Inflation Factors*

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Abstract: We propose a novel approach to identify inflation factors that provide timely insights on supply and demand conditions shaping goods- and services-related inflationary pressures. These factors are estimated from disaggregated Personal Consumption Expenditures (PCE) data on prices and quantities, using a new Sign-Restricted Dynamic Factor Model (SiR-DFM). Aggregate PCE inflation is then decomposed into the contributions of (i) common factors—encompassing goods demand, goods supply, services demand, services supply, and inflation expectations—and (ii) idiosyncratic components. By implementing a series of validation exercises, we show that the proposed inflation factors provide an informative and coherent narrative of inflation dynamics and can be used for forecasting and policy analyses.

KEYWORDS: Inflation, Goods, Services, Supply, Demand, Factor Models
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1 Introduction

The recent inflation episode has been highly unusual by historical standards. Because the COVID-19 pandemic threatened a severe and prolonged economic disruption, fiscal and monetary policies had to provide substantial stimulus to keep economic activity afloat. Consumers, wary of catching the virus, switched from spending on in-person services to goods available from online retailers. While aggregate demand remained strong, its composition changed drastically.

The pandemic also stymied the supply of goods and services. In particular, the supply of imported goods declined persistently because many countries that play a pivotal role in the global production chain struggled to vaccinate their populations quickly. Furthermore, a shortage of imported inputs spilled over into the domestic production sector. Labor shortages also contributed to a decline in supply, as an unusually large number of workers retired early. A decline in the inflow of foreign workers, due in part to pandemic-related travel restrictions, affected some service sectors particularly hard.

While many economists share the view that the imbalance between aggregate demand and aggregate supply contributed to the initial run-up in inflation, the extent to which inflation was driven by the demand or supply of goods and services is still debated. In this paper, we propose a set of factors, or indices, that measure the strength of supply and demand forces shaping both goods and services inflation over time. These indices are constructed (i) by exploiting the comovement embedded in Personal Consumption Expenditures (PCE) data on prices and quantities across the different sectors of the US economy, and (ii) by relying on the theoretical predictions about the effects that shifts in supply and demand curves exert on prices and quantities. Our identification of supply and demand conditions is based on an intuitive observation that lies at the heart of economic theory: When demand increases, both quantities and prices of products consumed increase; but when supply increases, quantities rise while prices fall.

To account for these empirical observations and theoretical predictions in the construction of the supply and demand condition indices, we propose a Sign-Restricted Dynamic Factor Model,

referred to as SiR-DFM. This model also takes into consideration two relevant aspects. First, it accounts for features typically observed in data at high levels of disaggregation, such as time-varying volatility and outliers, helping to deliver a more reliable monitoring of supply and demand conditions in real time. Second, it incorporates information that captures long-term trends inherent in inflation dynamics. This feature helps to isolate cyclical fluctuations associated with supply and demand conditions.

We employ the proposed empirical framework to decompose inflation into six underlying components: (i) supply of goods, (ii) supply of services, (iii) demand of goods, (iv) demand of services, (v) inflation expectations, and (vi) idiosyncratic or category-specific contribution. Our analysis suggests that during the initial stages of the pandemic, inflation remained relatively low because the recovery in demand was matched by easing supply-side pressures. However, this dynamic shifted in the later stages of the pandemic. Specifically, a surge in demand for goods, followed by a persistent increase in demand for services, sparked a significant rise in inflation. This demand-driven inflation, combined with supply-side disruptions caused by global production chain issues and pandemic-related labor shortages, significantly boosted overall inflation. Importantly, throughout this entire period, monetary policy played a crucial role in keeping inflation expectations anchored, preventing a self-reinforcing upward spiral in inflation. The central bank's actions helped to maintain price stability, even as the economy grappled with the complex interplay of demand and supply-side factors.

We provide a series of validation exercises in order to ensure that the proposed factors can be appropriately labeled as supply- and demand-driven. First, we compare our inflation factors with key supply- and demand-related macroeconomic variables, such as labor productivity and unemployment gap, respectively. Second, we evaluate the responsiveness of the inflation factors to demand-driven shocks, such as the ones associated with monetary policy decisions, and supply-driven shocks, such as those emerging from the oil market. These exercises suggest that variation in our supply and demand inflation factors is driven by unobserved supply and demand shocks, respectively, validating the factors' interpretation.

Next, we evaluate the predictive content of the proposed inflation factors to forecast inflation. We compare two versions of an econometric model typically used to forecast inflation. The first version contains information on the inflation factors, while the second version does not contain such information. The results show that including the inflation factors into the model leads to substantial improvements in terms of inflation forecasting accuracy. Moreover, forecasts of the inflation factors themselves can be used to learn about the outlook of demand- and supply-driven inflationary pressures.

The literature focused on using sign restrictions to infer supply and demand shocks is vast. In their seminal work, Blanchard and Quah (1989) use theoretical predictions similar to the ones described above to identify aggregate demand and aggregate supply disturbances. Fry and Pagan (2011) provide a comprehensive review of the literature that uses various sign-restriction strategies to identify demand and supply shocks.[1] While these approaches, and their subsequent variants or extensions, provide information on the innovations or structural shocks, their estimation uncertainty is typically very large due to the set-identifying procedure on which they are inferred. In contrast, our measures of supply and demand conditions are estimated with small uncertainty because they are constructed by exploiting a large cross-sectional variation in the information on disaggregated prices and quantities.

More recently, Shapiro (2024) and Sheremirov (2022) apply a sign restriction approach to disaggregated PCE inflation data by separately estimating multiple category-specific vector autoregression (VAR) models.[2] Our approach differs from Shapiro (2024) in three important ways. First, we rely on a single factor model that processes all the information on prices and quantities from the different categories of products simultaneously. Second, we separate aggregate demand and aggregate supply components from idiosyncratic demand and supply. Third, we estimate latent demand and supply factors and use their associated factor loadings to separate demand- and supply-driven inflation *within* each sector in a given period.

Perhaps the most related work to ours is Eickmeier and Hofmann (2025), who exploit factor ro-

[1] Also, Giannone and Primiceri (2024) employ a similar framework for the case of the euro area economy.

[2] Braun, Flaaen, and Hacioglu Hoke (2024) develop a similar analysis for the case of Producer Price Index inflation.

tation in principal component analysis (PCA) applied to a large set of real activity and price-related variables, which do not exhibit a direct correspondence, to compute supply and demand factors. Such lack of correspondence muddles the interpretation of the estimated factors. In contrast, our framework exploits the price and quantity correspondence in the PCE data, allowing us to straightforwardly decompose not only aggregate inflation but also product category–specific inflation into its demand and supply contributions.

The paper is structured as follows. Section 2 introduces our empirical framework, discusses the identification strategy, and describes the employed data. Section 4 presents the supply and demand factors and the associated decomposition of inflation. Section 5 focuses on validating our supply and demand indices.

2 Methodology

2.1 Identification

Let $\Delta q_{i,t}$ and $\Delta p_{i,t}$ be the month-on-month growth rates of quantities and prices associated with consumption category $i = 1, \ldots, N$ at time $t = 1, \ldots, T$, respectively, where N denotes the number of categories included in the PCE index at a given level of aggregation, and T denotes the sample size. We define category-specific supply and demand structural equations that account for aggregate supply, s_t, and aggregate demand, d_t, as follows,

$$\Delta q_{i,t} = \phi_i^p \Delta p_{i,t} + \varphi_i^p s_t + \varepsilon_{i,t}^p, \tag{1}$$

$$\Delta p_{i,t} = -\phi_i^q \Delta q_{i,t} + \varphi_i^q d_t + \varepsilon_{i,t}^q, \tag{2}$$

with $\phi_i^q, \varphi_i^q, \phi_i^p, \varphi_i^p > 0$, $\forall i$, and where $\varepsilon_{i,t}^p$ and $\varepsilon_{i,t}^q$ denote price and quantity category-specific structural innovations, respectively.

When rearranging equations (1) and (2), prices and quantities associated with category i can be expressed as a function of contemporaneous information on both aggregate and category-specific

innovations, according to the following reduced form:

$$\Delta q_{i,t} = \lambda_{s,i} s_t + \lambda_{d,i} d_t + \zeta_{i,t}, \quad (3)$$

$$\Delta p_{i,t} = \theta_{s,i} s_t + \theta_{d,i} d_t + \eta_{i,t}. \quad (4)$$

The mapping between the parameters associated with the structural and reduced-form representations of the system provides information on the restrictions needed to identify aggregate supply and demand from disaggregated on prices and quantities. These identifying restrictions are defined by,

$$\lambda_{s,i} = (1+\phi_i^p \phi_i^q)^{-1} \varphi_i^p > 0, \quad (5)$$

$$\lambda_{d,i} = (1+\phi_i^p \phi_i^q)^{-1} \phi_i^p \varphi_i^q > 0, \quad (6)$$

$$\theta_{s,i} = -(1+\phi_i^q \phi_i^p)^{-1} \phi_i^q \varphi_i^p < 0, \quad (7)$$

$$\theta_{d,i} = (1+\phi_i^q \phi_i^p)^{-1} \varphi_i^q > 0. \quad (8)$$

Also, the reduced-form idiosyncratic dynamics remains a function of both the structural category-specific innovations and structural parameters,

$$\zeta_{i,t} = (1+\phi_i^p \phi_i^q)^{-1} (\varepsilon_{i,t}^p + \phi_i^p \varepsilon_{i,t}^q), \quad (9)$$

$$\eta_{i,t} = (1+\phi_i^q \phi_i^p)^{-1} (\varepsilon_{i,t}^q - \phi_i^q \varepsilon_{i,t}^p). \quad (10)$$

Overall, our identifying restrictions assume that aggregate demand moves prices and quantities in the same direction. That is, an increase in aggregate demand would induce a rise in the prices and quantities across all the categories in the consumption basket. Instead, aggregate supply is assumed to move prices and quantities in the opposite direction. An increase in aggregate supply would also lead to a rise in the quantities, but to a decline in the prices associated with all the categories.

2.2 *Empirical Framework*

To incorporate the relationships between aggregate factors and disaggregated prices or quantities described above into a unified empirical framework, we propose a Sign-Restricted Dynamic Factor Model that enables us to disentangle common and idiosyncratic dynamics by also accounting for identifying restrictions. According to equations (3) and (4), the information contained in disaggregated prices and quantities is assumed to be influenced by three components: (i) aggregate supply, (ii) aggregate demand, and (iii) idiosyncratic dynamics. Both aggregate supply and aggregate demand components can be thought of as common factors influencing – and extracted from – the disaggregated data, according to the appropriate economic theory-based restrictions on the factor loadings defined in equations (5)-(8).

Motivated by the changing interplay between supply and demand forces in driving goods- and services-related inflation, especially during the post-pandemic period, our empirical framework is designed to extract four underlying common factors from the disaggregated data. This set of factors are intended to summarize the evolving conditions of supply of goods, $s_{g,t}$, supply of services, $s_{v,t}$, demand of goods, $d_{g,t}$, and demand of services, $d_{v,t}$.

Let $\Delta q_{i_g,t}$ and $\Delta p_{i_g,t}$ be the month-on-month growth rate of quantities and prices associated with category i_g at time t, respectively, for $i_g = 1,...,N_g$, where N_g denotes the number of goods-related categories included in the PCE index. Analogously, Let $\Delta q_{i_v,t}$ and $\Delta p_{i_v,t}$ be the month-on-month growth rate of quantities and prices associated with category i_v at time t, respectively, for $i_v = 1,...,N_v$, where N_v denotes the number of services-related categories included in the PCE index.[3] Then, the information on prices and quantities across goods and services can be decomposed as,

$$\Delta q_{i_g,t} = \lambda_{s,i_g} s_{g,t} + \lambda_{d,i_g} d_{g,t} + \zeta_{i_g,t}, \tag{11}$$

$$\Delta p_{i_g,t} = \theta_{s,i_g} s_{g,t} + \theta_{d,i_g} d_{g,t} + \eta_{i_g,t}, \tag{12}$$

$$\Delta q_{i_v,t} = \gamma_{s,i_v} s_{v,t} + \gamma_{d,i_v} d_{v,t} + \xi_{i_v,t}, \tag{13}$$

[3]Both prices and quantities are scaled by their corresponding standard deviation prior entering the model.

$$\Delta p_{i_v,t} = \delta_{s,i_v} s_{v,t} + \delta_{d,i_v} d_{v,t} + \vartheta_{i_v,t}. \tag{14}$$

The identifying restrictions on the factor loadings used to infer the set of supply and demand common factors are built upon the relation reduced-form and structural parameters defined in equations (5)-(8). In particular, we impose the following sign restrictions on the factor loadings:

$$\lambda_{s,i_g} > 0, \;\; \lambda_{d,i_g} > 0, \tag{15}$$

$$\theta_{s,i_g} < 0, \;\; \theta_{d,i_g} > 0, \tag{16}$$

$$\gamma_{s,i_v} > 0, \;\; \gamma_{d,i_v} > 0, \tag{17}$$

$$\delta_{s,i_v} < 0, \;\; \delta_{d,i_v} > 0. \tag{18}$$

This set of restrictions can be easily implemented when estimating the model with the Bayesian methods.

The common factors of supply associated with goods and services are assumed to evolve according to a vector autoregression (VAR) process of order k, allowing for a potential non-contemporaneous feedback between these two broad categories of products. Similarly, the goods and services demand factors also follow a VAR process. Moreover, to account for the time-varying trend inherent in inflation data, we include an observed variable in both VARs that is intended to absorb this source of non-stationarity. Specifically, we include data on long-term inflation expectations as an exogenous variable in the VAR equations, and define them as follows:

$$\begin{bmatrix} s_{g,t} \\ s_{v,t} \end{bmatrix} = \mathbf{\Phi}_{s,0} + \boldsymbol{\beta}_s \pi^e_{t-1} + \mathbf{\Phi}_{s,1} \begin{bmatrix} s_{g,t-1} \\ s_{v,t-1} \end{bmatrix} + \ldots + \mathbf{\Phi}_{s,k} \begin{bmatrix} s_{g,t-k} \\ s_{v,t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{s_g,t} \\ \varepsilon_{s_v,t} \end{bmatrix}, \tag{19}$$

$$\begin{bmatrix} d_{g,t} \\ d_{v,t} \end{bmatrix} = \mathbf{\Phi}_{d,0} + \boldsymbol{\beta}_d \pi^e_{t-1} + \mathbf{\Phi}_{d,1} \begin{bmatrix} d_{g,t-1} \\ d_{v,t-1} \end{bmatrix} + \ldots + \mathbf{\Phi}_{d,k} \begin{bmatrix} d_{g,t-k} \\ d_{v,t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{d_g,t} \\ \varepsilon_{d_v,t} \end{bmatrix}, \tag{20}$$

where the vectors containing the coefficients associated with the exogenous variable are defined

as $\beta_s = (\beta_{s,g}, \beta_{s,v})'$ and $\beta_d = (\beta_{d,g}, \beta_{d,v})'$, and the innovations associated with both supply and demand processes are assumed to be normally distributed, as $(\varepsilon_{s_g,t}\ \varepsilon_{s_v,t})' \sim N(\mathbf{0}, \Omega_s)$ and $(\varepsilon_{d_g,t}, \varepsilon_{d_v,t})' \sim N(\mathbf{0}, \Omega_d)$.

The idiosyncratic terms help to capture dynamics that are unrelated with aggregate supply or demand conditions, and that instead can be mainly associated with events affecting prices or quantities of a specific category. These terms are assumed to follow independent autoregressive processes of order m, and defined by:[4]

$$\zeta_{i_g,t}(1 - \psi_{i_g,1}L - \ldots - \psi_{i_g,m}L^m) = \nu_{i_g,t}, \tag{21}$$

$$\eta_{i_g,t}(1 - \varphi_{i_g,1}L - \ldots - \varphi_{i_g,m}L^m) = \nu_{i_g,t}, \tag{22}$$

$$\xi_{i_v,t}(1 - \rho_{i_v,1}L - \ldots - \rho_{i_v,m}L^m) = \omega_{i_v,t}, \tag{23}$$

$$\vartheta_{i_v,t}(1 - \rho_{i_v,1}L - \ldots - \rho_{i_v,m}L^m) = \varsigma_{i_v,t}, \tag{24}$$

where the innovations of the idiosyncratic terms are assumed to be normally distributed, with a flexible volatility process to account for features typically observed in highly disaggregated data on prices and quantities. In particular, we let the innovations of the idiosyncratic terms exhibit stochastic volatility with outlier adjustment. Let $\chi = \{\nu_{i_g}, \nu_{i_g}, \omega_{i_v}, \varsigma_{i_v}\}$, then the idiosyncratic term associated with each category-specific price or quantity is distributed as $\chi_t \sim N(0, o^2_{\chi,t} \times e^{h_{\chi,t}})$, where the log-volatility process follows a random walk,

$$h_{\chi,t} = h_{\chi,t-1} + \varpi_{\chi,t} \tag{25}$$

with $\varpi_{\chi,t} \sim N(0, \sigma^2_\chi)$. The outlier components, $o_{\chi,t}$, is defined following Stock and Watson (2016),

$$o_{\chi,t} = \begin{cases} 1 \ \text{ with probability } \ (1 - \alpha_\chi) \\ \mathscr{U}_{[2,10]} \ \text{ with probability } \ \alpha_\chi \end{cases}, \tag{26}$$

[4] In the empirical application, we set the lag order of both common factors and idiosyncratic term to be $k = m = 2$.

where $\mathscr{U}_{[a,b]}$ refers to the uniform distribution with support $[a,b]$.

We apply the parameter restrictions suggested by Bai and Wang (2015) in order to achieve statistical identification of the latent common factors, and set $\Omega_s = \Omega_d = \mathbf{I}$ and $\lambda_{d,1} = \gamma_{d,1} = 0$. The model is estimated with Bayesian methods by employing the Gibbs sampler, and following the procedures proposed in Kim and Nelson (1999) and Stock and Watson (2016) for sampling the common factor and the stochastic volatility processes, respectively. The identifying restrictions on the factor loadings, described in equations (15)-(18), are verified at every iteration of the sampler.

2.3 Decomposition

Our framework allows us to decompose the prices changes associated to each category in the PCE index into four category-specific underlying components: supply, demand, inflation expectations and idiosyncratic dynamics. In doing so, we derive the following historical decomposition of disaggregated prices:

$$\Delta p_{i_g,t} = \alpha_{i_g}\pi^e_{t-1} + \theta_{s,i_g}s^*_{g,t} + \theta_{d,i_g}d^*_{g,t} + \eta_{i_g,t}, \tag{27}$$

$$\Delta p_{i_v,t} = \alpha_{i_v}\pi^e_{t-1} + \delta_{s,i_v}s^*_{v,t} + \delta_{d,i_v}d^*_{v,t} + \vartheta_{i_v,t}, \tag{28}$$

where $\alpha_{i_g} = \theta_{s,i_g}\beta_{s,g} + \theta_{d,i_g}\beta_{d,g}$, and $\alpha_{i_v} = \delta_{s,i_v}\beta_{s,v} + \delta_{d,i_v}\beta_{d,v}$, measure the sensitivity of goods- and services-related prices, respectively, to lagged inflation expectations. The cyclical fluctuations of supply and demand conditions indices are defined as,

$$\begin{aligned}
s^*_{g,t} &= s_{g,t} - \beta_{s,g}\pi^e_{t-1}, \\
s^*_{v,t} &= s_{v,t} - \beta_{s,v}\pi^e_{t-1}, \\
d^*_{g,t} &= d_{g,t} - \beta_{d,g}\pi^e_{t-1}, \\
d^*_{v,t} &= d_{v,t} - \beta_{d,v}\pi^e_{t-1}.
\end{aligned}$$

The decomposition in equations (27) and (28) is obtained by substituting equations (19)-(20) into equations (11)-(14) and rearranging terms. Then, aggregate inflation can be defined as the weighted sum of the disaggregated price changes,

$$\pi_t = \sum_{i_g=1}^{N_g} \omega_{i_g,t} \Delta p_{i_g,t} + \sum_{i_v=1}^{N_v} \omega_{i_v,t} \Delta p_{i_v,t}, \tag{29}$$

where $\omega_{i_g,t}$ and $\omega_{i_v,t}$ denote the weights associated with the different goods- and services-related categories in the PCE. Hence, by plugging equations (27) and (28) into equation (29), and rearranging terms, we obtain a decomposition of aggregate inflation into the aggregate components associated with supply, demand, inflation expectations and idiosyncratic dynamics.

2.4 Model Selection

We estimate different variants of our model specification described in equations (11)-(26). These variants take into consideration several features of the model such as (i) using short- instead long-term inflation expectations, (ii) excluding information on inflation expectations, (iii) extracting only one demand and one supply factor instead of two supply and two demand factors, (iv) including exogenous information on inflation expectations in the measurement instead of transition equations, and (v) including additional sign restrictions relating information on quantities with inflation expectations.

After estimating the different variants of the model specification, we compare the goodness of fit associated with each of them based on the Deviance Information Criterion (DIC).[5] This comparison suggests that the specification that fits best the data, among the different variants, is the one described in Section 2.2. Further details on the comparison based on the DIC are provided in Online Appendix B.

[5]The DIC can be seen as a hierarchical modelling generalization of the Akaike Information Criterion employed in frequentist inference.

3 Data

We use disaggregated data on Personal Consumption Expenditures (PCE) prices and quantities associated with 51 categories of products, and a measure of long-term inflation expectations. Our sample starts in January 1968 and ends in January 2025.[6] Our preferred measure of long-term inflation expectations is based on the University of Michigan's Survey of Consumers. This series, which measures expected inflation five years forward, is available at a monthly frequency starting in April 1990. For the earlier period, we splice it with long-term expected PCE inflation from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. We adjust the spliced series by the mean difference between its two components over the period with overlapping observations, so that its level corresponds to average PCE inflation.

4 Results

4.1 Common Factors

Panel (a) of Figure 1 shows the inflation factors associated with demand of goods and services. These factors display two key features. First, they typically report positive values, illustrating the upward pressure that demand forces tend to exert on inflation, as described in equations (4) and (8). Second, the services demand factor exhibits a larger amount of persistence when compared to the goods demand factor. This stronger persistence associated with services when compared to goods can be attributed to labor intensity and wage growth, among other factors.

The inflation factors associated with supply of goods and services are then shown in Panel (b) of Figure 1. The supply factors tend to exhibit mostly negative values, unlike the demand factors. This feature is aligned with the downward pressures that supply is expected to exert on inflation according to equations (4) and (7). Similar to the case of demand, the services supply factor exhibits a stronger persistence than the goods supply factor.

A feature that is common across the four inflation factors is a time-varying trend, which is

[6] Table A.1 in the appendix provides a list of PCE categories.

downwards for the demand factors and upwards for the supply factors. This trend can be partially explained by the information contained in long-term inflation expectations. Hence, the difference between the estimated factors and the inflation expectations component can be interpreted as cyclical fluctuations of supply and demand of goods and services conditions.

4.2 Historical Inflation Decomposition

Understanding the sources of inflation dynamics is paramount for conducting effective monetary policy, because inflation caused by low aggregate supply creates trade-offs that do not exist when inflation is caused by aggregate demand. Specifically, when inflation results from rising demand, monetary policy can stabilize the economy by bringing demand back down to its sustainable level, thereby simultaneously making progress towards both stable prices and full employment. But when inflation is due to a contraction in supply, monetary policy can stabilize prices only by pushing the unemployment rate up. Our decomposition also enables us to separate persistent *aggregate* inflation components, which are more relevant for policy, from idiosyncratic sectoral inflation.

Figure 2 shows the historical decomposition of 12-month total PCE inflation for the period from April 1968 through December 2024. Demand-driven contributions to inflation, shown by the dark and light red areas, tend to be positive and sizable. This is particularly the case for the demand of services. However, the magnitudes of demand contributions have evolved over time, being more prominent from the 1970s to the Great Recession and somewhat smaller between 2010 and 2020.

Supply-driven contributions to inflation, shown by the dark and light blue areas in Figure 2, often follow an increase in commodity prices. This was the case not only in the 1970s and early 1980s, a period that includes two oil-price shocks, but also during the Great Recession, when supply-driven inflation offset demand-driven deflation. Indeed, a surge in oil prices can explain the so-called missing disinflation during this period.[7] Our decomposition indicates that, starting in the mid-1980s, goods supply-driven inflation was low—often below zero. The period coincides with

[7]For example, Coibion and Gorodnichenko (2015) argue that an increase in oil prices resulted in a material increase in short-term inflation expectations, as consumers tend to be particularly attentive to salient prices, such as gasoline prices.

persistent productivity growth. The expansion of international trade in the 2010s likely played a role in dampening goods supply-driven inflation further.

Inflation driven by expectations was remarkably stable starting in the 1990s, exemplifying the credibility of monetary policy to maintain low and stable inflation. While the inflation target, defined as a 2 percent PCE inflation rate, was not formally adopted until 2012, inflation expectations were already stable during the 1990s and 2000s, as if a target were in place.

While these aggregate components explain much of the variation in inflation, there is an important idiosyncratic component that can be seen in the gray area of Figure 2. This idiosyncratic component is due to factors specific to a particular PCE category and may comprise both demand and supply components. For example, our model identifies a persistent shock to commodity prices that propagates to non-commodity consumption categories as aggregate supply-driven inflation, whereas it identifies a one-time change in oil prices that is quickly reverted and that does not affect other categories as idiosyncratic inflation.

4.3 Pandemic Episode

Prior to the COVID-19 pandemic, demand-driven inflation was persistently positive, contributing about 1 percentage point to total inflation, whereas supply-driven inflation was persistently negative, due to productivity-driven economic growth. We now turn our attention to the bout of inflation induced by the pandemic. Our decomposition suggests that inflation dynamics evolved in different stages during the pandemic period (Figure 3).[8] During the first few months of the pandemic, both aggregate demand and aggregate supply collapsed. These two channels had opposite effects on inflation and approximately offset each other. Demand-driven inflation surged during the second half of 2020 and remained persistently high through 2022. Initially, supply-side improvements kept total inflation at bay. However, as supply-driven inflation picked up in the second half of 2021, both demand and supply factors pushed prices higher.

The stability of expectations-driven inflation indicates that monetary-policy credibility was

[8]In order to capture the turning points more accurately during this relatively short period, we use annualized 3-month inflation rates instead of 12-month rates.

never in question during the pandemic period. This result is in stark contrast with the 1970s and 1980s inflation episodes, during which the inflation expectations component increased by about 3 percentage points. Had inflation expectations not been anchored, the U.S. economy would have likely experienced double-digit inflation during the pandemic, as measured by the PCE price index.

As inflation has moderated over 2023 and 2024, both goods-demand and goods-supply components of inflation appear to be back in line with where they were before the pandemic. During this latest period, nearly all demand-driven inflation has been due to demand for services.

4.4 Supply-Chain Disruptions

Our model also helps us to better understand the role of the unprecedented disruptions to global supply chains, which have featured prominently in the narratives of the recent inflation episode. The strong positive correlation between PCE goods inflation and the widely used Federal Reserve Bank of New York's Global Supply Chain Pressures Index (GSCPI) can be interpreted as evidence that sharp increases in the later reflect adverse supply shocks, as exemplified by its surge owing to the widespread closures of production facilities during the pandemic.

Supply chain pressures, however, can also arise from demand-side factors—for example, if an unanticipated spike in demand for certain category of goods causes bottlenecks in the associated production chains. Panel A of Figure 4 shows the scatterplot of the GSCPI against our estimate of demand-driven goods inflation. Interestingly, during the 1998–2019 period (the red dots), there is no systematic relationship between the two measures, suggesting that in "normal" times, an increase in the GSCPI is a reliable indicator of supply-side pressures.

However, during the pandemic (the red diamonds), the GSCPI correlated positively and significantly with demand-driven goods inflation. This strongly suggests that the pandemic-induced spike in the GSCPI reflected to a significant extent the supply-chain bottlenecks resulting from a surging demand for goods. Indeed, after mid-2023 (the red squares), as supply chains normalized, the relationship between demand-driven goods inflation and the GSCPI is indistinguishable from

the one that prevailed before the pandemic.[9]

Panel B of Figure 4 shows a strong positive correlation between the GSCPI and our estimate of the supply-driven goods inflation, net of the part predicted by the demand-driven goods inflation.[10] This relationship appears quite stable across the three sample periods, indicating that the variation in the GSCPI over time also reflects supply-side fluctuations.

5 Validation

In this section, we present several exercises that provide external validation of our estimates of supply and demand factors and their contributions to inflation. First, we compare our measures to other commonly-used measures of demand and supply conditions. Second, we assess the responses of our measures to identified supply and demand shocks. Third, we evaluate the predictive content of the proposed factors to forecast inflation.

5.1 Comparison with Macroeconomic Indicators

We begin by examining the correspondence between common supply-driven inflation and aggregate productivity as measured by output per hour. Common supply-driven inflation is defined as the sum of the contributions associated with goods supply and services supply inflation factors. Figure 5 shows that the times of high supply-driven inflation generally correspond to the times when productivity falls below trend. Many of these episodes occur around recessions, but there are some during expansions as well, such as in the mid-1990s. Likewise, our estimation tends to uncover a disinflationary impact of supply conditions when productivity runs above trend.

Next, we compare our demand-driven inflation estimates with a measure of demand conditions such as the unemployment gap estimated by the Congressional Budget Office (CBO). Figure 7 shows that, for the most part, our estimate of the contribution of economic slack to inflation has a

[9] Benigno et al. (2022) acknowledge that while the GSCPI is intended to be purged from demand factors, it is not a perfect measure and its dynamics during the Global Financial Crisis may also capture some demand components.

[10] In netting out of the part predicted by the demand-driven goods inflation, we allow for a differential relationship before and since the pandemic.

close correspondence with this measure that is external to our estimation, falling during recessions and rising during expansions.[11]

5.2 Responsiveness to Shocks

In the next set of exercises, we estimate the impulse responses of our model's inflation components to oil supply shocks and monetary policy shocks from the literature using local projections (Jordà, 2005). Our results from these exercises indicate that our four estimated components of inflation are well-identified.

We begin with the oil supply news shocks from Känzig (2021), which are identified using oil futures price movements around Organization of the Petroleum Exporting Countries (OPEC) announcements. These shocks are scaled to represent an increase in the real price of oil of 10 percent on impact. We estimate the following specification for horizons up to 48 months using ordinary least squares (OLS):

$$y_{t+h} - y_{t-1} = \beta_0^h + \gamma^h \text{Oil}_t + \beta_1^{h\prime} \mathbf{x}_{t-1} + \varepsilon_t, \tag{30}$$

where y_t is the accumulated demand or supply component of one-month inflation for goods, services, or the sum of both; Oil_t is the oil supply news shock; and $\mathbf{x_{t-1}}$ is a vector of lagged controls.

We use monthly data from January 1990 through December 2019. Our sample thus excludes the period of elevated inflation expectations in the 1970s and 1980s as well as the unusual dynamics following the COVID-19 pandemic episode. We control for macroeconomic conditions by using twelve lags of the 1-year treasury yield, the 10-year treasury yield, the unemployment rate, the log total PCE price index, the excess bond premium from Gilchrist and Zakrajšek (2012), the log S&P 500 total return index, and the log commodity spot index from the Commodity Research Bureau. We use robust standard errors when computing the 90% and 95% confidence bands.

Figure 9 plots the estimated responses. We find that an oil news shock that raises the real price

[11] This pattern also holds when comparing our demand-driven inflation estimates with a measure of the output gap from the CBO.

of oil by 10% raises the supply-driven component of the PCE price level index by 2% after about two years. This rise occurs through both goods and services supply subcomponents. Demand-driven price contributions respond negligibly in comparison.

Next, we examine responses of the contributions to the PCE price level to monetary policy shocks from Nunes, Ozdagli, and Tang (2022) using the same regression specification. These shocks purify high-frequency monetary policy surprises from the Fed information effect. The shock is scaled to raise the 1-year treasury rate by 1 percentage point.

Figure 10 presents the estimated responses. In contrast to the oil supply shocks, the price level response to a monetary policy shock is mainly due to the demand-driven component. The demand-driven price level response reaches a trough of just over 5% about 2 years after the shock, and this decline in the price level occurs mainly through services demand. Supply-driven inflation responds little to monetary policy shocks.

These exercises show that our estimated supply and demand components are reacting (or not reacting) to well-identified supply and demand shocks from the literature in a theory-consistent manner, thus further validating our estimated inflation components.

6 Real-Time Forecasting

We illustrate the predictive content embedded in the inflation factor when used to forecast headline inflation in real time. We estimate two Bayesian Vector Autoregression (BVAR) models. The first model includes three standard macroeconomic variables: (i) PCE inflation, (ii) unemployment rate, (iii) unit labor cost, (iv) 2-year treasury nominal yield, and (v) energy CPI inflation. The second BVAR model includes the same five standard macroeconomic variables plus the four newly proposed inflation factors. For each of these two models, we consider two forecasts of PCE inflation: one made using available information as of December 2020, right before inflation started to surge; another using information as of March 2022, as inflation leveled off.

The initial surge in inflation detected in December 2020 can be better understood by incorporating information on demand and supply factors for goods and services. As shown in the left

panel of Figure 11, this approach reveals two important insights. First, while the model without inflation factors suggests a transitory spike in inflation, lasting only around six months above the Federal Reserve's 2 percent target, the model with inflation factors points to a much more rapid and potentially long-lasting surge. This indicates that the initial inflation spike was more severe and persistent than a simple model would have suggested. Second, the uncertainty around the inflation outlook increases substantially in the model with inflation factors, hinting at the highly unusual inflation dynamics that were to come.

Turning to the disinflation that began in mid-2022, the right panel of Figure 11 shows that the model without inflation factors would have failed to anticipate the swift decline in inflation. In contrast, the projection that incorporates the inflation factors captures remarkably well the pace of disinflation over the following year, which surprised many observers. This suggests that the model with inflation factors provides a more accurate and nuanced understanding of the inflationary dynamics, both in the initial surge and the subsequent disinflation.

To investigate which factor contributed most to the accuracy of the inflation forecasts, we reestimated the BVAR model by including the macroeconomic variables and one inflation factor at a time, and generated the associated forecasts. This exercise was repeated independently for each inflation factor.

When focusing on the inflation surge period, the forecasts shown in Figure 12 suggest that the services supply factor contributed the most to anticipating the upcoming large increase in inflation. While the services supply factor captures more of the surge, it is also more transitory in nature. In contrast, the goods components anticipate a more persistent elevated inflation. This is consistent with the short-lived nature of the pandemic-induced production shutdowns in the U.S., but the longer-lasting reshuffling of demand towards goods, the delayed supply shocks from abroad –as some countries experienced later waves of COVID-19–, and the fact that goods-demand-induced bottlenecks took longer to materialize. Instead, During the disinflation period, the forecasts associated with each individual factor look more similar, although the model including the goods supply factor appears to provide the most accurate predictions, see Figure 13.

This exercise also provides two key insights. First, the different inflation factors can contribute to sharpening inflation forecasts in distinct ways at different points in time. Second, all four factors are needed to provide the most accurate prediction of inflation in real time, at least based on these two reference periods.

7 Conclusions

This paper introduces a novel supply and demand decomposition of US inflation based on a Sign-Restricted Dynamic Factor Model that employs disaggregated PCE data on prices and quantities. Through the proposed empirical framework, we decompose inflation into six underlying components: (i) supply of goods, (ii) supply of services, (iii) demand of goods, (iv) demand of services, (v) inflation expectations, and (vi) idiosyncratic or category-specific contribution.

The estimation is validated internally through components that exhibit behavior in accordance with the historical narrative. Namely, we see large positive supply contributions to inflation during the 1970s and 1980s and negative contributions during the 1990s through 2010s, a period of trade expansion and accelerated productivity growth.

We also validate the estimation externally through favorable comparisons of our supply and demand contributions with other measures of supply and demand conditions, namely productivity and the unemployment gap. Our decomposition is further validated by the finding that the price level responds to well-identified supply and demand shocks from the literature primarily through our estimated supply and demand components, respectively. Lastly, we show that there is indeed predictive content embedded in our estimated supply and demand factors for forecasting headline inflation.

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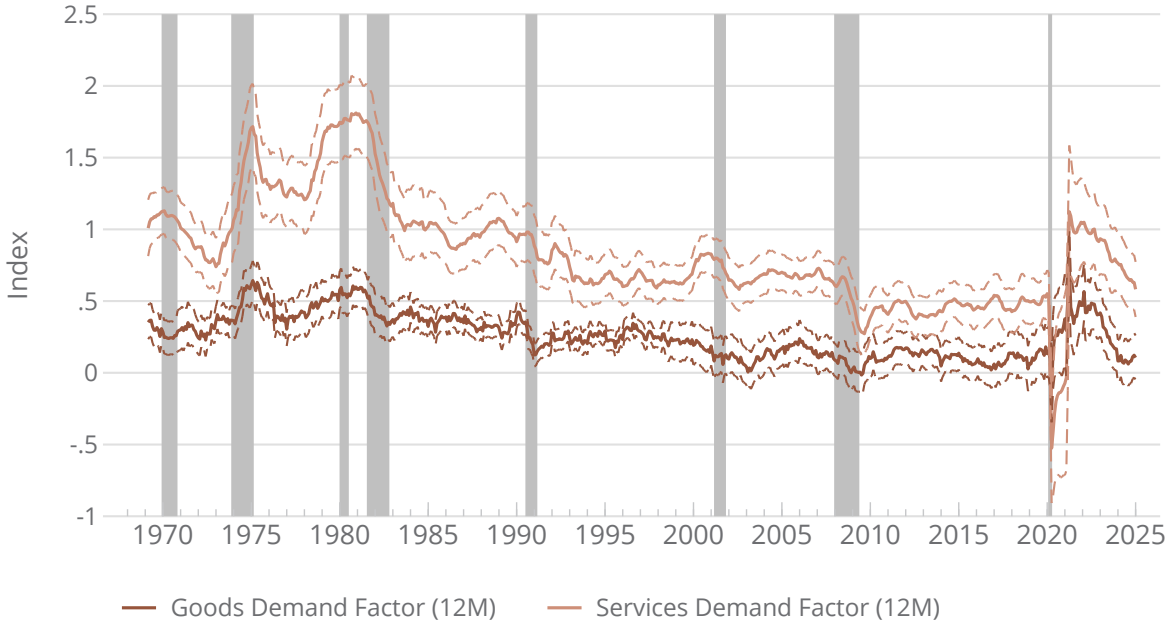
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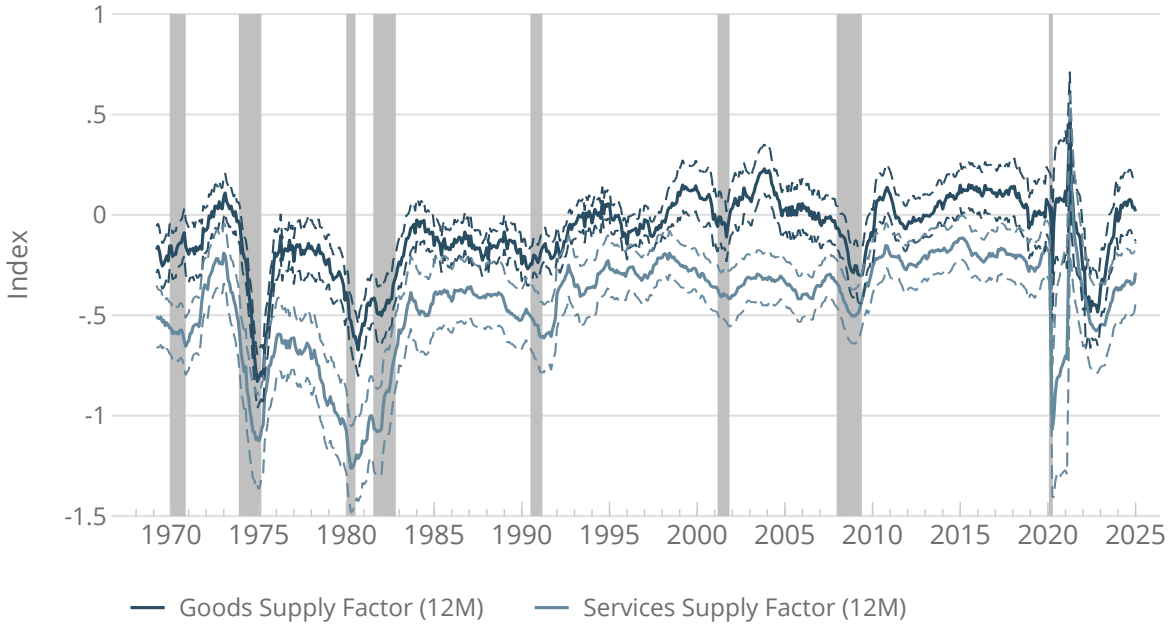
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Figure 1: Inflation Factors

(a) Demand Factors

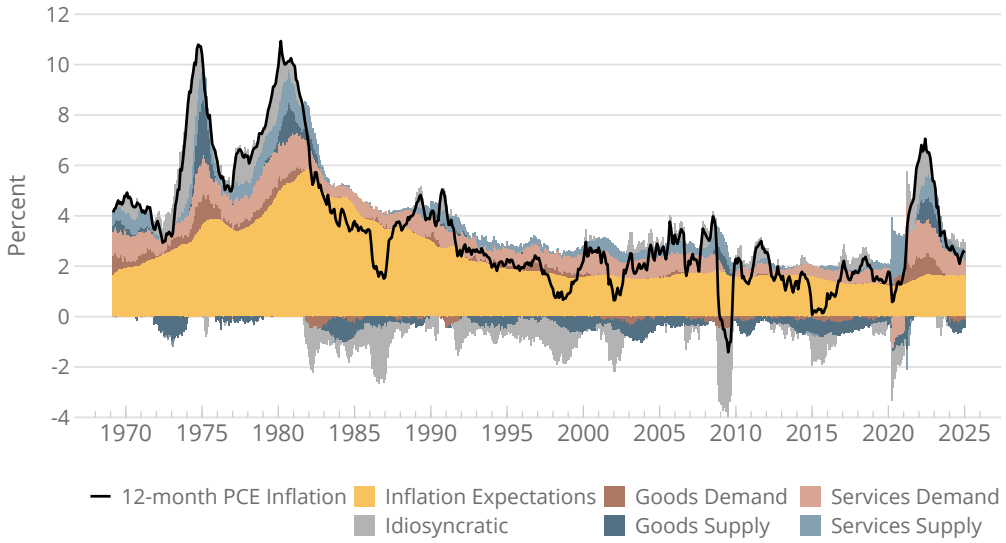


(b) Supply Factors



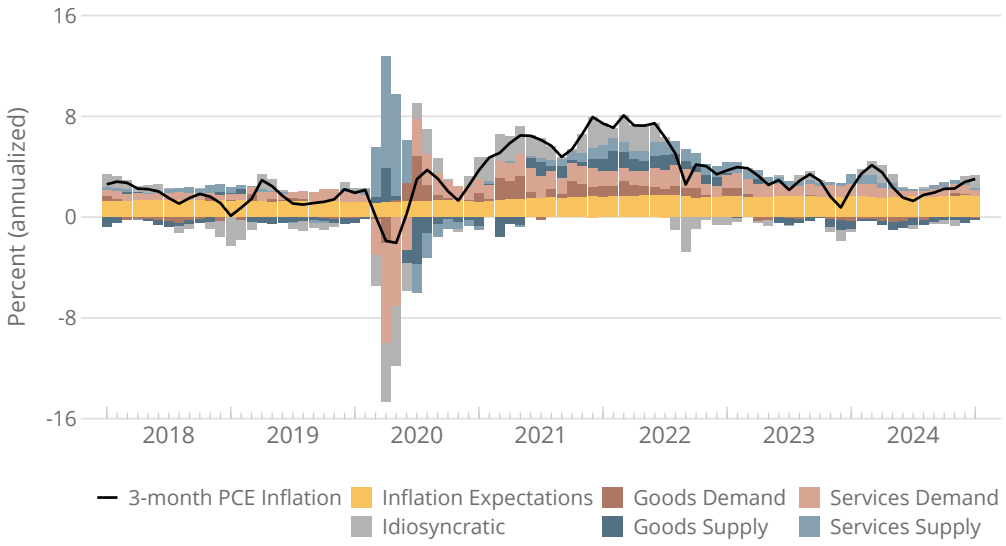
Note: The figure shows the goods and services demand and supply factors expressed as 12-month moving averages. The solid (dashed) lines represent the median (10th and 90th percentiles) of the associated posterior density. The shaded vertical bars depict recessions, as determined by the National Bureau of Economic Research.

Figure 2: Historical Decomposition of 12-Month PCE Inflation



Note: The figure shows the contributions of the different components to PCE inflation (colored areas) along with 12-month PCE inflation (solid black line).

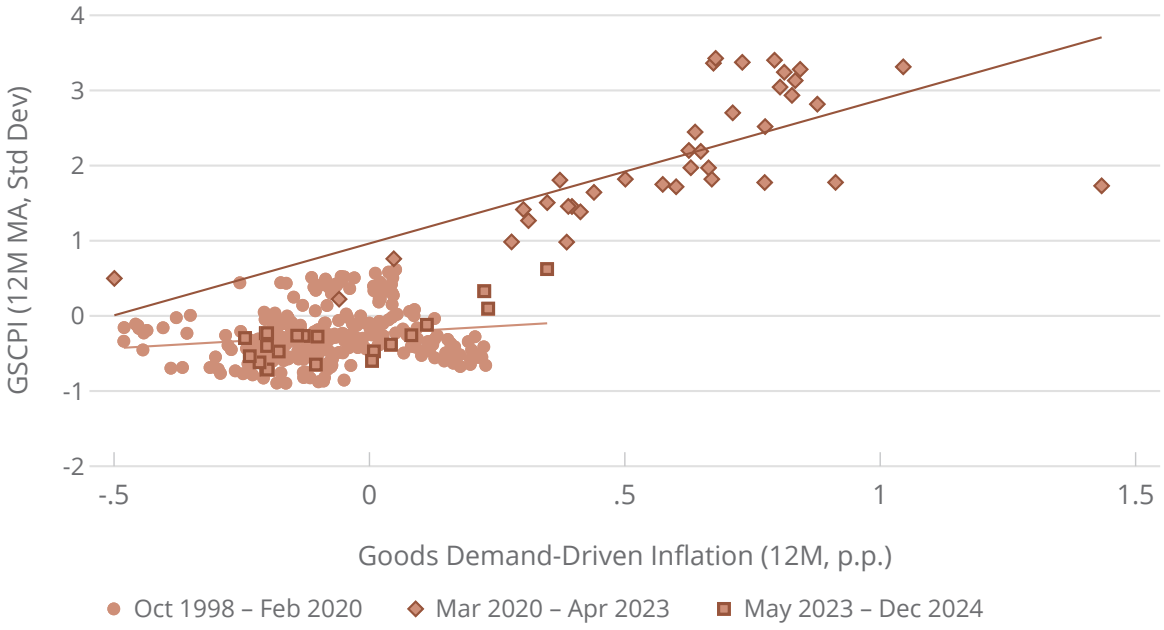
Figure 3: Historical Decomposition of 3-Month Inflation



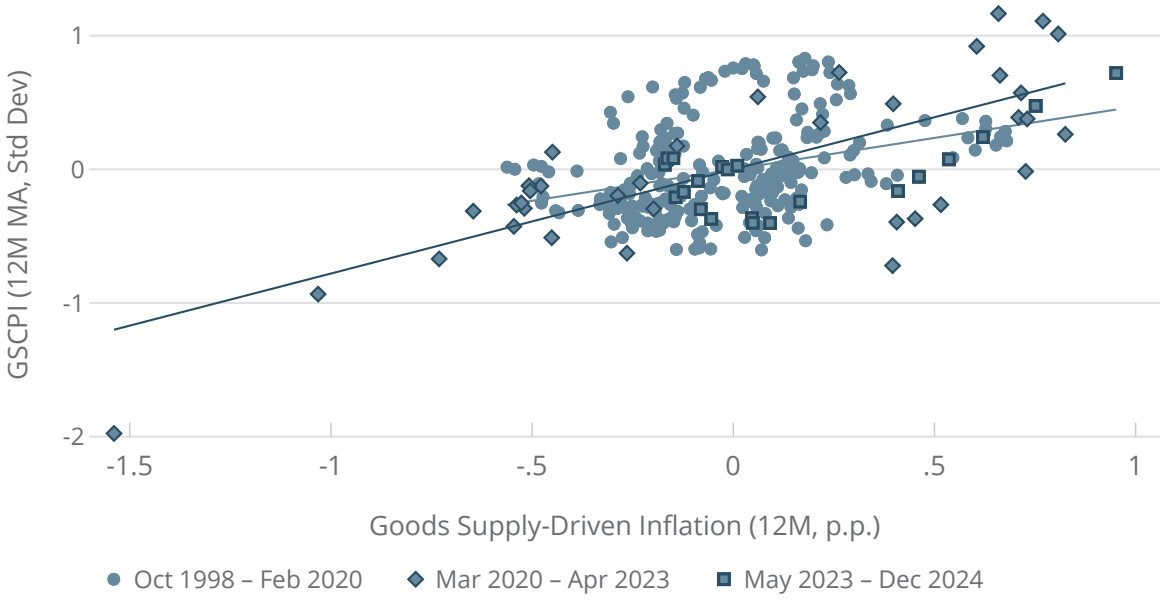
Note: The figure shows the contributions of the different components to PCE inflation (colored areas) along with three-month PCE inflation (solid black line).

Figure 4: Comparison with Global Supply Chain Pressures

(a) Demand-Driven Inflation versus GSCPI

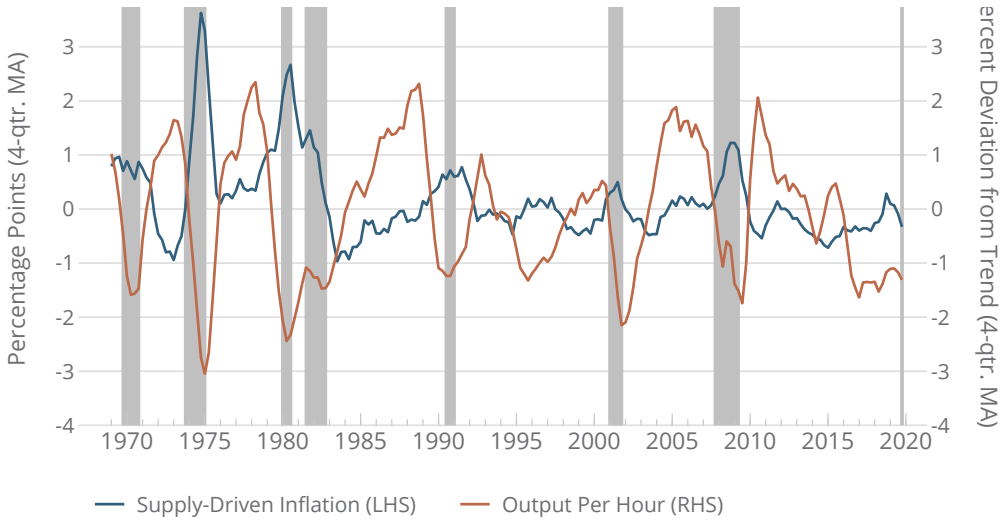


(b) Supply-Driven Inflation versus GSCPI



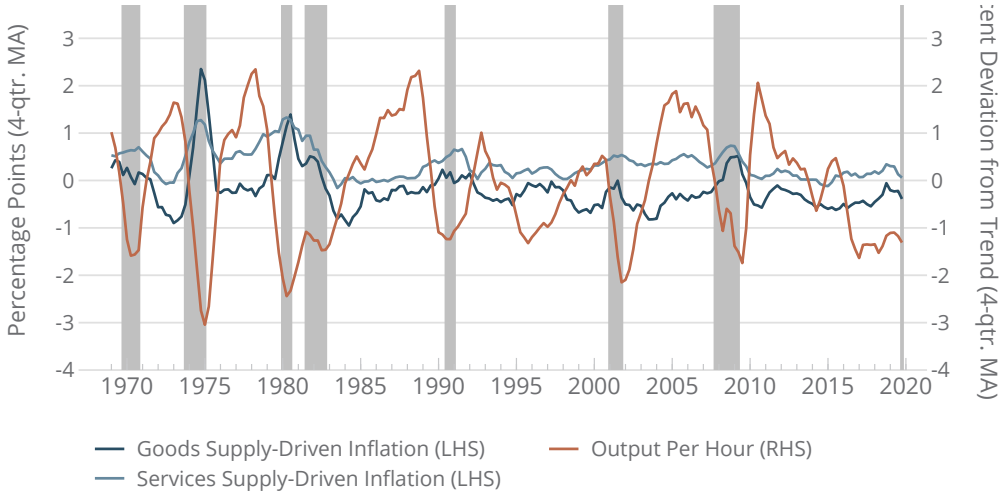
Note: *We control for goods demand-driven inflation and the COVID-19 pandemic for both variables.*

Figure 5: Supply Contribution to Inflation and Labor Productivity



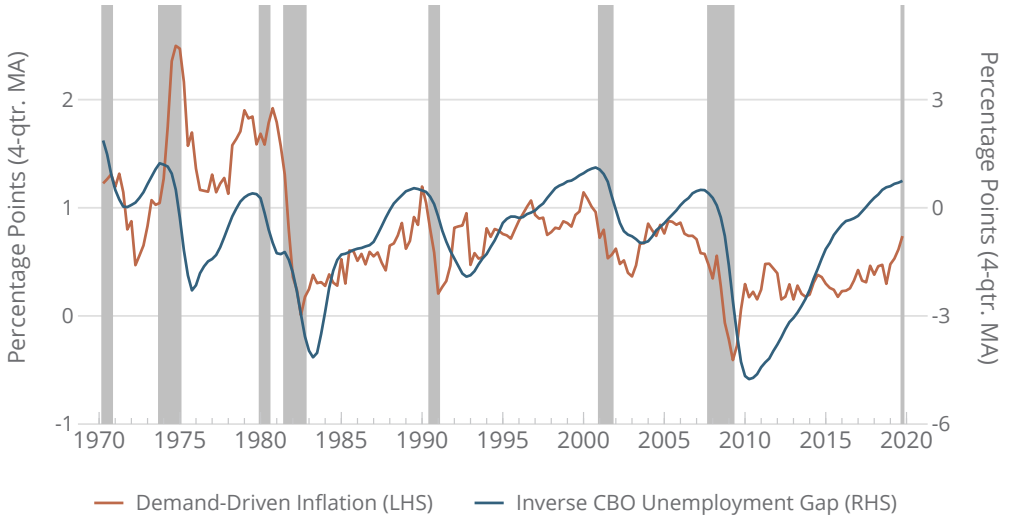
Note: The figure shows the four-quarter moving average of the common supply contribution to PCE inflation along with the percent deviation of the four-quarter moving average of output per hour from the trend.

Figure 6: Goods Supply and Services Supply Contributions to Inflation and Labor Productivity



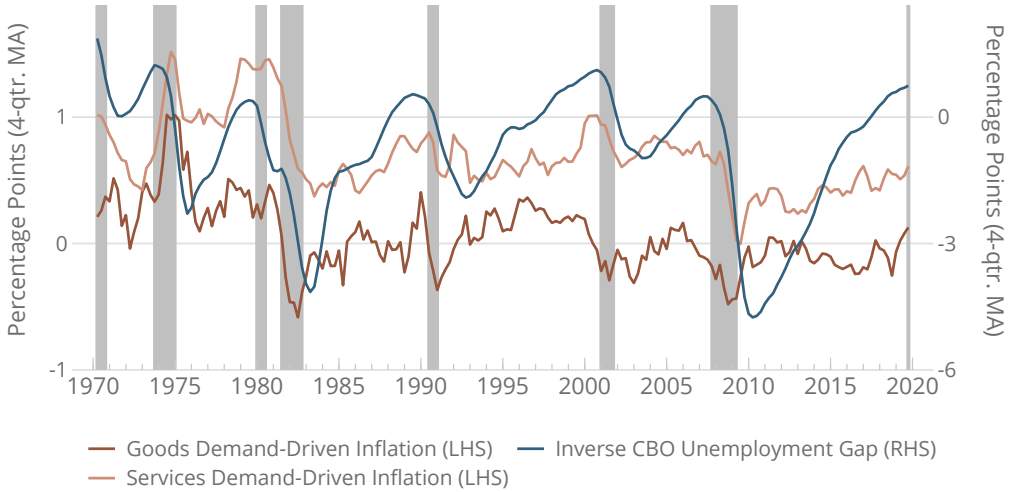
Note: The figure shows the four-quarter moving average of the goods supply and services supply contributions to PCE inflation along with the percent deviation of the four-quarter moving average of output per hour from the trend.

Figure 7: Common Demand Contribution to Inflation and the Unemployment Gap



Note: The figure shows the four-quarter moving average of the common demand contribution to PCE inflation along with the four-quarter moving average of the inverse unemployment gap as estimated by the CBO.

Figure 8: Goods Demand and Services Demand Contributions to Inflation and the Unemployment Gap



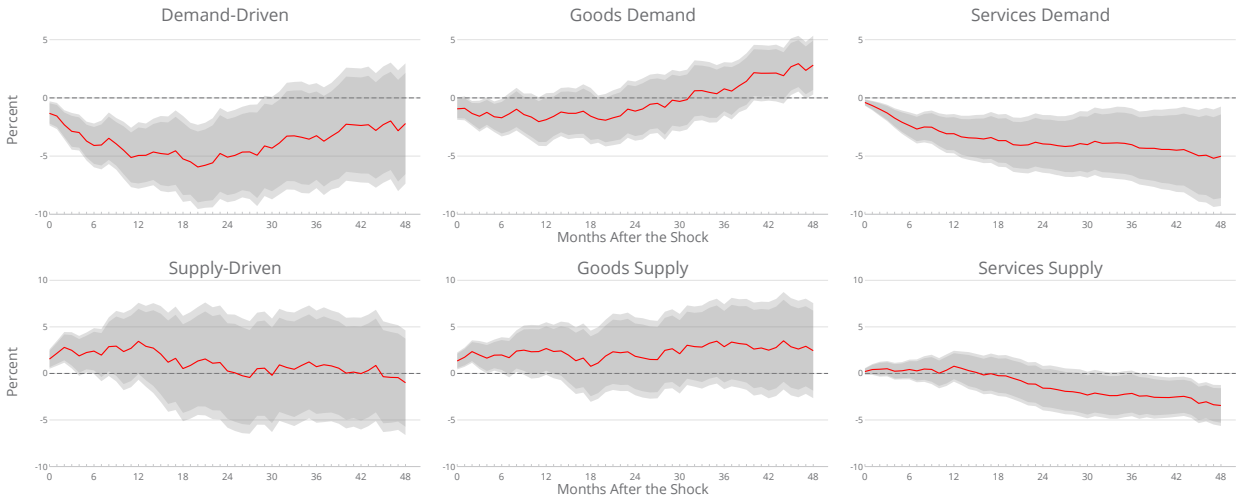
Note: The figure shows the four-quarter moving averages of the goods demand and services demand contributions to PCE inflation along with the four-quarter moving average of the inverse unemployment gap as estimated by the CBO.

Figure 9: Effects of Oil Supply News Shocks



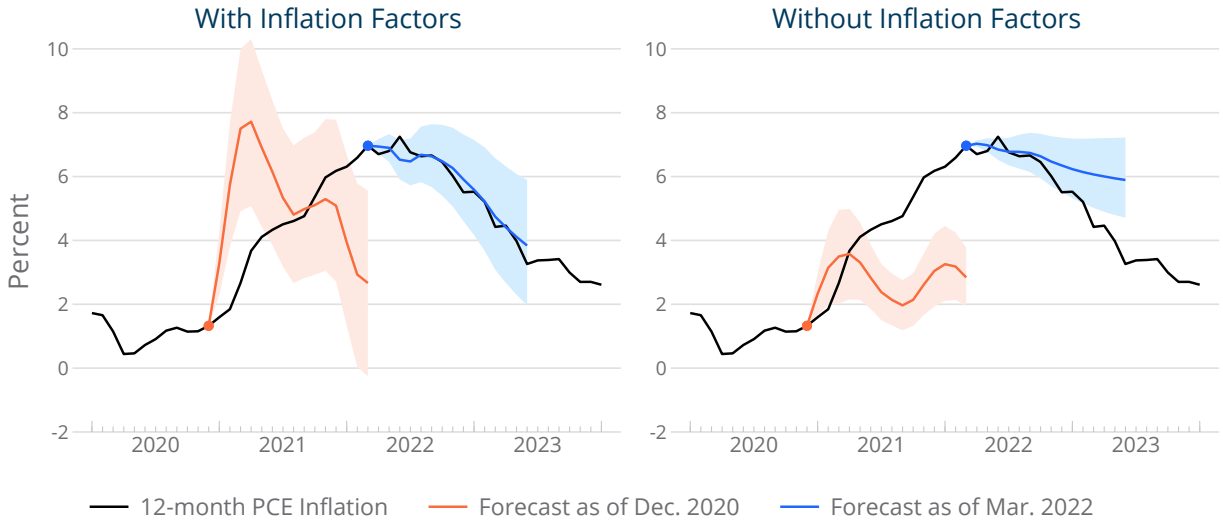
Note: Each panel shows the responses of the corresponding supply and demand factors to an oil supply news shock. Impulse responses are based on local projection regressions. The red line indicates the point estimate of the average effect, and the gray bands indicate the corresponding 90% and 95% confidence intervals.

Figure 10: Effects of Monetary Policy Shocks



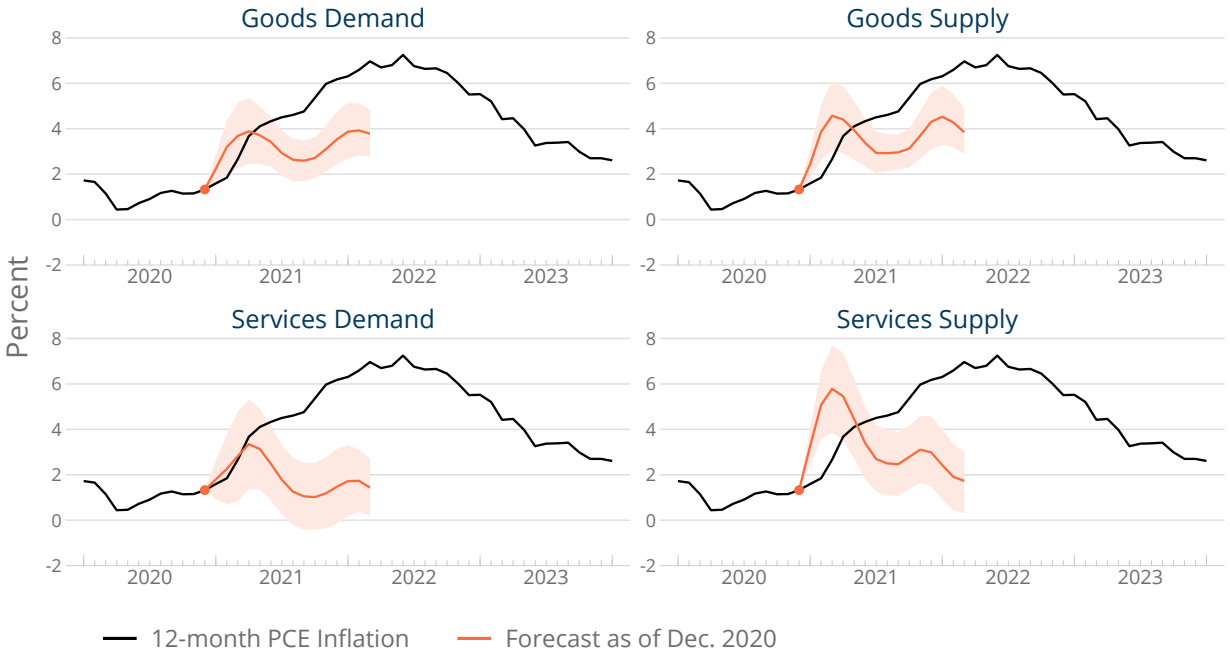
Note: Each panel shows the responses of the corresponding supply and demand factors to a monetary policy shock. Impulse responses are based on local projection regressions. The red line indicates the point estimate of the average effect, and the gray bands indicate the corresponding 90% and 95% confidence intervals.

Figure 11: Real-Time Inflation Forecasts



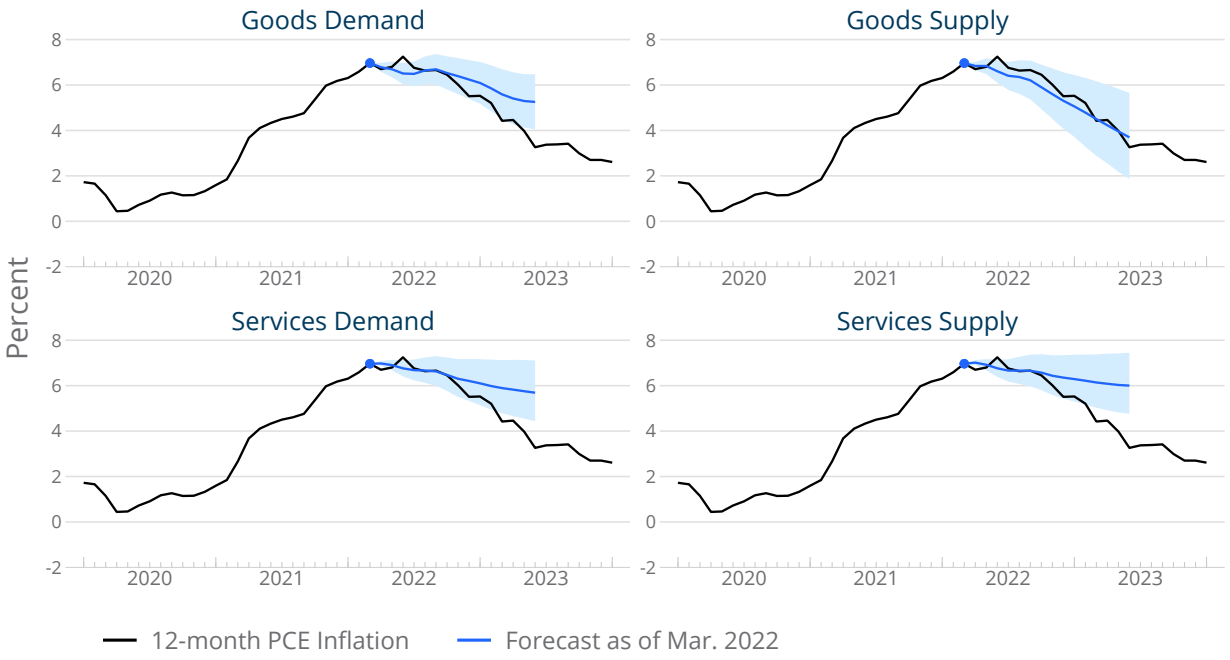
Note: The left panel plots the forecasts of PCE inflation obtained with a BVAR model that contains information on a set of macroeconomic variables and the proposed inflation factors. The model is estimated with data from June 1976 until December 2020. The forecasts are obtained from January 2021 until March 2022. The right panel plots the two-year-ahead forecasts of PCE inflation obtained with a BVAR model that contains information only on the set of macroeconomic variables. The model is estimated with data from June 1976 until March 2022. The forecasts are obtained from April 2022 until January 2025. The employed macroeconomic variables are: (i) PCE inflation, (ii) unemployment rate, (iii) unit labor cost, (iv) 2-year treasury nominal yield, and (v) energy CPI inflation. In each panel, the colored line (area) show the point (density) forecast, while the black line shows the realized PCE inflation for comparison purposes.

Figure 12: Real-Time Inflation Forecasts with One Factor - Dec. 2020



Note: Each panel plots the forecasts of PCE inflation obtained with a BVAR model that contains information on a set of macroeconomic variables (see note in Figure 11) and one inflation factors.

Figure 13: Real-Time Inflation Forecasts with One Factor - Mar. 2022



Note: Each panel plots the forecasts of PCE inflation obtained with a BVAR model that contains information on a set of macroeconomic variables (see note in Figure 11) and one inflation factors.

Supplementary Materials—For Online Publication Only

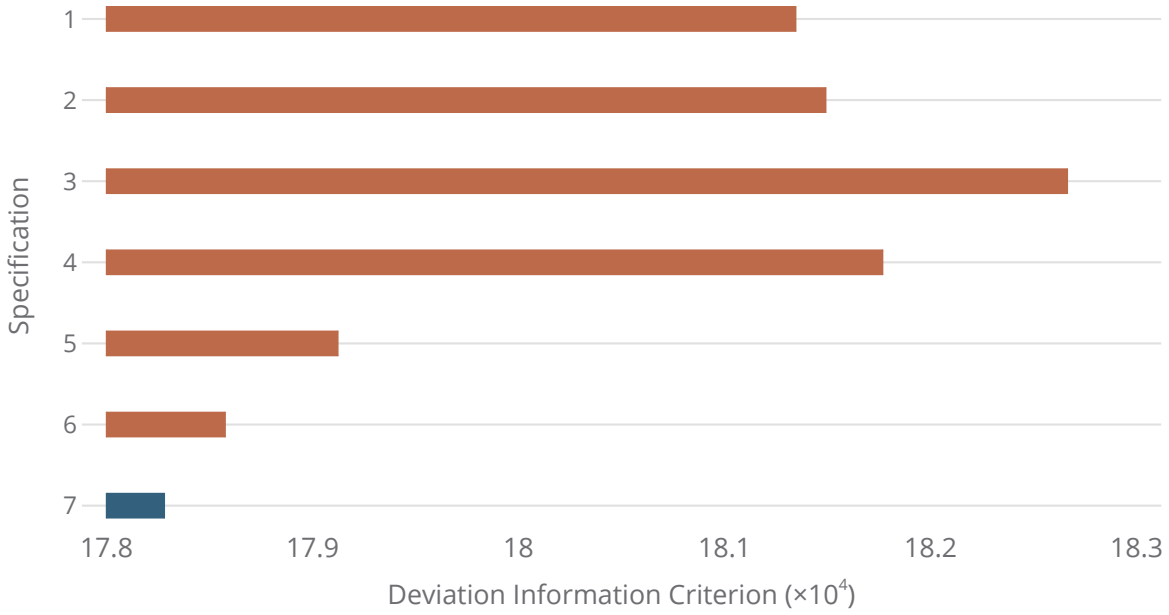
A Data

Table A.1: PCE (NIPA) Categories Used for Estimation

Line Number	**Line Description**
(1)	(2)
5	New motor vehicles (55)
12	Net purchases of used motor vehicles (56)
20	Motor vehicle parts and accessories (58)
24	Furniture and furnishings (parts of 31 and 32)
29	Household appliances (part of 33)
32	Glassware, tableware, and household utensils (34)
35	Tools and equipment for house and garden (35)
39	Video, audio, photographic, and information processing equipment and media (75, 76, and part of 93)
52	Sporting equipment, supplies, guns, and ammunition (part of 80)
53	Sports and recreational vehicles (79)
60	Recreational books (part of 90)
61	Musical instruments (part of 80)
63	Jewelry and watches (part of 119)
66	Therapeutic appliances and equipment (42)
69	Educational books (96)
70	Luggage and similar personal items (part of 119)
71	Telephone and related communication equipment
74	Food and nonalcoholic beverages purchased for off-premises consumption (4)
99	Alcoholic beverages purchased for off-premises consumption (5)
103	Food produced and consumed on farms (6)
105	Garments
109	Other clothing materials and footwear (13 and 17)
114	Motor vehicle fuels, lubricants, and fluids (59)
117	Fuel oil and other fuels (29)
121	Pharmaceutical and other medical products (40 and 41)
126	Recreational items (parts of 80, 92, and 93)
131	Household supplies (parts of 32 and 36)
137	Personal care products (part of 118)
141	Tobacco (127)
142	Magazines, newspapers, and stationery (part of 90)
153	Housing
165	Household utilities
173	Outpatient services
182	Hospital and nursing home services
191	Motor vehicle services
199	Public transportation
210	Membership clubs, sports centers, parks, theaters, and museums (82)
218	Audio-video, photographic, and information processing equipment services (parts of 77 and 93)
226	Gambling (91)
230	Other recreational services (81, 94, and part of 92)
235	Food services
249	Accommodations (104)
253	Financial services
270	Insurance
281	Communication
290	Education services
298	Professional and other services (121)
307	Personal care and clothing services (14 and parts of 17 and 118)
315	Social services and religious activities (120)
327	Household maintenance (parts of 31, 33, and 36)
342	Final consumption expenditures of nonprofit institutions serving households (NPISHs) (132)

B Model Comparison

Figure B.1: Model Comparison Based on the DIC



Note: The figure shows the DIC associated with each model specification. The preferred model is the one with the lowest DIC value.

- *Specification 1*: Estimates one supply factor and one demand factor from the disaggregated data on prices and quantities. It uses short-term inflation expectations as an exogenous explanatory variable for the factors.
- *Specification 2*: Estimates one supply factor and one demand factor from the disaggregated data on prices and quantities. It uses long-term inflation expectations as an exogenous explanatory variable for the factors.
- *Specification 3*: Estimates separate supply and demand factors for goods and services from the disaggregated data on prices and quantities. It uses long-term inflation expectations as an exogenous explanatory variable for the disaggregated data on prices, assuming a positive relationship.

- *Specification 4*: Estimates separate supply and demand factors for goods and services from the disaggregated data on prices and quantities. It uses long-term inflation expectations as an exogenous explanatory variable for the disaggregated data on prices (quantities), assuming a positive (negative) relationship.

- *Specification 5*: Estimates separate supply and demand factors for goods and services from the disaggregated data on prices and quantities. It does not include data on inflation expectations.

- *Specification 6*: Estimates separate supply and demand factors for goods and services from the disaggregated data on prices and quantities. It uses short-term inflation expectations as an exogenous explanatory variable for the factors.

- *Specification 7*: Estimates separate supply and demand factors for goods and services from the disaggregated data on prices and quantities. It uses long-term inflation expectations as an exogenous explanatory variable for the factors.