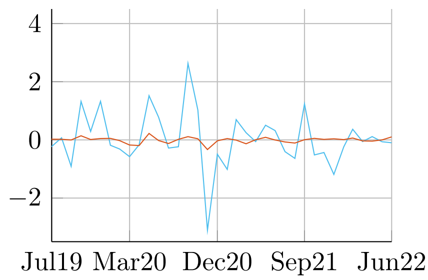
(e) HDs: Great Inflation period



(f) HDs: (Post-)COVID-19 period



(g) Shocks: Great Inflation period

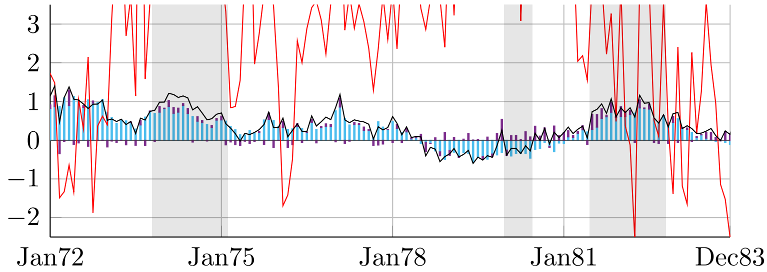


(h) Shocks: (Post-)COVID-19 period

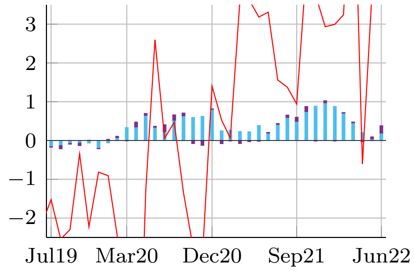
Textiles, apparel & leather (supply) | Clothing & footwear (demand)
Unconditional | Contr. of 2 sectoral shocks

Notes: See notes for Figure A.7.

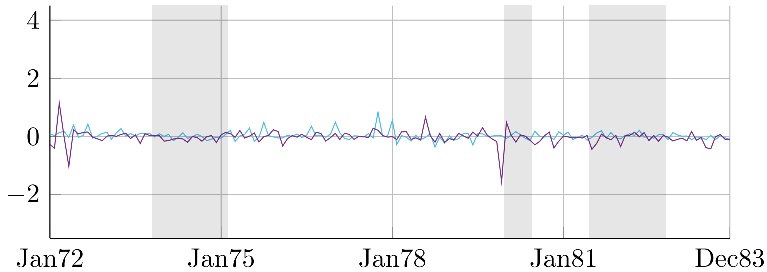
Figure A.10: Individual sector shocks and contributions to PCE inflation (4/5)



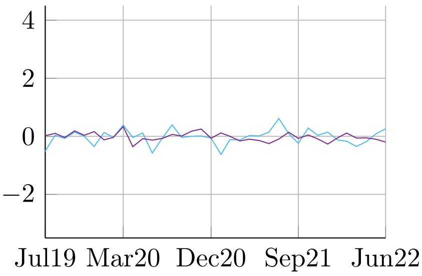
(a) HDs: Great Inflation period



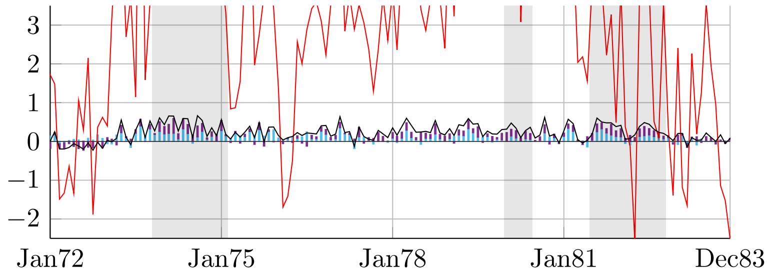
(b) HDs: (Post-)COVID-19 period



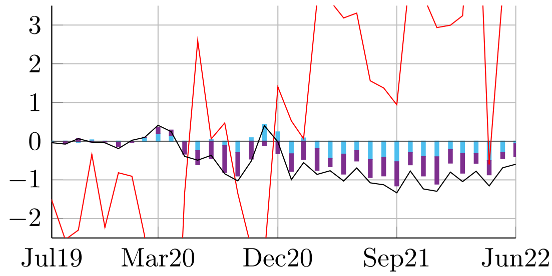
(c) Shocks: Great Inflation period



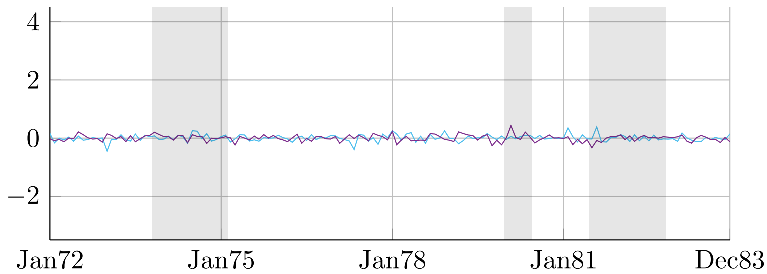
(d) Shocks: (Post-)COVID-19 period



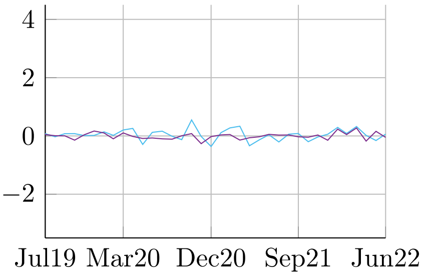
(e) HDs: Great Inflation period



(f) HDs: (Post-)COVID-19 period



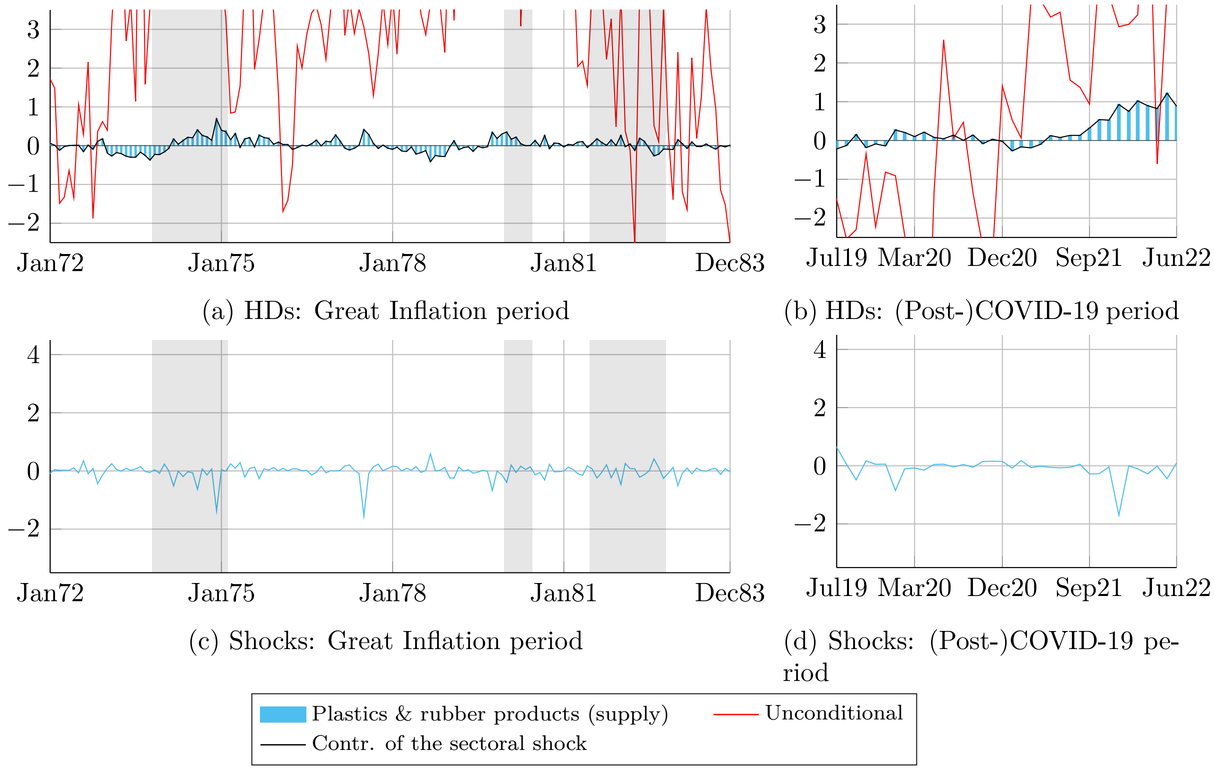
(g) Shocks: Great Inflation period



(h) Shocks: (Post-)COVID-19 period

Notes: See notes for Figure A.7.

Figure A.11: Individual sector shocks and contributions to PCE inflation (5/5)



(a) HDs: Great Inflation period

(b) HDs: (Post-)COVID-19 period

(c) Shocks: Great Inflation period

(d) Shocks: (Post-)COVID-19 period

Notes: See notes for Figure A.7