Structural Core Inflation*

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Abstract

We propose a novel approach to measuring core inflation using a dynamic stochastic general equilibrium model that disentangles trend, idiosyncratic, and common (core) inflation components. This approach identifies core inflation as the inflation component attributable to the structural business cycle, reflecting the underlying economic fundamentals and business cycle dynamics that influence core inflation. Our structural core inflation approach demonstrates superior out-of-sample forecasting and predictive abilities. Furthermore, we provide empirical evidence suggesting that the Federal Reserve's monetary policy has historically been more closely aligned with targeting core inflation rather than headline inflation. The flexibility of our structural core inflation framework effectively complements central bank and policymaker models.

Keywords: Phillips curve, price dynamics, inflation components, Bayesian estimation, DSGE modelling, dissagregated prices.

JEL Classification: C11, C38, C53, E31, E32, E52.

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1 Introduction

Central banks, including the Federal Reserve (Fed), consider the core Personal Consumption Expenditure (PCE) price index as a primary indicator for gauging economic conditions.[1] Current core inflation indexes are based on several approaches considering component selection (PCE without energy and food), weights decreasing for extreme observations (median and trimmed-mean), average frequency of price change to determine sticky-price aggregates (Bils and Klenow, 2004; Bryan and Meyer, 2010), factor approach with non-structural form (Fed's UIG underlying inflation), and cyclical components (Stock and Watson, 2020b).

In this paper, we introduce a new inflation block that decomposes each PCE inflation component into core, non-core, and trend inflation. This block is integrated into a dynamic stochastic general equilibrium (DSGE) model, through the Phillips curve. In comparison with other measures of core inflation, our structural inflation measure is more stable and related to the business cycle. In addition, our flexible approach can be applied to any other DSGE model.

Our approach to core inflation offers several advantages over other methods. First, we use the structure and variables of a medium-scale DSGE model of the economy, rather than variables reflecting only inflation components and activity (Stock and Watson, 2020b), to consider a wide range of macroeconomic variables interlinked in a structural way and the complex interdependencies among different economic dynamics. Specifically, this allows us to capture the underlying economic forces driving inflation rather than simply measuring the observed fluctuations in inflation. Second, our structural approach permits the analysis of the shocks driving core inflation and the design and transmission of monetary policy. Third, our filtering method provides structural forecasting of core inflation, which may improve the accuracy of economic forecasts. Finally, our method differentiates between three different inflation types (core, non-core, and trend), which depend on the historical levels of each PCE component inflation (trend inflation) and component-specific core and non-core inflation.

Our flexible inflation block for DSGE models decompose headline inflation to PCE component-specific core, non-core and trend, with a business cycle driven dynamic factor determining core inflation. Hence, our approach uses component inflation data, having stronger theoretical foundations than alternative methodologies, leading to findings consistent with other methods of measuring core inflation.

[1]To address the volatility of energy and food prices, alternative inflation measures that exclude these components, and statistical techniques to identify sticky prices and remove outliers, were devised. Nevertheless, these measures are not without their limitations, such as their unobservability, lack of solid theoretical fundations, inability to differentiate between various types of inflation, and inconsistent correlation with business cycles.

Inflation is a crucial variable that central banks must keep under control to ensure macroeconomic stability. Various approaches to measuring and decomposing inflation in the past decades were developed to understand its underlying dynamics better. According to the Fed's view on inflation (Hasenzagl et al., 2022), core inflation is the relevant price index of the economic stance. Consequently, monetary policy founded on core inflation should be better and less noisy than policies based on other price indexes (Aoki, 2001; Mankiw and Reis, 2003; Eusepi et al., 2011), and economic forecasts should be improved. Hasenzagl et al. (2022) present a semi-structural time series model of inflation dynamics that includes a long-term trend, a Phillips curve, and temporary fluctuations in energy prices. They find that a stable long-term inflation trend and a steep Phillips curve align with empirical data and identify an independent expectations channel through which energy prices impact headline inflation not only via the Phillips curve. In our model, headline inflation is the weighted sum of core inflation components that follow the Phillips curve dynamics and of the non-core components, which capture price movements that do not conform to the Phillips curve structure.

Following the literature on core inflation measures, we introduce *structural core inflation*, an innovative DSGE model-based approach to measure core inflation. Ball et al. (2023) propose a new measure of core inflation based on weighted median inflation. They argue that their measure is more reliable concerning underlying inflation dynamics and robust to outliers and noise than traditional measures of core inflation (e.g., trimmed mean inflation). They show that their core inflation measure predicts future inflation better than traditional measures. Wynne (2008) review some conceptual issues related to core inflation measures, arguing for multiple definitions of core inflation, which can have different implications for monetary policy (Mankiw and Reis, 2003). The choice of a core inflation measure should be based on the specific goals of monetary policy. Various measures of core inflation, their advantages and limitations, and the challenges associated with creating a reliable measure of core inflation are discussed.

Boivin and Giannoni (2006) examine the use of DSGE models in a data-rich environment. Instead of creating a DSGE-based core inflation index, they utilized rich data,[2] including core inflation, to estimate a DSGE model. They argue that incorporating large data sets can help improve the accuracy and robustness of DSGE models to provide a more realistic and nuanced view of the economy than traditional macroeconomic models.

[2]Bernanke et al. (2005) develop a factor-augmented vector autoregressive model to measure the effects of monetary policy and argue that such models can better capture the effects of monetary policy than traditional vector autoregressive (VAR) models by incorporating a rich data set of macroeconomic variables.

Stock and Watson (2016) decompose the PCE into trend and cyclical components for the US. Trend inflation is the long-run inflation rate, while cyclical inflation is the short-run deviation from trend inflation. They show that trend inflation is relatively stable, while cyclical inflation is more volatile. Stock and Watson (2016) propose a method to extract trend inflation, a better measure of underlying inflation dynamics than headline PCE inflation. Stock and Watson (2020b) study trend, seasonal, and sectorial inflation in the Euro area. They find that trend inflation in the Euro area has declined since the early 2000s. They also find that seasonal inflation is more pronounced in some sectors than others and that different factors influenced inflation dynamics in the Euro area than in the US, such as the heterogeneity of goods and services prices across sectors and countries. Stock and Watson (2020a) examine the flattening Phillips curve by measuring slack and find that several inflation components have strong and stable correlations with the cyclical component of real activity, while others have weak or unstable correlations. They construct a new inflation index, cyclically sensitive inflation, which weights the components by their joint cyclical covariation with real activity and provides a real-time measure of cyclical movements in inflation.

Using a dynamic factor model, Reis and Watson (2010) decompose quarterly changes in consumption goods' prices into three independent components: idiosyncratic relative-price changes, low-dimensional aggregate relative-price changes, and *pure inflation*, which is an index of equiproportional changes in all inflation rates. Pure inflation accounts for 15-20% of total inflation variability, while the aggregate relative-price index accounts for most of the remaining variability. They show that pure inflation is driven primarily by monetary policy shocks, whereas aggregate relative-price changes are driven by supply shocks.

Unlike previous studies focusing on a limited set of variables such as inflation and the output gap, the Smets and Wouters (2007) model allows us to incorporate a wide range of macroeconomic variables.[3] This enables us to capture the complex interdependencies among different aspects of the economy and provide a more accurate and comprehensive analysis of inflation dynamics. Based on this structural model providing strong theoretical micro-foundations and allowing transparent and interpretable identification of the sources of inflation, our approach has several advantages over existing methods. In addition, we offer a structural forecasting method for core inflation based on our filtering approach and consider the historical relationships among different inflation components and business cycle variables. Most importantly, our approach is flexible: our model block can be implemented for any other DSGE model, which makes it widely applicable and adaptable to different DSGE models.

[3]For instance, real and nominal variables, financial and labor market variables.

The structural core inflation measure is more stable, less volatile than other measures of core inflation, suggesting that our measure of core inflation is a reliable indicator of the business cycle. Our measure also has higher marginal log-likelihoods than when headline inflation is considered in the Taylor rule. These findings suggest that monetary policy decisions are based on core rather than headline inflation (Mankiw and Reis, 2003).

Our flexible methodology should contribute to the development of more effective and reliable monetary policies. Our approach is consistent with other methods of measuring core inflation and can provide valuable insights into inflation dynamics and the business cycle. Our approach is also helpful for policymakers and economic modeling compared to other methods of measuring core inflation.

The remainder of the paper is organized as follows. Section 2 describes the extended model composition and specificities. Section 3 delineates our data sources, calibration strategy, and econometric methodology. Section 4 presents our empirical findings, including both in-sample estimations and out-of-sample forecasting performance. Section 5 offers a comparative analysis of our core inflation measure against alternative metrics during the COVID-19 pandemic. Section 6 conducts comprehensive sensitivity analyses to validate the stability of our results. Section 7 compares the likelihood of our structural core inflation model against popular core inflation measures. Section 8 explores the policy implications of our findings and empirically examines whether the Fed's behavior is more consistent with targeting headline inflation or our structural core inflation measure. Section 9 synthesizes our key findings and broader implications, and the Appendix 10 replicates our analysis using the Consumer Price Index (CPI), demonstrating the generalizability of our approach across different inflation measures.

2 The Model

The main model block is the canonical Smets and Wouters (2007) model. This model block incorporates all equations determining economic dynamics, with the notable exceptions of those directly related to inflation—namely, the headline inflation equation (Phillips curve) and the price markup shock. Second, our core inflation equation, which is largely similar to the original Phillips curve equation. Building upon this, we introduce our core inflation equation, which closely resembles the original Phillips curve equation. The final and innovative element is a block of inflation components, consisting of subblocks that contain component-specific equations for core inflation, non-core inflation autoregressive processes, and trend inflation, which is treated as a constant. Our model also includes eight component-specific inflation shocks serving a dual purpose. These shocks are associated with both core and non-core inflation, through a component specific weight denoted as w_i^C.

We adopt the perspective of (Hasenzagl et al., 2022), and incorporate core inflation as the relevant indicator for the structural model in the main equations. The only exception is the Taylor rule, which responds to headline inflation, reflecting the assumption that the Fed does not target our unobserved index.[4]

2.1 Headline Inflation

According to Smets and Wouters (2007), the headline Phillips curve is given by

$$\begin{aligned}\pi_t &= \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\iota_p\gamma^{1-\sigma_c}}E_t\left[\pi_{t+1}\right] + \frac{\iota_p}{1+\beta\iota_p\gamma^{1-\sigma_c}}\pi_{t-1} \\ &\quad -\frac{1}{1+\beta\iota_p\gamma^{1-\sigma_c}}\frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_p\right)\left(1-\xi_p\right)}{\xi_p\left(1+\left(\phi_p-1\right)\varepsilon_p\right)}\mu_t^p + \varepsilon_t^p \qquad (1)\end{aligned}$$

where ι_p is the degree of indexation to past inflation, ξ_p the degree of price stickiness, ε_p the curvature of the Kimball (1995) goods market aggregator, $\phi_p - 1$ the steady-state price markup, ε_t^p the price markup shock and μ_t^p the price markup defined as a function of the wage, real rental rate on capital and technology shock.

The price markup shock, ε_t^p, follows a first-order autoregressive moving-average (ARMA) process such that

$$\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \eta_t^p - \mu_p \eta_{t-1}^p \qquad (2)$$

where $\rho_p \in [0,1]$ is the first-order autoregressive parameter, μ_p the moving average coefficient, and η_t^p the innovation term. This shock process is designed to capture high-frequency fluctuations in inflation markups.

Hasenzagl et al. (2022) explain that according to the Fed's view on inflation, Phillips curve dynamics are suitable to explain core inflation. Our enhanced model that nests the core inflation view builds upon this view.

Our core inflation equation is related to the Phillips curve except that rather than measuring inflation itself (with a measurement error), it measures only core inflation, and the innovation of the core inflation equation is not a single shock but rather a weighted sum of eight correlated component-specific shocks.

[4]Later in section 8, we will alter this assumption and consider the case where our core measure is the target of the monetary policy."

Hence, the new core inflation equation is

$$\begin{aligned}\pi_t^C &= \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\iota_c\gamma^{1-\sigma_c}} E_t\left[\pi_{t+1}^C\right] + \frac{\iota_c}{1+\beta\iota_c\gamma^{1-\sigma_c}}\pi_{t-1}^C \\ &\quad -\frac{1}{1+\beta\iota_c\gamma^{1-\sigma_c}} \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_c\right)\left(1-\xi_c\right)}{\xi_c\left(1+\left(\phi_c-1\right)\varepsilon_c\right)}\mu_t^C + \varepsilon_t^C \end{aligned} \tag{3}$$

where the core price markup shock, ε_t^C, follows an ARMA process such that

$$\varepsilon_t^C = \rho_c \varepsilon_{t-1}^C + \eta_t^C - \mu_c \eta_{t-1}^C \tag{4}$$

However, unlike the headline Phillips curve (Eq. 1), η_t^C represents a weighted sum of eight innovations to the inflation components, $\eta_{i,t}^C$, which follow a multivariate Normal distribution such that

$$\eta_t^C = \sum_i w_i w_i^C \eta_{i,t}^C \tag{5}$$

where w_i represents the component-specific weight at the average of the sample,[5] w_i^C denotes the component share of shock that is related to core inflation, and

$$\eta_t^C = \begin{pmatrix} \eta_{1,t}^C \\ \cdot \\ \cdot \\ \cdot \\ \eta_{8,t}^C \end{pmatrix} \sim \mathcal{N}\left(0, \Sigma\right) \tag{6}$$

where Σ is the covariance matrix characterizing the distribution of the component-specific innovations $\eta_{i,t}^C$, and the covariance between component-specific innovations i and j is given by $\Sigma_{i,j}$. To enhance model flexibility, we assume the innovations are correlated as they also enter the non-structural equations for the non-core inflation components[6] in Eq. 10.

2.2 Inflation Components

We define headline inflation as the weighted sum of eight inflation PCE components ($\pi_{i,t}$), such as

$$\pi_t = \sum_i w_i \pi_{i,t} \tag{7}$$

[5]This assumption is relevant for policy analysis and minimizes approximation errors at the end of the sample.

[6]The structural shock η_t^C is a linear combination of eight correlated shocks, which also follows a Normal distribution since the sum of Normal correlated variables is also Normal.

where headline inflation is the sum of aggregate trend inflation, π^T, aggregate core inflation, π_t^C, and aggregate non-core inflation, π_t^N, such that

$$\pi_t = \pi^T + \pi_t^C + \pi_t^N \tag{8}$$

and where each component, π_i^T, $\pi_{i,t}^C$, and $\pi_{i,t}^N$, represents the component-specific trend inflation, core inflation, and non-core inflation, respectively, such that

$$\pi_{i,t} = \pi_i^T + \pi_{i,t}^C + \pi_{i,t}^N \tag{9}$$

The component-specific inflation trend is a constant parameter that captures the different PCE component trends over time, but may also reflect a constant measurement error of each component.

The component-specific non-core inflation follows a modified AR(1) process expressed as

$$\pi_{i,t}^N = \rho_i^N \pi_{i,t-1}^N + \left(1 - w_i^C\right) \eta_{i,t}^C \tag{10}$$

where $\rho_i^N \in [0,1]$ is the component-specific first-order autoregressive parameter of non-core inflation, and $\eta_{i,t}^C$ is the component-specific shock, while the shock influences the observed component through non-core inflation with $\eta_{i,t}^C(1 - w_i^C)$, and core inflation with $\eta_{i,t}^C w_i^C$ (Eqs. 3 and 5, respectively).

The component-specific core inflation is expressed as

$$\pi_{i,t}^C = \beta_i^C F_t \tag{11}$$

where $\beta_i^C \in [0,1]$ is the component-specific weight of the dynamic factor F_t as in

$$\pi_t^C = \sum_i w_i \beta_i^C F_t \tag{12}$$

where the dynamic factor F_t is further explained in Section 2.4.

To summarize, we plug the components back into Eq. 8

$$\begin{aligned}\pi_t \quad = \quad & \overbrace{\sum_i w_i \pi_i^T}^{\text{Trend: } \pi^T} + \overbrace{\sum_i w_i \left(\rho_i^N \pi_{i,t-1}^N\right) + \sum_i w_i \left(\left(1 - w_i^C\right) \eta_{i,t}^C\right)}^{\text{Non-core: } \pi^T} \\ & + \overbrace{\begin{matrix} \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\iota_c\gamma^{1-\sigma_c}} E_t\left[\pi_{t+1}^C\right] + \frac{\iota_c}{1+\beta\iota_c\gamma^{1-\sigma_c}} \pi_{t-1}^C + \\ \frac{1}{1+\beta\iota_c\gamma^{1-\sigma_c}} \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_c\right)(1-\xi_c)}{\xi_c(1+(\phi_c-1)\varepsilon_c)} \mu_t^C + \rho_c \varepsilon_{t-1}^C + \eta_t^C - \mu_c \eta_{t-1}^C \end{matrix}}^{\text{Core: } \pi_t^C}\end{aligned} \tag{13}$$

Detrending and summing the shocks, we obtain

$$\begin{aligned}
\pi_t &= \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\iota_c\gamma^{1-\sigma_c}} E_t\left[\pi^C_{t+1}\right] + \frac{\iota_c}{1+\beta\iota_c\gamma^{1-\sigma_c}}\pi^C_{t-1} \\
&+ \frac{1}{1+\beta\iota_c\gamma^{1-\sigma_c}} \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_c\right)\left(1-\xi_c\right)}{\xi_c\left(1+\left(\phi_c-1\right)\varepsilon_c\right)}\mu^C_t + \rho_c\varepsilon^C_{t-1} \\
&- \mu_c\eta^C_{t-1} + \sum_i w_i\left(\rho^N_i\pi^N_{i,t-1}\right) + \sum_i w_i\eta^C_{i,t} \qquad (14)
\end{aligned}$$

This result allows us to examine how the headline observed inflation dynamics differ from those of a standard DSGE model with a Phillips curve, and to identify the main sources of divergence. In our model, only core inflation follows a Phillips curve relation, which is therefore influenced by the real economy through the marginal cost.

The residual of the Phillips curve is a complex combination of the original ARMA(1,1) process and eight AR(1) processes. Among the eight AR(1) processes, only a fraction of them (w^C_i) affects core inflation, thus appearing as lags in the future Phillips curve. The remaining fraction $(1-w^C_i)$ has a non-structural AR(1) lag.

2.3 Inflation Shocks Propagation

We consider the dynamics of the inflation components shocks, and their effect on headline inflation through both core and non-core inflation. Following the core inflation equation (Eq. 3), we define $\pi^{\tilde{C}}_t$ as the difference between core inflation and its innovation (η^C_t). This term captures the core inflation that stems from the structural model, reflecting the past and current effects of shocks, excluding the inflation shock at time t.

$$\begin{aligned}
\pi^{\tilde{C}}_t &= \frac{\beta\gamma^{1-\sigma_c}}{1+\beta\iota_c\gamma^{1-\sigma_c}} E_t\left[\pi^C_{t+1}\right] + \frac{\iota_c}{1+\beta\iota_c\gamma^{1-\sigma_c}}\pi^C_{t-1} \\
&- \frac{1}{1+\beta\iota_c\gamma^{1-\sigma_c}} \frac{\left(1-\beta\gamma^{1-\sigma_c}\xi_c\right)\left(1-\xi_c\right)}{\xi_c\left(1+\left(\phi_c-1\right)\varepsilon_c\right)}\mu^C_t + \rho_c\varepsilon^C_{t-1} - \mu_c\eta^C_{t-1} \qquad (15)
\end{aligned}$$

where

$$\pi^C_t = \pi^{\tilde{C}}_t + \eta^C_t \qquad (16)$$

and plugging in Eq. 5, we obtain

$$\pi^C_t = \pi^{\tilde{C}}_t + \sum_i w^C_i \eta^C_{i,t} w_i \qquad (17)$$

Non-core inflation dynamics are

$$\pi_t^N = \sum_i w_i \rho_i^N \pi_{i,t-1}^N + \sum_i w_i \left(1 - w_i^C\right) \eta_{i,t}^C \tag{18}$$

We define $\pi_{\overline{t}}^N$ as non-core inflation excluding the non-core innovation such as

$$\pi_{\overline{t}}^N = \sum_i w_i \rho_i^N \pi_{i,t-1}^N \tag{19}$$

where

$$\pi_t^N = \pi_{\overline{t}}^N + \sum_i w_i \left(1 - w_i^C\right) \eta_{i,t}^C \tag{20}$$

Combining Eq. 7 with Eqs. 16 and 20, we obtain

$$\begin{aligned} \pi_t &= \pi^T + \pi_{\overline{t}}^C + \sum_i w_i^C \eta_{i,t}^C w_i + \pi_{\overline{t}}^N + \sum_i w_i \left(1 - w_i^C\right) \eta_{i,t}^C \\ \pi_t &= \pi^T + \pi_{\overline{t}}^C + \pi_{\overline{t}}^N + \sum_i \eta_{i,t}^C \end{aligned} \tag{21}$$

Eq. 21 demonstrates that we adopt the same formulation as Smets and Wouters (2007) and many other models, where the observed inflation is decomposed into two terms: the contributions to inflation that depend on all sources except current inflation shocks that reflect both the lagged effects of past shocks and the current effects of non Phillips curve shocks ($\pi^T + \pi_{\overline{t}}^C + \pi_{\overline{t}}^N$), and the current Phillips curve shocks ($\sum \eta_{i,t}^C$). In our model, the residual ($\sum \eta_{i,t}^C$), which represents the difference between the observed inflation and all other components of the inflation equation except the residual, is allocated between core and non-core inflation types according to the weights w_i^C. This allocation is crucial for both backward-looking analysis and forward-looking projections, as core and non-core inflation processes exhibit distinct dynamics.

To understand how w_i^C affects the covariances between the component-specific shocks and core inflation, we denote the component-specific non-core inflation shock by $\eta_{i,t}^{NC}$, which equals $(1 - w_i^C)\eta_{i,t}^C$, where $\eta_{i,t}^C$ is the component-specific inflation shock. The term $w_i^C \eta_{i,t}^C$ represents the impact of the component-specific shock on all core components, not limited to component i.

The parameter w_i^C reflects the covariance between $\eta_{i,t}^{NC}$ and the core inflation shock η_t^C, derived as follows

$$\begin{aligned} Cov\left(\eta_{i,t}^{NC}, \eta_t^C\right) &= Cov\left(\left(1 - w_i^C\right)\eta_{i,t}^C, \sum_i w_i w_i^C \eta_{i,t}^C\right) \\ &= Cov\left(\left(1 - w_i^C\right)\eta_{i,t}^C, w_i w_i^C \eta_{i,t}^C\right) + Cov\left(\left(1 - w_i^C\right)\eta_{i,t}^C, \sum_{j \neq i} w_j w_j^C \eta_{j,t}^C\right) \\ &= w_i\left(1 - w_i^C\right) w_i^C \Sigma_{i,i} + \left(1 - w_i^C\right)\sum_{j \neq i} w_j w_j^C \Sigma_{i,j} \end{aligned} \tag{22}$$

where the term on the right depends on the covariances of the shocks. Higher covariances with lower values of w_i^C, which indicates more pronounced non-core shocks, lead to a higher covariance between the component-specific non-core inflation shock and the core inflation shock. The term on the left highlights that η_t^C affects both types of inflation simultaneously. This term is negligible when w_i^C is close to 1 or 0, implying that the shock mainly affects either core or non-core inflation. This term is maximized when w_i^C is 0.5, implying that the shock affects both types of inflation equally.

2.4 Dynamic Factor Core Inflation

Recent methodologies to measure core inflation often employ a dynamic factor analysis to capture the underlying inflationary pressures while disregarding short-term price fluctuations (Forni and Reichlin, 1998; Forni et al., 2000; Stock and Watson, 2002). Similarly, our model includes a dynamic factor, denoted as F_t, which captures the common variation in inflation across different components. Specifically, each core inflation component equals a parameter multiplied by the dynamic factor (Eq. 12).

According to Eq. 23, the dynamic factor is closely related to the component-specific core inflation through the following linear function

$$F_t = \frac{\pi_{i,t}^C}{\beta_i^C} \tag{23}$$

For the relationship between the dynamic factor and aggregate core inflation, we can use Eq 12 to obtain:

$$F_t = \frac{\pi_t^C}{\sum_i w_i \beta_i^C} \tag{24}$$

where F_t is the factor in common with each core inflation component.

According to Eq. 23 the behavior of core inflation is consistent across all components, with variations only in magnitude as determined by the transmission coefficient (β_i), This coefficient represents the relationship between the dynamic factor F_t and the component-specific core inflation ($\pi^C_{i,t}$).

Following Eq. 11, dividing two different core inflation components yields

$$\frac{\pi^C_{i,t}}{\pi^C_{j,t}} = \frac{\beta^C_i F_t}{\beta^C_j F_t} = \frac{\beta^C_i}{\beta^C_j} \tag{25}$$

Eq. 25 shows that the ratio of two core components is solely determined by the ratio of their corresponding β^C_i, whereas the absolute values are numerically arbitrary and unidentified. Thus we can calibrate the identifying restriction, that β^C_1 equals 9 minus the sum of the other β^C_i in Section 3.2, such that all the estimated parameters are identified:[7]

$$\beta^C_1 = 9 - \sum_{i=2:8} w_i \beta^C_i \tag{26}$$

In contrast to previous studies that employed factor models to capture inflation in Dynamic Stochastic General Equilibrium (DSGE) models, e.g., Boivin and Giannoni (2006), our factor model ensures that the link between component inflation and aggregate core inflation always transitions through the component weight (w_i). This approach offers two distinct advantages. Firstly, it enables us to easily decompose each inflation component into core, non-core, and trend types of inflation. Secondly, it *disciplines* the link between each component and core inflation. Even if the component is perfectly correlated with core inflation and the business cycle, a component with a small weight in the PCE basket will not significantly impact core inflation.

2.5 Inflation Data Filtering

A situation in which two inflation components move in opposite directions from the steady state, one increasing and the other decreasing, is difficult to interpret. Models with only headline inflation dynamics cannot interpret these evolutions since they offset one another.

Since one inflation component is higher than its trend and the other is lower than its trend, our model will attribute these changes to either core inflation or non-core inflation. We can also infer that at least one of the component changes will be driven primarily by non-core inflation since all core inflation components move in the same direction. Any component change attributed to core inflation depends on how closely related the component is to core inflation (mainly depending on β^C_i and w^C_i) and how other business cycle variables behave.

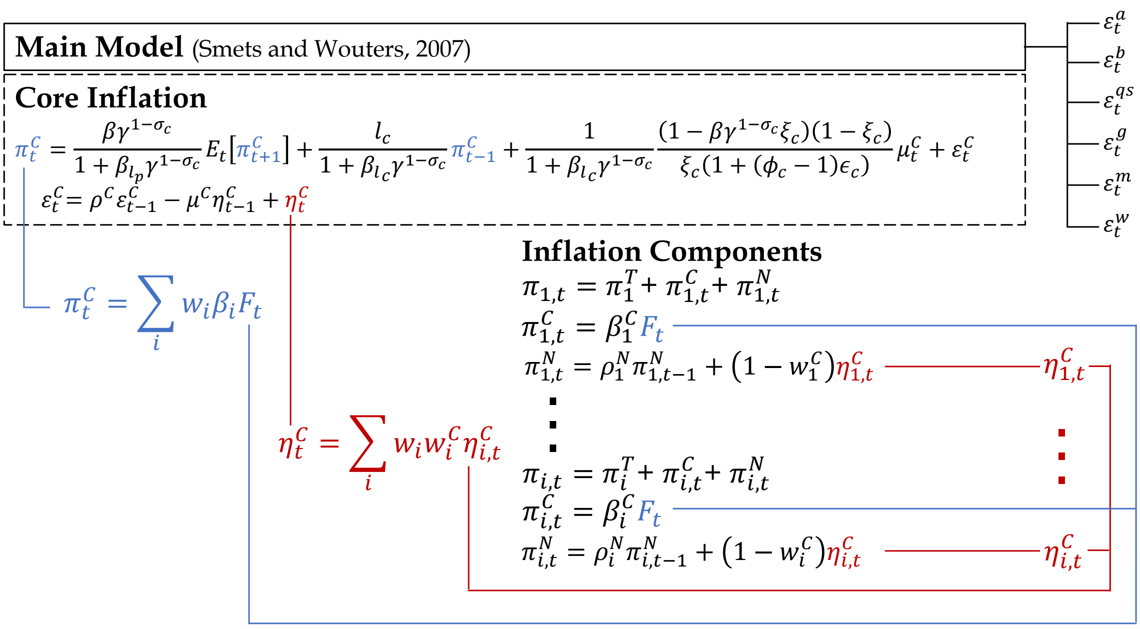
[7] 9 is a natural value for $\sum_{i=1:9} \beta^C_i$, since in the estimation, the prior for each β^C_i (except β^C_1) will be 1. Therefore, in the symmetrical case where all parameters equal their priors, all β^C_i will equal 1.

Inflation driven by core inflation or non-core inflation has different implications. Core inflation enters the future Phillips curve, while non-core inflation follows its component-specific AR(1) process. Both types of inflation have an autoregressive lag parameter, but the Phillips curve tends to have higher persistence than the non-core component-specific AR(1) process. The main difference is that only core inflation will have future co-movements with other core inflation components and affect other economic variables.[8] Non-core components may reflect various economic phenomena that deviate from the headline Phillips curve framework. These include sector-specific shocks, imported inflation, measurement errors and biases, and other forms of Phillips curve misspecification. Our model encompasses the original Smets and Wouters (2007) model as a particular case, where the estimation procedure can indicate that the data do not support our extensions accordingly.

2.6 Model Summary

The summary of the model is presented in Fig. 1.

Figure 1. Structural Model Representation



Notes: Inflation component shocks and factors are in red and blue, respectively. The dashed block represents the inflation (Phillips curve) and cost-push shock equations replacing the corresponding equations in the core model (Smets and Wouters, 2007).

Our model is composed of three main parts. First, the main model is the Smets and Wouters (2007) model excluding inflation and related price markup shock

[8] Except for the Taylor rule, which reacts to headline inflation in our baseline model.

equations. Second, the core inflation block, and third, the inflation components block.

The latter block contains eight component-specific equations, each comprising component-specific inflation trend (π_i^T), non-core ($\pi_{i,t}^N$), and core ($\pi_{i,t}^C$) equations, including a common factor (F_t) and a component-specific inflation innovation ($\eta_{i,t}^C$).

3 Estimation

To examine inflationary pressures and consumption patterns across diverse economic sectors, we employ a granular analysis of PCE inflation. A detailed examination of the CPI is provided in the Appendix 10.

3.1 Data

The model is estimated using quarterly U.S. data from 1993 to 2019, extending Smets and Wouters (2007) by considering disaggregated PCE inflation components (instead of the GDP deflator) and the shadow rate.[9] The measurement equations, data sources and transformations remain the same as in Smets and Wouters (2007).

We innovate by disaggregating PCE inflation into 16 major components, providing a granular view of price dynamics. To simplify and reduce computational complexity, we grouped these components into nine categories: Food and Beverages,[10] Housing and utilities, Clothing and Footwear, Health care, Recreation,[11] Energy,[12] Other durable goods,[13] Other nondurable goods, and Other services.[14]

We obtained the following tickers (series code) in parenthesis from FRED (Federal Reserve Economic Data, Federal Reserve Bank of St. Louis). From the U.S. Bureau of Economic Analysis, we obtain Real Gross Domestic Product (GDPC1, seasonally adjusted annual rate), Personal Consumption Expenditures (PCEC, seasonally adjusted), and Fixed Private Investment (FPI, seasonally

[9]For the interest rate, we use the Effective Federal Funds Rate. From December 16, 2008, to December 15, 2015, the effective federal funds rate was in the 0 to 1/4 percent range. In this zero lower bound environment, shadow rates capture the effects of unconventional monetary policy (Kim and Singleton, 2012; Krippner, 2013). Following Benchimol and Fourçans (2019), we use the shadow rate constructed by Wu and Xia (2016).

[10]Food and beverages purchased for off-premises consumption, Food services and accommodations.

[11]Recreational goods and vehicles, Recreation services.

[12]Gasoline and other energy goods.

[13]Motor vehicles and parts, furnishings and durable household equipment, other durable goods.

[14]Transportation services, Financial services and insurance, Other services, Final consumption expenditures of nonprofit institutions serving households (NPISHs) (132).

adjusted). The U.S. Bureau of Labor Statistics provides Civilian Employment (CE16OV, seasonally adjusted), Civilian Noninstitutional Population (CNP16OV, not seasonally adjusted), Average Weekly Hours in the Nonfarm Business Sector (PRS85006023, seasonally adjusted), and Compensation Per Hour in the Nonfarm Business Sector (COMPNFB, seasonally adjusted).

For PCE, we utilize a detailed breakdown of 16 components, each represented by two series: one for real expenditures and one for price indices.[15] These components from the U.S. Bureau of Economic Analysis include Motor Vehicles and Parts (DMOTRG3Q086SBEA, DMOTRC1Q027SBEA), Furnishings and Durable Household Equipment (DFDHRG3Q086SBEA, DFDHRC1Q027SBEA), Recreational Goods and Vehicles (DREQRG3Q086SBEA, DREQRC1Q027SBEA), Other Durable Goods (DODGRG3Q086SBEA, DODGRC1Q027SBEA), Food and Beverages Purchased for Off-Premises Consumption (DFXARG3Q086SBEA, DFXARC1Q027SBEA), Clothing and Footwear (DCLORG3Q086SBEA, DCLORC1Q027SBEA), Gasoline and Other Energy Goods (DGOERG3Q086SBEA, DGOERC1Q027SBEA), Other Nondurable Goods (DONGRG3Q086SBEA, DONGRC1Q027SBEA), Housing and Utilities (DHUTRG3Q086SBEA, DHUTRC1Q027SBEA), Health Care (DHLCRG3Q086SBEA, DHLCRC1Q027SBEA), Transportation Services (DTRSRG3Q086SBEA, DTRSRC1Q027SBEA), Recreation Services (DRCARG3Q086SBEA, DRCARC1Q027SBEA), Food Services and Accommodations (DFSARG3Q086SBEA, DFSARC1Q027SBEA), Financial Services and Insurance (DIFSRG3Q086SBEA, DIFSRC1Q027SBEA), Other Services (DOTSRG3Q086SBEA, DOTSRC1Q027SBEA), Final Consumption Expenditures of Nonprofit Institutions Serving Households (DNPIRG3Q086SBEA, DNPIRC1Q027SBEA).

This granular approach reveals significant heterogeneity in price behavior and consumption patterns. Health care and housing consistently account for a large and growing share of personal consumption expenditures, reflecting long-term structural trends of the U.S. economy. Conversely, categories such as clothing and footwear have seen their share of total expenditures decline over time, possibly due to globalization and changes in consumer preferences.

The price indices for these PCE components also exhibit varying degrees of volatility and persistence. Energy-related categories, such as gasoline and other energy goods, show high volatility, often reflecting global commodity price fluctuations. In contrast, services like health care and education demonstrate more persistent price increases, potentially indicating structural factors influencing these sectors.

[15] All PCE component series are from the Bureau of Economic Analysis and are seasonally adjusted.

3.2 Calibration

The calibration of the prior means and distributions follows Smets and Wouters (2007) regarding all the equations except those related to inflation.

The prior means and distributions used for PCE component and shock process parameters are presented in Table 1.

Table 1. Inflation Processes and Shock Parameters: Priors

Parameter	Distribution	Prior Mean	Prior Std.
π_i^T	Normal	Sample mean	1.0
β_i^C	Generalized Beta*	1.0	0.4
ρ_i^N	Beta	0.5	0.2
w_i^C	Beta	0.5	0.2
$\Sigma_{i,i}$	Inverse Gamma	0.1	2.0
$\Sigma_{i,j}$	Generalized Beta**	0.0	0.2

Notes: * Generalized Beta distribution defined in the interval [0;2]. As explained in Section 2.4, β_1^C is calibrated to 9 minus the 8 other betas ($\beta_2^C ... \beta_9^C$), such that the sum of β_i^C equals 9. ** Generalized Beta distribution defined in the interval [-1;1].

3.3 Methodology

Following An and Schorfheide (2007) and Smets and Wouters (2007), we utilize Bayesian methods to estimate our models for different PCE inflation and monetary policy rules.[16] Our model poses some numerical challenges for the estimation procedure. In particular, the mode-finding process, which involves an algorithm that searches for the maximum of the posterior likelihood, was not satisfied with the standard methods available in Dynare (Adjemian et al., 2011). We addressed these challenges by applying different mode-finding algorithms sequentially, starting each one after the previous one had converged. We found that this technique yielded a significantly higher likelihood for the mode than using each algorithm separately. The sequence we followed that proved to be most efficient was Chris Sims's *csminwel*, then Marco Ratto's *newrat*, and finally Monte-Carlo-based optimization routine.

The estimation of parameters, including those presented in Table 1, covers the period from 1993Q2 to 2019Q4. For the Markov Chain Monte Carlo (MCMC) algorithm, we employ 2,000,000 draws divided into two parallel chains.

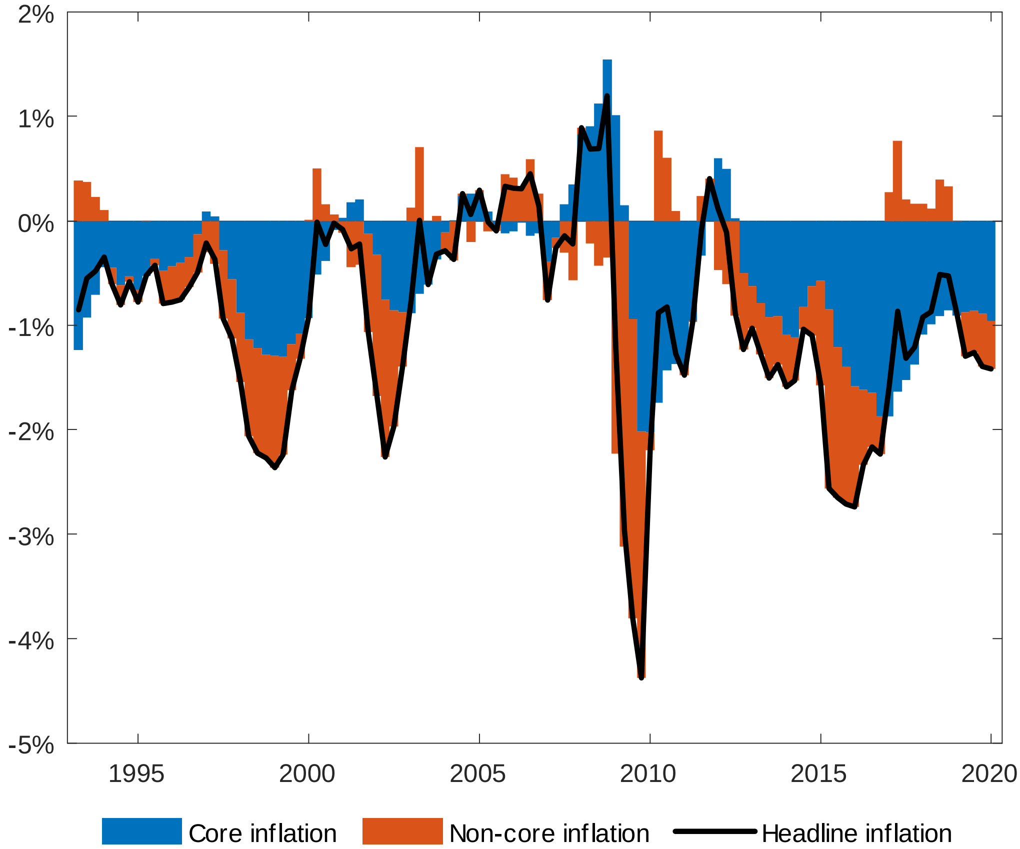
All the estimated parameters are identified through the Jacobian of steady state and reduced-form solution matrices (Iskrev, 2010), steady state and minimal system (Komunjer and Ng, 2011), and mean and spectrum (Qu and Tkachenko, 2012).

[16] The complete estimation results and replication files are available upon request.

4 Results

Fig. 2 shows the historical decomposition of the detrended headline PCE inflation into aggregate core and non-core parts.

Figure 2. Historical Decomposition: Headline PCE Inflation



Notes: Deviations from aggregate trend inflation (2.96%). Based on Bayesian estimations from 1993 to 2019.

Table 2 presents a new approach to measuring core inflation by decomposing each component into core and non-core inflation, allowing us to identify which inflation components are more closely related to the underlying economic fundamentals and which are more influenced by temporary shocks. To measure the component-specific coreness degree, we introduce an index that calculates the mean (across years) of the ratio of annual core inflation to annual non-core inflation, both in absolute value. A value of one for this index indicates that core and non-core inflation are equally important in the component, while a value greater than unity indicates that the component is more core-related.

Table 2 shows that the degree of coreness varies across different inflation components. For example, Food and Beverages have a coreness index of about 2.14, indicating that core inflation is significantly more important than non-core

Table 2. Component importance of core relative to non-core

Component	Coreness
Food and Beverages	2.14
Housing	0.87
Health Care	0.50
Energy	0.06
Recreation	0.30
Clothing and Footwear	0.29
Other Durable Goods	0.47
Other Nondurable Goods	1.88
Other Services	0.64

Notes: Values are reported rounded to two decimal places for ease of comprehension and simplicity.

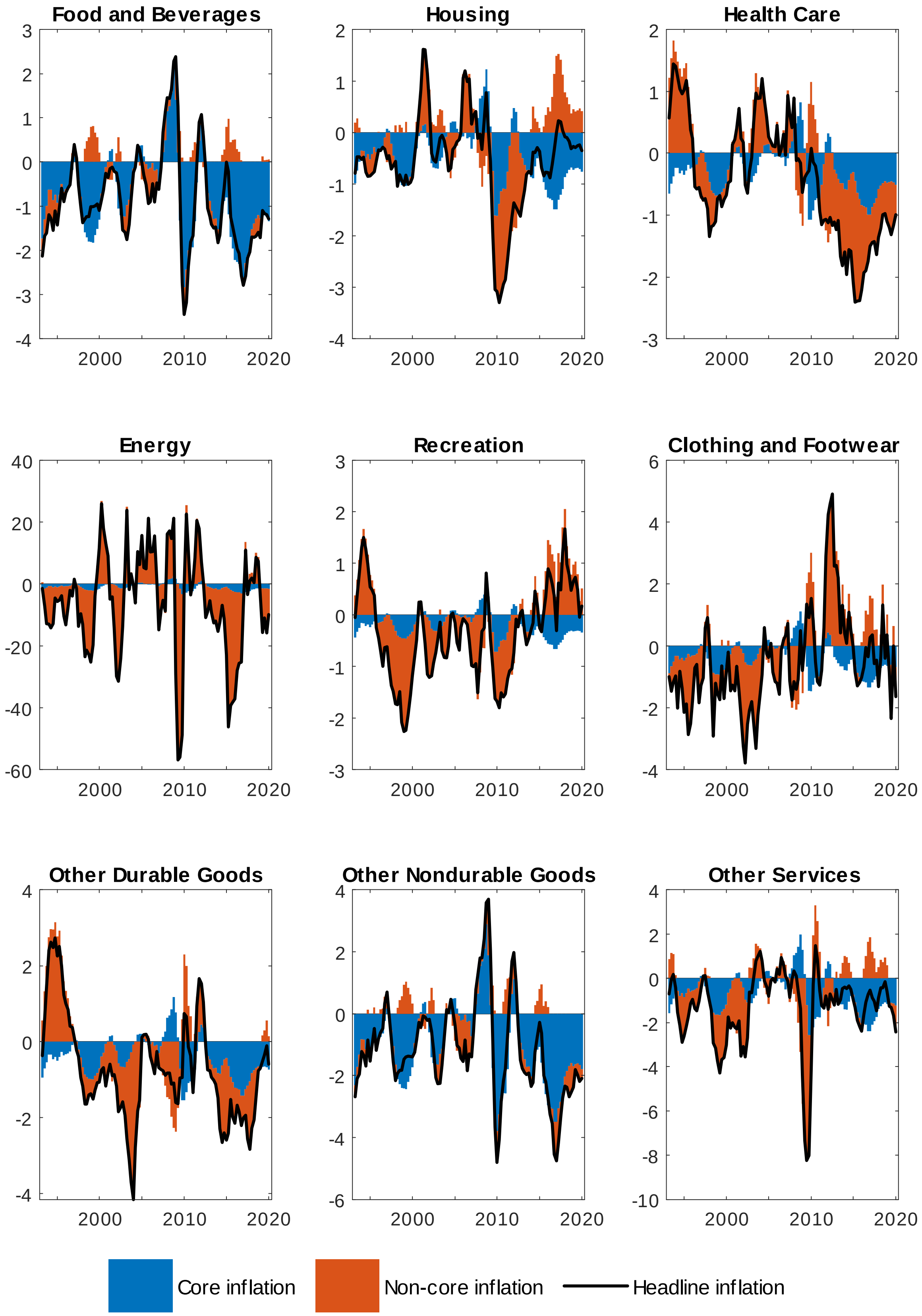
inflation in this component. Other Nondurable Goods also has a high coreness index of about 1.88, suggesting a similar emphasis on core inflation. On the other hand, Housing maintains a coreness index of about 0.87, indicating that non-core inflation is more important in this component. Other Durable Goods and Health Care have coreness indices of 0.47 and 0.5, respectively, showing a moderate importance of non-core inflation. Recreation, Clothing and Footwear, and Energy have much lower coreness indices of 0.3, 0.29, and 0.06, respectively, suggesting that non-core inflation is significantly more important in these components. Other Services have a coreness index of 0.64, indicating a moderate predominance of non-core inflation.

Our results confirm Kohlscheen (2022), which examine the relationship between food and beverages prices and the output gap in many countries over the last 30 years, supporting the existence of a Phillips curve relation specifically for food inflation. Kohlscheen (2022) suggest that broader economic overheating leads to a systematic increase in food prices and quantify the impact of food production, imports, and exports on food inflation, revealing a weak connection between domestic and global food prices (limited pass-throughs).

Fig. 3 shows the historical decomposition of each detrended component into core and non-core parts.

Table 3 details the component-specific trends (π_i^T). The results highlight the distinction between goods and services as the main difference between the PCE components. Goods have experienced lower inflation than the overall PCE, such as Clothing and Footwear (-0.1%) and recreation (-0.9%). These goods may have been influenced by increased competition from low-cost producers abroad, technological change, and changing consumer preferences. On the other hand, services have experienced higher inflation than the overall PCE, such as Health Care (2.9%), education and communication (1.9%), and other services (5.1%).

Figure 3. Historical Decomposition: PCE Inflation Components



Notes: Derived from Bayesian estimations from 1993 - 2019.

These services may have been influenced by rising labor costs. Also, Other Nondurable goods (3%) have seen larger trend than Other Durable Goods (0.6).

Table 3. PCE Component-specific Trends

Component	Trend
Food and Beverages	3.0%
Housing	3.3%
Health Care	2.9%
Energy	9.5%
Recreation	-0.9%
Clothing and Footwear	-0.1%
Other Durable Goods	0.6%
Other Nondurable Goods	3.0%
Other Services	5.1%

Notes: Based on Bayesian estimations from 1993 to 2019.

4.1 In-sample Fit

According to the log marginal data density, our structural core model fits the data better than the benchmark Smets and Wouters (2007) model. Indeed, the log marginal data density of the structural core model is -1414, compared to -1531 for the benchmark model.[17]

The estimated log marginal data density measures how well the model matches the data, considering the number of variables, parameters, and quantity of data used in the estimation. A higher log marginal data density indicates a better fit to the data, where the log marginal data density is calculated as the log of the product of the likelihood function and the prior density.[18]

[17] The benchmark model is the same as in Smets and Wouters (2007), with minimal adjustments for using PCE components as observables instead of headline PCE.

[18] The likelihood function measures how likely the data is given the model parameters, and the prior density measures the researcher's belief about the values of the parameters before the data is observed. The log marginal data density controls the number of variables, parameters, and quantity of data in two ways. First, the likelihood function is a product of the marginal likelihood for each variable, and the marginal likelihood for a variable decreases as the number of parameters in the model increases. This means that the log marginal data density will be lower for a model with more parameters, even if the model fits the data equally well. Second, the prior density is a function of the number of variables and parameters in the model. The prior density for a parameter typically decreases as the number of variables in the model increases. This means that the log marginal data density will be lower for a model with more variables, even if the model fits the data equally well. As a result, the log marginal data density is a more accurate measure of the fit of a DSGE model to the data than the likelihood function or the prior density alone.

4.2 Out-of-sample Fit

Fig. 4 and 5 present out-of-sample root mean square errors (RMSE) of all non-inflation and inflation observed variables, respectively. The structural core model accuracy is better or similar for all variables except for employment and of long horizons interest rate.

Table 4 presents conditional predictive ability (CPA) tests comparing the out-of-sample performance of the structural core and benchmark models for various variables. Table 4 indicates the sign and magnitude of the p-value for the corresponding variable and model.

A positive t-statistic means the structural core model has a better CPA than the benchmark model and vice versa. Each cell shows the numerical value of the t-statistic in the first line and the p-value of the test in the second line. The results show that the structural core model performs significantly better out-of-sample than the benchmark model for most variables and horizons, with the noticeable exception of employment and interest rate forecasts.

5 The COVID-19 Pandemic

Fig. 6 illustrates the actual inflation (solid black line) alongside our structural core inflation measure, including its trend (dashed line). It also compares these with two other core inflation measures based on PCE. During the COVID-19 inflationary period, there is a clear correlation between the structural core and the cyclical core measures. All measures display similar patterns, highlighting the alignment and consistent trends among them during this time.

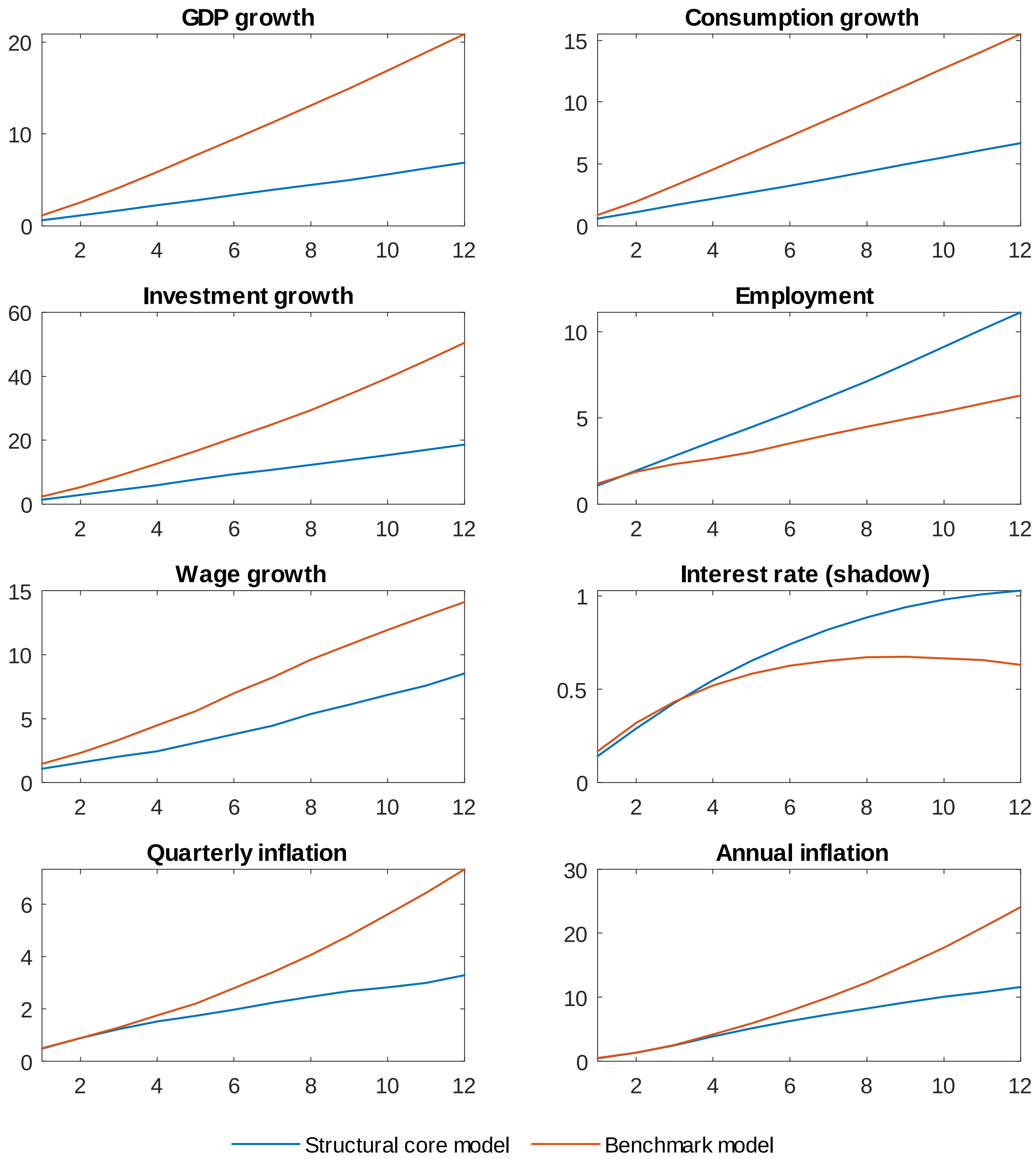
6 Sensitivity Analysis

Our approach to core inflation goes beyond traditional methods that rely solely on inflation components. By incorporating both inflation components and broader macroeconomic data, our decomposition method provides a more comprehensive and responsive analysis of inflation dynamics. In this section, we demonstrate the robustness and flexibility of our approach through counterfactual scenarios that highlight how different shocks—both component-specific and broader economic—affect headline and core inflation.

6.1 Food and Energy Price Shocks

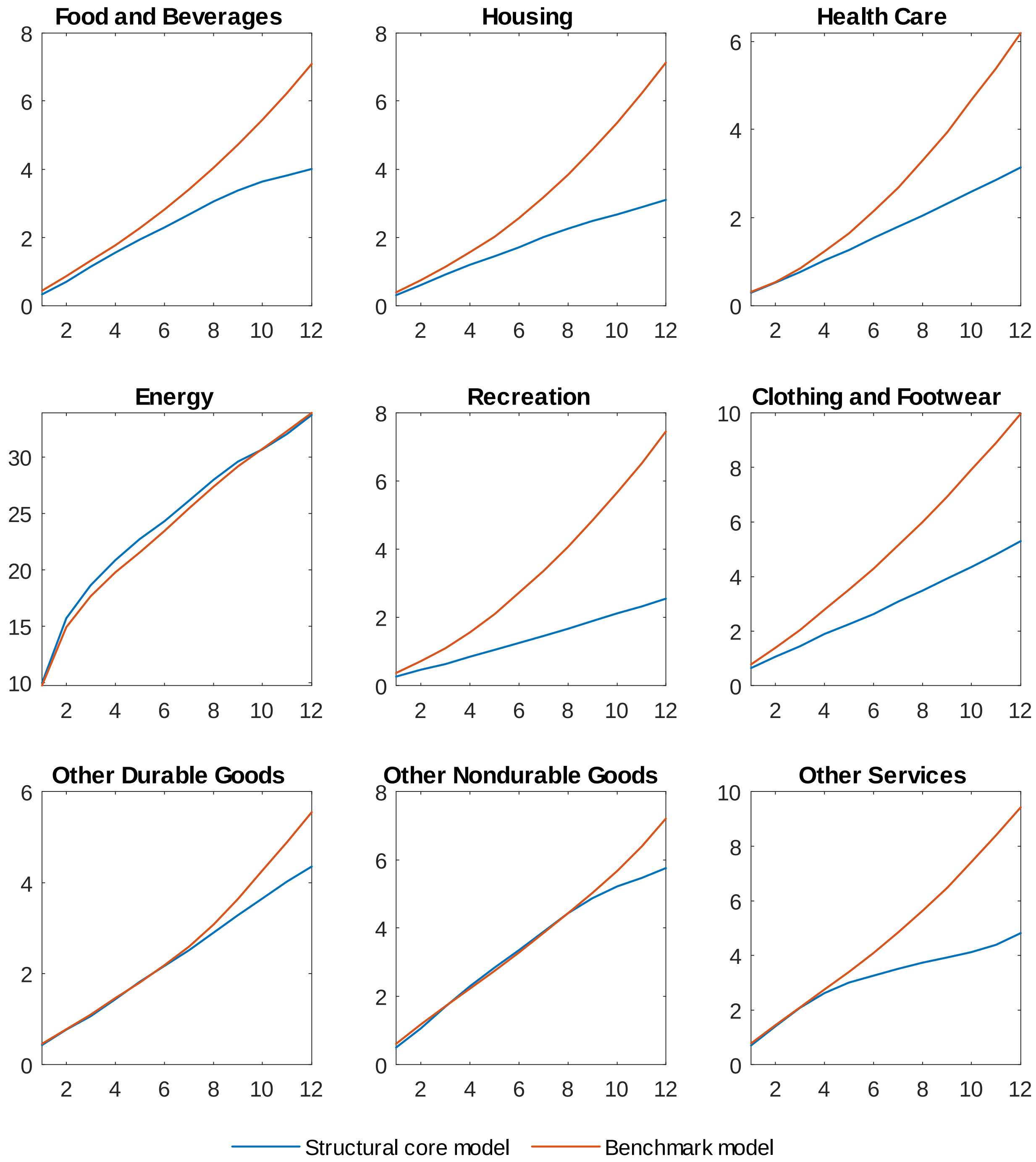
Fig. 7 presents the impulse response functions of aggregate PCE price inflation to exogenous shocks in food and energy prices. Each shock is calibrated to produce

Figure 4. RMSE Comparison Between Models and Variables



Notes: Cumulative RMSE of 1-12 quarters horizon. Derived from Bayesian estimations over the sample 1993-1999, and expanding over the testing sample 2000-2019.

Figure 5. RMSE Comparison Between Models and Components



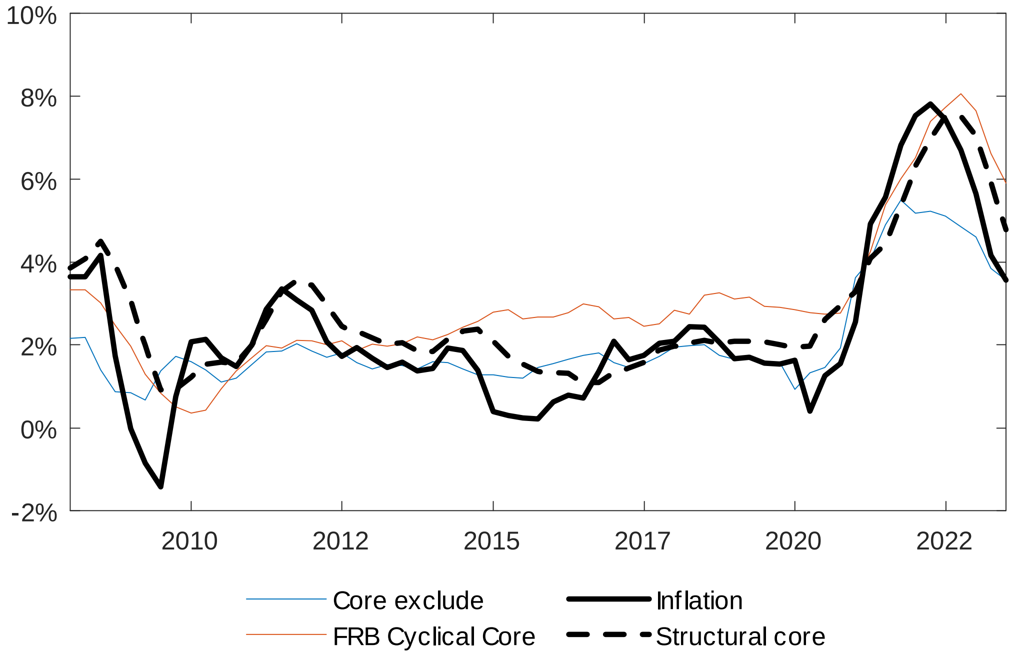
Notes: Cumulative RMSE of 1-12 quarters horizon. Derived from Bayesian estimations over the sample 1993-1999, and expanding over the testing sample 2000-2019.

Table 4. Conditional Predictive Ability Tests

	1	2	3	4	5	6	7	8	9	10	11	12
GDP	10.8 (0)	15.3 (0)	11.6 (0)	13.4 (0)	13.2 (0)	16.5 (0)	22.8 (0)	17.3 (0)	20 (0)	15.7 (0)	33.6 (0)	20.5 (0)
Consumption	6.9 (0.03)	11 (0)	10.4 (0.01)	9.2 (0.01)	14.7 (0)	12.7 (0)	24 (0)	19.8 (0)	19.7 (0)	16.8 (0)	27.1 (0)	23.1 (0)
Investment	5.3 (0.07)	5.6 (0.06)	5 (0.08)	4.9 (0.09)	5.6 (0.06)	6.1 (0.05)	5.6 (0.06)	7.3 (0.03)	7.3 (0.03)	8.3 (0.02)	11.2 (0)	14.1 (0)
Employment	1.6 (0.46)	1.8 (0.41)	-1.1 (0.58)	-4.7 (0.1)	-5.1 (0.08)	-11 (0)	-8.7 (0.01)	-7.1 (0.03)	-7.1 (0.03)	-7.7 (0.02)	-8.6 (0.01)	-11 (0)
Wage	9.9 (0.01)	16 (0)	23.3 (0)	27.2 (0)	34.8 (0)	23.8 (0)	21.6 (0)	17 (0)	14.7 (0)	12.4 (0)	11.1 (0)	9.7 (0.01)
Interest rate	1.3 (0.52)	1.5 (0.48)	1.7 (0.42)	0.6 (0.73)	-0.2 (0.89)	-1.6 (0.46)	-0.9 (0.62)	-3.4 (0.18)	-3.6 (0.17)	-9.3 (0.01)	-11.3 (0)	-12.5 (0)
Inflation	0.4 (0.8)	1.8 (0.41)	0.3 (0.86)	0.3 (0.87)	0.7 (0.7)	1.9 (0.39)	1.5 (0.47)	1.7 (0.43)	1.9 (0.39)	2 (0.37)	2.1 (0.36)	2.2 (0.33)
Food and Beverages	3.4 (0.18)	7.8 (0.02)	6.5 (0.04)	4.2 (0.12)	8.9 (0.01)	11.5 (0)	3.7 (0.16)	3.5 (0.17)	6.7 (0.04)	3.7 (0.16)	3.9 (0.14)	3.6 (0.17)
Housing	5.2 (0.07)	2.8 (0.25)	6.3 (0.04)	3.7 (0.16)	5.2 (0.08)	5.3 (0.07)	5.7 (0.06)	6.2 (0.05)	6.3 (0.04)	6.1 (0.05)	7.9 (0.02)	8 (0.02)
Health Care	2.1 (0.35)	3 (0.23)	0.7 (0.7)	0.9 (0.63)	4.7 (0.09)	2.1 (0.36)	3.3 (0.19)	1.2 (0.56)	1.5 (0.48)	0.8 (0.66)	1.5 (0.47)	1.8 (0.41)
Energy	-2.3 (0.32)	-2.5 (0.28)	-2 (0.36)	-2.1 (0.35)	-1.1 (0.57)	-2 (0.36)	-0.6 (0.73)	-1.9 (0.39)	-1 (0.61)	-0.5 (0.78)	-0.3 (0.85)	-0.3 (0.86)
Recreation	7.7 (0.02)	10.3 (0.01)	12.7 (0)	14.9 (0)	15.3 (0)	14.7 (0)	15.4 (0)	13.4 (0)	12.9 (0)	12.8 (0)	12.3 (0)	13.4 (0)
Clothing and Footwear	6.5 (0.04)	5.9 (0.05)	5.5 (0.06)	5.8 (0.05)	6 (0.05)	6.3 (0.04)	6.4 (0.04)	6.8 (0.03)	6.5 (0.04)	7.4 (0.02)	7.4 (0.02)	7.8 (0.02)
Other Durable Goods	2.7 (0.26)	0.6 (0.75)	0.9 (0.64)	0.6 (0.75)	1.1 (0.56)	0.1 (0.93)	0.2 (0.93)	1.2 (0.54)	4.2 (0.13)	6 (0.05)	7.3 (0.03)	5.6 (0.06)
Other Nondurable Goods	2.4 (0.29)	4.1 (0.13)	3.3 (0.19)	1.6 (0.45)	5.9 (0.05)	-5.7 (0.06)	-7.8 (0.02)	-1.7 (0.42)	-0.5 (0.76)	0.2 (0.92)	4.4 (0.11)	3.9 (0.14)
Other Services	3.2 (0.21)	0.5 (0.76)	2.8 (0.25)	3.4 (0.18)	0.5 (0.76)	1.2 (0.56)	1.2 (0.56)	1.3 (0.52)	1.4 (0.49)	1.8 (0.41)	1.8 (0.41)	1.8 (0.41)

Notes: The darker the cell, the better our structural core inflation forecast is over the benchmark model regarding p-values. Derived from Bayesian estimations over the sample 1993-1999, and expanding over the testing sample 2000-2019.

Figure 6. Core PCE Inflation During the Covid-19: Structural and Alternative Measures

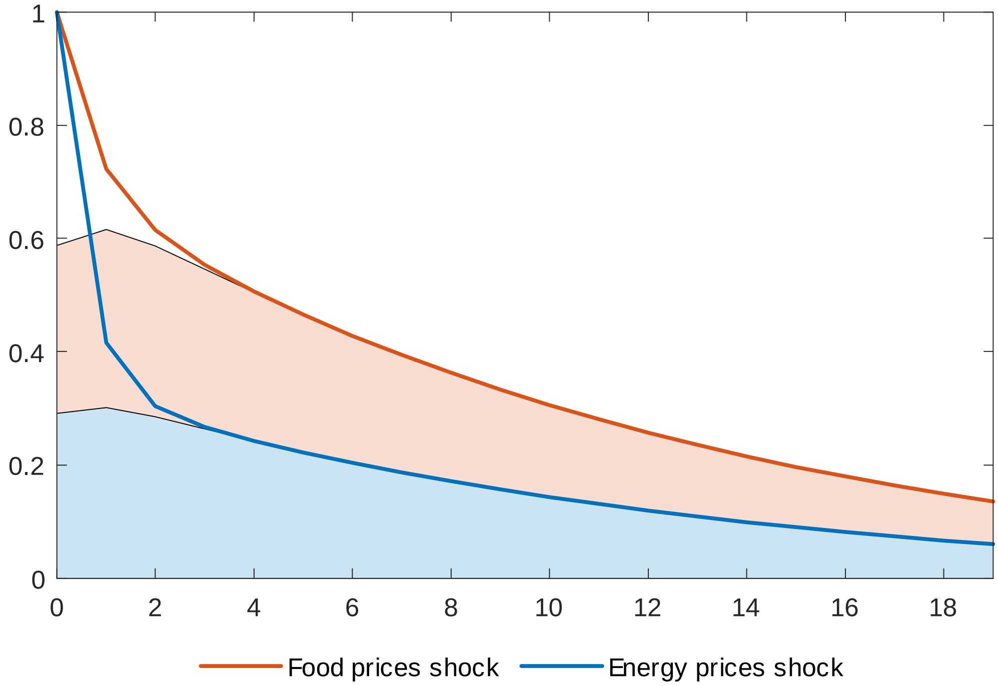


Notes: All indexes are for annual inflation. Structural core is our model core inflation, estimated in Section 3. The estimation sample is 1993-2019, and the model is used to filter the 2021-2022 data with the same parameters.

a 1% on-impact effect on the respective price component. The response to the food price shock is illustrated by the orange line, while the response to the energy price shock is represented by the blue line. The analysis reveals that the immediate effects of both shocks on non-core inflation are largely transient, dissipating significantly within the first four quarters. After this initial period, core inflation becomes the dominant driver of the inflation response.

The slower decline in the food price shock's impact reflects its deeper integration into core inflation dynamics, leading to a more lasting effect on headline inflation. In contrast, the energy price shock's rapid decline highlights the more temporary nature of energy price fluctuations, with a quicker reduction in its effect on headline inflation. This distinction between the impacts of different price shocks is a key feature of our model. Unlike traditional DSGE models, which typically focus solely on aggregate inflation, our approach provides a more detailed understanding of inflation dynamics by incorporating specific inflation components. This allows for a more nuanced analysis of how component-specific shocks affect both headline and core inflation, offering valuable insights for monetary policy formulation.

Figure 7. Inflation Decomposition Under Alternative Scenarios



Notes: impulse response functions of headline inflation (solid lines) and core inflation (shaded areas) to 1% shocks in food (orange) and energy prices (blue). The x-axis shows time in quarters, and the y-axis represents the percentage change in inflation.

6.2 Productivity Shocks

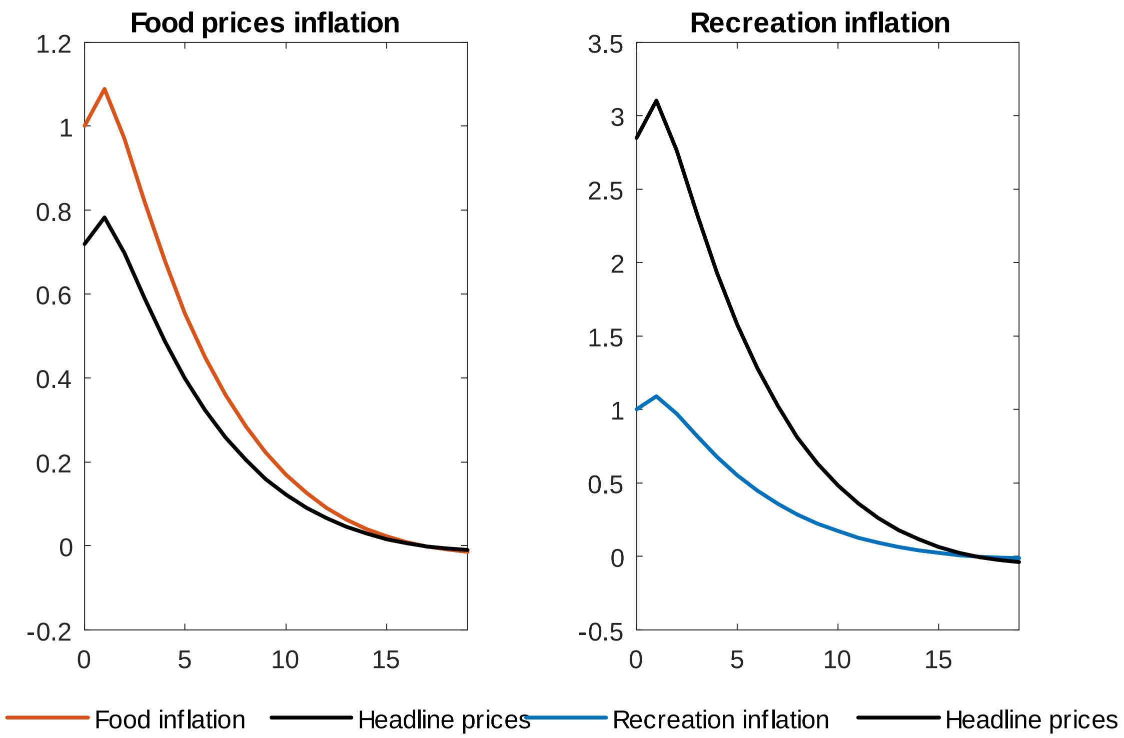
Fig. 8 displays the impulse response functions of aggregate PCE price inflation to negative productivity shocks of varying magnitudes. The figure consists of two panels: the first illustrates the response to a productivity shock calibrated to achieve a 1% on-impact effect on food prices, depicted by the orange line, alongside the black line representing headline inflation. The second panel presents the response to a productivity shock calibrated to achieve a 1% on-impact effect on recreation prices, shown by the blue line, again with the black line representing headline inflation.

The analysis reveals distinct differences in the magnitude of the inflation responses. For food prices, which are closely related to core inflation, a relatively moderate productivity shock is sufficient to induce a 1% on-impact effect. Consequently, the impact on headline inflation is approximately 0.72% on impact, as depicted by the orange line in the first panel. The headline inflation response closely follows the food price inflation curve, though with slightly less intensity, reflecting the strong connection between food prices and core inflation.

In contrast, the recreation price shock, shown in the second panel, requires a much larger productivity shock to achieve the same 1% on-impact effect. This larger shock results in a stronger impact on headline inflation, reaching approximately 2.85% on impact, as shown by the black line in the second panel. The recreation price inflation, depicted by the blue line, shows a less direct correlation with headline inflation, necessitating a larger shock to produce a similar on-impact effect.

These findings highlight the differential sensitivity of inflation components to productivity shocks. Components more closely related to core inflation, like food prices, require smaller shocks to achieve significant on-impact effects, while components with a weaker connection to core inflation, such as recreation prices, require much larger shocks. This differential sensitivity underscores the importance of considering component-specific inflation dynamics when assessing the impact of shocks on headline inflation, providing a more nuanced perspective for monetary policy analysis.

Figure 8. Inflation Decomposition Under Alternative Scenarios



Notes: impulse response functions of headline inflation (black lines) and component inflation to productivity shocks. The first panel shows the response to a shock calibrated to achieve a 1% impact on food prices (orange line), and the second panel shows the response to a shock calibrated to achieve a 1% impact on recreation prices (blue line). The x-axis represents time in quarters, and the y-axis indicates the percentage change in inflation.

7 Alternative Approaches

In this section, we compare the performance of the structural Core inflation index with other core inflation measures available from the Atlanta Fed's underlying inflation dashboard. These measures include PCE excluding food and energy, trimmed mean PCE, median PCE, and sticky components PCE. We also include the gross inflation rate as a benchmark.

To evaluate the different measures of core inflation, we estimate the original Smets and Wouters (2007) model using alternative measures of core inflation using Bayesian methods. For each estimation, we estimate the log marginal data density, which measures the fitting of the model to the data and considers the model complexity and the prior information.

Table 5. Log Marginal Data Densities: Alternative Measures of Core Inflation

Inflation	Excl. Food & Energy	Cyclical	Structural
-730.98	-631.02	-635.73	-610.36

Notes: A higher log marginal data density implies a better fit compared to models presenting a lower one.

Table 5 shows that our structural core inflation has the highest log marginal data density compared to the alternative measures of core inflation, indicating that structural core inflation is the most informative and reliable indicator of inflation dynamics in the context of the Smets and Wouters (2007) model. The other measures of core inflation have significantly worst estimated log marginal data density, with sticky-price PCE being the closest to our structural core inflation.

8 Fed's Policy

Following Aoki (2001) and Mankiw and Reis (2003) that the central bank should target core inflation instead of headline inflation, we investigate the empirical implications, assuming this policy choice. Core inflation is often considered a better indicator of the underlying inflationary pressures and the main rationale for using it as a target. Our previous analysis assumed that the Fed followed a Taylor rule that responded to headline inflation.

We reestimated the model under the alternative assumption that the Fed targets core PCE inflation, and find that the model with core PCE inflation in the monetary policy rule has a higher marginal likelihood (-1400.4) than the model with headline PCE inflation (-1414.4), suggesting that the data provide evidence favoring core PCE inflation targeting by the Fed. We obtain the same result when considering core CPI inflation in the monetary policy rule (-1432.4) compared to headline CPI inflation (-1439.3), which confirms the Fed likely targets core inflation rather than headline inflation.

One of the main objectives of monetary policy is to understand and control inflation and its determinants. However, not all sources of inflation are equally relevant for monetary policy decisions. There is a general agreement that monetary policy should respond vigorously to inflation caused by excess demand in the economy, but there is less consensus on how to deal with inflation caused by sector-specific shocks. Some may suggest that monetary policy should ignore or at least partially accommodate such shocks.

Our model offers a comprehensive and empirically grounded framework to address this issue. Structural core inflation reflects the proportion of inflation consistent with cyclical economic fluctuations.

For instance, if the output is high, the labor market is tight, and inflation mainly originates from components historically correlated with core inflation, the model will tend to attribute most of the inflation to core inflation. Conversely, if the output is low and inflation is high mainly due to components that have historically shown low correlation with business cycles and high volatility, then the model will tend to produce a decomposition that assigns a much lower weight to core inflation.

9 Conclusion

Our study presents a new index of structural core inflation that incorporates structural features of the economy, potentially offering more accurate estimates of underlying inflation dynamics than traditional measures. Our approach is based on a canonical microfounded medium-scale DSGE model that can capture a wide range of macroeconomic dynamics, including inflation, output, and employment. While our approach has several strengths, such as its theoretical foundation, economic structure, and ability to study the effects of policy on inflation, it also has weaknesses, such as the need for more data and computational resources.

Our structural core inflation contributes to the literature by offering an innovative and improved way of measuring core inflation, incorporating a wide range of economic and inflation data, and providing a structural indicator of the business cycle. Our results suggest that structural core inflation can enhance our understanding of inflation dynamics and improve the accuracy of economic forecasts, which is essential for central banks and policymakers. Our flexible methodology should contribute to developing more effective and reliable monetary policies.

Our approach, differing from the methods developed in the literature, provides ampler structure, more technical flexibility for policymakers, and enables analysis of business cycles and policy implications. Our contribution offers a unique perspective on measuring core inflation and has the potential to enhance future research in this area. Our study provides a comprehensive approach helpful for policymakers and economic modeling compared to other methods of modeling and measuring core inflation.

References

Adjemian, S., Bastani, H., Karamé, F., Juillard, M., Maih, J., Mihoubi, F., Perendia, G., Pfeifer, J., Ratto, M., Villemot, S., 2011. Dynare: Reference Manual Version 4. Dynare Working Papers 1, CEPREMAP.

An, S., Schorfheide, F., 2007. Bayesian analysis of DSGE models. Econometric Reviews 26 (2-4), 113–172.

Aoki, K., 2001. Optimal monetary policy responses to relative-price changes. Journal of Monetary Economics 48 (1), 55–80.

Ball, L. M., Carvalho, C., Evans, Christopher ando Ricci, L. A., 2023. Weighted median inflation around the world: A measure of core inflation. NBER Working Papers 31032, National Bureau of Economic Research.

Benchimol, J., Fourçans, A., 2019. Central bank losses and monetary policy rules: a DSGE investigation. International Review of Economics & Finance 61 (1), 289–303.

Bernanke, B. S., Boivin, J., Eliasz, P., 2005. Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. Quarterly Journal of Economics 120 (1), 387–422.

Bils, M., Klenow, P. J., 2004. Some evidence on the importance of sticky prices. Journal of Political Economy 112 (5), 947–985.

Boivin, J., Giannoni, M. P., 2006. Has monetary policy become more effective? Review of Economics and Statistics 88 (3), 445–462.

Bryan, M. F., Meyer, B., 2010. Are some prices in the CPI more forward looking than others? We think so. Economic Commentary 2010 (02), 1–6.

Eusepi, S., Hobijn, B., Tambalotti, A., 2011. CONDI: a cost-of-nominal-distortions index. American Economic Journal: Macroeconomics 3 (3), 53–91.

Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2000. The generalized dynamic-factor model: Identification and estimation. Review of Economics and Statistics 82 (4), 540–554.

Forni, M., Reichlin, L., 1998. Let's get real: A factor analytical approach to disaggregated business cycle dynamics. Review of Economic Studies 65 (3), 453–473.

Hasenzagl, T., Pellegrino, F., Reichlin, L., Ricco, G., 2022. A model of the Fed's view on inflation. Review of Economics and Statistics 104 (4), 686–704.

Iskrev, N., 2010. Local identification in DSGE models. Journal of Monetary Economics 57 (2), 189–202.

Kim, D. H., Singleton, K. J., 2012. Term structure models and the zero bound: an empirical investigation of Japanese yields. Journal of Econometrics 170 (1), 32–49.

Kimball, M. S., 1995. The quantitative analytics of the basic nqeomonetarist model. Journal of Money, Credit and Banking 27 (4), 1241–1277.

Kohlscheen, E., 2022. Understanding the food component of inflation. BIS Working Papers 1056, Bank for International Settlements.

Komunjer, I., Ng, S., 2011. Dynamic identification of dynamic stochastic general equilibrium models. Econometrica 79 (6), 1995–2032.

Krippner, L., 2013. Measuring the stance of monetary policy in zero lower bound environments. Economics Letters 118 (1), 135–138.

Mankiw, N. G., Reis, R., 2003. What measure of inflation should a central bank target? Journal of the European Economic Association 1 (5), 1058–1086.

Qu, Z., Tkachenko, D., 2012. Identification and frequency domain quasi-maximum likelihood estimation of linearized dynamic stochastic general equilibrium models. Quantitative Economics 3 (1), 95–132.

Reis, R., Watson, M. W., 2010. Relative goods' prices, pure inflation, and the Phillips correlation. American Economic Journal: Macroeconomics 2 (3), 128–157.

Smets, F., Wouters, R., 2007. Shocks and frictions in US business cycles: a Bayesian DSGE approach. American Economic Review 97 (3), 586–606.

Stock, J. H., Watson, M. W., 2002. Macroeconomic forecasting using diffusion indexes. Journal of Business & Economic Statistics 20 (2), 147–162.

Stock, J. H., Watson, M. W., 2016. Core inflation and trend inflation. Review of Economics and Statistics 98 (4), 770–784.

Stock, J. H., Watson, M. W., 2020a. Slack and cyclically sensitive inflation. Journal of Money, Credit and Banking 52 (S2), 393–428.

Stock, J. H., Watson, M. W., 2020b. Trend, Seasonal, and Sectorial Inflation in the Euro Area. In: Castex, G., Gal'i, J., Saravia, D. (Eds.), Changing Inflation Dynamics, Evolving Monetary Policy. Vol. 27 of Central Banking, Analysis, and Economic Policies Book Series. Central Bank of Chile, Ch. 9, pp. 317–344.

Wu, J. C., Xia, F. D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. Journal of Money, Credit and Banking 48 (2-3), 253–291.

Wynne, M. A., 2008. Core inflation: a review of some conceptual issues. Federal Reserve Bank of St. Louis Review 90 (3), 205–228.

10 Appendix

A Consumer Price Index

In this appendix, we replicate the results of the paper using CPI inflation components and show that almost all of our previous findings with PCE inflation also hold with CPI inflation.

A.1 Data

The contribution of this section lies in the disaggregation of CPI inflation into its eight primary components, as defined by the Bureau of Labor Statistics' CPI for All Urban Consumers in the U.S. City Average,[19] which are: Food and Beverages (CPIFABSL), Housing (CPIHOSSL), Apparel (CPIAPPSL), Transportation (CPITRNSL), Medical Care (CPIMEDSL), Recreation (CPIRECSL), Education and Communication (CPIEDUSL), and Other Goods and Services (CPIOGSSL). All CPI component series are seasonally adjusted.

Our analysis of these CPI components reveals significant heterogeneity in their behavior. Transportation prices exhibit the highest volatility, likely due to fluctuations in energy prices, while housing costs show the least variation. Medical care prices display the highest persistence, potentially indicating greater

[19] This decomposition is presented in the CPI Handbook of Methods Appendix 2: Content of CPI Entry Level Items.

price stickiness in this sector, while apparel prices show the least persistence. In terms of relative weights, housing costs constitute the largest share of the total CPI at approximately 42%, while apparel accounts for only about 3%.

We observe divergent trend behaviors among the CPI components through a Hodrick-Prescott filter decomposition. Medical care and education exhibit steeper upward trends compared to the overall CPI, possibly reflecting rising costs due to factors such as technological advancements and increased demand. Conversely, apparel and recreation show relatively flatter trends, which may be attributed to globalization and technological improvements in production and distribution.

Examining correlations with real GDP growth reveals that transportation and recreation prices demonstrate pro-cyclical behavior, suggesting increased demand for these goods and services during economic expansions. In contrast, food and beverages and medical care exhibit counter-cyclical tendencies, possibly reflecting their nature as necessity goods and services.

A.2 Results

Fig. 9 shows the historical decomposition of the detrended headline CPI inflation component into aggregate core and non-core parts.

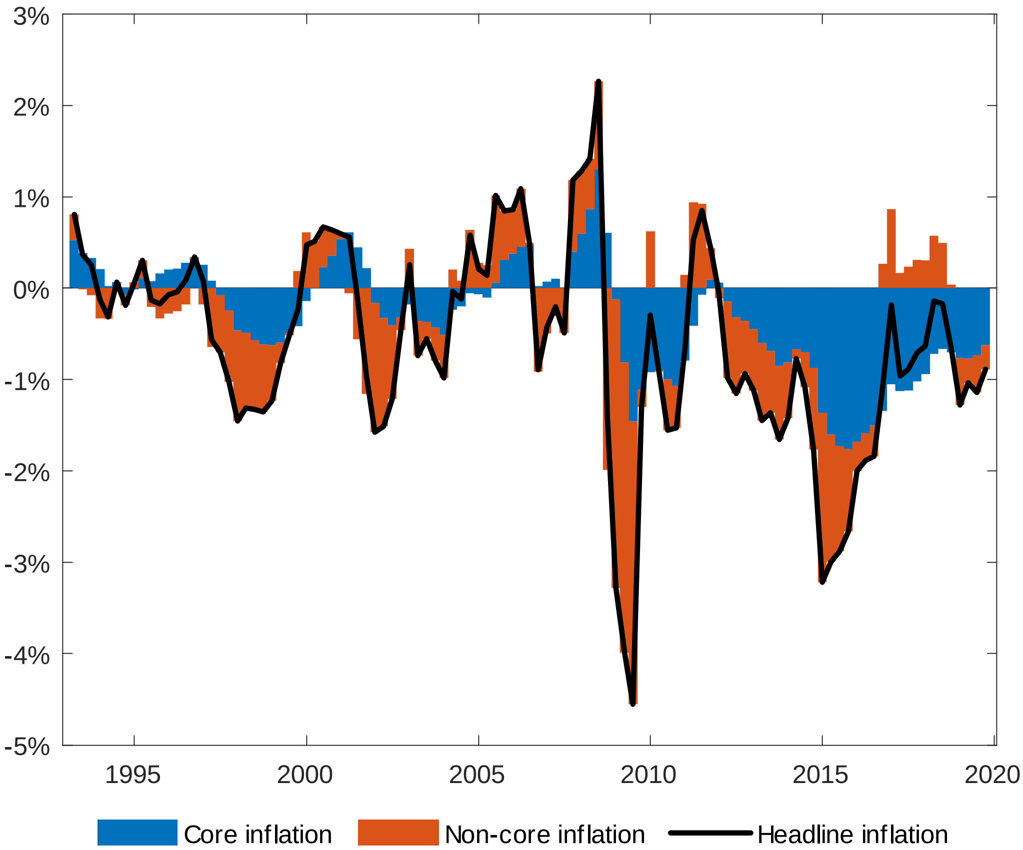
Table 2 presents a new approach to measuring core inflation by decomposing each component into core and non-core inflation, allowing us to identify which inflation components are more closely related to the underlying economic fundamentals and which are more influenced by temporary shocks. To measure the component-specific coreness degree, we introduce an index that calculates the mean (across years) of the ratio of annual core inflation to annual non-core inflation, both in absolute value. A value of one for this index indicates that core and non-core inflation are equally important in the component, while a value greater than unity indicates that the component is more core-related.

Table 6. Component importance of core relative to non-core

Component	**Coreness**
Food and Beverages	1.21
Housing	0.87
Apparel	0.77
Transportation	0.51
Medical Care	0.29
Recreation	0.41
Education and Communication	0.14
Other Goods and Services	0.45

Notes: Values are reported rounded to two decimal places for ease of comprehension and simplicity.

Figure 9. Historical Decomposition: Headline CPI Inflation



Notes: Deviations from aggregate CPI trend inflation (2.87%). Based on Bayesian estimations from 1993 to 2019.

Table 2 shows that the degree of coreness varies across different inflation components. For example, Food and Beverages have a coreness index of about 1.21, indicating that core inflation is slightly more important than non-core inflation in this component. On the other hand, housing has a coreness index of about 0.87, suggesting that non-core inflation is more important in this component. Medical Care, Education and Communication, Recreation, Transportation, Apparel, and Other Goods and Services have coreness indices between 0.14 and 0.77, indicating that non-core inflation is more important in these components.

Our results confirm Kohlscheen (2022), which examine the relationship between food and beverages prices and the output gap in many countries over the last 30 years, supporting the existence of a Phillips curve relation specifically for food inflation. Kohlscheen (2022) suggest that broader economic overheating leads to a systematic increase in food prices and quantify the impact of food production, imports, and exports on food inflation, revealing a weak connection between domestic and global food prices (limited pass-throughs).

Fig. 10 shows the historical decomposition of each detrended component into core and non-core parts.

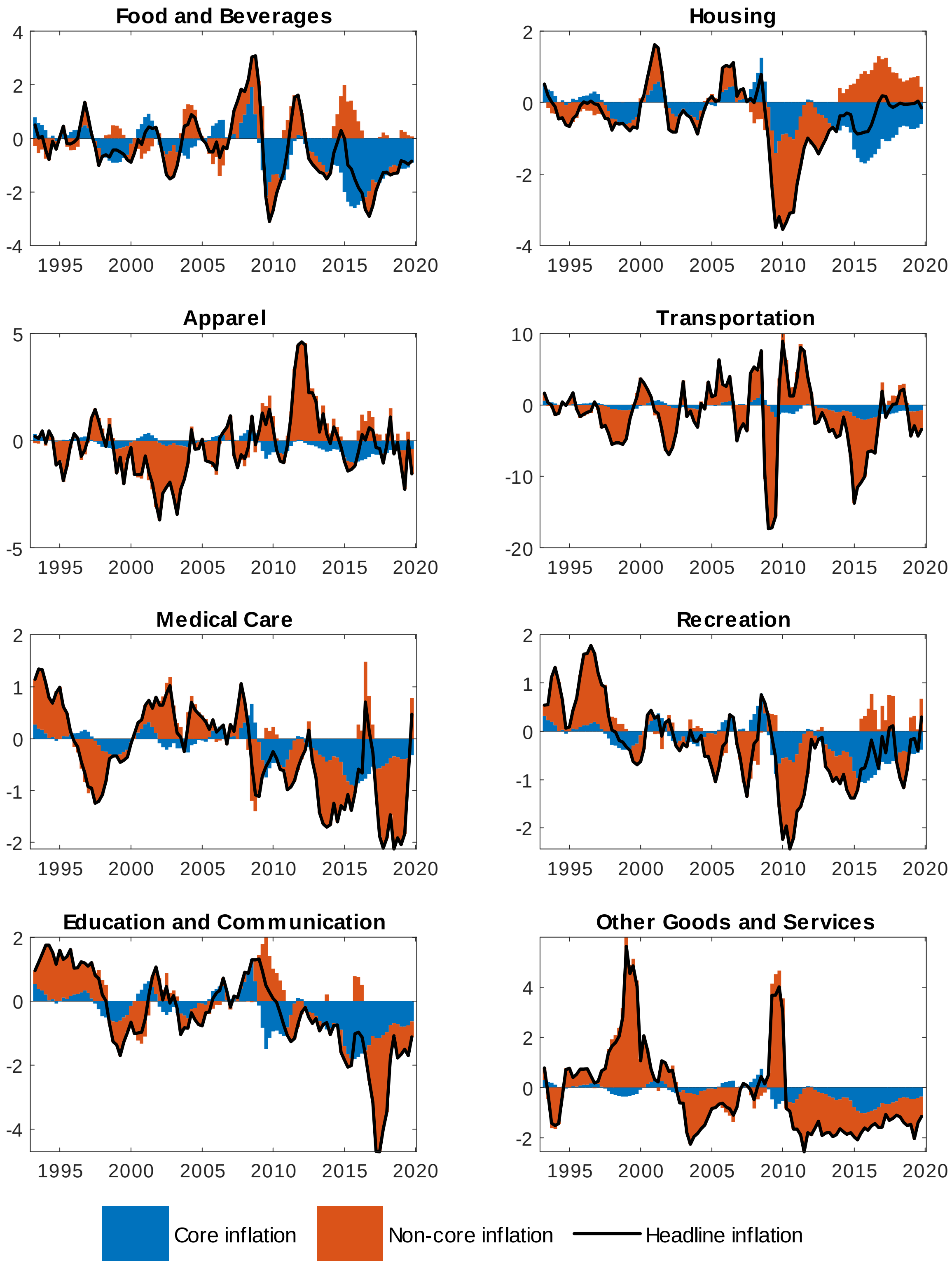
Table 7 details the component-specific trends (π_i^T). The results highlight the distinction between goods and services as the main difference between the CPI components. Goods have experienced lower inflation than the overall CPI, such as apparel (-0.2%) and recreation (1.2%). These goods may have been influenced by increased competition from low-cost producers abroad, technological change, and changing consumer preferences. On the other hand, services have experienced higher inflation than the overall CPI, such as medical care (3.6%), education and communication (1.9%), and other goods and services (3.2%). These services may have been influenced by rising labor costs.

Table 7. CPI Component-specific Trends

Component	**Trend**
Food and Beverages	2.3%
Housing	2.6%
Apparel	-0.2%
Transportation	3.5%
Medical Care	3.6%
Recreation	1.2%
Education and Communication	1.9%
Other Goods and Services	3.2%

Notes: Based on Bayesian estimations from 1993 to 2019.

Figure 10. Historical Decomposition: CPI Inflation Components



Notes: Derived from Bayesian estimations from 1993 - 2019.

A.3 In-sample Fit

According to the log marginal data density, our structural core model fits the data better than the benchmark Smets and Wouters (2007) model. Indeed, the log marginal data density of the structural core model is -1423, compared to -1656 for the benchmark model.[20]

The estimated log marginal data density measures how well the model matches the data, considering the number of variables, parameters, and quantity of data used in the estimation. A higher log marginal data density indicates a better fit to the data, where the log marginal data density is calculated as the log of the product of the likelihood function and the prior density.[21]

A.4 Out-of-sample Fit

Fig. 11 and 12 present out-of-sample root mean square errors (RMSE) of all non-inflation and inflation component variables, respectively. The structural core model accuracy is better for all variables except for employment.

Table 8 presents conditional predictive ability (CPA) tests comparing the out-of-sample performance of the structural core and benchmark models for various variables. Table 8 indicates the sign and magnitude of the p-value for the corresponding variable and model.

A positive t-statistic means the structural core model has a better CPA than the benchmark model and vice versa. Each cell shows the numerical value of the t-statistic in the first line and the p-value of the test in the second line. The results show that the structural core model performs better out-of-sample than the benchmark model for most variables and horizons.

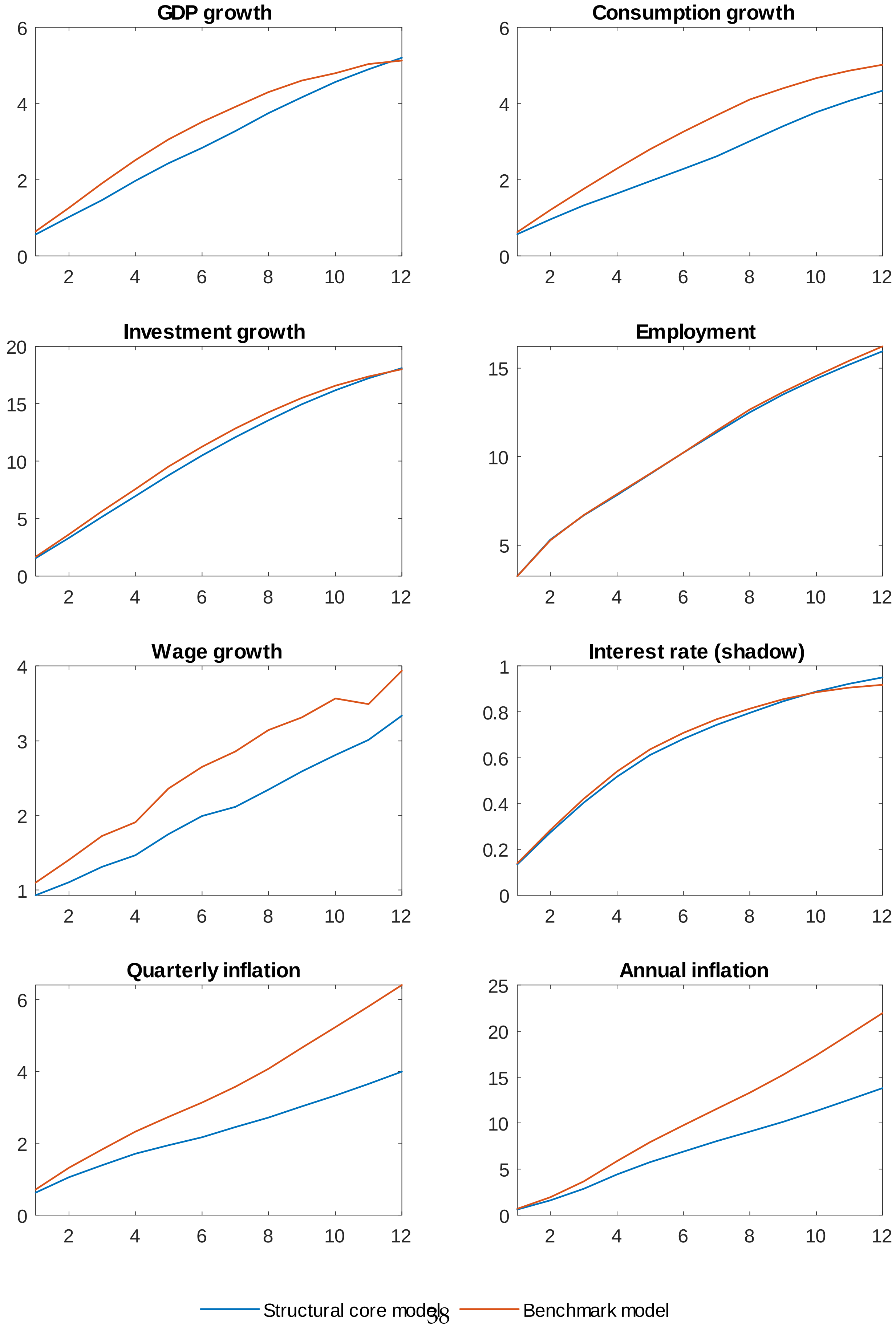
A.5 The COVID-19 Pandemic

Fig. 13 shows actual inflation (solid black line) and our structural core inflation, including the trend (dashed line). It also compares four other core inflation

[20] The benchmark model is the same as in Smets and Wouters (2007), with minimal adjustments for using CPI components as observables instead of headline CPI.

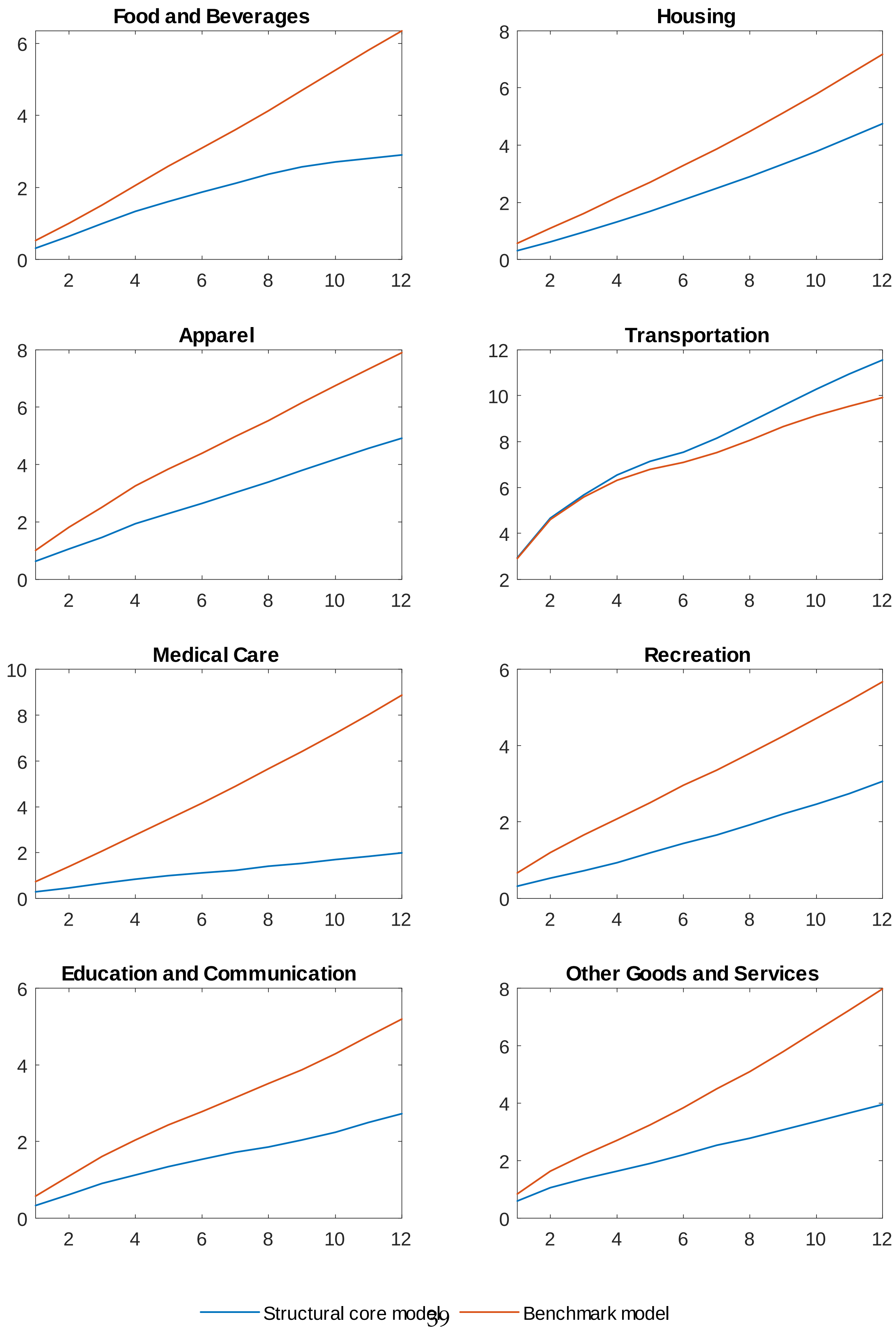
[21] The likelihood function measures how likely the data is given the model parameters, and the prior density measures the researcher's belief about the values of the parameters before the data is observed. The log marginal data density controls the number of variables, parameters, and quantity of data in two ways. First, the likelihood function is a product of the marginal likelihood for each variable, and the marginal likelihood for a variable decreases as the number of parameters in the model increases. This means that the log marginal data density will be lower for a model with more parameters, even if the model fits the data equally well. Second, the prior density is a function of the number of variables and parameters in the model. The prior density for a parameter typically decreases as the number of variables in the model increases. This means that the log marginal data density will be lower for a model with more variables, even if the model fits the data equally well. As a result, the log marginal data density is a more accurate measure of the fit of a DSGE model to the data than the likelihood function or the prior density alone.

Figure 11. RMSE Comparison Between Models and Variables



Notes: Cumulative RMSE of 1-12 quarters horizon. Derived from Bayesian estimations over the sample 1993-1999, and expanding over the testing sample 2000-2019.

Figure 12. RMSE Comparison Between Models and Components



Notes: Cumulative RMSE of 1-12 quarters horizon. Derived from Bayesian estimations over the sample 1993-1999, and expanding over the testing sample 2000-2019.

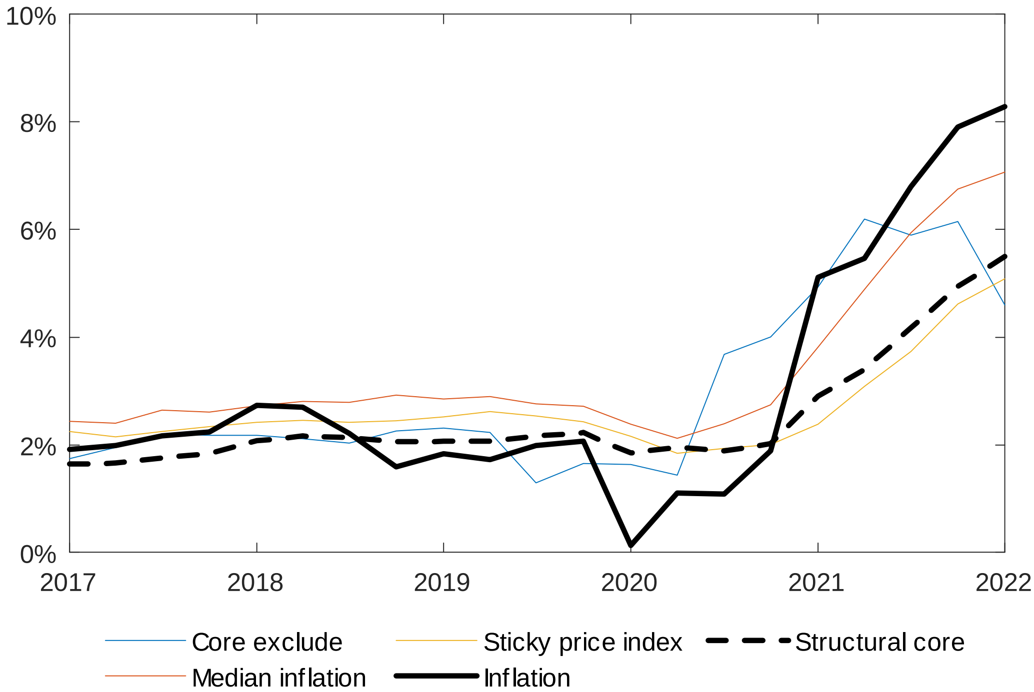
Table 8. Conditional Predictive Ability Tests

	1	2	3	4	5	6	7	8	9	10	11	12
GDP	8 (0.02)	8.6 (0.01)	8.1 (0.02)	9.9 (0.01)	8.9 (0.01)	10.6 (0.01)	8.3 (0.02)	7.8 (0.02)	13.1 (0)	7.5 (0.02)	9.4 (0.01)	8.8 (0.01)
Consumption	10.8 (0)	10.5 (0.01)	9.8 (0.01)	11 (0)	10.6 (0.01)	12.3 (0)	10.3 (0.01)	10.3 (0.01)	15.3 (0)	10.9 (0)	9.8 (0.01)	11.3 (0)
Investment	-0.6 (0.76)	-0.1 (0.93)	3.5 (0.17)	0.9 (0.62)	4.4 (0.11)	1.4 (0.5)	4.5 (0.11)	1.4 (0.49)	0.8 (0.65)	0.8 (0.67)	1.3 (0.53)	1 (0.6)
Employment	-5.5 (0.06)	-3.7 (0.16)	-2.2 (0.33)	-0.5 (0.79)	-4.3 (0.12)	0 (0.99)	-0.6 (0.74)	-0.1 (0.96)	-0.8 (0.67)	0.5 (0.77)	0.9 (0.63)	2.6 (0.27)
Wage	-0.3 (0.86)	4.9 (0.09)	5.4 (0.07)	8 (0.02)	7.8 (0.02)	11.5 (0)	7.6 (0.02)	6.7 (0.04)	14.4 (0)	5.7 (0.06)	5.8 (0.05)	5.3 (0.07)
Interest rate	-3.3 (0.19)	-3 (0.23)	-1.6 (0.45)	-3.7 (0.16)	-2.5 (0.28)	-2 (0.37)	-7.6 (0.02)	-1.2 (0.55)	-0.5 (0.78)	-0.3 (0.85)	-0.9 (0.62)	4 (0.13)
Inflation	1.5 (0.47)	3.3 (0.19)	5.2 (0.07)	6.7 (0.04)	11.1 (0)	14.8 (0)	18.2 (0)	21.4 (0)	25.6 (0)	32.4 (0)	42.5 (0)	58.2 (0)
Food & Beverages	2.8 (0.25)	4.5 (0.11)	8.3 (0.02)	13.9 (0)	16.3 (0)	20.7 (0)	19.7 (0)	22.4 (0)	26 (0)	30.3 (0)	36.7 (0)	46.5 (0)
Housing	4.9 (0.09)	7.6 (0.02)	11.4 (0)	15.3 (0)	18 (0)	20.7 (0)	21.5 (0)	24.2 (0)	27.7 (0)	33.6 (0)	41.2 (0)	60.9 (0)
Apparel	-40.7 (0)	-96.9 (0)	-64.9 (0)	-38.8 (0)	-25.5 (0)	-14.2 (0)	-8 (0.02)	-4.9 (0.09)	-3.2 (0.2)	-2.5 (0.28)	-1.7 (0.43)	-3.5 (0.17)
Transportation	-15.1 (0)	-9.4 (0.01)	-5 (0.08)	-3 (0.22)	-7.6 (0.02)	-7.7 (0.02)	10.5 (0.01)	3.6 (0.16)	1.5 (0.48)	1.3 (0.51)	1.7 (0.43)	2.2 (0.33)
Medical Care	30.1 (0)	101.4 (0)	118.4 (0)	146.6 (0)	154 (0)	151.1 (0)	125.8 (0)	125.7 (0)	116.4 (0)	115.1 (0)	126.2 (0)	140.4 (0)
Recreation	-14.2 (0)	-15 (0)	-3.1 (0.21)	-0.7 (0.72)	5 (0.08)	1.8 (0.42)	9 (0.01)	6.2 (0.05)	8.7 (0.01)	9.7 (0.01)	12.1 (0)	16.7 (0)
Educ & Comms	2.6 (0.28)	9 (0.01)	20.3 (0)	30.4 (0)	33.4 (0)	34.7 (0)	34.4 (0)	36.8 (0)	37.7 (0)	41.4 (0)	46.8 (0)	53.7 (0)
Other	20.9 (0)	70.2 (0)	124.4 (0)	154.8 (0)	182.8 (0)	187.6 (0)	169.1 (0)	167.7 (0)	151.3 (0)	155.7 (0)	172.1 (0)	205.2 (0)

Notes: The darker the cell, the better our structural core inflation forecast is over the benchmark model regarding p-values. Derived from Bayesian estimations over the sample 1993-1999, and expanding over the testing sample 2000-2019.

measures based on CPI. All measures have some similarities. Our structural measure rises later than the others (except the sticky prices index). A key insight is that according to the structural and sticky prices indexes, core inflation is still rising at the end of the sample (2022Q1), while the other indexes suggest that core inflation has peaked and started to fall.

Figure 13. Core CPI Inflation During the Covid-19: Structural and Alternative Measures



Notes: All indexes are for annual inflation. Structural core is our model core inflation, estimated in Section 3. The estimation sample is 1993-2019, and the model is used to filter the 2021-2022 data with the same parameters.

The stability of each index for the 1993-2019 period, measured by the mean absolute change (MAC), is shown in Table A.5.

Table 9. Core Index Stability

Core index	MAC
Core exclude	9.42%
Median inflation	6.97%
Trimmed inflation	8.23%
Sticky price index	4.81%
Structural core	5.76%

Notes: Based on annual inflation measures for 1993-2019. The MAC measures the statistical dispersion by averaging absolute differences between periods.

The structural and sticky price core indexes have the lowest MAC values, confirming their stability characteristic. Stability is usually considered a desirable property for a core inflation index but is not the only criterion. The sticky price index selects the components with the least price changes, which explains why this index is more stable than others. Our structural core index chooses the components based on their co-movements with each other and with the business cycle fluctuations.

A.6 Alternative Approaches

In this section, we compare the performance of the structural Core inflation index with other core inflation measures available from the Atlanta Fed's underlying inflation dashboard. These measures include CPI excluding food and energy, trimmed mean CPI, median CPI, and sticky components CPI. We also include the gross inflation rate as a benchmark.

To evaluate the different measures of core inflation, we estimate the original Smets and Wouters (2007) model using alternative measures of core inflation using Bayesian methods. For each estimation, we estimate the log marginal data density, which measures the fitting of the model to the data and considers the model complexity and the prior information.

Table 10. Log Marginal Data Densities: Alternative Measures of Core Inflation

Inflation	Excl. Food & Energy	Median	Sticky	Structural
-743.66	-709.00	-675.98	-686.59	-664.75

Notes: A higher log marginal data density implies a better fit compared to models presenting a lower one.

Table 10 shows that our structural core inflation has the highest log marginal data density compared to the alternative measures of core inflation, indicating that structural core inflation is the most informative and reliable indicator of inflation dynamics in the context of the Smets and Wouters (2007) model. The other measures of core inflation have significantly worst estimated log marginal data density, with sticky-price CPI being the closest to our structural core inflation.