Team Persistent or Team Transitory? Sectoral Linkage and Inflation Persistence*

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Abstract

This paper develops a high-dimensional VAR framework augmented with unobserved common factors and employs the Lasso shrinkage method for estimation to explore sectoral spillovers and their implications for aggregate inflation persistence in the US. The analysis finds that accounting for sectoral spillovers increases aggregate inflation persistence, especially during high inflation periods. Empirically, spillover-driven persistence outweighs own-sector persistence in 11 out of 16 PCE sectors. Counterfactual analysis shows eliminating spillovers would have reduced average quarterly inflation by 34% during the Great Inflation and 22% in the recent post-COVID surge, with the latest inflation reverting to the mean three quarters earlier.

Key words: Inflation, inflation persistence, inflation dynamics, sectoral spillover, Lasso
JEL code: E3, E5

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1 Introduction

The surge in inflation that swept through the United States and the global economy after 2020 has significantly affected consumer welfare, raising critical questions for policymakers. Central to these discussions is the persistence of inflation, which has sparked intense debates within policy and academic circles, splitting opinions into two camps: "Team Persistent" and "Team Transitory."

At the same time, the COVID-19 pandemic highlighted the crucial role of sectoral disruptionsâsuch as supply chain breakdowns, uneven shifts in demand, and cross-sector spillovers in amplifying economic shocks. This leads to a fundamental question: Are the post-COVID inflationary pressures primarily driven by aggregate shocks or by sector-specific shocks? Moreover, what factors made post-COVID inflation more persistent than initially expected?

To address these questions, we analyze U.S. quarterly PCE sectoral inflation from 1959 to 2023 using a high-dimensional, factor-augmented VAR model estimated with Lasso shrinkage. This approach allows us to decompose aggregate inflation into contributions from aggregate factors and sector-specific shocks, providing a unified framework to analyze their relative significance for inflation persistence.

The decomposition highlights three main channels through which inflation persistence manifests. First, aggregate shocks such as inflation expectations and oil price fluctuations affect all sectors and drive persistence across the board (Gagliardone and Gertler, 2023). Second, sectoral heterogeneity implies that a skewed distribution of sectoral inflation persistence, with a few highly persistent sectors, can amplify aggregate shocks. Third, intersectoral spillovers, driven by production networks or demand complementarities, can transform even temporary shocks into persistent aggregate inflation as they ripple through the economy.

The VAR model captures these channels flexibly and separately. The unobserved factors represent aggregate shocks affecting all sectors, while the autoregressive coefficient matrix encodes rich information about sector-specific persistence and spillover effects. Specifically, the diagonal elements of this matrix reveal the persistence of sectoral inflation, while the off-diagonal elements illustrate intersectoral spillovers. Mathematically, the persistence of aggregate inflation hinges on the largest eigenvalue of the autoregressive coefficient matrix. Inter-sector spillover could potentially amplify aggregate inflation persistence, as it may increase the dispersion of eigenvalues.

Our key findings underscore the critical role of intersectoral spillovers. We observe that the autoregressive coefficient matrix contains 30% non-zero elements, predominantly positive, indicating widespread inflation spillovers across sectors. Notably, some sectors, like food services and accommodation, have relatively low self-persistence but are highly central in

the spillover network, contributing substantially to aggregate persistence. Overall, inflation persistence driven by spillovers exceeds that from sector-specific persistence in 11 out of 16 sectors, ultimately dominating inflation persistence dynamics. Sectoral heterogeneity also plays a role.

On top of sector spillover, differences in consumption weights and sectoral self-persistence, captured by the diagonal elements of the autoregressive matrix, increase inflation persistence in two ways. A shock in a sector with high self-persistence has a more prolonged impact, and a shock in a heavily weighted sector further amplifies aggregate persistence. Empirically, sectors with greater consumption weights, such as housing and utilities, tend to exhibit higher self-persistence, reinforcing these effects. Yet, the overall contribution from heterogeneity remains much less significant compared to spillover effects.

Our framework also accounts for common shocks, which are estimated to be relatively transitory. Statistical tests favor a single common factor, which we find to be highly correlated (correlation of 0.5) with oil price changes and has minimal persistence (an autocorrelation of 0.02). The sectors most affected by this factor exhibit transitory inflation, underscoring the contrast between common and sectoral shocks.

The above analysis delivers a key message: whether inflation remains transitory or persistent hinges on the relative contribution of these shocks. We conduct a variance decomposition analysis. In the low inflation period such as 2010-2019, common factor explains about 90% of the total variation. During the early pandemic period in 2020, common shocks also led to a significant decline in inflation. However, from 2021Q2 to 2023, sectoral shocks became more important, accounting for about half of aggregate inflation. The rise in the relative contribution of sector shocks results in the more persistent inflation. In a forecasting exercise, our model generates more realistic and persistent inflation forecast than professional forecasters. A counterfactual that shutdown the off-diagonal sectoral spillover would have lowered post COVID period inflation by 22% on average, with gaps of up to 0.6 log points at the inflation peak and aggregate inflation would have reverted to the mean three-quarters earlier.

Estimating the latent sectoral linkages and unobserved common factors simultaneously is crucial for understanding their roles in aggregate inflation. First, without accounting for common factors, sector spillovers estimated from a conventional VAR model may be attributed to these unobserved factors, and high persistence in sectoral inflation may also be driven by persistent common factors. Second, as Foerster et al. (2011) points out, without accounting for sectoral spillovers, the estimated common factors in traditional factor models may capture not only aggregate shocks but also idiosyncratic sector-specific shocks propagating through sectoral linkages. Our FAVAR model, integrating a VAR model with a

factor model, not only provides a simple econometric framework to estimate latent sectoral linkages and insights into how sectoral spillovers propagate shocks through the economy, but also allows us to decompose aggregate inflation into aggregate shocks and sectoral shocks.

However, estimating the autoregressive coefficient matrix in the FAVAR model imposes challenges for accurate statistical estimation due to the high-dimensionality problem. To address this issue, we adopt the state-of-the-art Lasso techniques developed by Miao et al. (2023), which enables the feasible estimation of a high-dimensional FAVAR that permits robust cross-sectional dependence.[1] More importantly, the Lasso method also serves as a statistical tool to detect latent patterns of inter-sectoral spillovers. By applying a penalty in estimation that shrinks some off-diagonal coefficients in the autoregressive coefficient matrix towards zero, it identifies trivial cross-sectoral linkages, and therefore highlights substantial sectoral spillovers through the remaining non-zero coefficients.

Estimating sector linkage using this data-driven approach has three advantages over other commonly used methods such as imposing sector relationships using a production input-output matrix. First, it captures the relevant consumer prices persistence for monetary policy, without the need to estimate or assume the relationship between production prices and consumer prices. Second, it flexibly captures sector spillovers that go beyond the production input-output relationship. As we will see in the main analysis, healthcare sector inflation has spillover to multiple sectors that are not captured in the production input-output matrix. Lastly, the estimation does not require additional bilateral relationships across sectors. Therefore it is less data-demanding, can be applied in real-time without data delays, and free from measurement errors.

Literature Review. Our paper contributes to the literature examining sector-specific versus aggregate sources of business cycle variations, following foundational work by Long and Plosser (1987) and Forni and Reichlin (1998). Several studies, such as Barrot and Sauvagnat (2016), Acemoglu et al. (2016), Atalay (2017) ,Li and Martin (2019) and Carvalho et al. (2021), take a more empirical approach to this question. Meanwhile, other research has taken a structural approach to incorporate multisector or production networks into formal models, including works by Gabaix (2011), Acemoglu et al. (2012), Baqaee and Farhi (2020) and Baqaee and Farhi (2019). Our study is closely aligned with Foerster et al. (2011), who demonstrate that an approximate factor model can be derived from a multisector growth model. Our empirical specification is nearly identical; however, due to high-dimensional issues, they directly impose the production input-output matrix as the sector spillover matrix.

[1]The Lasso method (Tibshirani, 1996) is the well-known econometric technique for model selection. Lasso and its variants have also been intensively studied in econometrics in recent years (Kock and Callot, 2015; Su et al., 2016; Lee et al., 2022).

Our contribution is to address this limitation by employing a Lasso method, which allows for a more empirically flexible approach to capture latent relationships and extend this understanding to inflation persistence.

The recent surge in U.S. inflation has sparked discussions about its causes. The uneven sectoral pressures and supply chain disruptions during COVID-19 have motivated several discussions on sectoral supply shock implications, including Guerrieri et al. (2022), Acharya et al. (2023), Comin et al. (2023), and Ascari et al. (2024). Additionally, the Russia-Ukraine conflict has spurred analyses of oil prices and inflation, as discussed by Gagliardone and Gertler (2023) and Kilian and Zhou (2022). Benigno and Eggertsson (2023) and Bernanke and Blanchard (2023) demonstrate that supply-side effects and labor market tightness contribute to the recent inflation surge. We contribute to this discussion by empirically demonstrating the strong relevance of sectoral shocks, the characteristics of specific sectors, and their spillover effects during the post-2020 inflation period.

The literature on inflation persistence has recognized sector heterogeneity; early examples include Zaffaroni (2004), Pesaran and Chudik (2014), and Altissimo et al. (2009). Boivin et al. (2009) examines how price adjustments respond differently to common shocks and idiosyncratic shocks. While these studies highlight substantial heterogeneity in sectoral persistence, they do not directly account for sectoral spillovers and network effects. Conversely, recent literature on inflation sector heterogeneity and monetary policy has taken a more theoretical approach, explicitly considering production network structures, including Afrouzi and Bhattarai (2023), La'O and Tahbaz-Salehi (2022), Rubbo (2023), and Minton and Wheaton (2023). Our paper complements these theoretical approaches by providing an empirical framework that captures aggregate shocks, sector heterogeneity, and sector spillovers together.

Layout. We first provide a data description in Section 2. Section 3 describes the estimation procedure and the estimated coefficients. Section **??** applies the econometric model to inflation data and provides an analysis of inflation persistence.

2 Data Description

In this empirical application, we apply our econometric methods to the US sectoral inflation. The dataset comprises quarter-on-quarter changes in sixteen sectoral seasonal-adjusted personal consumption expenditure (PCE) price indices. The Bureau of Economic Analysis reports those sixteen disaggregated sectoral price indices (at the lowest level) in the NIPA Table 2.3.4, covering four durable goods sectors, four nondurable goods sectors, and eight service sectors. The sample's raw data consists of quarterly observations spanning from

1959Q1 to 2023Q3. Inflation is measured in log percentage points at a quarterly rate,

$$y_{it} = \text{inflation}_{it} = \left(\log \text{PCE}_{it}^{\text{index}} - \log \text{PCE}_{it-1}^{\text{index}}\right) \times 100\%.$$

The sectoral expenditure share weights can be computed using the nominal PCE values in NIPA table 2.3.5. Given the very low-frequency change of the sector weight, for simplicity, we assume that the sector weights are constant across the sample period and equal to the sample average of the quarterly weights,

$$w_i = \frac{1}{T}\sum_{t=1}^{T} w_{it} \times 100\% = \frac{1}{T}\sum_{t=1}^{T} \frac{\text{PCE}_{it}^{\text{value}}}{\text{PCE}_{t}^{\text{value}}} \times 100\%.$$

Table 1: Summary Statistics of Sectorial Inflation Rates (Unit: %)

Sector	Weight	Mean	Std.	Min	Max
Durable Goods					
Motor vehicles and parts	5.15	0.56	1.09	-1.55	6.74
Furnishings and durable household equipment	3.44	0.27	0.87	-1.58	3.83
Recreational goods and vehicles	2.89	-0.52	1.04	-3.02	2.21
Other durable goods	1.54	0.42	1.09	-1.72	6.97
Nondurable Goods					
Food and beverages purchased for off-premises consumption	11.30	0.80	0.99	-1.01	4.64
Clothing and footwear	5.09	0.27	0.86	-5.91	3.06
Gasoline and other energy goods	3.58	1.06	6.78	-41.77	19.91
Other nondurable goods	7.86	0.77	0.71	-0.53	4.71
Services					
Housing and utilities	17.86	0.94	0.60	-0.06	2.90
Health care	12.01	1.18	0.78	-0.33	3.50
Transportation services	3.18	0.92	1.00	-2.58	6.03
Recreation services	3.07	0.89	0.47	-0.32	2.87
Food services and accommodations	6.45	1.02	0.64	-0.32	3.81
Financial services and insurance	6.29	0.99	1.38	-4.09	7.41
Other services	8.15	0.92	0.60	-0.18	3.25
Final consumption expenditures of nonprofit institutions serving households (NPISHs)	2.15	0.40	1.51	-4.12	5.26

Notes: All sectors have 258 observations of inflation.

The summary statistics of sectoral inflation of 16 sectors and their expenditure share weights are given in Table 1. The three sectors with the largest weight among them are "Housing and Utilities" (17.86%), "Health Care" (12.01%), and "Food and Beverages Purchased for Off-premises Consumption" (11.30%). Over the span of the last sixty years, the

average inflation in the services sector has exceeded that of the goods sector. The "Health Care" sector, whose weight is the second largest, has the highest average inflation rate of the 16 PCE sectors, reaching 1.18%. Inflation in the durable goods sectors is typically modest, and it has even gone negative for recreational goods and vehicles. The sector of "Gasoline and Other Energy Goods" is unique since it experiences exceptionally high volatility (6.78%). Other than that, the inflation volatility of other sectors is roughly about 1

3 Econometric Models

In this section, we lay out the general econometric framework in Section 3.1. Given the objective of interest is high-dimensional in nature, in Section 3.2, we describe a lasso procedure to estimate the model.

3.1 High-dimensional VAR Model with Common Factors

Let y_{it} be the inflation of the i-th sector at time t, and the N sectors are stacked into $\mathbf{Y}_t = (y_{it})_{i=1}^N$. We write a VAR($p$)

$$\mathbf{Y}_t = \sum_{k=1}^{p} \mathbf{A}_k \mathbf{Y}_{t-k} + \boldsymbol{\mu} + \mathbf{e}_t, \quad t = 1, 2 \ldots, T \tag{1}$$

where $\boldsymbol{\mu} = (\mu_i)_{i=1}^N$ is the individual specific fixed effects, $\mathbf{A}_k = (a_{ij,k})_{i,j\in[N]}$ is $N \times N$ coefficient matrix, and $\mathbf{e}_t = (e_{it})_{i=1}^N$ is the vector unobservable error term. To capture potential common shocks, we allow factor structures to enter the error term via

$$\mathbf{e}_t = \boldsymbol{\Lambda}\mathbf{f}_t + \mathbf{u}_t,$$

where $\mathbf{f}_t = (f_{lt})_{l=1}^r$ consists of r latent factors, the $N \times r$ matrix $\boldsymbol{\Lambda}$ stores the factor loadings, and $\mathbf{u}_t = (u_{it})_{i=1}^N$ is the vector of idiosyncratic shocks. To identify the VAR coefficients $\mathbf{A}_k$ for $k \in [p]$, we assume $E[\mathbf{u}_t | \mathbf{Y}_{t-1}, \ldots, \mathbf{Y}_{t-p}, \mathbf{f}_t, \boldsymbol{\mu}] = 0$. Without loss of generality, we normalize $\boldsymbol{\Lambda}'\boldsymbol{\Lambda}/N = \mathbf{I}_r$ to identify $\boldsymbol{\Lambda}$ and $\mathbf{f}_t$.

Compared to textbook VAR models, our model includes unobserved common factors and allows the factor loading to vary across sectors. Common factors are used to capture unobserved common shocks including oil price shocks, monetary policy, fiscal policy, inflation expectations, and news shocks, etc. Factor loading reflects the contemporary sensitivity of sectoral inflation in response to common factors. Previous studies adopting the VAR framework to model the dynamics of sectoral inflation usually did not include common

factors in the model and thus suffered criticism that omitting the common shocks would lead to biased estimation, pseudo-persistence in sectoral inflation, and spurious correlation between sectoral inflation. For example, the high correlation between sectoral inflation may be caused by a common factor and high persistence in sectional inflation may be driven by a persistent common factor. Moreover, including common factors allows us to separate aggregate and sectoral shocks, and thus we can explore the impulse responses of sectoral and aggregate inflation to both shocks.[2]

3.1.1 Theoretical Implications on Inflation Dynamics

In our empirical estimation, the information criteria strongly select one common factor ($\widehat{r} = 1$) and one vector autoregressive lag ($\widehat{p} = 1$) as well. Thus, we use the VAR(1) model with a single factor

$$\mathbf{Y}_t \quad = \quad \mathbf{A}_1 \mathbf{Y}_{t-1} + \mathbf{\Lambda} f_t + \mathbf{u}_t \tag{2}$$

to discuss the implication of the model for inflation dynamics. For simplicity, we suppress the fixed effect $\mathbf{Y}_t$ in the above expression as we demean for each sector before estimation to remove the sectoral fixed effects. To avoid confusion with the individual specific vector $\boldsymbol{\lambda}_i$, we keep using the upper case $\mathbf{\Lambda}$ here as a $N \times 1$ matrix of factor loadings for the sole common factor.

3.1.2 Impulse Responses

When all eigenvalues of $\mathbf{A}_1$ lie in $(-1, 1)$, we can write the VAR(1) as to the moving average representation:

$$\mathbf{Y}_t = \left(\mathbf{I} - \mathbf{A}_1(\mathbb{L})\right)^{-1} \left(\mathbf{\Lambda} f_t + \mathbf{u}_t\right) = \sum_{s=0}^{\infty} \mathbf{A}_1^s \left(\mathbf{\Lambda} f_{t-s} + \mathbf{u}_{t-s}\right).$$

[2]Our model is closely related to the models in Altissimo et al. (2009) and Mayoral (2013), which mainly focus on the heterogeneity in the diagonal coefficients a_{ii}, while ignoring inter-sectoral spillover by assuming the off-diagonal coefficients $a_{ij} = 0$ for $j \neq i$. Our model captures the heterogeneity in sectoral persistence and the spillover between sectors through the VAR specification. The diagonal coefficients a_{ii} in $\mathbf{A}_1$ capture the autoregressiveness of each sector i, and the off-diagonal coefficients $a_{ij}, j \neq i$ capture the impact of the lagged inflation in sector j on the inflation of sector i in period t. This is an important generalization of our model from the literature.

Define the information set $\mathcal{I}_t = ((\mathbf{u}_s, f_s)_{s=-\infty}^{t})$. The conditional expectation is

$$\begin{aligned}\mathbb{E}_t\left[\mathbf{Y}_{t+h}\right] &= \mathbb{E}\left[\sum_{s=0}^{\infty}\mathbf{A}_1^s\left(\mathbf{\Lambda} f_{t+h-s}+\mathbf{u}_{t+h-s}\right)|\mathcal{I}_t\right] \\ &= \sum_{s=0}^{h-1}\mathbf{A}_1^s\mathbb{E}\left[\left(\mathbf{\Lambda} f_{t+h-s}+\mathbf{u}_{t+h-s}\right)|\mathcal{I}_t\right]+\sum_{s=0}^{\infty}\mathbf{A}_1^{h+s}\left(\mathbf{\Lambda} f_{t-s}+\mathbf{u}_{t-s}\right). \qquad (3)\end{aligned}$$

Assume $\mathbf{u}_t$ is a martingale difference sequence (m.d.s.) with respect to the natural filtration so that $\mathbb{E}\left[\mathbf{u}_{t+s}|\mathcal{I}_t\right]=0$ for all $s\geq 1$. Regarding f_t, Foerster et al. (2011) and Mayoral (2013) models it as a static factor whereas Altissimo et al. (2009) model it as a dynamic factor.

In our empirical context, we observe that f_t has very low persistence with AR(1) coefficient 0.025. Therefore, we assume that $(\mathbf{u}_t', f_t)$ is m.d.s. to spare the modeling of the dynamics in the common factor.[3] Under this assumption, the sectoral impulse response functions (IRFs), defined as the h-period ahead responses of $\mathbf{Y}_t$ to unit changes in $\mathbf{u}_t$ and $\mathbf{f_t}$ are:

$$\mathbf{IRF}_{\mathbf{Y}}^{\mathbf{u}}(h) = \partial\mathbb{E}_t\left[\mathbf{Y}_{t+h}\right]/\partial\mathbf{u}_t' = \mathbf{A}_1^h \qquad (4)$$

$$\mathbf{IRF}_{\mathbf{Y}}^{f}(h) = \partial\mathbb{E}_t\left[\mathbf{Y}_{t+h}\right]/\partial f_t = \mathbf{A}_1^h\mathbf{\Lambda} \qquad (5)$$

The aggregate inflation is the weighted average of sectoral inflation, $\pi_t = \mathbf{w}'\mathbf{Y}_t$, where $\mathbf{w} = (w_i)_{i=1}^{N}$ are the consumption basket weights of PCE of N sectors. Thus, the h-period-ahead IRF of aggregate inflation is the convex combination of the corresponding sectoral IRFs based on Equation (4) and (5):

$$\mathbf{IRF}_{\pi}^{\mathbf{u}}(h) = \partial\mathbb{E}_t\left[\mathbf{w}'\mathbf{Y}_{t+h}\right]/\partial\mathbf{u}_t' = \mathbf{w}'\mathbf{IRF}_{\mathbf{Y}}^{\mathbf{u}}(h) = \mathbf{w}'\mathbf{A}_1^h \qquad (6)$$

$$\mathbf{IRF}_{\pi}^{f}(h) = \partial\mathbb{E}_t\left[\mathbf{w}'\mathbf{Y}_{t+h}\right]/\partial f_t = \mathbf{w}'\mathbf{IRF}_{\mathbf{Y}}^{f}(h) = \mathbf{w}'\mathbf{A}_1^h\mathbf{\Lambda}. \qquad (7)$$

Note that the impulse responses to uniform sectoral shocks and common shocks are similar except for the factor loading.

We can further define the percentage contribution of sector i to the aggregate IRF to common shocks at horizon h as follows:

$$\mathbf{PC}_i(h) = \frac{w_i\mathbf{IRF}_{\mathbf{Y}_i}^{f}(h)}{\mathbf{IRF}_{\pi}^{f}(h)} = \frac{w_i\left(\mathbf{A}_1^h\right)_{i\bullet}\mathbf{\Lambda}}{\mathbf{w}'\mathbf{A}_1^h\mathbf{\Lambda}} \qquad (8)$$

[3]This is a simplification based on the very low persistence of the common factor and we discuss this further below in section [x]. Note that if the common factor is persistent, for example, its DGP is an AR(1) process, i.e., $f_t = \rho f_{t-1}+\epsilon_{f,t}$, the IRF of sectoral inflation to common shocks is given by: $\mathbf{IRF}_{\mathbf{Y}}^{\epsilon_{f,t}}(h) = \mathbf{\Lambda}\sum_{i=0}^{h}\mathbf{A}_1^i\rho^{h-i}$. Clearly, when $\rho=0$, this IRF reduces to the Equation (5). When $\rho>0$, the $\mathbf{IRF}_{\mathbf{Y}}^{\epsilon_{f,t}}(h)$ for this general case shows the interplay between the persistence of common shocks and the propagation of common shocks through sectoral linkages.

where $\left(\mathbf{A}_1^h\right)_{i\bullet}$ is the ith row of the matrix. Note we use IRFs to measure the persistence of sectoral and aggregate inflation, as Mayoral (2013) has pointed out that the average of the individual IRFs to common shocks is identical to the aggregate IRF to common shocks,[4] while averages of other popular scalar measures, such as the sum of the autoregressive coefficients (SAC), the largest autoregressive root (LAR), and the half-life (HL), tend to be different from the aggregation level.

3.2 Estimation Procedure

The data we employed is a panel data containing 257 quarterly time series observations of 16 sectors. As a result, each $\mathbf{A}_k$ has 256 ($= 16 \times 16$) unknown coefficients to be estimated from the data. Given the high-dimensional nature of the matrices, this creates challenges related to computational constraints, overfitting, spurious relationships, and high variance in the estimation. We introduce our regularization approach with Lasso in this section.

The choice of regularization method depends critically on the economic context, as it must align with the structural characteristics of the data. In this sense, the specifications proposed by Altissimo et al. (2009) and Mayoral (2013) can be interpreted as a special case of a sparse model, where $p = 1$ and all $a_{ij,k} = 0$ for $i \neq j$, effectively shutting off cross-sector interactions. Here, "sparsity" refers to the fact that most elements in $\mathbf{A}_k$ are zero, with only the diagonal elements estimated from the data. Recent studies on input-output production matrix spillovers, such as those by Foerster et al. (2011), Baqaee and Farhi (2018), and Rubbo (2023), have highlighted the sparse nature of the input-output matrix, which reflects that most industries interact with only a limited subset of sectors. Inspired by this, we adopt the Lasso procedure (Tibshirani, 1996), a well-known technique, to produce a data-driven sparse estimator. Lasso and its variants have also been intensively studied in econometrics in recent years (Kock and Callot, 2015; Su et al., 2016; Lee et al., 2022).

Collect all observable regressors as an Np-dimensional vector $\mathbf{X}_t = \left(\mathbf{Y}_{t-1}', \mathbf{Y}_{t-2}', \ldots, \mathbf{Y}_{t-p}'\right)'$. Stack the $N \times T$ matrix $\mathbf{Y} = (\mathbf{Y}_1, \ldots, \mathbf{Y}_T)$ and the $Np \times T$ matrix $\mathbf{X} = (\mathbf{X}_1, \ldots, \mathbf{X}_T)$. The unknown parameters in this model to be estimated is the $r \times T$ matrix $\mathbf{F} = (\mathbf{f}_1, \ldots, \mathbf{f}_T)$, the $N \times r$ factor loading matrix $\mathbf{\Lambda}$, and the stacked slope coefficients (an $N \times Np$ matrix) $\mathbf{B} = (\mathbf{A}_1, \ldots, \mathbf{A}_p)$. The sum of squared residual is

$$\mathrm{SSR}\left(\mathbf{\Theta}\right) = \left\|\mathbf{Y} - \mathbf{B}\mathbf{X} - \mathbf{1}_N\boldsymbol{\mu}' - \mathbf{\Lambda}\mathbf{F}'\right\|_{\mathcal{F}}^2,$$

[4]This still holds when the spillover is allowed. The individual aggregation is to take partial derivative with respect to f_t first to get the individual IRF, and then use the weight to aggregate. The aggregate IRF is to use weighted average first, and then take the partial derivative with respect to f_t. The exchange of the linear operators leads to the same results.

where $\|\cdot\|_{\mathcal{F}}$ is the matrix Frobenius norm, and the parameters is $\mathbf{\Theta} = \{\mathbf{B}, \boldsymbol{\mu}, \mathbf{\Lambda}, \mathbf{F}\}$. This is the criterion function that the OLS estimator minimizes.

We use Lasso to estimate unknown coefficients. Denote $\mathbf{A}_k^\circ = \mathbf{A}_k - \text{diag}(\mathbf{A}_k) = (a_{ij,k}\mathbb{I}\{i \neq j\})_{i,j\in[N]}$ as a copy $\mathbf{A}_k$ with the diagonal elements suppressed at 0. Similarly, denote $\mathbf{B}^\circ = \left(\mathbf{A}_1^\circ, \ldots, \mathbf{A}_p^\circ\right)$. A Lasso estimator can minimize

$$\min_{\mathbf{\Theta}} \left\{ \frac{1}{NT} \text{SSR}(\mathbf{\Theta}) + \gamma \|\mathbf{B}^\circ\|_1 \right\}$$

where $\|\mathbf{A}\|_1 = \sum_{i,j} |a_{ij}|$ is the L_1-norm of a generic matrix $\mathbf{A}$ which spares the diagonal elements from the penalty.

Our econometric model and estimation method have three distinct advantages. First, the Lasso method can deal with the high-dimension problem of estimating the autoregressive coefficient matrix. In our context, the total number of time series is moderate ($T = 257$). If we do not impose any regularization on the parameters, the ordinary least squares fitting will exhaust too many degrees of freedom, and thus induce a large variance in the estimator. Moreover, the conventional OLS estimator can not detect the sparsity of the autoregressive matrix. Lasso's penalty shrinks some coefficients toward zero, sacrificing some finite-sample bias to exchange for a substantial reduction in the variance, thereby balancing the two bias-variance trade-offs for a small mean-squared error.[5]

Second, the Lasso method, used here to estimate the sparse autoregressive matrix, also serves as a statistical tool to detect latent patterns of inter-sectoral spillover. By applying a penalty that shrinks some off-diagonal coefficients toward zero, Lasso identifies which cross-sectoral linkages are trivial. Conversely, the remaining non-zero off-diagonal coefficients signify substantial sectoral spillovers. This data-driven approach estimates potential sectoral spillover without requiring prior information about the underlying sectoral linkages, such as input-output table.[6]

[5]The side effect of the shrinkage is that the bias will be comparable with the variance, which invalidates the standard statistical inference. To fix this problem, we will use Miao et al. (2023)'s multi-step estimation procedure to refine the estimator by re-centering it around the true coefficients. Moreover, in practical estimation, the number of lags p and the number of factors r must be determined; Miao et al. (2023) provide a systematic procedure for these important hyperparameters. We adopt this methodology for our estimation, with further details provided in Appendix A.

[6]We are not the first to use the data-driven method to estimate the unobserved connectedness (or spillover) between individuals based on the panel VAR framework. In the finance literature, two seminal studies Diebold and Yılmaz (2014) and Demirer et al. (2018) adopt a large VAR system (with no common factor) to estimate the network connectedness of financial institutions based on the variance decomposition. Since then, this method has been a standard toolbox in the field of finance to estimate the interdependence and network between financial institutions. By contrast, our focus is not on the descriptive network via the vector moving average system (implied by the AR coefficient matrix and the error's covariance matrix), but on the sectoral spillover of shocks from sectoral and common factors and its contribution to aggregate inflation persistence. Methodologically, our model includes unobserved common factors, which makes the estimation

Third, a key challenge in traditional factor models (without VAR) is that estimated common factors may capture not only aggregate shocks but also idiosyncratic sector-specific shocks that propagate through production linkages. To address this issue, Foerster et al. (2011) adopt a two-step approach: first, they develop a dynamic multisector growth model accounting for these linkages and compute a filtered sectoral industrial growth rate to eliminate the propagation effects of idiosyncratic shocks. Second, they apply a standard factor model to the filtered growth rates to estimate the relative contributions of aggregate and sector-specific shocks to the variability of aggregate output. By contrast, following Miao et al. (2023), our model estimates the sectoral spillover linkage and common factors simultaneously, without relying on the prior knowledge of input-output linkages and the complicated filtering procedure based on the dynamic multisector structural model. Thus, this study also makes a methodological contribution to this area by providing a simple and direct method of factor analysis that accounts for sectoral spillover effects.

3.3 Simulation

To show the effectiveness of the Lasso method in detecting the hidden inter-sector spillover, we conduct a simple simulation exercise in Appendix B. We specify the true autoregressive matrix $\mathbf{A}_1^0$ in Figure A1, where $\mathbf{A}_1^0$ is a sparse matrix with diagonals equal to 0.6 and each row has two additional random cells with values 0.2 and -0.2. Figure A2 presents the estimated autoregressive matrix without using Lasso, in which the cells with green rectangles indicate the true values are non-zero. It shows that the off-diagonal estimates are poor, as many cells with zero true values are estimated with non-zero (false positive). In other words, without Lasso, it tends to overestimate the presence of spillovers across sectors. By contrast, the Lasso method performs quite well in capturing the sparsity of the true $\mathbf{A}_1^0$ matrix, as shown in Figure A3. It not only detects all non-zero cells but also captures the majority of cells with zeros. For a few cells with true values equal to zero, it yields non-zero estimates, but many of those estimates are actually close to zero. This simulation exercise and comparison show that the Lasso method is useful for detecting the underlying inter-sector spillovers.

We summarize the superior performance of Lasso method with a few statistics in terms of model selection accuracy and root mean squared errors (RMSEs). We further conduct this simulation exercise for 500 replications. According to Table A1, the Lasso method achieves significantly lower RMSEs overall (0.0001) and for nonzero entries (0.0009) compared to the standard method without Lasso, which reports RMSEs of 0.0027 and 0.0038, respectively. This indicates that the Lasso method provides more precise estimates. In terms of the

more challenging.

estimation accuracy of non-zero entries and zero entries, both methods achieve a perfect true positive rate (TPR) of 100%, indicating that all non-zero entries of the true matrix $\mathbf{A}_1^0$ are accurately estimated as non-zero. However, there is a stark contrast in the false positive rate (FPR), with the standard method without Lasso reporting an FPR of 100%, suggesting a high rate of incorrectly estimating zero entries as non-zero. In contrast, the Lasso method shows a much lower FPR of 8.96%, indicating a much better performance in penalizing false positives and thus providing a more accurate sparse autoregressive matrix. Overall, the exercise demonstrates superior performance of the Lasso method in terms of both RMSE and FPR, highlighting its effectiveness in regularization and estimation.

4 Estimated Autoregressive Coefficient Matrix

In this section, we start to present our empirical analysis. We first present the empirical estimate of auto correlation matrix in equation 2. We then examine the implications of inflation persistence through three broad channels discussed in the introduction: sector spillovers, sector heterogeneity, and common factors in section [x], [x] and [x], respectively, then we account for the covid inflation in section [x]

Figure 1 presents the estimated values of autoregressive coefficient matrix $\widehat{\mathbf{A}}_1$ using a heat map, where an element , $\widehat{a}_{ij}$, represents the estimated influence of the lagged inflation in column sector j on the row sector i's current inflation. Positive and negative effects are represented by the red and blue cells and white cells for no impact.

There are a few noteworthy discoveries. First, 75 of the 256 total elements are non-zero (about 30 percent), and most non-zero estimates are positive. The Lasso method has reduced certain parameters for estimation, thus making the model more parsimonious and offering a conservative estimate of the spillover. Despite the conservative estimate of the non-zero elements, none of the sectors is isolated. Looking at each row, all sectors' inflation is associated with at least 2 additional sectors. This indicates many important cross-sector relationships.

Secondly, the diagonal elements capture the impact of each sector's inflation in the previous period on its own inflation in the current period. Our estimation suggests that all diagonal elements in $\widehat{\mathbf{A}}_1$ are positive, but the values vary across sectors. This is consistent with the previous literature that finds substantial heterogeneity in sectoral inflation persistence (Altissimo et al., 2009). A high value of the diagonal elements will result in persistent sectoral inflation; however, it should be noted that the diagonal elements do not fully capture sectoral inflation persistence due to the spillover effects across sectors. To ease the comparison, we rank the sectors by the estimates of $\widehat{a}_{ii}$ from the largest to the smallest in

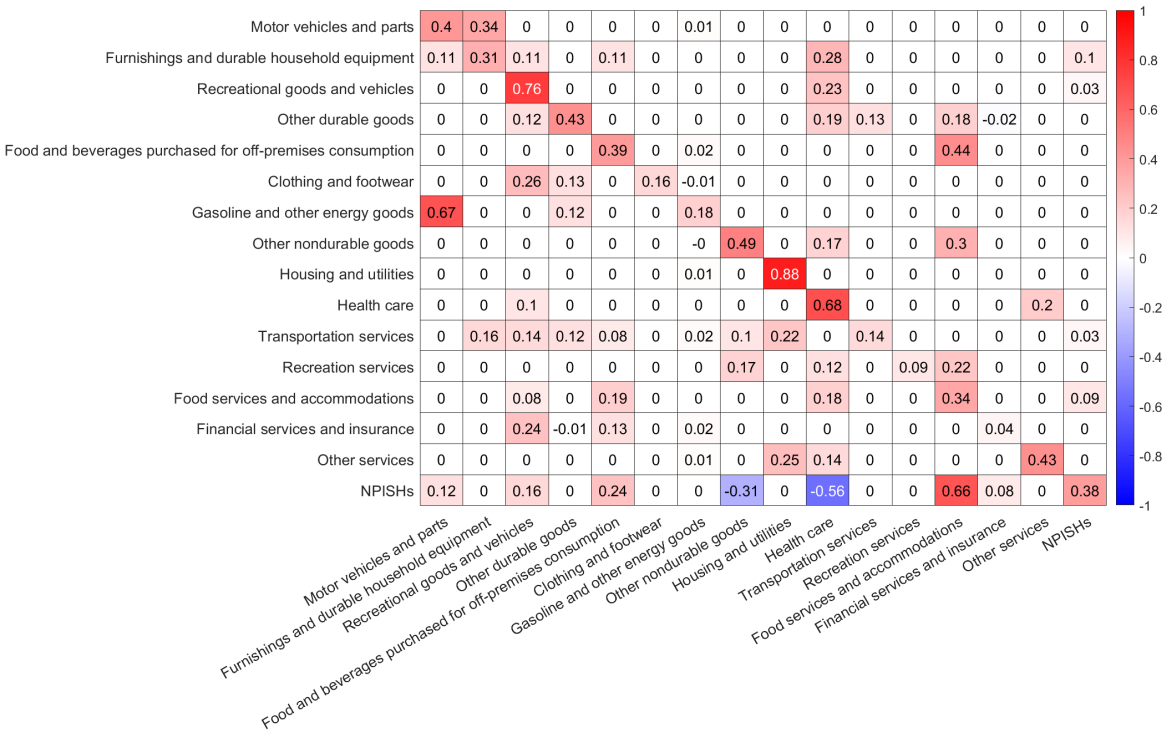


Figure 1: Autoregressive Matrix $\widehat{\mathbf{A}}_1$

Notes: The values of the elements of autoregressive matrix $\widehat{\mathbf{A}}_1$, i.e., $\widehat{a}_{ij}$, are represented by the different color cells. Positive and negative effects are represented by the red and blue cells and white cells for no impact. The color intensity of every cell shows the value of $\widehat{a}_{ij}$.

Table 2. It shows that the sectors with high values of $\widehat{a}_{ii}$ are "Housing and Utilities" (0.88), "Recreational Goods and Vehicles" (0.76), and "Health Care" (0.68), which tend to have high persistence in sectors' own inflation. By contrast, the "Financial Services and Insurance," "Clothing and Footwear," and "Transportation Services" sectors have low values of $\widehat{a}_{ii}$, which tend to have low persistence in their own inflation.

Third, most non-zero off-diagonal elements are positive, indicating a positive intersectoral spillover in sectoral inflation. For example, a positive price shock of "Motor Vehicles and Parts" (0.67 in the first column of Figure 1, perhaps due to demand shock) tends to increase the price of gasoline and other energy goods. A positive price shock in "Food Services and Accommodations" also leads to a hike in the price of "Food and Beverages Purchased for Off-Premises" in the next period.[7]

[7]We find that inflation shocks in health care and other nondurable goods have negative effects on the inflation of final consumption expenditures of nonprofit institutions serving households (NPISHs). This is perhaps due to the measurement of the final consumption expenditures of NPISHs. More specifically, NPISHs provide various social services, including health care, education, and social welfare to households. Final consumption expenditures by NPISHs is the portion of PCE that represents the services provided to

Table 2: Ranking of Sectoral Inflation Persistence

Sector	$\widehat{a}_{ii}$ (i = Sector)	Sector	$\widehat{a}_{ii}$ (i = Sector)
Housing and utilities	0.88	Final consumption expenditures of non-profit institutions serving households (NPISHs)	0.38
Recreational goods and vehicles	0.76	Food services and accommodations	0.34
Health care	0.68	Furnishings and durable household equipment	0.31
Other nondurable goods	0.49	Gasoline and other energy goods	0.18
Other services	0.43	Recreation services	0.16
Other durable goods	0.43	Transportation services	0.14
Motor vehicles and parts	0.40	Clothing and footwear	0.09
Food and beverages purchased for off-premises consumption	0.39	Financial services and insurance	0.04

Lastly, Table A2 in the Appendix lists the modulus of the eigenvalues of the autoregressive matrix, as some eigenvalues are complex numbers with small imaginary parts. The largest modulus of the eigenvalues is 0.91, higher than the autoregressive coefficient of the housing sector (0.88), indicating the persistence of impulse responses generated from the VAR system.

Comparison with production input-output matrix

We can highlight the results in $\widehat{\mathbf{A}}_1$ by comparing them with a more traditional measure, such as the inflation spillover implied by the production input-output matrix. This comparison is non-trivial since the focus here is consumer prices , whereas the production network primarily considers production prices and may omit certain service costs. Nevertheless, we attempt to construct a consumer price spillover matrix derived from the production input-output matrix, denoted as $\widehat{\mathbf{A}}_{IO}$. We make use of the information from, detailed commodity-by-commodity input-output table, PCE bridge table and Concordance table to create $\widehat{\mathbf{A}}_{IO}$. The resulting table is reported in Figure 2 and the detailed procedure for its construction is described in Appendix E.

Several key differences emerge from this comparison. First, as is well-documented in the production network literature, the input-output matrix is highly sparse, reflecting the fact that most products require only a limited range of other products as inputs. This sparsity translates into a similarly sparse $\widehat{\mathbf{A}}_{IO}$. Specifically, focusing on the off-diagonal elements, only 12% of the entries in $\widehat{\mathbf{A}}_{IO}$ are non-zero, which is relatively low compared to that about 25% in $\widehat{\mathbf{A}}_1$.

households by NPISHs without explicit charge, which is equal to their gross output (measured as operating costs) less their sales to households. Upon inflation shocks to health care and nondurable goods, the price of the service provided by NPISH to households may increase more than the operating cost of NPISHs as part of their service to households has no explicit charge. That's why the price of final consumption expenditures by NPISHs decreases. In other words, the price of the services that are provided to households by NPISHs without explicit charge decreases.

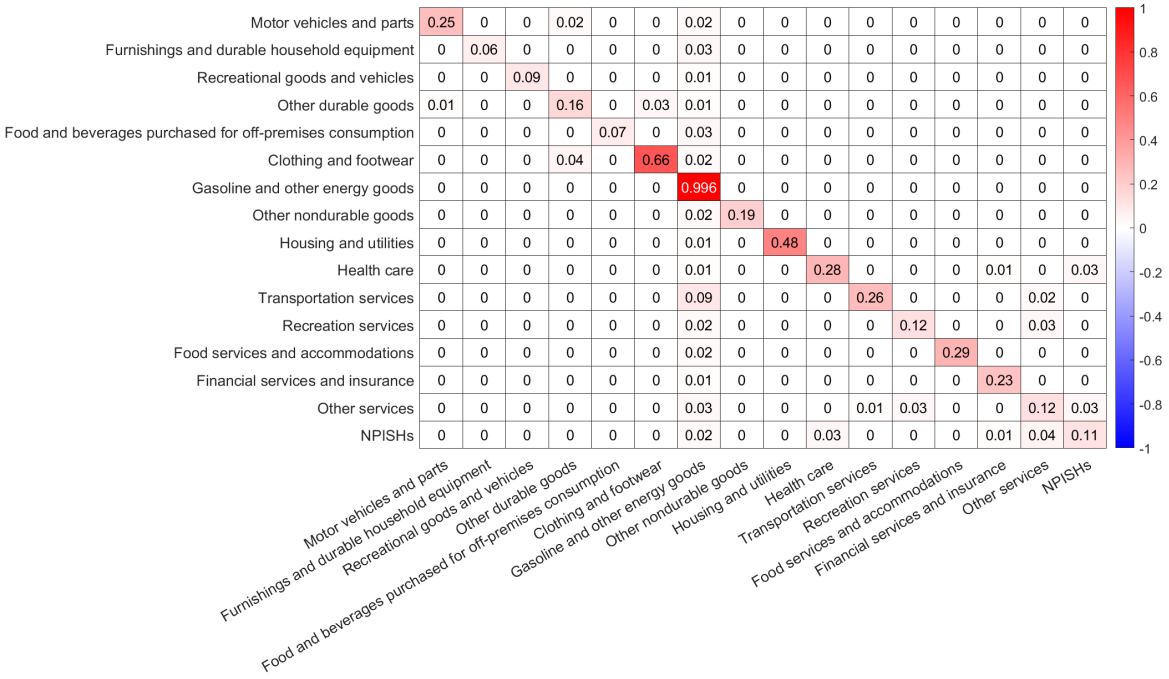


Figure 2: Production Input-Output Matrix $\widehat{\mathbf{A}}_{IO}$

Notes: The values of the elements of production input-output matrix $\widehat{\mathbf{A}}_{IO}$, i.e., $\widehat{a}_{IO,ij}$, are represented by the different color cells. Positive and negative effects are represented by the red and blue cells and white cells for no impact. The color intensity of every cell shows the value of $\widehat{a}_{IO,ij}$.

Second, we see that some of the spillover that $\widehat{\mathbf{A}}_1$ captures are missed out in $\widehat{\mathbf{A}}_{IO}$. For example, the "Health care" sector and "Food services and accommodations" sectors are almost like an island by itself in $\widehat{\mathbf{A}}_{IO}$. However, $\widehat{\mathbf{A}}_1$ reasonably captures a positive spillover from "Food services and accommodations" to "Food and beverages purchased for off-premises consumption", "Recreation services" and three more sectors. Similarly, "Health care" creates a spillover to eight sectors in total. These findings suggest that $\widehat{\mathbf{A}}_1$ captures broader spillover effects, likely reflecting increases in health care costs, which drive up employee compensation and thereby influence labor costs in production.

Third, the only column that $\widehat{\mathbf{A}}_{IO}$ exhibits a broader sectoral spillover than $\widehat{\mathbf{A}}_{IO}$ is the "gasoline and other energy goods" sector. As we will explain in detail in section [x], oil and energy price effects are incorporated as a common factor in Equation **??**. which equation? Therefore, the high spillover of the gasoline sector is present in $\widehat{\mathbf{A}}_{IO}$ but not $\widehat{\mathbf{A}}_1$.

In sum, the findings here indicatees $\widehat{\mathbf{A}}_1$ captures additional latent spillover relationships that go beyond the $\widehat{\mathbf{A}}_{IO}$.

5 Inflation Persistence Implication of Sectoral Spillover

In this subsection, we demonstrate that sectoral spillovers are a significant driver of inflation persistence. We analyze the implications of sectoral shocks on both sectoral and aggregate inflation persistence through the lens of sectoral spillovers. First, we present a directional network graph to provide an overview of the spillover dynamics. Next, we illustrate sectoral spillovers using four specific examples. Finally, we highlight the importance of sectoral spillovers across nearly all sectors and identify a few "VIP" sectors that play particularly critical roles.

To better illustrate the sectoral spillover, we present $\widehat{\mathbf{A}}_1$ using a directional network graph of sectoral inflation in Figure 3, based on the estimates of the autoregressive matrix. Each green circle represents the sector PCE basket weight. The thickness of the connection shows the value of $\widehat{a}_{ij}$ with diagonal elements $\widehat{a}_{ii}$ represented by a self-pointing curve. Positive and negative effects are represented by the red and blue curves. The arrow indicates the direction of cross-sector spillover. Sectors that have more connections are presented at the center of the figure.

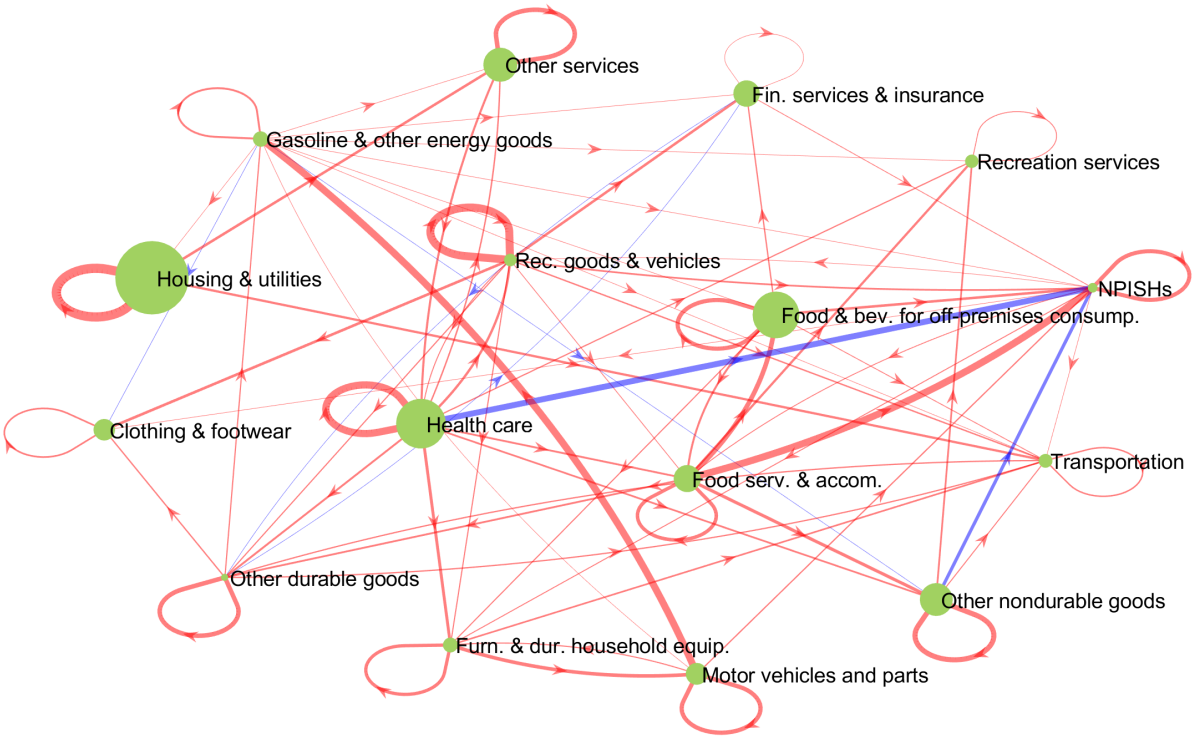


Figure 3: Network Graph of the Autoregressive Matrix $\widehat{\mathbf{A}}_1$

Notes: The value of $\widehat{a}_{ij}$ is shown by the thickness of the connection. Positive and negative effects are represented by the red and blue curves with the arrow. The weights of 16 sectors are represented by the size of the circle. The arrow indicates the direction of cross-sector spillover.

The network graph reveals two broad types of sectors that contribute more to inflation. The first type is sectors that are highly self-persistent and with a high consumption basket weight. The prime example is the "Housing and utilities" sector. The second type is some "hubs" sectors that are highly centered in the network, significantly influencing inflation in other parts of the economy via sectoral linkages. These hub sectors include Health Care, Recreational Goods and Vehicles, Food and Beverages Purchased for Off-premises Consumption, and Food Services and Accommodations.

When these hub sectors experience inflation shocks, the effects rapidly spread to many other parts of the economy through the web of cross-sectoral spillovers. This hub-like behavior suggests that inflation shocks originating in these key sectors can have outsized impacts on aggregate inflation dynamics. The amplification and propagation of inflationary pressures through these intersectoral linkages underscores the importance of accounting for the network-like structure of the economy when analyzing the drivers of sustained high inflation.

5.1 Impulse Responses to Four Selected Sectoral Shocks

To further examine these dynamics, we first study inflation impulse responses of four economically meaningful sectors: "Housing and Utilities," characterized by high own persistence and a high consumption basket weight; "Food Services and Accommodations," notable for high spillovers and a high consumption basket weight; "Health Care," distinguished by high own persistence, high spillovers, and a high consumption basket weight; and finally, "Recreational Goods and Vehicles," which exhibits high own persistence and high spillovers but a low consumption basket weight. The impulse responses of all sixteen sectors are reported in Appendix E.

Sectoral Impulse Responses to Four Selected Sectoral Shocks. We first present in Figure 4 the sectoral inflation impulse responses to a 1% sector shock from four distinct sectors. By definition, all of these figures have the shock sector's own sector inflation response by 1% on impact.

As shown in Panel (a) of Figure 4, the "Housing and Utilities" shock primarily has a significant and long-lasting effect on its own inflation, remarkably holding half the initial size a year and a half later. This high own-persistence allows the sector to directly transmit inflationary pressures to the aggregate level. Meanwhile, the housing sector's spillover effects, while limited initially, increase gradually over time. Notably, we observe a cascading effect (Acemoglu et al., 2012), as the housing shock first spills over to "Other Services" (including household maintenance, personal care, and education service, etc.) and then affects the key "Health Care" hub sector, further propagating the inflation pressures. The combination

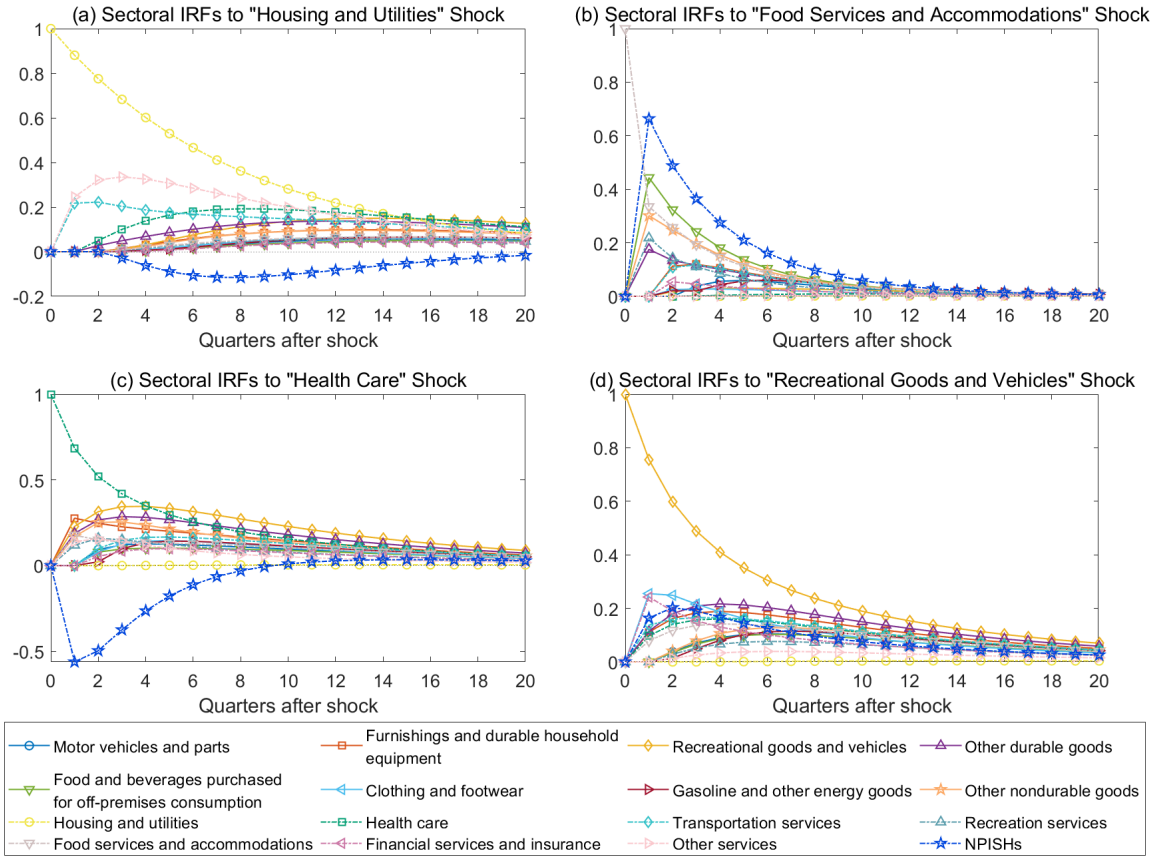


Figure 4: Sectoral Impulse Responses to Four Sectoral Shocks

of strong own persistence and growing spillovers underscores the housing sector's outsized influence on aggregate inflation.

In contrast, as depicted in Panel (b), the "Food Services and Accommodations" sector does not exhibit a strong own-sector response, with its 1% inflation shock dropping to 0.34% after one quarter. However, this sector's shock extends to other sectors, such as "Food services and accommodations" and "Food and Beverages Purchased for Off-premises Consumption", with responses even stronger than its own, indicating powerful spillover effects.

Panels (c) and Panel (d) show that the "Health Care" and "Recreational Goods and Vehicles" sectors play a pivotal "hub" role in the transmission of inflationary shocks. These sectors exhibit a high degree of own-persistence, as seen in their strong self-driven responses, but also widely spread their effects through intersectoral spillovers.

Specifically, the "Health Care" shock leads to spillover effects on seven other sectors in the first quarter, offsetting the negative initial reaction of "NPISHs", as shown in Panel (c). Interestingly, the initial shock to healthcare sectors dies out slowly. The rest of the spillover peaks around 4-5 quarters after the shock, leading to persistent inflation.

Similarly, Panel (d) shows that the "Recreational Goods and Vehicles" shock affects eight other sectors in the first quarter, including "Furnishings and Durable Household Equipment", "Health Care", and "Food Services and Accommodations". These spillovers then trigger further propagation, as sectors like "Motor Vehicles and Parts", "Food and Beverages Purchased for Off-premises Consumption", and "Recreation Services" exhibit subsequent positive responses. These findings underscore the pivotal role played by certain key sectors in amplifying and propagating inflationary shocks through the economy.

Aggregate Impulse Responses to Four Selected Sectoral Shocks. To quantify the implications of the relative importance of the two channels - sectoral self-persistence and spillover effects - on aggregate inflation dynamics, we employ the following decomposition of the aggregate inflation IRFs to a shock in sector i:

$$\underbrace{\mathbf{IRF}_{\pi}^{u_i}(h) = \mathbf{w}'\left(\mathbf{A}_1^h\right)_{\bullet i}}_{\textit{Aggregate IRF to the sector shock}} = \underbrace{w_i\left(\left(\mathbf{A}_1\right)_{ii}\right)^h}_{\textit{own persistence}} + \underbrace{\mathbf{w}'\left(\mathbf{A}_1^h\right)_{\bullet i} - w_i\left(\left(\mathbf{A}_1\right)_{ii}\right)^h}_{\textit{spillover-driven persistence}} \tag{9}$$

Figure 5 shows this decomposition for the 1% shocks in the four sectors discussed in Figure 4. The black lines indicate the aggregate inflation IRF to a 1% sector shock. The initial values of the IRF at $h = 0$ does not start at 1% because the origin sector inflation is now multiplied by the sector weight. The blue and red lines represent the breakdown of the aggregate IRF into own persistence and spillover-driven persistence, respectively. The decomposition here clearly quantifies the importance of spillover-driven inflation. The relative importance of the spillover effects increases as the horizon h expands.

For example, in the case of the "Housing and Utilities" sector, the own-persistence channel accounts for the majority of the impact on aggregate inflation during the initial quarters. Due to the high own-inflation autocorrelation (0.88), the inflation driven by own persistence lasts for an extended period. However, spillover effects gradually become more influential, rising to nearly half of the total effect by the sixth quarter. The IRF of the "Health Care" sector exhibits a similar dynamic, with spillover-driven persistence overtaking own persistence approximately two quarters after the shock. This is because the own-inflation autocorrelation is lower (0.68), and the spillover effects in health care are more pronounced.

The right panels of Figure 5 show that inflation associated with the "Food Services and Accommodations" and "Recreational Goods and Vehicles" sectors can exhibit significant persistence even when own persistence is low. In these IRFs, inflation due to own persistence (blue lines) becomes negligible after 2-3 quarters, but spillover-driven inflation quickly takes over, resulting in a hump-shaped inflation response and prolonged inflation persistence. The half-life of aggregate inflation is approximately 10 quarters following a "Food Services

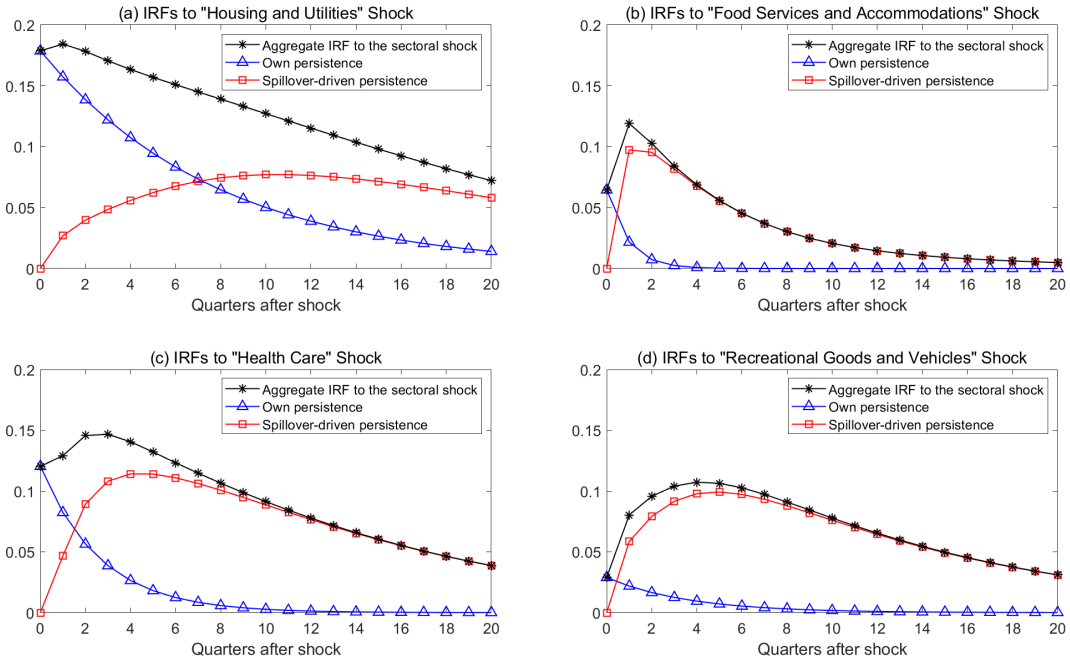


Figure 5: Decomposition of Impulse Responses to Four Sectoral Shocks

and Accommodations" shock and over 20 quarters for a "Recreational Goods and Vehicles" inflation shock.

5.2 Inflation Persistence Implication of Sectoral Shocks

We now summarize the message of Figure 5 but for each sector by computing the relative contribution of the sector's own inflation persistence and the spillover-driven persistence to the aggregate inflation IRF. Figure 6 presents aggregate inflation responses to 1% inflation shock to each sector and relative contributions of two channels for the short run (a one-period horizon) and the long run (the sum of infinite periods ahead). For the long-run case, it is equivalent to the area under the curve in Figure 5 as h approaches infinity. The numbers in the red bars indicate the contribution of the spillover-driven persistence to the total inflation.

In Panel (a) of Figure 6, we observe that for one period ahead, the spillover-driven persistence accounts for more than 50% of the aggregate inflation response in 6 out of the 16 sectors. The spillover-driven persistence becomes even more dominant in the long run, as shown in Panel (b). For 11 out of the 16 sectors, the spillover-driven persistence exceeds 50% of the aggregate inflation IRF. This highlights the critical role of cross-sector linkages in propagating and amplifying inflationary pressures in the long run.

Moreover, the x-axis of Figure 6 further illustrates the magnitude of the aggregate infla-

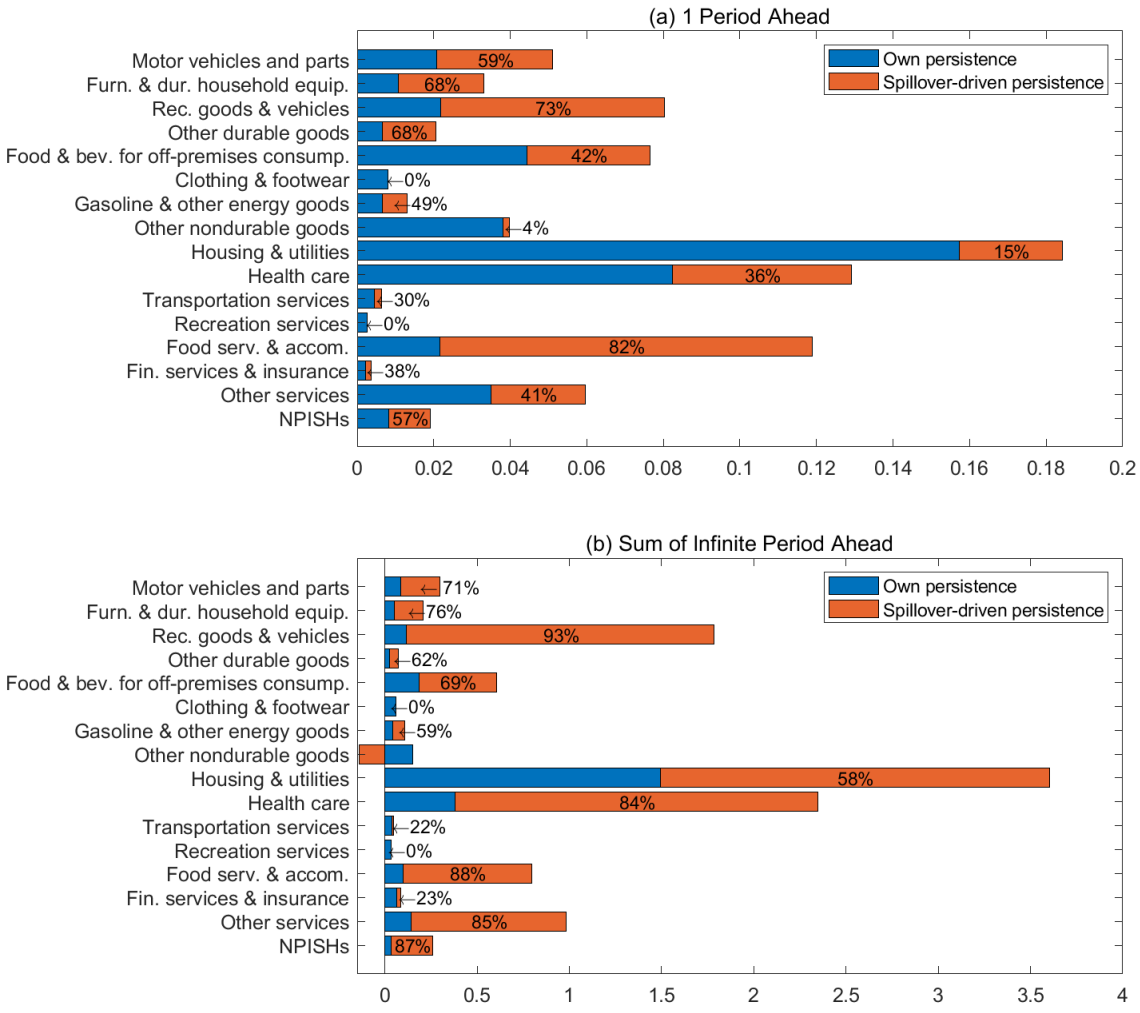


Figure 6: Decomposition of Aggregate Inflation Responses to Sectoral Shocks

Notes: (a) and (b) plot aggregate inflation responses to 1% inflation shock in each sector for the 1-period ahead and the sum of infinite period ahead, respectively, decomposed by the sector's own persistence and spillover-driven persistence. The percentages on the bars (or arrow sides) represent the share of spillover-driven persistence. For the summation of the infinite period ahead, we sum over from $h = 0$ to $h = 258$, consistent with our sample period.

tion responses to 1% inflation shock to each sector. For example, aggregate inflation rises by 18 and 13 basis points, respectively, one period after the shock to housing and health care. However, the cumulative long-run inflation effect of these two sectors is more substantial, reaching 3.6% for Housing and 2.3% for Health Care, and this is largely attributable to the spillover-driven persistence.

Panel (b) of Figure 6 clearly shows that some sectors, such as the Housing & Utilities sector, are systematically more important in contributing to inflation persistence and long-run inflation. . To further illustrate this point, we compute the sectoral contribution to the

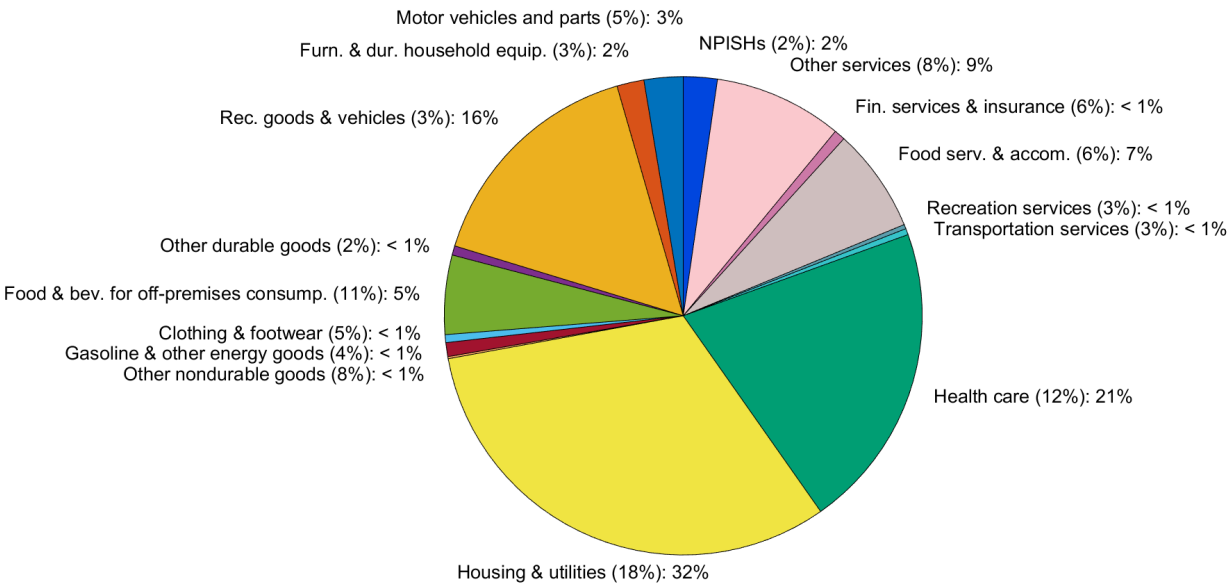


Figure 7: Sectoral Contribution to the Sum of the Infinite Period Ahead Aggregate Inflation IRFs to 1% Inflation Shocks in All Sectors

Notes: Percentages in parentheses indicate the basket weights of each sector and percentages after the colon indicate the contribution of each sector to the sum of the infinite period ahead aggregate inflation IRFs to 1% inflation shocks in all sectors.

cumulative sum of aggregate inflation IRFs in infinite horizons to a uniform of 1% inflation shocks in all sectors:

$$S_i = \frac{\sum_{h=0}^{\infty} \mathbf{IRF}_{\pi}^{u_i}(h)}{\sum_{i=1}^{N} \sum_{h=0}^{\infty} \mathbf{IRF}_{\pi}^{u_i}(h)}, \tag{10}$$

which is presented in Figure 7. It shows that the five important sectors, including housing, health care, recreational goods and vehicles, and food (including the sector of food services & accommodations and the sector of food & beverage purchased for off-premises consumption), contribute about 81% in total for aggregate inflation cumulative responses in infinite horizons. Notably, the contribution of those five sectors is much higher than their total weights in the PCE price index listed in Table 1, indicating the heterogeneity in the sector's own persistence and inter-sectoral spillovers may amplify the sectoral granularity, and shocks in those granular sectors could be particularly important for aggregate inflation. However, we should not interpret this result as inflation shocks in other sectors are trivial for aggregate inflation because this exercise assumes the same 1% inflation shock for each sector, while in reality, the sectoral inflation shocks are certainly heterogeneous.

Our discussion on the granular nature of sectoral shocks is closely related to the notion of "broad-based" supply shocks in Beaudry et al. (2024), where they argue that due to bounded rationality, households adjust their inflation expectations in response to broad-base supply

shocks that affect many sectors, and thus even though those shocks are temporary, they can have a persistent effect on aggregate inflation in a quasi-self-fulfilling way. Our study complements their theoretical predictions by providing empirical evidence that granular sector shocks, which affect many other sectors through spillover effects, have persistent effects on aggregate inflation.

6 Inflation Persistence Implication of Sectoral Heterogeneity

We now shift our focus to sectoral heterogeneity and its implications for aggregate inflation. Specifically, we examine how differences in sectoral basket weights and sector-specific inflation persistence contribute to overall inflation dynamics. While these aspects of sectoral heterogeneity present interesting economic insights, their implications for inflation persistence are largely overshadowed by the impact of sectoral spillovers.

Even in the absence of inter-sectoral spillovers, inflation can remain persistent if individual sectors exhibit high inflation persistence and if sectors with larger consumption basket weights are disproportionately affected by inflation shocks. As shown in Table 2, there is substantial variation in sector-specific inflation persistence, with diagonal elements a_{ii} of the A matrix ranging from 0.88 to 0.04. Importantly, when an inflation shock hits a highly persistent sector with a high basket weight, the effect on aggregate inflation persistence is amplified.

Figure 8 illustrates this relationship by plotting sectoral self-persistence coefficients (a_{ii}) against the consumption basket weights assigned by the BEA. The figure reveals a clear positive correlation, with a slope of about 3, indicating that sectors with higher persistence tend to have greater consumption basket weights.[8]

This positive relationship naturally leads to the concept of "systematically more important" sectors in driving inflation dynamics. For instance, a one percent inflation shock in the "Housing and Utilities" sector is expected to have a more persistent impact on aggregate inflation due to this sector's combination of the highest consumption weight (18%) and the highest self-persistence (0.88). In contrast, a one percent inflation shock to the "Financial Services and Insurance" sector is less concerning for aggregate inflation dynamics. This sector not only has a low self-persistence (0.04) but also constitutes a smaller portion (approximately 6%) of the overall consumption basket.

[8]Note that when we estimate the FAVAR model in equation 1, consumption basket weight is not explicitly provided to the model so there is no mechanical relationship between the self-persistence and consumption basket weight.

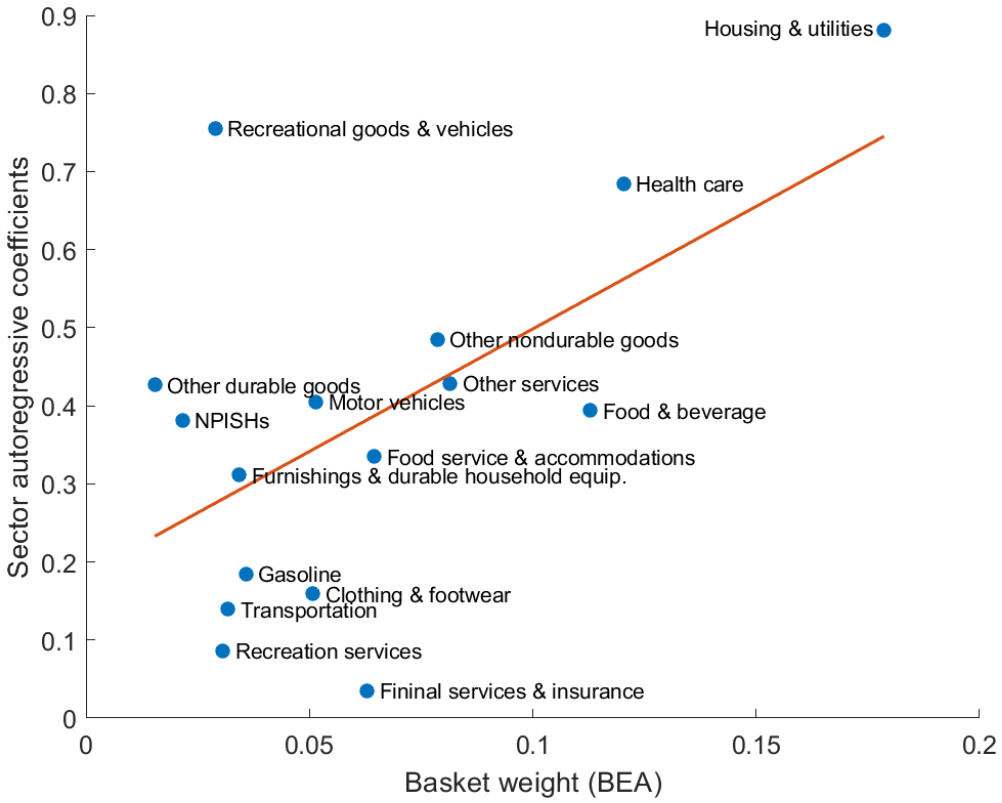


Figure 8: Relationship between self-persistence and consumption basket weight

We now demonstrate the relative contributions of sectoral heterogeneity and spillovers to aggregate inflation persistence, showing that sectoral spillovers are the dominant driver. To do so, we compute three hypothetical impulse responses of aggregate inflation to uniform 1% inflation shocks across all sectors. In the first scenario, we remove both sectoral spillovers and heterogeneity by setting the off-diagonal entries of the estimated matrix $\widehat{\mathbf{A}}_1$ to zero, using the average of the diagonal elements of the estimated autoregressive matrix, $\widehat{\mathbf{A}}_1$, and apply equal basket weights across all sectors to construct a counterfactual autoregressive coefficient scalar, denoted as $\widehat{a}_1^c$. This scenario is referred to as "homogeneous autoregressive without spillover." In the second scenario, we introduce heterogeneous sectoral self-persistence but remove spillovers and apply equal basket weights across all sectors, referred to as "equal weighted heterogeneous autoregressive without spillover." The third scenario isolates the effect of sectoral spillovers by setting the off-diagonal entries of $\widehat{\mathbf{A}}_1$ to zero while keeping both self-persistence and consumption basket heterogeneity, denoted as $\widehat{\mathbf{A}}_1^c$ and labeled "heterogeneous autoregressive without spillover."

We incorporate these three counterfactual matrices into Equation (7) to derive the corresponding impulse responses to a 1% uniform sector shock. The results, shown in Figure **??**, are presented alongside the baseline impulse response function (IRF) using the empirically

estimated autoregressive matrix.

The figure highlights the step-by-step increase in inflation persistence due to sector heterogeneity. In the first scenario, where both spillovers and heterogeneity are eliminated, aggregate inflation rises by 1% but rapidly decays to 0.38% by the end of the first quarter, with a half-life of less than one quarter. The shock dissipates almost entirely by the end of the first year.

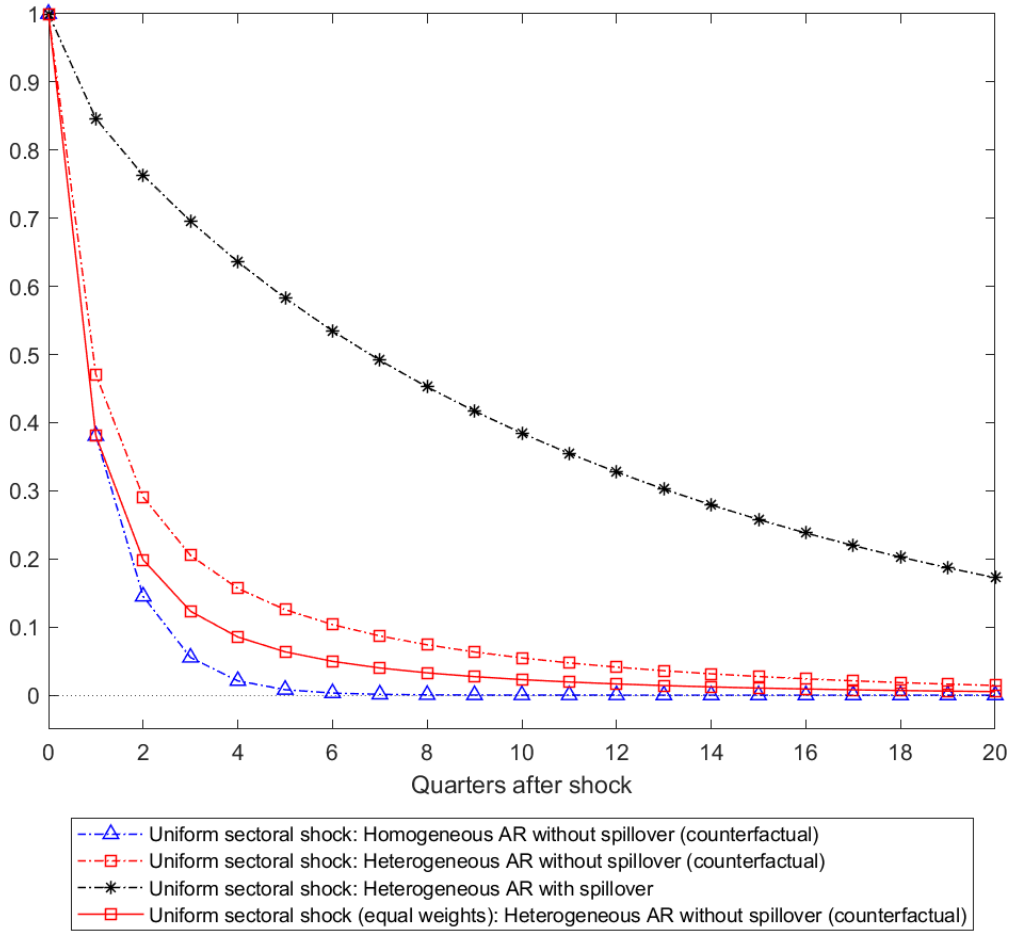


Figure 9: Aggregate Impulse Responses to Uniform Sectoral Shocks

In the second scenario, where heterogeneous sector self-persistence is introduced but basket weights remain equal, the IRF shifts marginally. The initial 1% rise still declines to 0.38% by the end of the first quarter, but the persistence increases slightly due to the presence of more persistent sectors. The decay of inflation slows down, extending the tail of the IRF.

In the third scenario, where both sectoral heterogeneity in self-persistence and consumption basket weight are introduced, inflation persistence rises further. The half-life of the

shock extends to approximately one quarter, and the IRF shows a slightly fatter tail. This amplification is a direct consequence of the positive relationship between basket weight and persistence, as illustrated in Figure 8.

However, none of these heterogeneity effects compare to the persistence generated by sectoral spillovers, as discussed in the previous section. The baseline IRF, shown by the black line, exhibits significantly greater and more prolonged inflation persistence. Inflation drops only to 0.85% in the first quarter following the shocks and remains above 0.5% until the seventh quarter. Furthermore, the long-term impact is substantial, with inflation still elevated at 17 basis points even five years after the initial shock.

These results underscore the pivotal role of sectoral spillovers in sustaining and amplifying inflationary pressures within the economy. Policymakers must carefully consider the potential for spillovers when formulating inflation-targeting strategies. A deeper understanding of these intersectoral dynamics can lead to more effective interventions, helping to mitigate the risk of persistent inflation.

Sectoral Heterogeneity and Relative Contribution of Sector Inflation. How does sector heterogeneity change the relative importance of sectors? Figure 7 makes the case that the top 5 sectors account for 80% aggregate inflation. In the simplest case when there are no sector spillovers and no sector heterogeneity in self-persistence and basket weight, each of the sixteen sectors will contribute equally 6.25% to the inflation and its persistence. To understand the role of sector heterogeneity in changing the relative importance of sectors. We consider in Table 3 two intermediate cases between Figure 7 and the simplest case.

The table reports the relative contribution of the top 5 sectors and the Herfindahl - Hirschman Index (HHI) to the infinite sum of inflation. In the simplest case, the top five sectors would account for 31.25% and the HHI is 5.8%. We then consider the intermediate case with equal basket weight and no sector spillover. In this case, each sector's basket weight is 6.25% and the uneven contribution is coming from different sectors' persistence. We can see that most of the sectors contribute to total inflation roughly in the range of 6%. There are three sectors that stand out, "Housing and utilities", "Rec. goods and vehicles" and "Health care" because they have relatively more persistent inflation. Their contribution to the total inflation is 24%, 12%, and 9%, respectively. In this case, we observe the top five sectors account for 58% of the total inflation and have an HHI of 10.5%. This indicates heterogeneous persistence increases the inflation contribution of some sectors and increases the inflation share concentration.

In the second intermediate case, which is reported in the third column, we consider equal basket weight but with sector spillover. We can compare column 2 with column 3 to see the importance of the spillover effect. With the sector spillover considered, there are notable

increases in contribution for the high spillover sector, such as "Health care" from 9% to 21% and "Rec. goods and vehicles" from 12% to 19%. At the same time, we observe that the top five sectors account for a high 79% of the total inflation and a HHI of 15.7%.

When we compare column 3 with column 4, which is the full case in Figure 7, we can see the change in the contribution of equal basket weights to BEA basket weights in the presence of spillover. Some sectors most notably "Housing and utilities" sector, are becoming more important because of the basket weight gain. The top 5 share and HHI further increase to 85% and 18.7%.

In summary, our findings highlight that sectoral heterogeneity plays a meaningful role in drawing greater attention to certain systematically important sectors. While these contributions are important, the spillover effects we emphasized in the previous section emerge as a more significant driver, amplifying the overall impact across sectors.

Table 3: Relative sector contribution measured by top 5 share and Herfindahl - Hirschman Index

	Simple case (1)	Equal basket weight and no sector spillover (2)	Equal basket weight with sector spillover (3)	Full case (4)
Top 5 sectors		Housing & Utilities 24% (6.25%) Rec. goods & vehicles 12% (6.25%) Health Care 9% (6.25%) Other durable goods 8% (6.25%) Food & bev. 5% (6.25%)	Housing & Utilities 23% (6.25%) Health care 21% (6.25%) Rec. goods & vehicles 19% (6.25%) Other services 8% (6.25%) Food serv. & accom. 8% (6.25%)	Housing & Utilities 32% (18%) Health care 21% (12%) Rec. goods & vehicles 16% (3%) Other services 9% (8) Food serv. & accom. 7% (6%)
Top 5 share	31.25%	58%	79%	85%
HHI	5.8%	10.5%	15.7%	18.7%

Notes: HHI stands for Herfindahl - Hirschman Index. Percentage written in parenthesis is the assigned consumption basket share. The simple case refers to the case where all heterogeneity is assumed away. The full case allows for sector spillover, heterogenous sector persistence and consumption basket weight.

7 Inflation Persistence Implication of Common Factors

In this subsection, we analyze the implications of common factors. We show that the common factor is very similar to oil price changes. We then show that the common factor is very transitory, supporting the idea of employing a static factor model. Most importantly, we illustrate common factor shock implies a fairly transitory inflation.

7.1 Common Factors and Crude Oil Price Changes

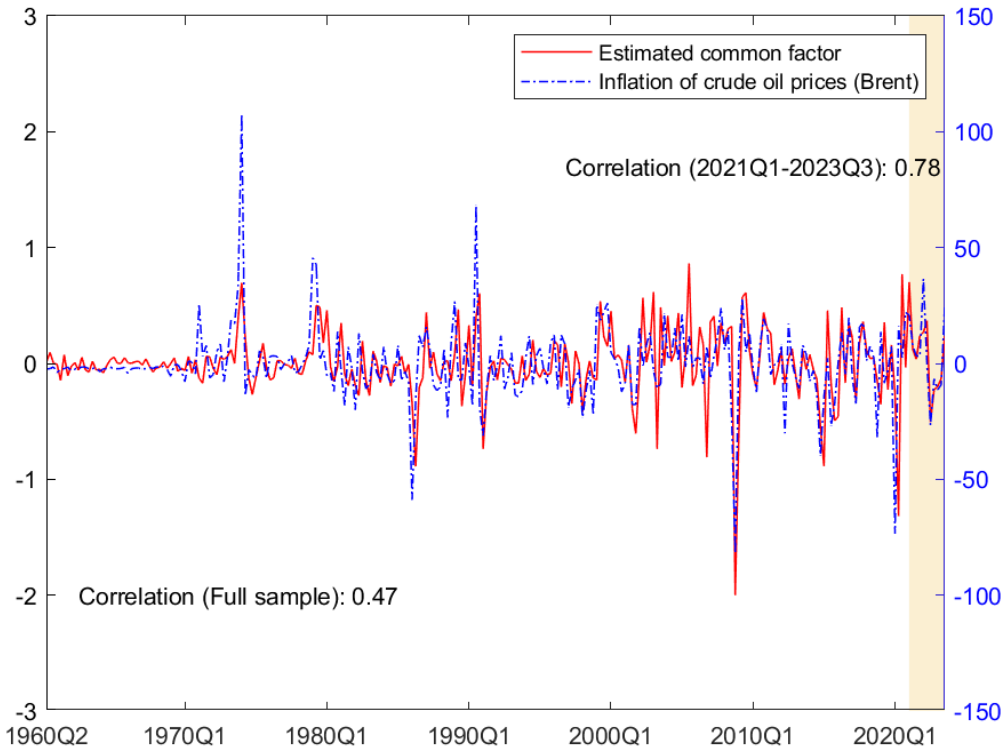


Figure 10: Common Factors and Inflation of Crude Oil Prices (Brent)

Notes: Inflation of crude oil prices (Brent) is demeaned because data is normalized by demeaning when estimating common factors through our model.

Based on BIC information criteria, our model strongly suggests the use of a one-factor model. Our model identifies the common factor that exhibits a strong correlation with changes in crude oil prices, as depicted in Figure 10. The time series of the estimated common factor and Brent crude oil price changes show a correlation of 0.47 over the whole sample from 1960Q2 to 2023Q3. This correlation is notably higher during periods of high inflation, reaching 0.54 during the Great Inflation era (from 1970Q1 to 1985Q4) and 0.78 during the COVID-19 pandemic (from 2021Q1 to 2023Q3). Hence, it is likely that the

estimated common factor predominantly captures movements in oil price changes.[9] Crude oil price shocks not only affect production costs, but also affect household and firm expectations of future inflation, and thus have effects on aggregate inflation (Coibion and Gorodnichenko, 2015; Känzig, 2021). Our finding is also in line with Gagliardone and Gertler (2023), which shows that the oil price shock, in addition to monetary policy easing, played an important role in the post-COVID inflation surge before 2023.

7.2 Persistence in the Common Factor

As in Miao et al. (2023) and Foerster et al. (2011), we employ a static factor model. To support the idea of using a static model to capture the common factor, we estimate the persistence in the common factor, with an AR(1) model, i.e., $f_t = \rho f_{t-1} + \epsilon_{f,t}$, where $\epsilon_{f,t}$ denotes the common shocks. The estimation yields AR(1) coefficient $\rho = 0.025$, which is economically and statistically insignificant.[10] Zero lag is also the optimal lag chosen by the BIC, reported in Appendix [x]. This implies that the common factor itself tends to be transitory, and thus the persistence in the common factor itself could not account for the persistence in the post-COVID inflation hike. However, it's important to note that a temporary common shock impacting all sectors, albeit with varying exposures, can potentially exert a persistent influence on aggregate inflation through inter-sectoral propagation.

7.3 Aggregate Impulse Responses to Common Shock

After discussing the empirical characteristics of the common shock, we now turn our attention to analyzing its implications for inflation persistence. In this context, the black line in Figure 11 illustrates the aggregate inflation impulse response following a 1% common shock. The IRF suggests that the inflationary response to this shock is relatively short-lived, showing a fairly transitory pattern. Specifically, the half-life of the shock is approximately 0.75 quarters and after 10 quarters, inflation is reduced to only about one-tenth of the initial shock size. However, it is important to note that while the initial effect of the shock wanes over time, its longer-term effects are still apparent. This is demonstrated by the impulse response of aggregate inflation, which, five years after the initial shock, remains elevated by 5 basis points, indicating that the influence of common shocks endures, albeit at a much lower level.

[9] This relationship is further supported by the observation that gasoline prices are highly responsive to the common factor, as evidenced by the high factor loading of gasoline sector. Additionally, this insight helps explain the previous surprising finding of the relatively low sectoral spillover from the gasoline sector, as oil price changes are primarily captured by the common factor, influencing all sectoral inflations with varying exposures.

[10] Note here we estimate the common factor first and then fit it with an AR(1) model. However, this two-step approach still delivers a consistent estimate of the autoregressive coefficient of the common factor.

To show how sectoral heterogeneity and inter-sectoral spillover in shaping the dynamic impact of common shocks on aggregate inflation persistence, we conduct two similar counterfactual exercises as in Section 6 and compute the corresponding hypothetical IRFs upon 1% increase in the common shock. The first experiment, labeled as "heterogeneous autoregressive without spillover", removes inter-sectoral spillovers by setting off-diagonal elements of the autoregressive matrix $\widehat{\mathbf{A}}_1$ to zero in computing the IRF. This experiment focuses on how sectoral heterogeneity alone affects inflation persistence after a common shock. While in the second experiment, labeled as "homogeneous autoregressive without spillover", both spillovers and heterogeneity in sectoral own persistence are eliminated by using an average scalar equal to the average of the diagonal elements of $\widehat{\mathbf{A}}_1$.

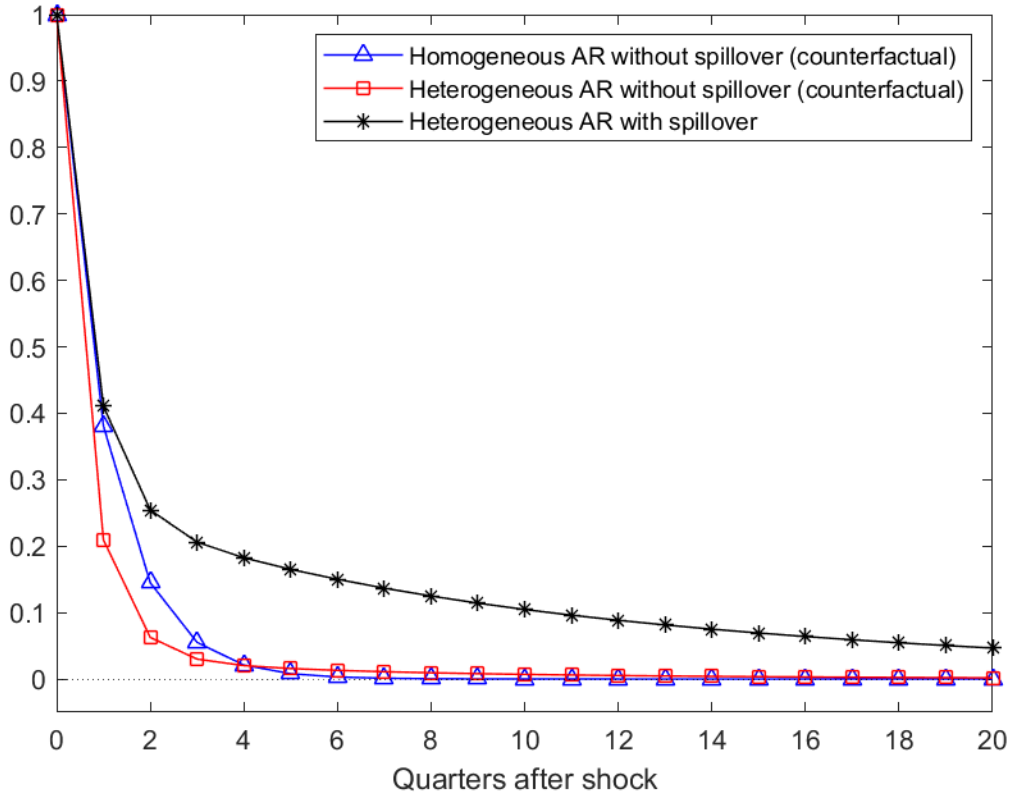


Figure 11: Aggregate Impulse Responses to Common Shock

Notes: Lines marked with upward-pointing triangles, squares, and asterisks represent the aggregate IRFs to 1% common shock from the counterfactual experience of homogeneous autoregressive coefficients without spillover, the counterfactual experience of heterogeneous autoregressive coefficients without spillover, and our general model, respectively.

Upon the 1% common shock, the two counterfactual IRFs exhibit very low persistence, and both decline quickly to zero within a year. This comparison highlights the importance of inter-sectoral spillover in making aggregate inflation more persistent upon common shocks. However, it also indicates that the role of sectoral heterogeneity in their own persistence is

very limited for the persistence of aggregate inflation.

It is important to note that the IRF of aggregate inflation is much more persistent upon 1% uniform sectoral shocks (half-life of 7 quarters) than the corresponding IRF upon the 1% common shock (half-life of 0.75 quarters) , by comparing the black lines with asterisks in Figure **??** and Figure 11. This is simply because the factor loadings for the common factor vary across sectors, with the highest value for the gasoline sector, which has very low sectoral persistence. Meanwhile, the factor loadings for many other sectors have relatively small values.

To better illustrate this, we quantify each sector's contribution to aggregate persistence upon common shocks, which helps to understand the significant roles different sectors play in aggregation inflation persistence.

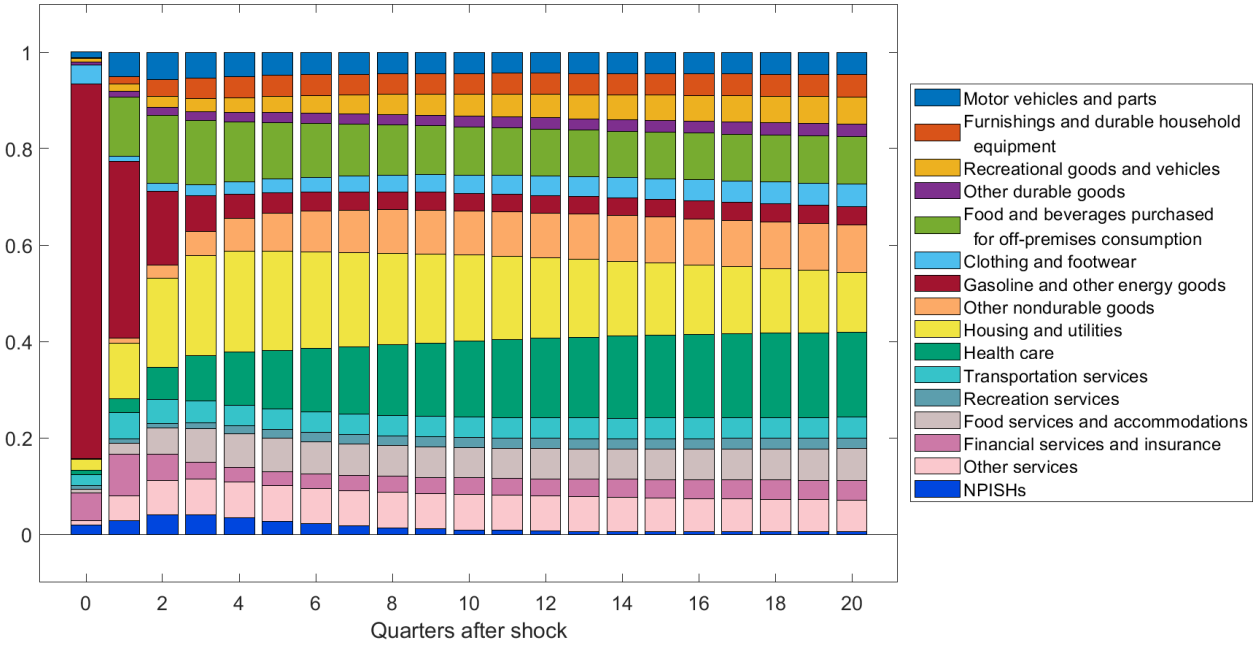


Figure 12: Sectoral Contribution to Aggregate Inflation Persistence

The sectoral contribution to aggregate inflation persistence can be calculated by the share of sectoral inflation IRF to common shock (multiplied by weights) in the aggregate IRF to common shocks at horizon h according to (8). Figure 12 shows the results of the percentage contribution of each sector to the aggregate inflation persistence for $h = 1, ..., 20$.

The sectoral contributions to the aggregate inflation persistence upon common shocks exhibit distinct temporal patterns. In the first 3 months after a common shock, the "Gasoline and Other Energy Goods" sector contributes the most, peaking at 77%, but this contribution sharply declines thereafter. The persistence of aggregate inflation is primarily driven by the "Housing and Utilities" sector, whose contribution remains steady at around 19% between

6 months and 3 years after the shock, ranking it as the top contributor during this period. However, after 3 years, the "Health Care" sector surpasses "Housing and Utilities" and becomes the leading contributor, with its contribution rate increasing over time and reaching 18% in the fifth year. Unlike the "Housing and Utilities" sector, which relies mainly on its own strong persistence, the "Health Care" sector's contribution to aggregate inflation persistence is also significantly driven by sectoral spillover effects.

7.4 Alternative approach to evaluating spillover

In previous sections, we conduct counterfactual experiments to evaluate the role of inter-sectoral spillover and sectoral heterogeneity in aggregate inflation persistence. An alternative approach is to estimate restrictive models without those features and compare the corresponding IRFs to sectoral and common shocks. More specifically, we estimate the following two restrictive models:

(a) Heterogeneous autoregressive coefficients without spillover:

$$\mathbf{Y}_t = \mathbf{A}_1 \mathbf{Y}_{t-1} + \mathbf{\Lambda} f_t + \mathbf{u}_t,\ t = 1, ..., T \tag{11}$$

where $\mathbf{A}_1$ is a diagonal matrix.

(b) Homogeneous autoregressive coefficients without spillover:

$$\mathbf{Y}_t = a_1 \mathbf{Y}_{t-1} + \mathbf{\Lambda} f_t + \mathbf{u}_t,\ t = 1, ..., T \tag{12}$$

where a_1 is a scalar.

Model (a) is designed to assess the impact of shutting down sectoral spillover while retaining sectoral persistence heterogeneity, whereas model (b) assumes homogeneous sectoral persistence with no spillover effects. For ease of comparison with our baseline model, we maintain consistency by setting the number of common factors to 1 when estimating these two restrictive models, aligning with the estimates of our general model.

After estimating these three models, we compute the impulse responses of aggregate inflation to 1% uniform sectoral shock and 1% common shock. The resulting impulse response functions are displayed in Figure 13, allowing for a direct comparison of how different modeling assumptions affect aggregate inflation dynamics.

Figure 13 presents a similar pattern in our previous counterfactual experiments for uniform sectoral shocks and common shocks in Figure **??** and Figure 11. First, our general

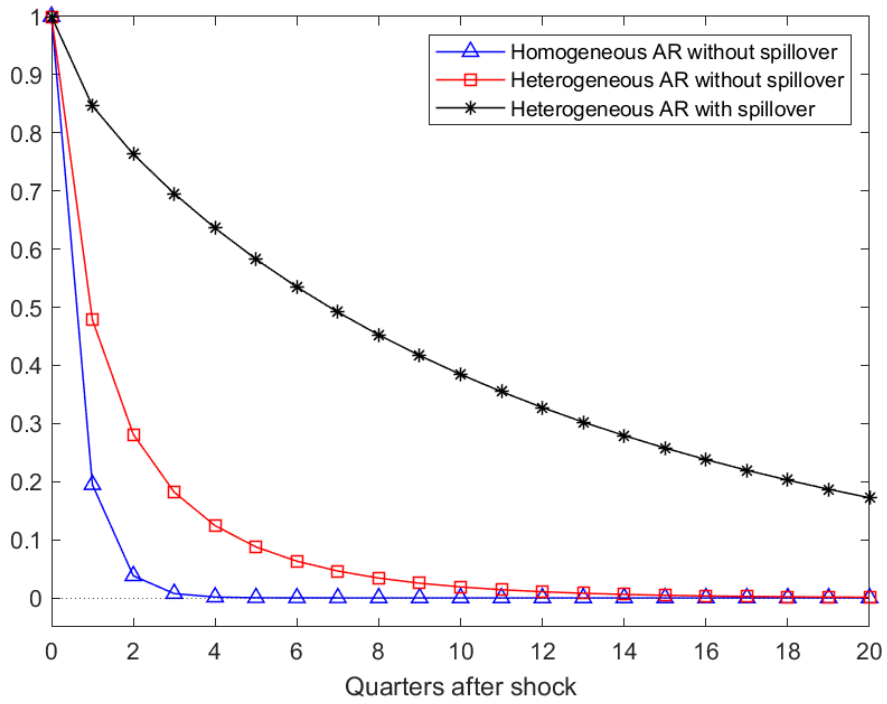
model, which incorporates inter-sectoral spillover effects, has higher persistence as a response to both uniform sectoral shocks and common shocks compared with the two restrictive models, particularly for sectoral shocks. Second, although both shocks are temporary, longer-term effects of both shocks remain evident, as indicated by the impulse response of aggregate inflation still standing at 18 and 5 basis points five years after the initial shock at sectoral or aggregate level, respectively.

By contrast, the performance of the two restrictive models falls short in adequately capturing the persistence of aggregate inflation. In the homogeneous autoregressive coefficients model without spillover, the impulse responses of aggregate inflation to two types of shocks nearly vanish within a year, with the IRFs quickly declining to zero. This outcome underscores the limitation of ignoring inter-sectoral spillover and sectoral heterogeneity.

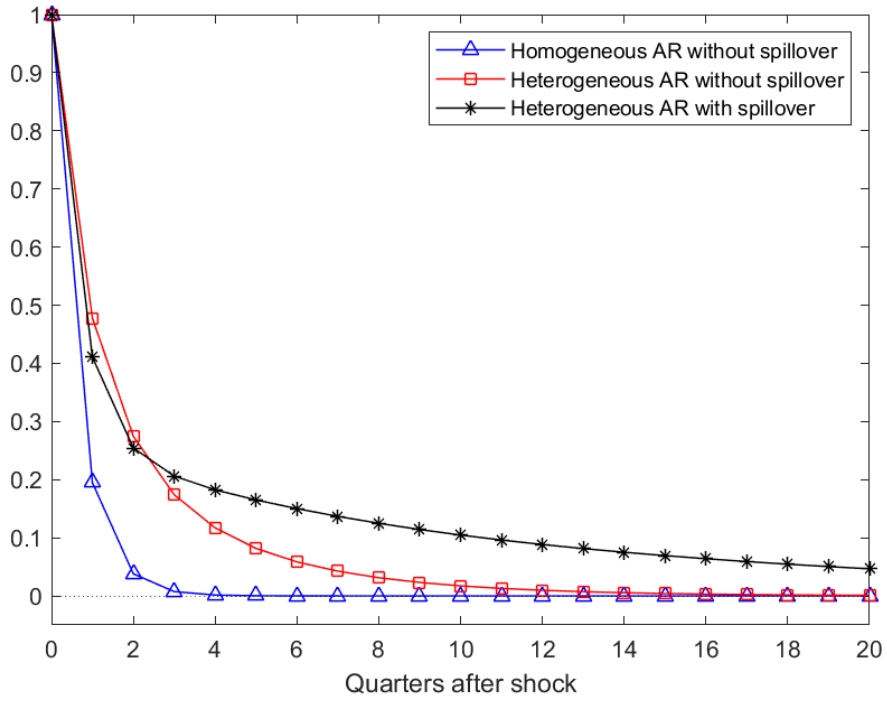
Similarly, in the model that only accounts for sectoral heterogeneity while ignoring inter-sectoral spillover, the IRF of aggregate inflation reduces to one-tenth the size of the initial shock approximately four quarters following a uniform sectoral or a common shock. Subsequently, the reduction in IRFs accelerates significantly, and the impact almost vanishes after three years. However, the model with heterogeneous autoregressive coefficients without spillover still demonstrates relatively more persistent IRFs than the homogeneous autoregressive coefficients model without spillover, indicating that sectoral heterogeneity in persistence still plays a role in increasing aggregate inflation persistence; however, its role is quite limited compared with the spillover.

8 Accounting for the Post-COVID-19 period inflation

Understanding the relative contributions of sectoral shocks and common shocks is crucial, as the analysis above highlights their significantly different implications for inflation. In this section, we explore how these shocks have influenced historical inflation. First, we examine the full sample starting from the 1960s. Then, we decompose aggregate inflation during the post-COVID-19 period. Our findings reveal that sectoral shocks have played a substantial role in the post-COVID-19 era, leading to higher and more persistent inflation due to their spillover effects.



(a) Aggregate Impulse Responses to Uniform Sectoral Shocks



(b) Aggregate Impulse Responses to Common Shock

Figure 13: Comparing with Two Restrictive Models

Notes: Lines marked with upward-pointing triangles, squares, and asterisks represent the aggregate IRFs to 1% uniform sectoral and common shock from the model of homogeneous autoregressive coefficients without spillover, the model of heterogeneous autoregressive coefficients without spillover, and our general model, respectively.

8.1 Decomposition of Aggregate Inflation

Using the moving average representation of a VAR model, the aggregate inflation can be decomposed into three parts:

$$\begin{aligned}\pi_t = \mathbf{w}'\mathbf{Y}_t &= \mathbf{w}' \sum_{s=0}^{\infty} (\mathbf{A}_1)^s \, \mathbf{\Lambda} f_{t-s} + \mathbf{w}' \sum_{s=0}^{\infty} (\mathbf{A}_1)^s \, \mathbf{u}_{t-s} \\ &= \mathbf{w}' (\mathbf{A}_1)^t \, \mathbf{Y}_0 + \underbrace{\mathbf{w}' \sum_{s=0}^{t-1} (\mathbf{A}_1)^s \, \mathbf{\Lambda} f_{t-s}}_{common\ shock\ component} + \underbrace{\mathbf{w}' \sum_{s=0}^{t-1} (\mathbf{A}_1)^s \, \mathbf{u}_{t-s}}_{sectoral\ shock\ component} . \end{aligned} \tag{13}$$

That is, a starting inflation, the past and current common shock component associated with the common factors and factor loading and the past and current sectoral shock component connected to the sectoral shocks, as shown in the following equation (13). In practice, as we have a finite sample, the calculation of decomposition terminates the iteration at the time index $t = 0$. The first term of (13), $\mathbf{w}' (\mathbf{A}_1)^t \, \mathbf{Y}_0$, are close to zero after 1970 because it decreases quickly as t increases.

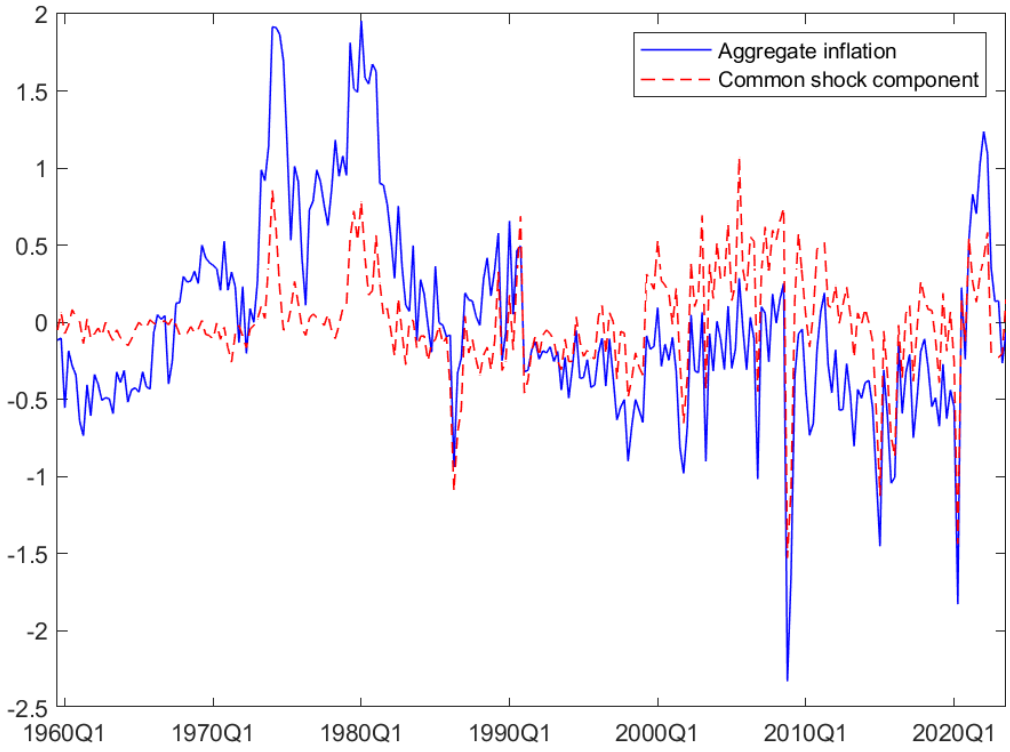


Figure 14: Aggregate Inflation and Common Shock Component

Notes: Aggregate inflation is demeaned because data is normalized by demeaning when estimating and calculating the common shock component through our model.

Figure 14 shows the aggregate inflation, π_t versus its common shock component— the second term of the right-most expression of (13). The aggregate inflation and common shock component have a relatively strong association (0.6 for 1970Q1-2023Q3), indicating the necessity of the inclusion of a common factor in the VAR model. Meanwhile, we find that aggregate inflation is noticeably more volatile than the common shock component, particularly during high inflation periods, including the Great Inflation period and the recent post-COVID inflation hike. This indicates the relative rise in the contribution of sectoral shock components to aggregate inflation.

8.2 Sources of Aggregate Inflation in Post-COVID-19 Period

By using the decomposition method above, we explore the sources of the post-COVID inflation hike. Figure 15 presents the breakdown of aggregate inflation into the sectoral (red bars) and common shock (blue bars) components in the post-COVID period from 2020Q1 to 2023Q3.

In the figure, we report the demeaned QoQ inflation. Initially, during 2020Q1 and 2020Q2, aggregate inflation experienced a significant decline, predominantly driven by common shocks. This period was marked by the outbreak of COVID-19, which led to widespread lockdowns and a severe reduction in economic activity globally. Additionally, the crude oil price slump during this time, induced by a combination of reduced demand from the pandemic and an oil price war between major producers, exacerbated the decline in inflation. For instance, crude oil prices fell dramatically, with West Texas Intermediate (WTI) futures even reaching negative territory in April 2020.

As the economy began to recover in 2020Q3, inflation saw a substantial rebound, with common shocks being the primary contributors, particularly in 2021Q1. There is a substantial rise in post-COVID-19 inflation from 2021Q2 to 2022Q2, where both common and sectoral shocks significantly influenced the inflation surge, with sectoral shocks becoming more prominent. On average, the sectoral shock component contributed about two-thirds of aggregate inflation during the peak inflation period (2021Q2 to 2022Q2), while the common shocks component accounts for about one-third.

Figure 16 further decomposes the sectoral shock component into the 16 distinct sectors and reveals that motor vehicles and parts, furnishings and durable household equipment, gasoline and other energy goods, and housing and utilities were among the most influential in driving inflation. The motor vehicles and parts sector particularly impacted inflation throughout the 2021Q2-2022Q2 due to severe production bottlenecks caused by the global semiconductor shortage and supply chain disruptions (Datta et al., 2022). Similarly, the

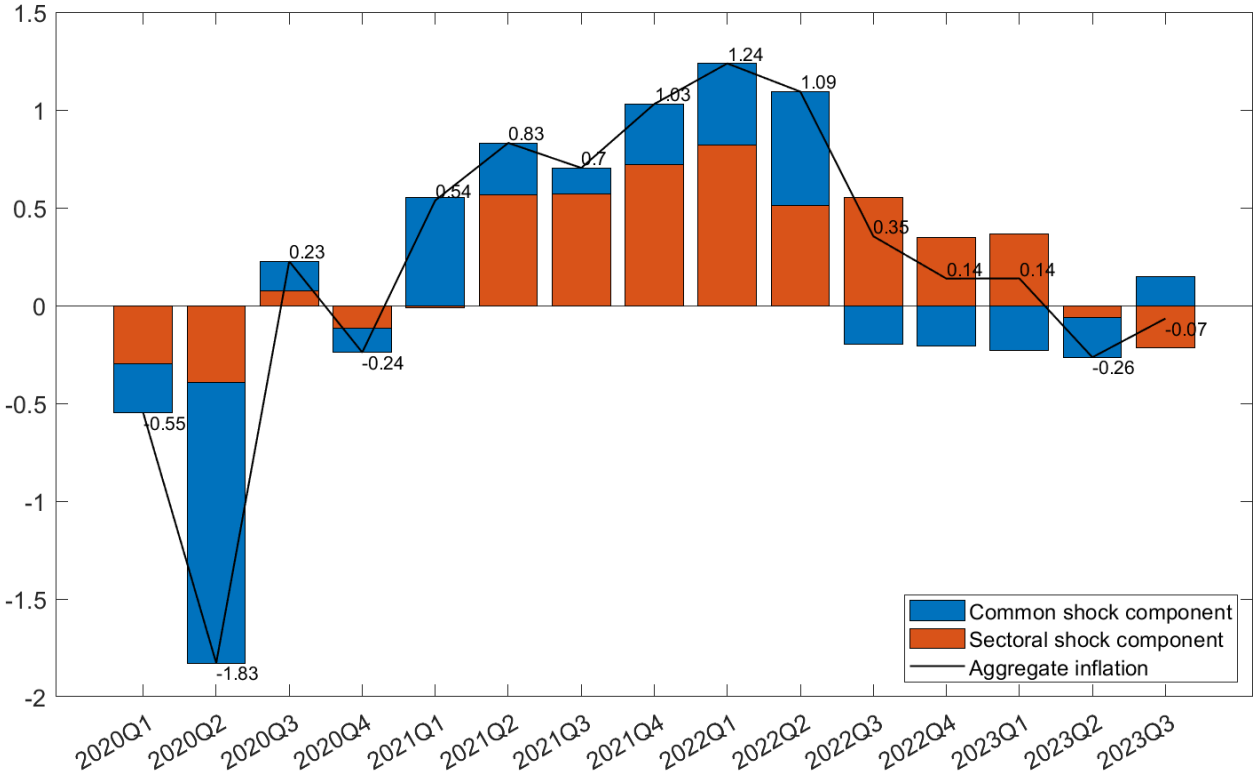


Figure 15: Decomposition of Aggregate Inflation: Post-COVID-19 Period

Notes: Aggregate inflation is demeaned because data is normalized by demeaning when estimating and calculating the common shock component and sectoral shock components through our model. The numbers on the dash-dotted line represent the demeaned aggregate inflation equal to the sum of the common shock component and sectoral shock component.

food and beverages purchased for off-premises consumption sector contributed steadily to inflation throughout the period, with marked price increases in early 2022 driven by the pandemic-induced shift toward more at-home dining and persistent supply chain challenges.

Energy prices, particularly gasoline, surged notably in the latter half of 2021 and early 2022 due to the outbreak of the Russia-Ukrane war and the recovery in travel and transportation demand combined with ongoing supply constraints (Kilian and Zhou, 2022). The furnishings and durable household equipment sector saw substantial price increases during the second half of 2021, driven by heightened consumer demand for home improvement and persistent supply chain issues. Additionally, rising housing costs and utility prices were particularly impactful during 2021Q4 and 2023Q1, as increased demand for housing and supply limitations drove significant price increases (Glaeser et al., 2021).

These sector-specific dynamics underscore the multifaceted nature of inflation during this period, influenced by a combination of supply chain disruptions, shifts in consumer demand, and broader economic recovery trends. Moreover, sectoral shocks spill over to other sectors

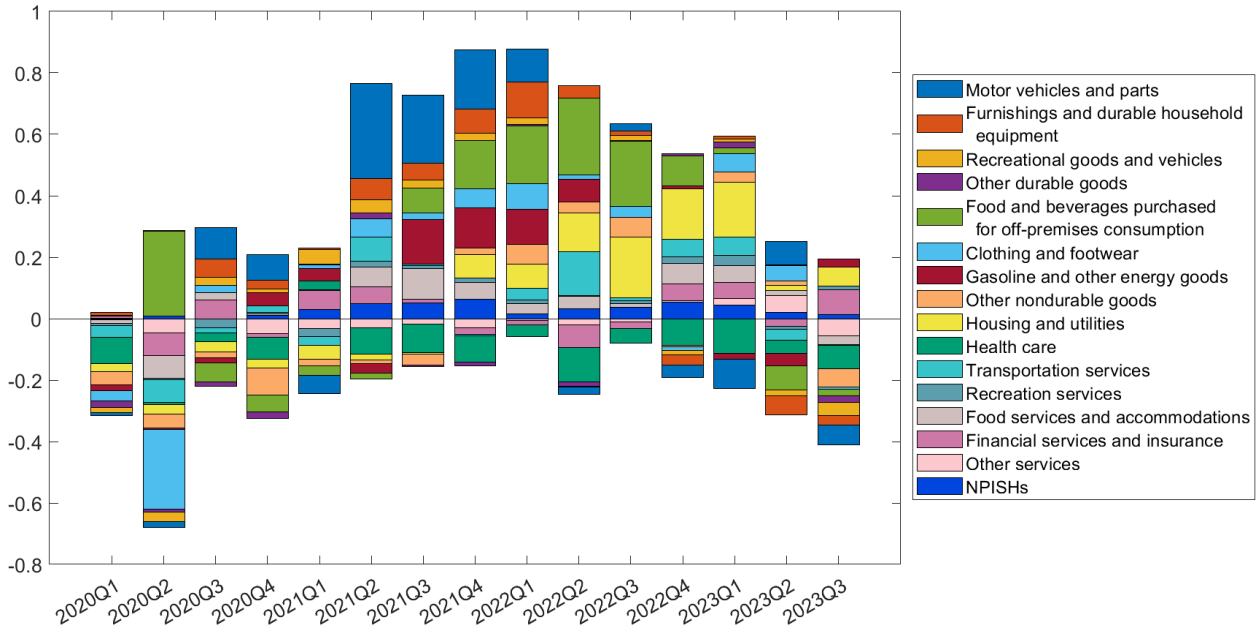


Figure 16: Decomposition of Sectoral Shock Component: Post-COVID-19 Period

through the spillover network, and thus, their effects do not simply average out.

Returning to Figure 15, we observe a gradual decline in aggregate inflation from 2022Q3 onwards, with a notable dip in 2023Q2. This decline can be primarily attributed to a reduction in common shocks, which aligns with the Federal Reserve's deliberate tightening of monetary policy to curb high and persistent inflation. Beginning in March 2022, the Fed implemented a series of interest rate hikes, raising the federal funds rate from near zero to over 5% by mid-2023, and also reduced its balance sheet through quantitative tightening.

Moreover, as we discussed above, a significant component of the common shocks is associated with crude oil prices, which have experienced a notable decline since the middle of 2022. This decline can be attributed to a combination of factors, including increased production from major oil-producing countries, a slowdown in global economic activity, and the effects of tighter monetary policy reducing overall demand. The reduction in crude oil prices lowered energy costs throughout the economy, reducing transportation and production costs across various sectors, thereby playing a pivotal role in tempering overall inflation rates.

Interestingly, while the common shock component experienced a significant decline, sectoral shocks remained relatively persistent, particularly in the food and housing sectors, which were still affected by ongoing supply chain disruptions, labor shortages, and other logistical challenges. This sectoral persistence prevented aggregate inflation from returning to its average level, highlighting the importance of sector-specific factors in driving aggregate

inflation dynamics.

In summary, this decomposition analysis of aggregate inflation underscores the dynamic interplay between common and sectoral shocks in driving inflation trends during the post-COVID period. Our study highlights the pivotal role of sectoral shocks in driving the peak inflation phase and their persistent nature, even as aggregate inflation subsequently declined due to the decrease in the common shock component. The findings suggest that policymakers should consider both aggregate and sector-specific factors when addressing inflationary pressures, as the persistence of sectoral shocks can hinder the effectiveness of monetary policy in stabilizing overall price levels.

8.3 Counterfactual Experiments

To quantify the impact of sectoral spillover and sectoral heterogeneity in persistence on aggregate inflation, we conduct two counterfactual experiments by simulating the hypothetical aggregate inflation under conditions where sectoral spillover or both sectoral spillover and sectoral heterogeneity are eliminated, while holding other parameters and shocks constant. Specifically, for the first experiment, we construct a counterfactual autoregressive coefficient matrix, denoted as $\widehat{\mathbf{A}}_1^c$ and labeled as "heterogeneous autoregressive without spillover", by setting the off-diagonal entries of the estimated matrix $\widehat{\mathbf{A}}_1$ to zero, thereby retaining only the original diagonal coefficients. This adjustment effectively disables the sectoral spillover channel, isolating its influence from the model. For the second experiment, we shut down both sectoral spillover and sectoral heterogeneity and use the average of the diagonal of the estimated matrix $\widehat{\mathbf{A}}_1$ to construct another counterfactual autoregressive coefficient scalar $\widehat{a}_1^c$, denoted as "homogeneous autoregressive without spillover". Utilizing the estimated shocks and factor loading ($\widehat{f}_t$, $\widehat{\mathbf{u}}_t$, and $\widehat{\mathbf{\Lambda}}$), along with the modified autoregressive matrix/scalar (matrix $\widehat{\mathbf{A}}_1^c$ or scalar $\widehat{a}_1^c$), we compute the two counterfactual time series data for aggregate inflation using the following formula:

$$\widehat{\pi}_t^{c1} = \mathbf{w}'\widehat{\mathbf{Y}}_t^{c1} = \mathbf{w}'\left(\widehat{\mathbf{A}}_1^c\right)^t \mathbf{Y}_0 + \mathbf{w}'\sum_{s=0}^{t-1}\left(\widehat{\mathbf{A}}_1^c\right)^s \widehat{\mathbf{\Lambda}}\widehat{f}_{t-s} + \mathbf{w}'\sum_{s=0}^{t-1}\left(\widehat{\mathbf{A}}_1^c\right)^s \widehat{\mathbf{u}}_{t-s}. \tag{14}$$

$$\widehat{\pi}_t^{c2} = \mathbf{w}'\widehat{\mathbf{Y}}_t^{c2} = \mathbf{w}'\left(\widehat{a}_1^c\right)^t \mathbf{Y}_0 + \mathbf{w}'\sum_{s=0}^{t-1}\left(\widehat{a}_1^c\right)^s \widehat{\mathbf{\Lambda}}\widehat{f}_{t-s} + \mathbf{w}'\sum_{s=0}^{t-1}\left(\widehat{a}_1^c\right)^s \widehat{\mathbf{u}}_{t-s}. \tag{15}$$

Figure 17 illustrates the comparison between actual aggregate inflation and two counterfactual counterparts for the whole sample period. It is important to note that sectoral spillovers tend to amplify both common and sectoral shocks during high inflation episodes, such as the Great Inflation of the 1970s and early 1980s, as well as the post-COVID inflation

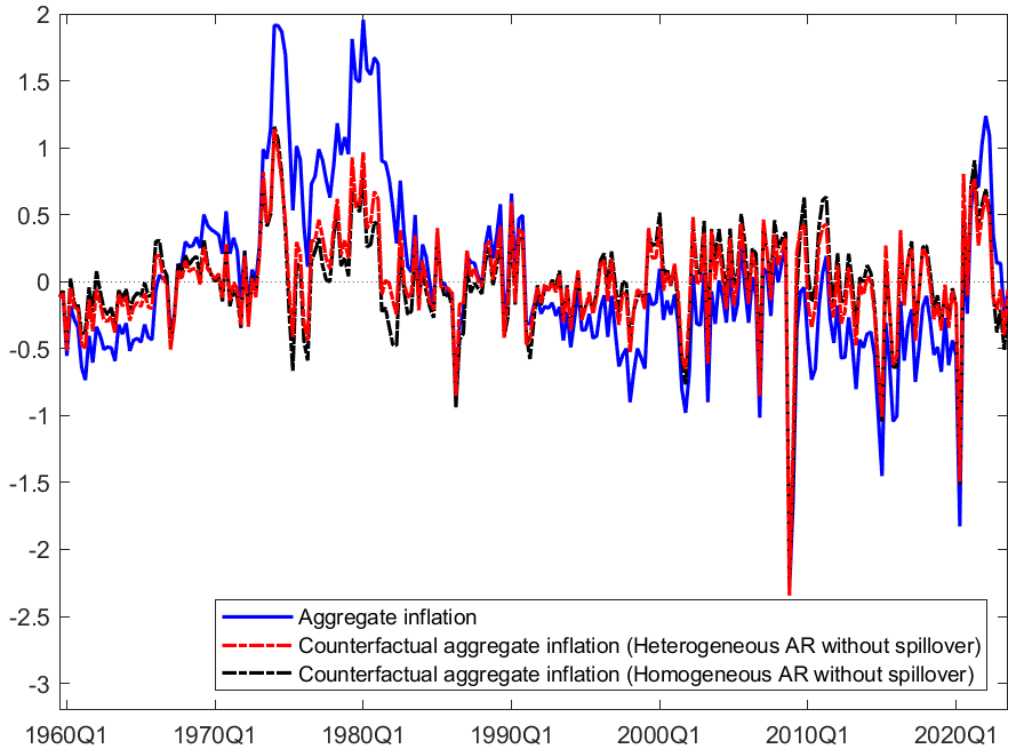


Figure 17: Aggregate Inflation with and without Spillover

Notes: Aggregate inflation and counterfactual aggregate inflation are demeaned because data is normalized by demeaning when estimating our model.

surge. Consequently, it is unsurprising that the two counterfactual inflation consistently underestimate the actual inflation rate during these periods. In contrast, the two counterfactual inflation rates closely approximate actual inflation levels observed during the low inflation period spanning from the late 1980s to 2020. Moreover, aggregate inflation patterns in the two counterfactuals are quite similar, indicating that sectoral heterogeneity contributes little to inflation persistence.

In Figure 18, we zoom in to highlight the role of sectoral spillovers and sectoral heterogeneity in persistence during two distinct high inflation episodes: the post-COVID period (2021Q1-2023Q3) and the Great Inflation period (1970Q1-1985Q4). Both subfigures demonstrate that eliminating sectoral spillovers would substantially dampen aggregate inflation during these periods, while sectoral heterogeneity does only slightly contribute.

Figure 18(a) examines recent inflation dynamics, illustrating that shutting down sectoral spillovers would have, on average, lowered quarterly aggregate inflation by 0.3 log points, representing a substantial 22% reduction during the period from 2021Q1 to 2023Q3, as shown in Table 4. The largest observed gap between counterfactual (heterogeneous autoregressive without spillover) and actual aggregate inflation was approximately 0.6 log points in 2022Q1

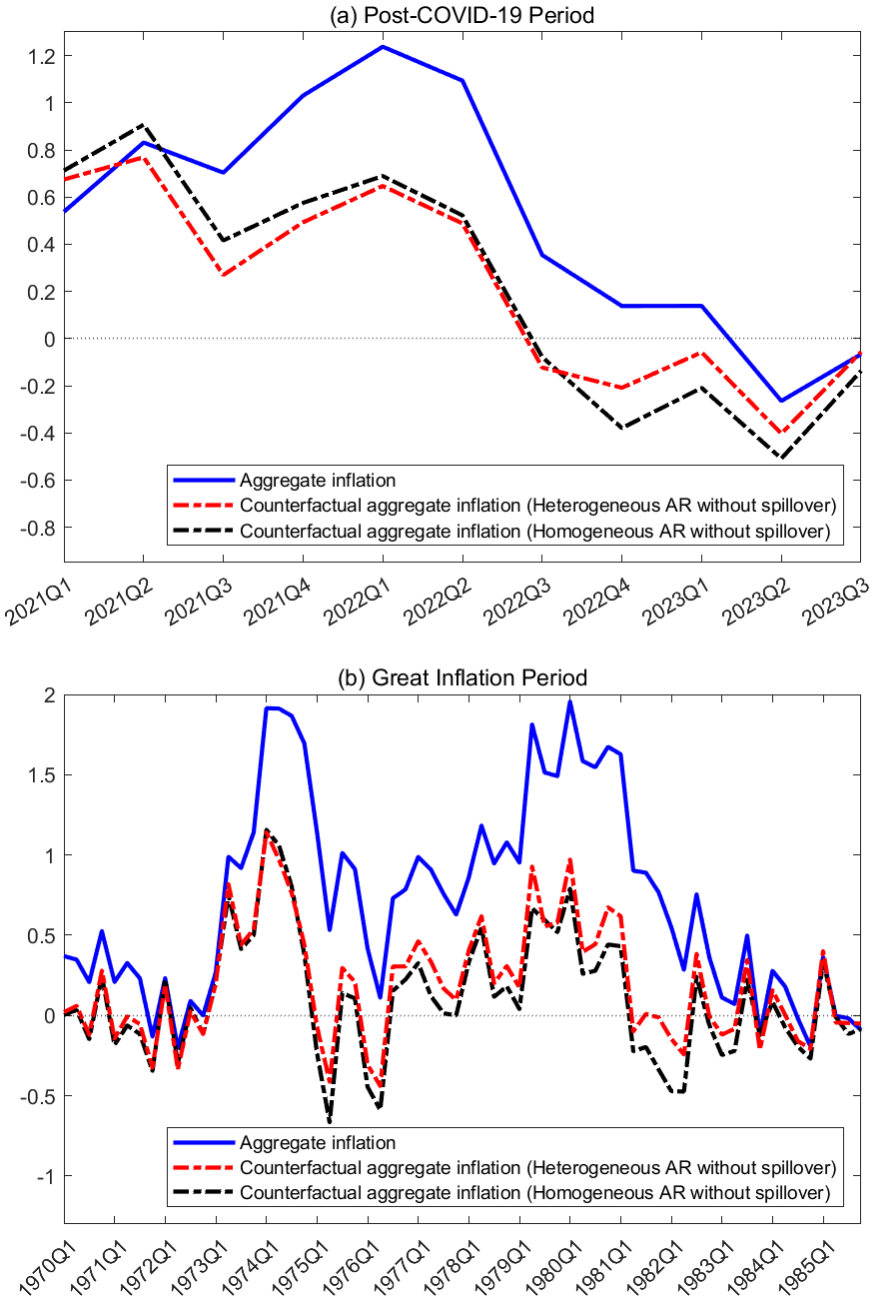


Figure 18: Aggregate Inflation and Two Counterfactual Predictions in Post-COVID-19 Period and Great Inflation Period

Notes: Aggregate inflation and counterfactual predictions are demeaned because data is normalized by demeaning when estimating the model.

and Q2, coinciding with the peak inflation rate. Moreover, shutting down sectoral spillovers, aggregate inflation would have reverted to the mean three quarters earlier, that is 2022Q3, instead of 2023Q2 as observed in the data, given the same shocks and parameters. This finding underscores the contribution of sectoral spillovers to the persistence of aggregate

inflation. By contrast, on average further eliminating the sectoral heterogeneity in persistence does not alter the counterfactual results substantially, as shown in Table 4, indicating that sectoral heterogeneity contributes little in the persistence of post-COVID inflation. Only after 2022Q2, further eliminating the sectoral heterogeneity in persistence could further lower aggregate inflation, compared with the counterfactual prediction without spillover effects only.

In Figure 18(b), focusing on the Great Inflation period, we observe that eliminating sectoral spillover effects would have reduced average quarterly aggregate inflation by 0.52 log points, equivalent to a notable 34% decline in the inflation rate, as shown in Table 4. Notably, the largest discrepancy between counterfactual prediction without spillover only and actual aggregate inflation, reaching 1.26 log points, occurred in 1974Q4. Meanwhile, aggregate inflation patterns in the two counterfactual predictions are largely similar, but the gap tends to be slightly larger between 1975 and 1983. As shown in Table 4, shutting down both the sectoral heterogeneity in persistence and spillover would have reduced the aggregate inflation by 40% on average during the Great Inflation period, indicating that sectoral heterogeneity may play a more important role than its role in post-COVID inflation.

In summary, this quantitative exercise underscores the critical role of sectoral spillover in amplifying and propagating temporary sectoral and common shocks, thereby enhancing the persistence of aggregate inflation during high inflation episodes.[11] By contrast, sectoral heterogeneity in persistence contributes little to post-COVID inflation but slightly more to the Great Inflation period.

Table 4: Average Reduction in Aggregate Inflation in Two Counterfactual Experiments

Counterfactual	Post-COVID period (2021Q1-2023Q3)	Great inflation period (1970Q1-1985Q4)
Heterogenous AR without spillover	-22.13%	-34.02%
Homogenous AR without spillover	-22.01%	-39.94%

Notes: The average reduction in aggregate quarterly inflation is calculated by dividing the mean difference between aggregate inflation and counterfactual inflation by the average aggregate inflation (without demean) for the given sample period.

[11]The counterfactual results are robust if we set the number of common factors equal to two, as shown in Appendix H.

9 Conclusion

In this paper, we demonstrate that inflation spillover across sectors highlights an important new aspect of inflation persistence. Inflation spillover across sectors is particularly important during high inflation periods. The empirical model we employed to capture inflation spillover is very flexible. The model can be broadly applied to various settings to study the persistence of other macro variables.

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Appendix

A Estimation Procedure

The estimation procedure. In our context, we have 256 ($= 16 \times 16$) slope coefficients in the VAR system. Our observation is a panel data of 16 time series with each of the length 257 time periods. We will need regularization to control the quality of estimation.

First-step estimator:

(a) Estimate preliminarily $\mathbf{B}$ and $\mathbf{\Psi}$ by running the following ℓ_1-nuclear-norm regularized regression:

$$\left(\widetilde{\mathbf{B}}, \widetilde{\mathbf{\Psi}}\right) = \underset{(\mathbf{B},\mathbf{\Psi})}{\operatorname{argmin}} \frac{1}{2NT} \|\mathbf{Y} - \mathbf{XB} - \mathbf{\Psi}\|_F^2 + \frac{\gamma_1}{N} |\operatorname{vec}(\mathbf{B})|_1 + \frac{\gamma_2}{\sqrt{NT}} \|\mathbf{\Psi}\|_*$$

where $\mathbf{\Psi} = \mathbf{F}\mathbf{\Lambda}^\top$, γ_1 and γ_2 are tuning parameters. This step gives us consistent estimation of the slope coefficients B when $\gamma_1, \gamma_2 \to 0$ asymptotically. This step will introduce non-trivial shrinkage bias, which produces non-standard distribution in the slope coefficient estimation. In other to estimate the factor and the factor loading, we must also determine the number of factors at the first place. That motivates the second step.

(b) Estimate the number of factors R by singular value thresholding as follows:

$$\widehat{R} = \sum_{i=1}^{\min(N,T)} \mathbb{I}\left\{\psi_i\left(\widetilde{\mathbf{\Psi}}\right) \geq \left(\gamma_2 \sqrt{NT} \left\|\widetilde{\mathbf{\Psi}}\right\|_2\right)^{1/2}\right\}$$

where $\psi_i\left(\widetilde{\mathbf{\Psi}}\right)$ are the singular values of $\widetilde{\mathbf{\Psi}}$.

(c) Let the singular value decomposition of $\widetilde{\mathbf{\Psi}}$ be $\widetilde{\mathbf{\Psi}} = \widetilde{\mathbf{U}}\widetilde{\mathbf{D}}\widetilde{\mathbf{V}}^\top$, where $\widetilde{\mathbf{D}} = \operatorname{diag}\left(\psi_1\left(\widetilde{\mathbf{\Psi}}\right), \ldots, \psi_{\min(N,T)}\left(\widetilde{\mathbf{\Psi}}\right)\right)$. Then obtain a preliminary estimate of $\mathbf{F}$:

$$\widetilde{\mathbf{F}} = \sqrt{T}\widetilde{\mathbf{U}}_{*,\left[\widehat{R}\right]}$$

The factors is estimated as the left-eigenvectors (standardized by $\sqrt{T}$).

Second-step estimator (Lasso): Since N is of high-dimension, when we estimate the slope coefficients we impose sparsity. Notice that we don't need penalize the factor loadings,

which is common in the literature of interactive fixed effect with a large N. For each $i \in N$, solve the Lasso problem:

$$\left(\dot{\mathbf{B}}_{*,i}^{\top}, \dot{\boldsymbol{\lambda}}_i^{\top}\right)^{\top} = \underset{\left(\mathbf{B}_{*,i}^{\top}, \boldsymbol{\lambda}_i^{\top}\right)^{\top}}{\operatorname{argmin}} \frac{1}{2T} \left\| \mathbf{Y}_{*,i} - \mathbf{X}\mathbf{B}_{*,i} - \widetilde{\mathbf{F}}\boldsymbol{\lambda}_i \right\|_F^2 + \gamma_3 \left|\mathbf{B}_{*,i}\right|_1$$

where γ_3 is tuning parameter. (We will need to define $\mathbf{Y}_{*,i}$ as the $(T-1) \times 1$ vector for each individual i.)

Notice the above optimization problem is for a single i (time-fixed effect must be handled prior to this step). There we focus on the consistency, instead of seeking efficiency by exploring the covariance structure of the errors. The equation-by-equation (for each i) estimation is consistent with no problem.

The purpose of the second step is to refresh a preliminary consistent so that in terms of econometrics we can establish selection consistency.

The second-step estimators of $\mathbf{B}$ and $\boldsymbol{\Lambda}$ are given by $\dot{\mathbf{B}} = \left(\dot{\mathbf{B}}_{*,1}, \cdots, \dot{\mathbf{B}}_{*,N}\right)$ and $\dot{\boldsymbol{\Lambda}} = \left(\dot{\lambda}_1, \cdots, \dot{\lambda}_N\right)^{\top}$.

Third-step estimator (Conservative Lasso):

(a) Set $\widehat{\mathbf{F}}^{(0)} = \widetilde{\mathbf{F}}$. For integer $\ell \geq 1$, update the estimates of $\mathbf{B}$ and $\boldsymbol{\Lambda}$ using:

$$\left(\widehat{\mathbf{B}}_{*,i}^{(\ell)\top}, \widehat{\boldsymbol{\lambda}}_i^{(\ell)\top}\right)^{\top} = \underset{\left(\mathbf{B}_{*,i}^{\top}, \boldsymbol{\lambda}_i^{\top}\right)^{\top}}{\operatorname{argmin}} \frac{1}{2T} \left\| \mathbf{Y}_{*,i} - \mathbf{X}\mathbf{B}_{*,i} - \widehat{\mathbf{F}}^{(\ell-1)}\boldsymbol{\lambda}_i \right\|_F^2 + \gamma_4 \sum_{k=1, k\neq i}^{N} w_{k,i} \left|B_{k,i}\right|$$

where $w_{k,i} = \mathbf{I}\left(\left|\dot{B}_{k,i}\right| < \gamma_4\right)$, and γ_4 is tuning parameter. (This step is still for each individual i)

(b) Update $\widehat{\mathbf{F}}^{(\ell)}$ the singular value decomposition of $\mathbf{Y} - \mathbf{X}\widehat{\mathbf{B}}^{(\ell)}$. ($F$ is global here so it requires all individuals)

(c) Iterate steps 1-2 for a finite time ℓ^*. Denote the final estimators by $\widehat{\mathbf{B}} = \widehat{\mathbf{B}}^{(\ell^*)}$, $\widehat{\mathbf{F}} = \widehat{\mathbf{F}}^{(\ell^*-1)}$, and $\widehat{\boldsymbol{\Lambda}} = \widehat{\boldsymbol{\Lambda}}^{(\ell^*)}$. (Basically, once F is provided, then estimate B and lambda for each individual separately).

B Simulation

We consider the order $p = 1$ and specify that the true autoregressive matrix $\mathbf{A}_1^0$ is a sparse matrix with diagonals equal to 0.6 and each row has two additional random cells with values 0.2 and -0.2, as shown in Figure A1. We generate data from the following high-dimensional VAR(1) system with one common factor.

$$\mathbf{Y}_t = \mathbf{A}_1^0 \mathbf{Y}_{t-1} + \mathbf{\Lambda}^0 f_t^0 + \mathbf{u}_t,$$

where $\mathbf{\Lambda}^0 = (\lambda_j^0)_{j=1}^N$. The factor loadings λ_j^0 $(j = 1, \ldots, N)$ are independently and identically distributed (i.i.d.) standard normal random variables. The factor f_t^0 follows the autoregressive process

$$f_t^0 = \rho_f f_{t-1}^0 + \epsilon_t,$$

where $\rho_f = 0.025$, which is equal to the AR(1) coefficient of the estimated common factor. $\mathbf{u}_t$ and ϵ_t are i.i.d. $N(0, 1)$.

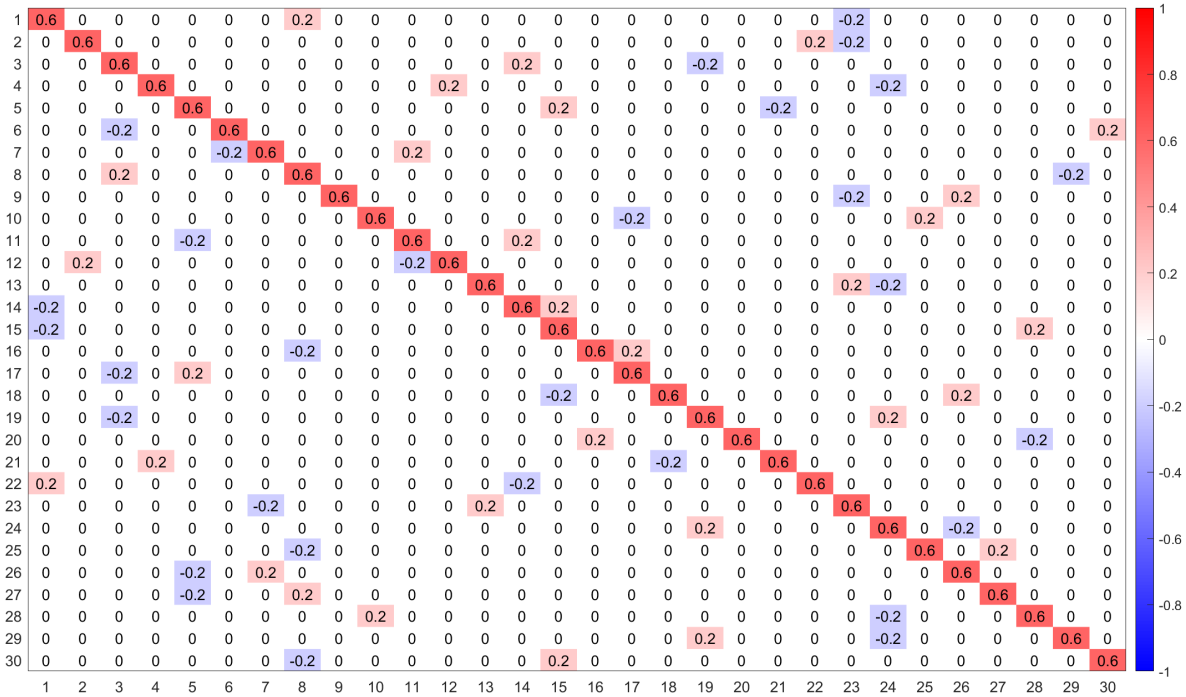


Figure A1: True Autoregressive Matrix

Notes: The values of the entries of the autoregressive matrix are represented by the color intensity of every cell. Positive and negative effects are represented by the red and blue cells and white cells for no impact.

For such DGP, we consider $N = 30$, and $T = 500$. The number of replications is set to be 500. Figure A2 and A3 present the estimated autoregressive matrix without and with

using Lasso in one replication. The estimated matrix without using Lasso fails to capture the sparsity of the true $\mathbf{A}_1^0$ matrix, while the Lasso method performs quite well.

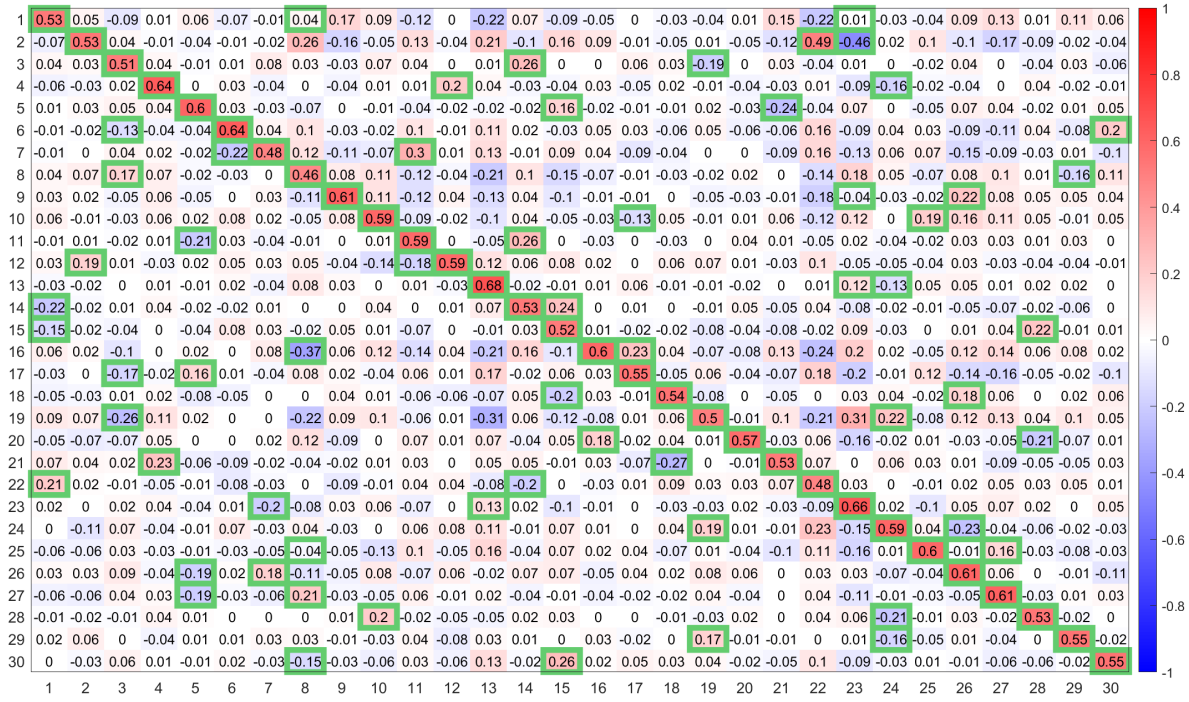


Figure A2: Estimated Autoregressive Matrix without Lasso

Notes: The values of the entries of the autoregressive matrix are represented by the color intensity of every cell. Positive and negative effects are represented by the red and blue cells and white cells for no impact. Specifically, we highlight in green those non-zero entries in the true autoregressive matrix.

Table A1: Model Selection Accuracy and Root Mean Squared Errors (RMSEs) of the Autoregressive Matrix

N	T		Without Lasso	Lasso
30	500	RMSEs	0.0027	0.0001
		RMSEs (Nonzero entries)	0.0038	0.0009
		TPR	100%	100%
		FPR	100%	8.96%

Notes: The RMSEs for all entries and nonzero entries in the true autoregressive matrix $\mathbf{A}_1^0$ are reported respectively. The TPR reports the average percentage that non-zero entries of the true autoregressive matrix $\mathbf{A}_1^0$ are estimated to be non-zero. The FPR reports the average percentage that zero entries of the true autoregressive matrix $\mathbf{A}_1^0$ are estimated to be non-zero.

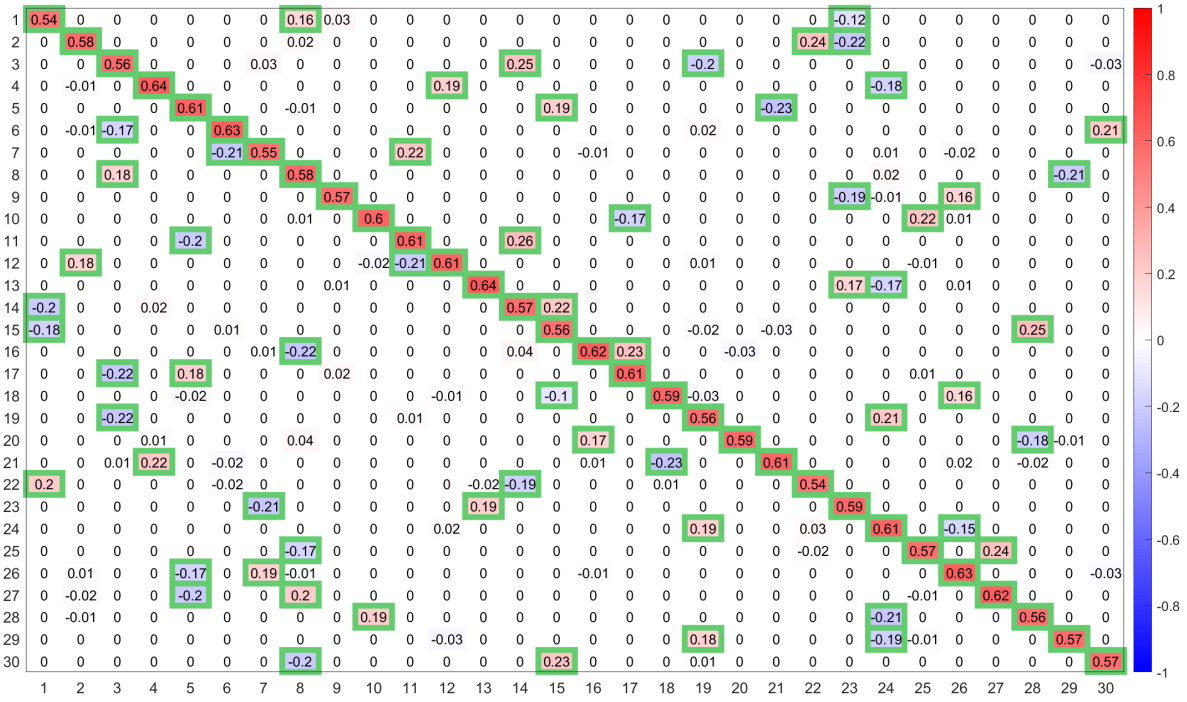


Figure A3: Estimated Autoregressive Matrix with Lasso

Notes: The values of the entries of the autoregressive matrix are represented by the color intensity of every cell. Positive and negative effects are represented by the red and blue cells and white cells for no impact. Specifically, we highlight in green those non-zero entries in the true autoregressive matrix.

C Estimated Autoregressive Matrix without Lasso

To show the importance of using Lasso method to improve the estimation of the VAR augmented factor model, we present the estimated autoregressive matrix without using Lasso in Figure A4. We observe many elements of the estimated autoregressive matrix are indeed close to zero. Moreover, there are some problems with a few estimated entries. For example, for the gasoline sector, some of the absolute values of the coefficients of lagged sectoral inflation are larger than one, suggesting the incidence of over-fitting.

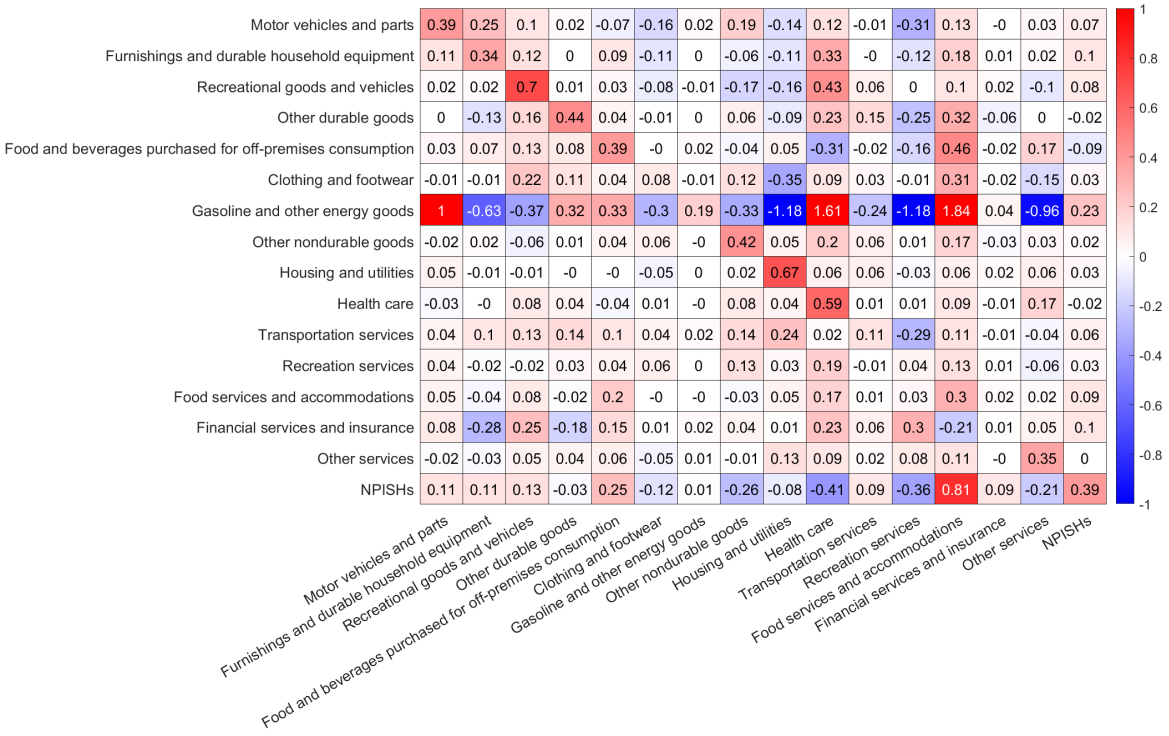


Figure A4: Autoregressive Matrix without Lasso

Notes: The values of the elements of the estimated autoregressive matrix are represented by the different color cells. Positive and negative effects are represented by the red and blue cells and white cells for no impact. The color intensity of every cell shows the value of the elements.

D Eigenvalues of the Estimated Autoregressive Matrix

Table A2: Modulus of the eigenvalues of the estimated autoregressive matrix $\widehat{\mathbf{A}}_1$ (Sort descending)

No.	Modulus of eigenvalues
1	0.914
2	0.869
3	0.764
4	0.645
5	0.559
6	0.486
7	0.486
8	0.344
9	0.344
10	0.160
11	0.160
12	0.159
13	0.098
14	0.086
15	0.045
16	0.018

E Procedure of Constructing Production Input-Output Matrix

Commodity-by-commodity input-output table. We obtained the detailed commodity-by-commodity input-output table from the Bureau of Economic Analysis (BEA) titled "Commodity-by-Commodity Total Requirements, After Redefinitions", which encompasses 402 commodities. This table presents the total inputs required by commodity (both directly and indirectly) to deliver one dollar of commodity output to final users. For the detailed level, BEA provides input-output tables for the years 2007, 2012, and 2017. Given the similarities of the results across these three tables, we select the 2012 table for our analysis.

PCE bridge table. BEA also provides the PCE bridge table, which outlines the commodity composition of PCE. We utilize the purchasers' value from the PCE bridge table for the same year to establish the relationship between the detailed commodity items and the 16 PCE sectors.

Construction Procedure:

(a) Acquire the detailed commodity-by-commodity input-output table IO, which is a 402 by 402 matrix.

(b) Construct a 16 by 402 bridge matrix B using the purchasers' value from the PCE bridge table, where the rows and columns correspond to the PCE sectors and the detailed commodities. Each row of the bridge matrix is normalized so that the sum of each row equals one; thus, the entry b_{ij} represents the proportion of commodity j within the respective PCE sector i.

(c) Condense the detailed commodity-by-commodity input-output table IO to the 16 by 16 input-output matrix A_{IO} using the bridge matrix B:

$$A_{IO} = B \times IO \times B^T$$

F Aggregate inflation impulse responses to each sector shock

We examine the impulse response of aggregate inflation to sectoral shocks. Figure A5 presents a striking illustration of the significant heterogeneity in how aggregate inflation responds to a 1% inflation shock originating from each sector. Note that the initial responses to each sectoral shock naturally equal the respective sectoral weights in the price index.

The dynamics of the aggregate inflation IRFs reveal some notable departures from the monotonic decay that would be anticipated in the absence of sectoral spillover effects for certain sectors. For example, for shocks originating from "Recreational Goods and Vehicles" and "Health Care", the aggregate inflation IRFs continue to rise for an extended period, extending over 9 months and even up to a full year. Similarly, the sectoral shocks in the sectors of "Housing and Utilities" and "Food Services and Accommodations" also exhibit an initial increase in their impact on aggregate inflation before gradually declining.

By contrast, the impacts of some sectoral inflation shocks are short-lived and have limited effects on aggregate inflation. This is the case for sectors like Clothing and Footwear, Recreation Services, Other Nondurable Goods, Other Durable Goods, and Financial Services. Surprisingly, the shock to gasoline and other energy goods has a very small effect on aggregate inflation, possibly attributed to the fact that the estimated common shocks are associated with the fluctuations in crude oil prices, which will be discussed in more detail later.

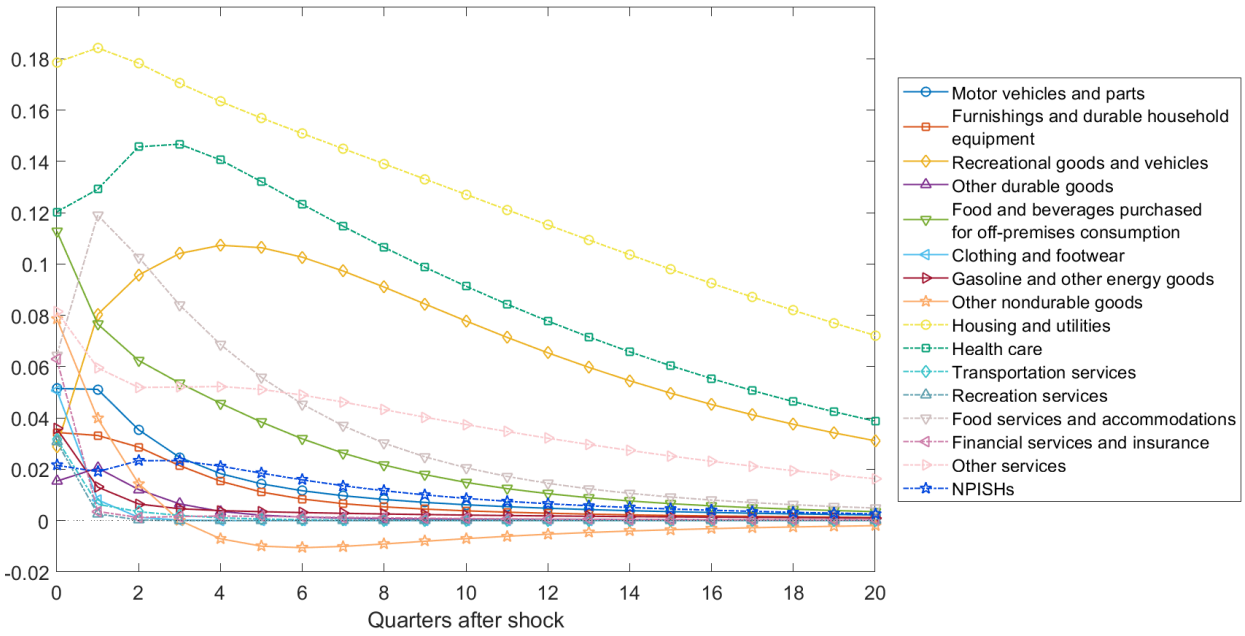


Figure A5: Aggregate Impulse Responses to Sectoral Shocks

G Sources of Aggregate Inflation in Great Inflation Period

Utilizing the previously mentioned decomposition, we attempt to comprehend the drivers contributing to inflation during the Great Inflation. The contribution of sectoral and common shock components to aggregate inflation from 1965Q1 to 1984Q4 is depicted in Figures A6 and A7.

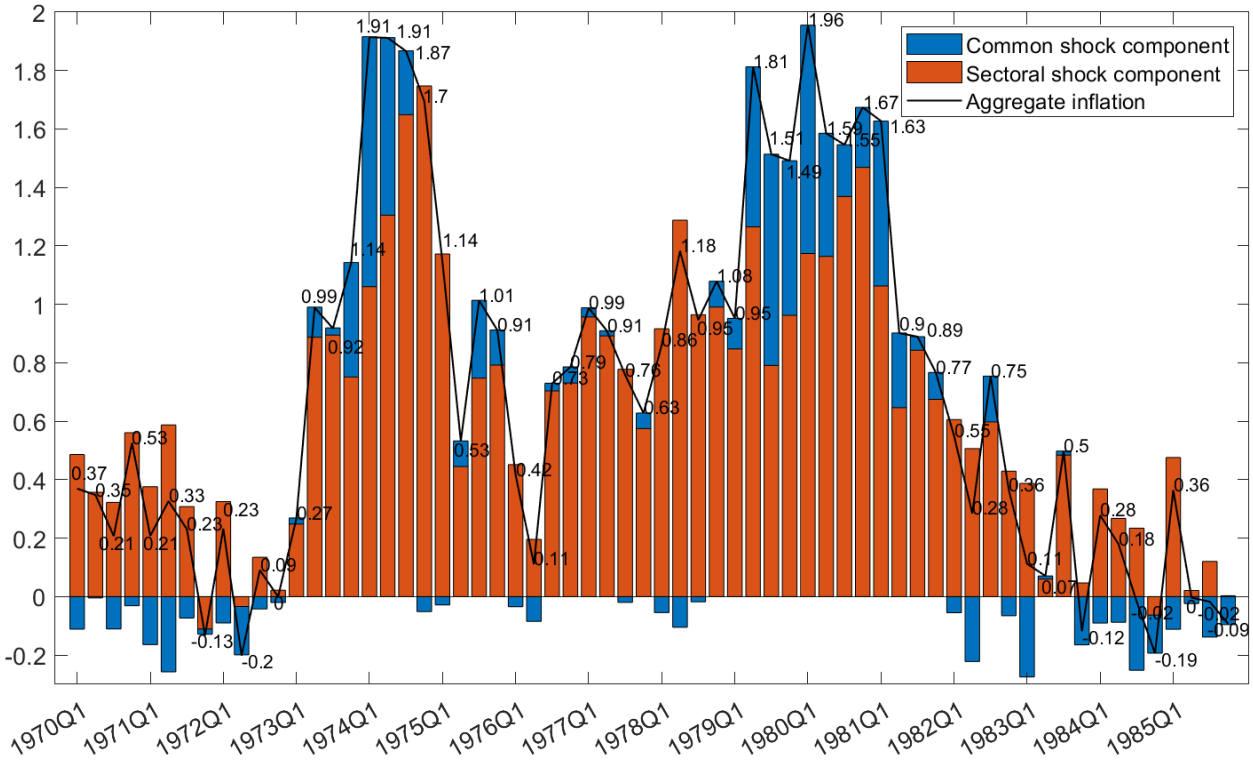


Figure A6: Decomposition of Aggregate Inflation: Great Inflation Period

Notes: Aggregate inflation is demeaned because data is normalized by demeaning when estimating and calculating the common shock component and sectoral shock components through our model. The numbers on the dash-dotted line represent the demeaned aggregate inflation equal to the sum of the common shock component and sectoral shock component.

During the early years of this period, which lasted from 1970Q1 to 1972Q4, aggregate inflation was relatively constant. However, there were indications of rising volatility during this time, mostly caused by sectoral shocks. Throughout this time, the sector shock component remained remarkably consistent and mostly positive, indicating that inflation was progressively driven by sector-specific forces. Increased demand, subpar harvests, and global agricultural disruptions raised food costs, a significant factor in early 1970s inflation.

Inflation sharply rose between 1973Q1 and 1976Q2 and reached the first peak, propelled

by both common and sectoral shocks. The 1973 oil embargo imposed by the Organization of Arab Petroleum Exporting Countries (OAPEC) caused oil prices to spike sharply, which significantly affected the common shock component. Furthermore, the sectoral shock component grew, particularly impacting energy-dependent industries like manufacturing and transportation, whose production costs surged as a result of the spike in oil prices. Food prices continued to rise due to the ongoing global food scarcity and growing expenses for agricultural inputs. Inflationary pressures also affected the price of homes, particularly the cost of building and upkeep. On average, the sectoral shock component contributed 82.5% of aggregate inflation during the peak period (1973Q1-1974Q3), while the common shocks component accounts for just 17.5%. Aggregate inflation gradually declined after 1974Q4. Such a large contribution indicates that sector shocks were a much bigger factor in this period's inflation than the general belief that oil prices were the only factor.

By the late 1970s (1976Q3 to 1979Q1), the common shock component was more volatile, reflecting ongoing economic adjustments. The sector shock component continued to be the key driver of inflation, contributing positively with time and showing less volatility than it did in the middle of the 1970s.

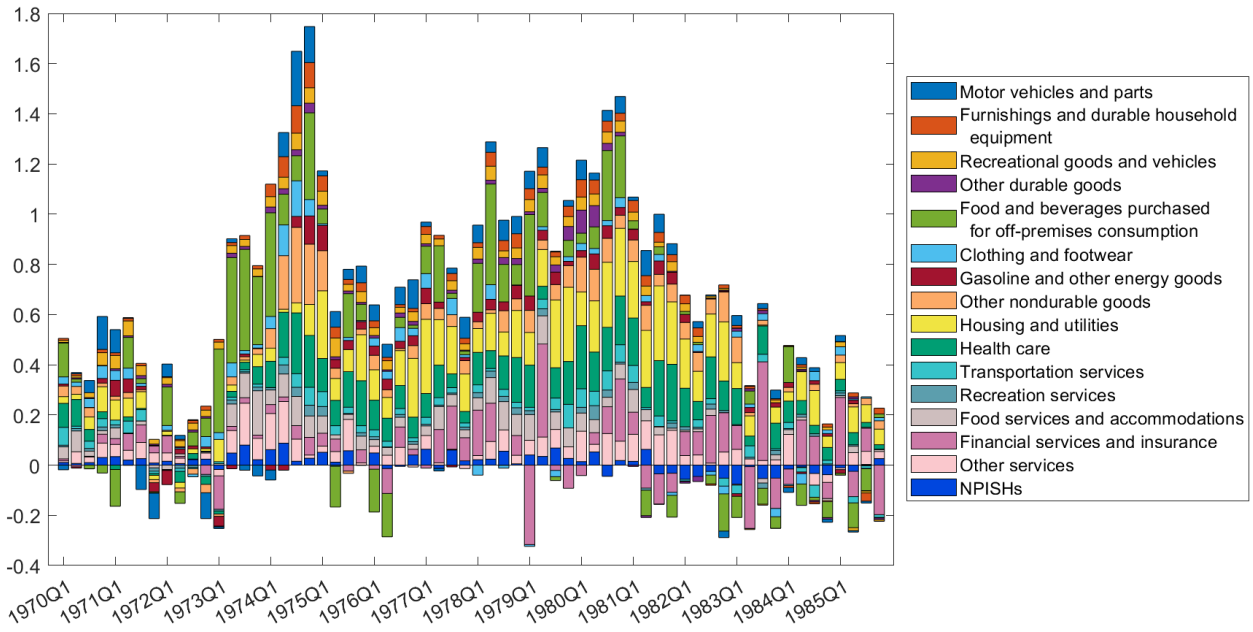


Figure A7: Decomposition of Sectoral Shock Component: Great Inflation Period

Between 1979Q2 and 1981Q1, inflation peaked for the second time. The Iranian Revolution and other geopolitical events precipitated the second oil shock of 1979, which increased oil prices and made the common shock component worse. Sector shock components, such

as severe price increases in the food, housing, and energy sectors, also had a significant impact. Restricted supply had a particularly negative impact on the energy sector, while tight monetary policy and rising interest rates drove up housing costs. During this peak period, the sectoral shock component had an average contribution of 70.2% to aggregate inflation, whereas the common shocks component only accounted for 29.8%.

Aggregate inflation started to decrease from 1981Q2, mostly as a result of fewer common shocks. This time frame matched the Federal Reserve's vigorous monetary tightening, which involved the application of high interest rates to combat ongoing inflation. Because of these measures, economic activity slowed down and inflationary pressures decreased. Nonetheless, sectoral shocks persisted, especially in the housing sector, which hampered the overall decrease in inflation.

H Robustness of Counterfactual Results: Two common factors

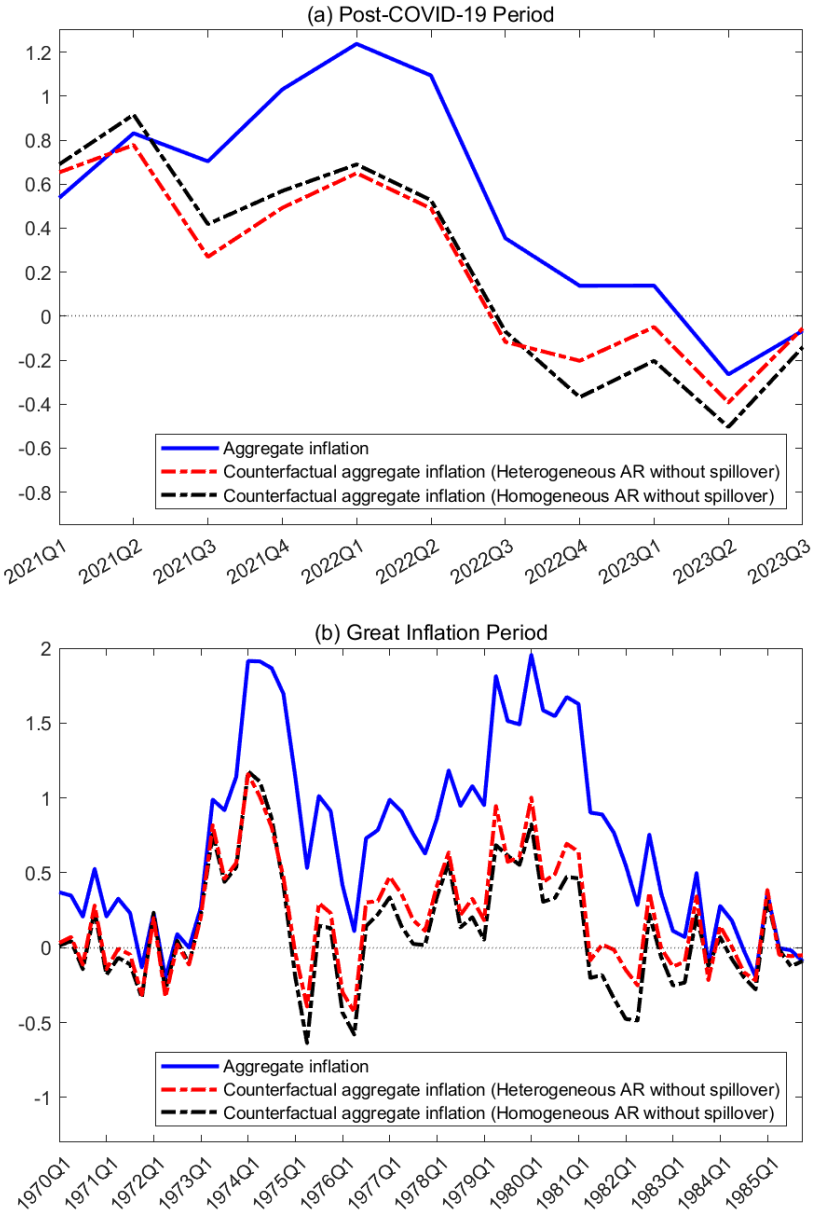


Figure A8: Aggregate Inflation with and without Spillover in Great Inflation Period and Post-COVID-19 Period (Set the Number of Common Factors Equal to Two)

Notes: Aggregate inflation and counterfactual aggregate inflation are demeaned because data is normalized by demeaning when estimating our model.