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An Alternative Measure of Core Inflation: The Trimmed Persistence PCE Price Index

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An Alternative Measure of Core Inflation: The Trimmed Persistence PCE Price Index

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ABSTRACT

I introduce the "trimmed persistence PCE," a new measure of core inflation in which component prices are weighted according to the time-varying persistence of their price changes. The components of trimmed persistence personal consumption expenditures (PCE) display less tendency to mechanically pass-through the level of the prior period's inflation to the current period; thus, the impact of the current stance of monetary policy and real economic factors are more likely to be visible in recent trimmed persistence inflation compared to headline inflation. Trimmed persistence inflation performs comparably to existing popular measures of core inflation in terms of volatility and relationship with economic slack. Model selection procedures confirm trimmed persistence PCE contributes additional information to inflation forecasting models when stacked against other popular measures of core inflation. Applying the new index in a Taylor rule analysis suggests the Fed's aggressive path of federal funds rate hikes during the pandemic may have achieved appropriately restrictive levels by the fourth quarter of 2022, clearing the way for more measured policy adjustment thereafter as risks of policy overshooting became more salient.

Keywords: inflation, core inflation, inflation persistence, time-varying, inflation dynamics

JEL Classification Numbers: C22, E31, E37, E52

I. Introduction

Following the shock of the COVID-19 pandemic and the subsequent fiscal and monetary policy response, inflation in the United States reached multidecade highs. As shown in Figure 1, inflation as measured by year-over-year growth in the personal consumption expenditures (PCE) price index rose to 7.12 percent in June 2022, which was the highest rate since December 1981.

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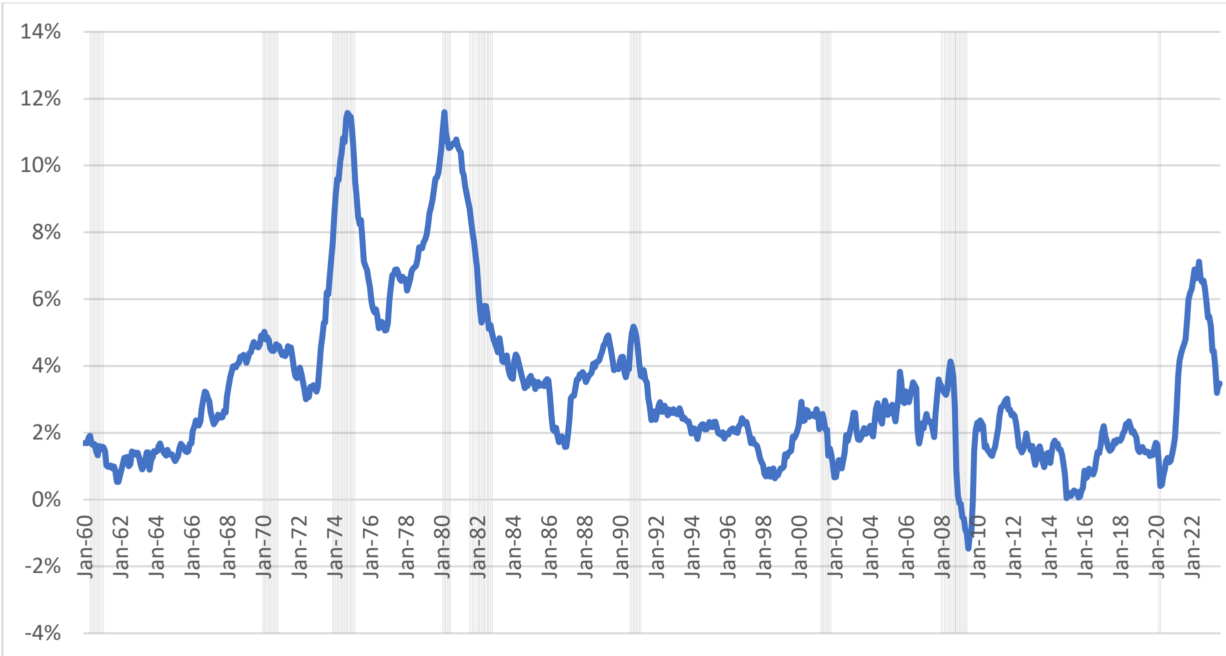


Figure 1 Personal consumption expenditure (PCE) price inflation, 1:1960-5:2023. Gray shading indicates recessions.

Interpreting the rise in inflation was a major challenge for policymakers on the Federal Open Market Committee (FOMC), who referred to a number of different inflation metrics when they communicated to the public.

In parsing the inflation data during the pandemic, one challenge that became particularly salient was judging the extent to which disaggregated pricing data contained useful information about the trajectory of future inflation. As shown in Figure 2, the period of elevated inflation in PCE ex food and energy (PCExFE) prices beginning in 2021 initially manifested as an outsized contribution of used vehicle prices to month-over-month growth rates, before broadening in scope. In early diagnoses of rising inflation in 2021, policymakers and academics debated whether the used vehicle price increase represented a transitory relative price change or the initial manifestation of inflation resulting from a broader imbalance between aggregate supply and demand.[2]

[2] As an example of one such public debate, Nobel laureate Paul Krugman stated on Twitter, "Inflation [is] somewhat higher than expected, but I don't think we should get too worked up about the prices of used cars." (https://twitter.com/paulkrugman/status/1392458554578247685, 12 May 2021, accessed 14 Dec. 2022). Former Council of Economic Advisers chair Jason Furman expressed a contrary view, stating, "You want to be cautious about taking different sectors out of your price basket in assessing inflation trends ... If people have a lot more money to spend and car prices did not go up then maybe they would have spent even more on other stuff and inflation would have been similar in aggregate, just spread out differently." (https://twitter.com/jasonfurman/status/1458886069093556229, 11 Nov. 2021, accessed 14 Dec. 2022).

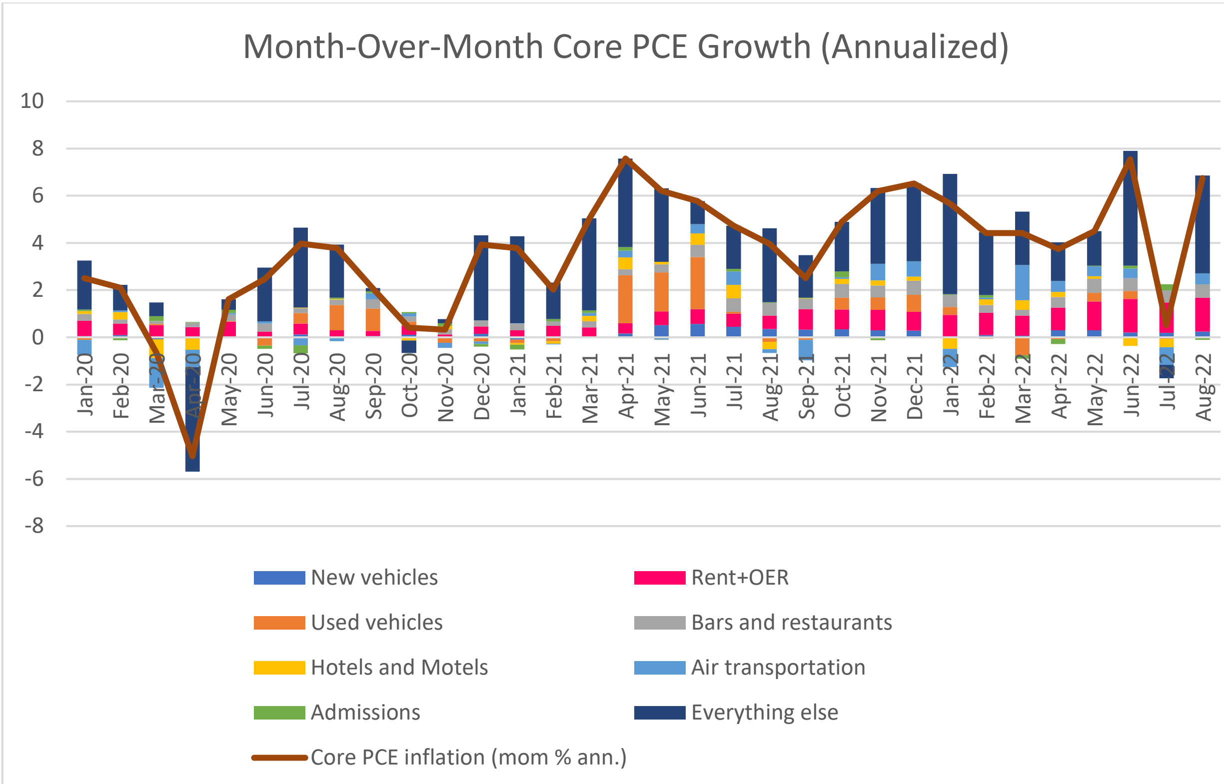


Figure 2 PCExFE inflation by selected expenditure categories, 2020-2022

The resulting debate renewed public interest in measuring inflation and in the differences between popular price indices. *The Economist* calculated an alternative core price index, commenting on the popular PCExFE and trimmed mean PCE inflation measures that "both of these methods have flaws. Changes in food and energy prices are not necessarily unusually large or short-lived. And trimmed means' weighting schemes are plagued by abrupt cliffs." (*The Economist*, 2021)

Leigh et al. (2021) distinguish core price indices according to "fixed-exclusion" and "outlier-exclusion" categories based on whether the indices exclude signals from fixed categories of consumer expenditure (i.e., food and energy, or “sticky price” categories), or whether large price changes are dropped from the index. During the COVID-19 pandemic, they find PCExFE performed poorly for most of 2020-2021 because large industry price changes occurred outside of the food and energy sectors. Other fixed-exclusion measures such as the Atlanta Fed sticky consumer price index (CPI) omitted more industries and fared better than PCExFE during the pandemic. However, outlier-exclusion measures such as the trimmed mean and median PCE inflation measures displayed superior performance on the basis of volatility and negative comovement with economic slack.

In this article, I propose an alternate measure of core inflation called the “trimmed persistence PCE.” The trimmed persistence PCE price index is neither a fixed-exclusion measure, as it does not omit changes in a pre-specified group of expenditure components, nor an outlier-exclusion measure, as it does not necessarily omit all large component-level price changes. Similar to the popular trimmed mean and median measures of PCE inflation, trimmed persistence PCE takes inflation signals from a subset of the PCE expenditure basket. But in contrast to existing measures which exclude expenditure categories based on realized monthly price changes, trimmed persistence inflation excludes price categories based on the time-varying persistence of price changes in each category. Large price changes for a spending category are omitted from the trimmed persistence PCE index only when they cause the category's estimated time-varying persistence coefficient to cross an optimal inclusion threshold. Trimming the relatively persistent components, which are more variable, reduces the volatility of trimmed persistence inflation compared to headline PCE inflation. In addition, the trimming process results in an inflation measure that is less prone to mechanically inheriting the prior period's level of inflation and is arguably more responsive to real-time changes in real economic and monetary policy factors determining inflation.

During the post-COVID-19 recession inflationary episode, trimmed persistence PCE displayed less volatility than headline PCE inflation with a standard deviation of monthly annualized inflation prints falling between those of median PCE and PCExFE. However, over a longer sample beginning in 1988, trimmed persistence was more volatile than trimmed mean and median PCE. Nevertheless, the benefit of this approach is that it preserves potentially useful signals about changes in inflation dynamics which might have been dropped from the trimmed mean and median PCE. For example, in times of accelerating inflation, it may be particularly important to retain such signals from outlying relative price changes if a high-inflation regime initially manifests as large price changes in a smaller number of categories before becoming more broad-based across multiple categories. Trimmed persistence inflation also performs comparably to other core inflation measures in displaying a negative relationship with economic slack, with a correlation coefficient falling between that of PCExFE and median PCE inflation following the pandemic recession.

Despite the visual similarity between twelve-month changes in trimmed persistence PCE and PCExFE, as well as the similarity of the two measures in terms of the volatility of monthly annualized inflation and inverse comovement with resource slack, trimmed persistence PCE contributes a distinct perspective about the trajectory of inflation and implications for policy. Model selection procedures applied to statistical inflation forecasting models that pit trimmed persistence inflation against other core inflation measures show evidence that trimmed persistence inflation contributes to improved forecast accuracy for inflation at horizons up to three years ahead.

The remainder of the paper proceeds as follows. Section II discusses how this article fits into the existing literature on inflation. Section III discusses the basic intuition and motivation behind the trimmed persistence PCE. Section IV describes the methodology underlying the construction of the index, along with data sources. Section V examines the behavior of trimmed persistence PCE inflation during the pandemic with an application to policy, and Section VI offers concluding thoughts.

II. Literature Review

This paper is related to studies exploring time-variation in inflation dynamics. In an early contribution, Barsky (1987) presents evidence that inflation persistence evolved from a white noise process in the pre-World War I years to a highly persistent, nonstationary ARIMA process after 1960. Cogley and Sargent (2002) use a time-varying parameter Bayesian vector autoregression (TVP-VAR) model to characterize inflation as weakly persistent in the 1960s and strongly persistent in the 1970s, with persistence declining again in the 1990s. Williams (2006) studies time variation in inflation persistence by estimating Phillips curves over different samples of historical data, finding some evidence that inflation has become less persistent since the 1990s. Stock and Watson (2007) fit an unobserved components model with stochastic volatility on inflation data finding further evidence of time variation in inflation persistence. Beechey and Österholm (2012) find that inflation persistence declined rapidly during the Volcker and Greenspan tenures compared to the experience of the 1970s. In contrast, Pivetta and Reis (2007) find very wide Bayesian credible sets associated with estimated persistence coefficients and conclude that inflation persistence has essentially been unchanged between 1965 and 2001. Cogley et al. (2010) document inflation persistence increasing during the Great Inflation and falling after the Volcker disinflation. In this article—unlike these studies which focus on aggregate inflation measures—I study time-varying dynamics of the price indices of disaggregated expenditure categories.

This article is most closely related to those which focus on extracting core inflation from disaggregated inflation data. Bryan and Pike (1991) examine the CPI, finding that median price changes give a superior signal of underlying inflation compared to headline CPI because the median purges noise from transitory relative price movements. Bryan et al. (1997) introduce a version of the trimmed mean CPI. In a cross-country study, Brischetto and Richards (2006) find that trimmed mean CPI inflation outperforms headline and exclusion-based core CPI inflation (such as CPIxFE inflation) at separating inflation signals from noise, and in terms of near-term predictive ability. Bryan and Meyer (2010) group CPI components into sticky and flexible categories based on the speed at which prices adjust, calculating a sticky-price CPI which displays superior inflation forecasting performance relative to the headline CPI measure. Meyer et al. (2013) and Meyer and Venkatu (2014) find that the median CPI outperforms other trimmed mean inflation measures in predicting CPI inflation, and that it also outperforms PCExFE in predicting PCE inflation.

Other contributions, including this paper, focus on the PCE price index which is the Fed's preferred measure of consumer prices. Dolmas (2005) introduces the trimmed mean PCE measure, which strips out expenditure components associated with the largest absolute monthly price changes. In a related study, Dolmas and Koenig (2019) explain that while trimmed mean PCE does not dominate PCExFE in terms of forecasting, it is more successful at filtering out transitory variation from the headline PCE inflation number. Carroll and Verbrugge (2019) calculate median PCE inflation rates and find that these measures perform comparably to other trend inflation estimators such as trimmed mean PCE. Mahedy and Shapiro (2017) sort PCE spending categories into procyclical and acyclical groups according to their sensitivity to the unemployment gap, developing alternative measures of cyclical and acyclical core inflation. Stock and Watson (2019) introduce a similar measure of cyclically sensitive inflation, which re-weights seventeen broad components of PCE inflation according to their correlation with a broad measure of economic slack estimated during the 1984-2019 period. Shapiro (2022) classifies PCE components into supply- and demand-driven groups based on the comovement of price and quantities of each component in response to unexpected shocks.

The motivation of the trimmed persistence PCE index is similar to that of Stock and Watson (2016) who use disaggregated data on sectoral inflation to construct indices of core inflation that feature time-varying sectoral weights. These authors use a multivariate unobserved-components stochastic volatility model to recover common volatilities and trends, sector-specific volatilities and trends, sector-specific factor loadings, common and sector-specific outlier factors, and the aggregate inflation trend from quarterly inflation series of seventeen components of the PCE price index. The model is computationally intensive, and the authors note that extending the approach to more finely disaggregated data presents substantial challenges due to instability in measurement. In a more recent contribution, Almuzara and Sbordone (2022) introduce the Multivariate Core Trend, extending the Stock and Watson (2016) approach to monthly data from seventeen sectors, although their MCT index ultimately excludes the food and energy sectors. In contrast to these authors, I use a simpler approach on even more granular monthly data, using 180 components of PCE. My approach allows a more disaggregated level analysis of the contributors to core inflation while preserving the use of monthly data to provide higher-frequency information to policymakers making decisions in real time.

As mentioned in the previous section and shown in Table 1, these alternative measures of core inflation can largely be classified into fixed-exclusion and outlier-exclusion categories. In contrast, the trimmed persistence PCE measure introduced in the next section is neither a fixed- nor outlier-exclusion measure.

	Fixed-exclusion	**Outlier-exclusion**	**Neither fixed- nor outlier-exclusion**
CPI-based	CPI ex food and energy, Atlanta Fed Sticky CPI	Cleveland Fed 16 percent trimmed mean CPI, Cleveland Fed median CPI	
PCE-based	PCE ex food and energy, San Francisco Fed cyclical and acyclical core PCE, San Franscisco Fed supply- and demand-driven PCE, Stock and Watson (2019) cyclically sensitive inflation, Almuzara and Sbordone (2022) Multivariate Core Trend	Dallas Fed trimmed mean PCE, Cleveland Fed median PCE	Stock and Watson (2016) unobserved components stochastic volatility trend inflation, Trimmed persistence PCE

Table 1 Classification of core inflation measures

III. Motivation

How is time-varying inflation persistence related to identifying underlying "core" inflation? To motivate the basic intuition behind the trimmed persistence PCE index, consider the AR(1) process:

$$\pi_t = \alpha(1-\rho) + \rho\pi_{t-1} + \epsilon_t, \quad (1)$$

where $\epsilon_t \sim \mathrm{IID}(0, \sigma_\epsilon^2)$. We assume that the random variable π_t has some degree of persistence, so that $0 \leq \rho \leq 1$. π_t is covariance-stationary if $\rho < 1$, which then implies $E(\pi_t) = \alpha$. Importantly, the variance of π_t is $\sigma_\pi^2 = \frac{\sigma_\epsilon^2}{1-\rho^2}$, which is increasing in ρ.

If $\rho = 1$, then setting $\alpha = 0$ to prevent π_t from trending, π_t follows the driftless random walk process:

$$\pi_t = \pi_{t-1} + \epsilon_t. \tag{2}$$

Given initial condition π_0, by repeated substitution of lagged values into (2) it can be shown that π_t follows the moving average representation:

$$\pi_t = \pi_0 + \sum_{j=0}^{t-1} \epsilon_{t-j} . \tag{3}$$

Thus, if π_t follows a random walk, ϵ_{t-j} shocks have a permanent effect on π_t. Furthermore, the variance of π_t does not exist: initializing $\pi_0 = 0, \pi_t = \epsilon_t + \epsilon_{t-1} + \cdots + \epsilon_1 \sim IID(0, t\sigma_\epsilon^2)$. In other words, the variance of π_t grows linearly with t, and as t increases without bound, so too will the variance of π_t.

This has implications for building a price index. Suppose our goal is to construct a price index that smooths out the impact of its most volatile underlying components. If we can estimate an AR(1) process for the price index of each component i, we can assess its volatility $\sigma_{\pi_i}^2$ by judging how far ρ_i is from 1: in other words, how far away the price index for i is from being a random walk. Giving greater weight to components with lower estimated persistence would reduce the variance of the aggregated index compared to headline PCE which is essentially weighted by expenditure shares. An index constructed in this manner would arguably better reflect changes in present conditions versus echoes of the past, compared to the headline index. The higher ρ_i, the more that current inflation π_{it} will mechanically inherit its level from the prior period π_{it-1}, and the less visible that current period changes in other determinants of inflation, such as cumulative policy effects and real economic activity as of date t, will be.

As a further refinement to the index, we can take into account evidence of time-varying inflation dynamics discussed in the prior section by allowing ρ and α to vary over time. This entails estimating a time-varying parameter version of Equation (1) as follows:

$$\pi_t = \alpha_t (1 - \rho_t) + \rho_t \pi_{t-1} + \epsilon_t. \tag{4}$$

The basic idea that the variance of π_t is increasing in ρ_t continues to hold with some slight modifications.

A. Determining inclusion criteria

Having established that the AR(1) persistence coefficient is a potentially useful criterion for including category-level prices in a trimmed persistence core PCE price index, the question remains: how persistent is too persistent? In other words, at what levels of $|\rho_{it}|$ should we discount the signals from π_{it}?

I draw on Dolmas (2005), who outlines a trimming process that minimizes the discrepancy between the inflation rate captured by a newly constructed price index and three proxies for core inflation. The first proxy of core inflation is a centered thirty-six-month moving average of monthly inflation rates, first proposed by Bryan et al. (1997). The second proxy is obtained by applying a Christiano-Fitzgerald bandpass filter to monthly headline inflation; Dolmas (2005) describes this measure, which discards high-frequency movements in PCE inflation lasting less than thirty-nine months, as the inflation rate that the FOMC appears to have responded to in setting monetary policy. The last proxy represents an inflation signal that contains information about future inflation and is calculated as a moving average of inflation in the current month and twenty-four coming months.

B. The optimal trimming problem

The optimal trimming problem chooses the threshold ρ^* to minimize the root mean square deviation between trimmed persistence inflation and the proxy of core inflation. Letting $\{\overline{\pi_t}\}_{t=1}^{T}$ denote the proxy of core inflation, the optimal threshold ρ^* solves:

$$min_{\rho^*} \sqrt{T^{-1} \sum_{t=1}^{T} \left(\pi_t^{(\rho^*)} - \overline{\pi_t}\right)^2} . \qquad (5)$$

Table 2 shows the optimal trim for each core proxy. The selection process chooses an optimal threshold value of $\rho^* = 0.23$ for all three proxies.

Core proxy	**Optimal threshold ρ***
36-month centered moving average	0.23
Trend correlated with Fed Funds Rate	0.23
Forward-looking moving average	0.23
Average across alternative proxies	0.23

Table 2 Optimal trimming for various core proxies

IV. Data and methodology

A. Data

Data on the underlying components of the PCE price index are retrieved from the Bureau of Economic Analysis (BEA) and accessed via Haver Analytics. The data are also publicly available on the BEA's website in the Underlying Detail tables 2.4.4U and 2.4.5U for chain-type price indices and nominal personal consumption expenditures (used to calculate monthly PCE shares) by detailed type of product, respectively.

When choosing the degree of disaggregation, there is a trade-off between sample length and finer granularity. For the purposes of this study, I include 180 subcategories of PCE consumption whose expenditure weights add up to 100 percent of the PCE consumption basket. This level of aggregation is very similar to that used in the trimmed mean PCE index. While the many component price indices have data starting as early as January 1959, the price indices for digital videos, personal computers and tablets, and computer software are only available post-1977. Furthermore, the price indices for personal computers and computer software were constant from January 1977-March 1979; this further restricts the sample for estimating time-varying persistence and delays the starting date for the trimmed persistence PCE until 1979. Further information on the components is presented in Appendix Table 1.

B. Estimating time-varying persistence

For each of the 180 components of the PCE consumption basket, I fit a time-varying AR(1) model to the month-over-month annualized change in the component's corresponding price index similar to Equation (4):

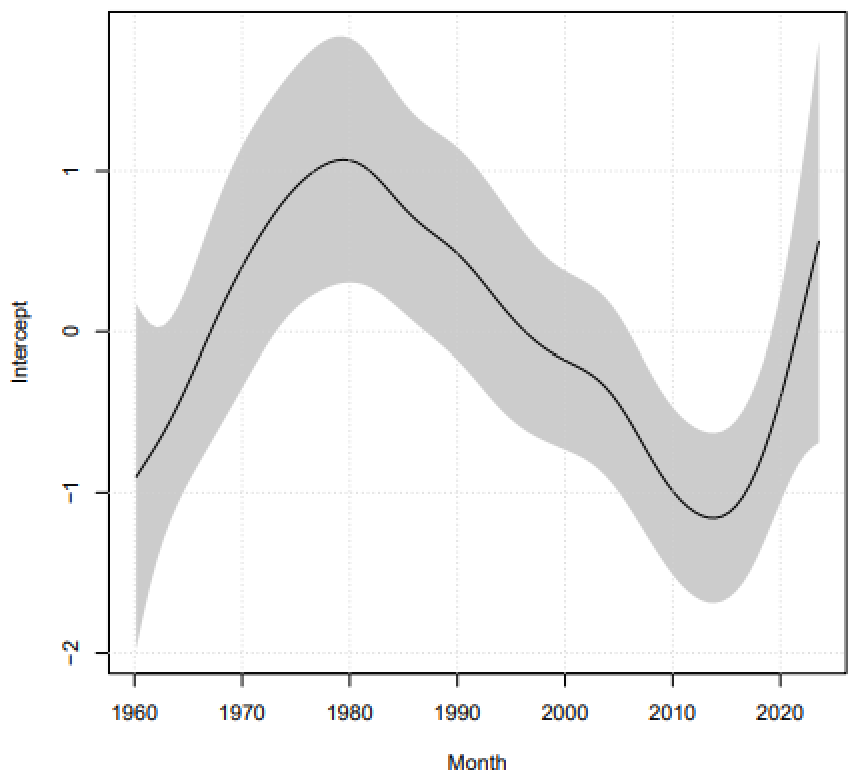
$$\pi_{it} = \widetilde{\alpha_{it}} + \rho_{it}\,\pi_{it-1} + \epsilon_{it}, \qquad (6)$$

where i is the index for component i and $\widetilde{\alpha_{it}} \equiv \alpha_{it}(1-\rho_{it})$ is the time-varying intercept term. Our main object of interest is the $T \times i$ matrix $\mathcal{P}$ of time-varying AR1 persistence parameters ρ_{it}.

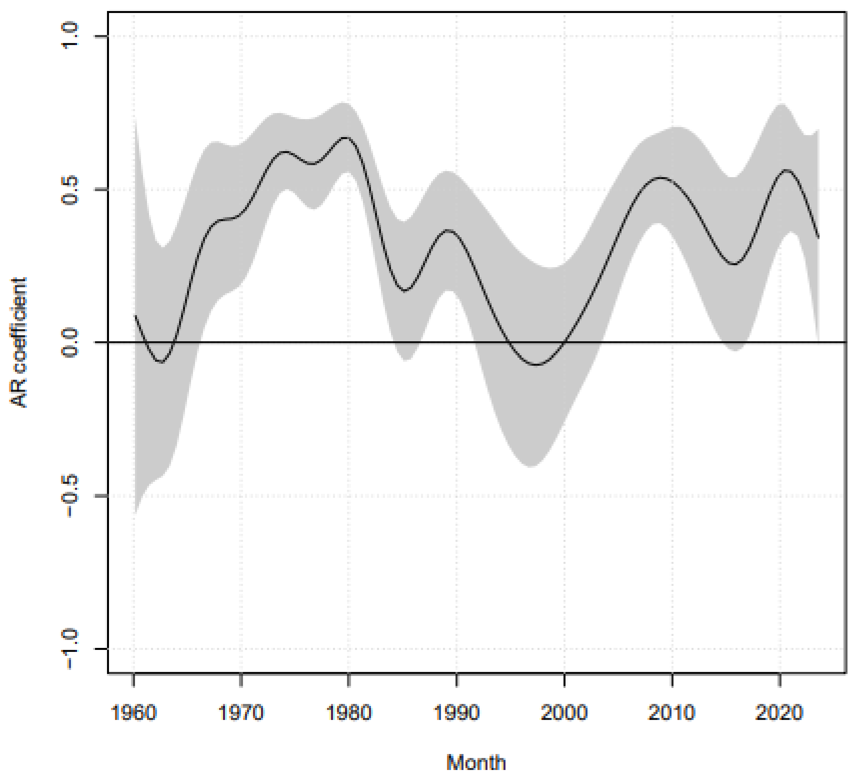
Equation (6) is estimated via a generalized additive model approach (Hastie & Tibshirani, 1986; Hastie & Tibshirani, Generalized Additive Models, 1990; Wood, 2017), which models price growth as a sum of smooth basis functions of covariates (i.e., time and lagged price changes). For the underlying basis functions, I use twenty thin plate regression splines, an approximation of optimal thin plate spline smoothers which, unlike some other basis function alternatives, allow bases to represent smooths of multiple predictor variables and avoid subjectivity in choosing knot locations.

The assumption that changes in the dynamics of inflation happen smoothly over time, rather than suddenly and abruptly, is key to the construction of the trimmed persistence PCE index and is built into the methodology. It allows for large relative price changes to potentially be retained in the computation of the index, so long as these changes do not push the estimated AR(1) coefficient in the current period above the optimal inclusion threshold. As discussed in Wood (2017), the prior belief that the “truth” is more likely to be smooth rather than volatile and wiggly can also be formalized through a Bayesian interpretation of the smoothing penalty. However, there may exist real-world scenarios where inflation dynamics are highly unstable, such as in episodes of hyperinflation observed in some emerging markets, where this underlying assumption of the methodology is invalid.

To illustrate an application of this methodology, Figure 3 plots estimates of $\widetilde{\alpha_t} \equiv \alpha_t(1-\rho_t)$ and ρ_t when Equation (4) is fitted to monthly annualized PCE inflation from January 1959 through August 2023; the shaded gray region indicates the 95 percent Bayesian credible sets associated with each estimate. As shown in the first panel, during the COVID-19-related inflationary episode, the estimated time-varying intercept sharply increased, while the second panel suggests a decline in the persistence of headline PCE inflation after 2020.



(a) Time-varying intercept $\widetilde{\alpha_t}$



(b) Time-varying AR1 coefficient ρ_t

Figure 3 Time-varying coefficient estimates of fitted AR(1) model of month-over-month annualized headline PCE inflation, January 1959-August 2023

C. Building the index

Following Wolman and Ding (2005), I construct the trimmed persistence PCE price index as an expenditure-share weighted average of the rates of change of component price indices.

Specifically, let $\{P_{i,t}, Q_{i,t}\}_{i=1}^{N}$ denote a set of prices and real quantities for N expenditure categories that make up the PCE price index at time t. The growth rate of the PCE price index p_t between $t+1$ and t is given by the Fisher ideal index formula:

$$\pi_t = \frac{p_{t+1}}{p_t} = \sqrt{\frac{\sum_i Q_{i,t} P_{i,t+1}}{\sum_i Q_{i,t} P_{i,t}} \frac{\sum_i Q_{i,t+1} P_{i,t+1}}{\sum_i Q_{i,t+1} P_{i,t}}}. \quad (7)$$

This can be rewritten as:

$$\pi_t = \sqrt{\left[\sum_{i=1}^{N} \omega_{i,t-1}\pi_{i,t}\right]\left[\sum_{i=1}^{N} \theta_{i,t}\pi_{i,t}\right]}, \tag{8}$$

where $\pi_{i,t}$ is the rate of price change for category i from period $t-1$ to period t, and

$$\omega_{i,t} \equiv \frac{x_{i,t}}{\sum_{j=1}^{N} x_{j,t}} \tag{9}$$

$$\theta_{i,t} \equiv \frac{x_{i,t}/\pi_{i,t}}{\sum_{j=1}^{N}(x_{j,t}/\pi_{j,t})} \tag{10}$$

for $i = 1, \dots, N$, with $x_{i,t} \equiv P_{i,t} \times Q_{i,t}$ referring to period t dollar expenditures on category i.

In equation (8), both objects in square brackets are weighted averages of the rates of price change for each expenditure category. The weights $\omega_{i,t-1}$ are expenditure weights for category i in period $t-1$, while the weights $\theta_{i,t}$ are hypothetical expenditure shares that combine period t real quantities with period $t-1$ prices. PCE inflation π_t is the geometric average of the two weighted averages.

From here, I employ a further approximation that aggregates prices for each expenditure category using a Divisia index. As described in Ding and Wolman (2005), the Divisia index is a simpler calculation that gives a good approximation of the true PCE inflation rate, and it is obtained by using the expenditure share of component i at time t, $\omega_{i,t}$, as the weight for the price change of component i between t and $t+1$:

$$\pi_{t+1}^{D} = \sum_i \omega_{i,t}\, \pi_{i,t+1}. \tag{11}$$

As described in Section III.B, only a subset of PCE expenditure components whose estimated AR(1) coefficients ρ_{it} fall below the optimal inclusion threshold ρ^* will be included in the trimmed persistence PCE at time t. The weight for component i in the trimmed persistence PCE is:

$$\omega_{i,t}^{TP} = \frac{I(\rho_{it} \le \rho^*)\omega_{i,t}}{\sum_{i=1}^{N} I(\rho_{it} \le \rho^*)\omega_{i,t}}, \tag{12}$$

where $I(\cdot)$ is equal to one if the argument in parentheses is true, and zero otherwise. Month-over-month changes in the trimmed persistence PCE are calculated as:

$$\pi_{t+1}^{TP} = \sum_i \omega_{i,t}^{TP}\, \pi_{i,t+1}. \tag{13}$$

The level of the trimmed persistence PCE, which is used to calculate year-over-year inflation rates, is computed by setting the period preceding the first π_t^{TP} equal to 100, and cumulatively applying the month-over-month growth rates.

The composition of the trimmed persistence PCE index thus changes over time as shown in Figure 4. During the COVID-19 inflation episode, the number of expenditure components included in the index declined from 128 in December 2019 to 98 as of August 2023, as the estimated persistence of many inflation components rose above the inclusion threshold. The share of PCE expenditure included in the index, plotted on the right axis, declined from 60.1 percent in December 2019 to 51.1 percent in August 2023.

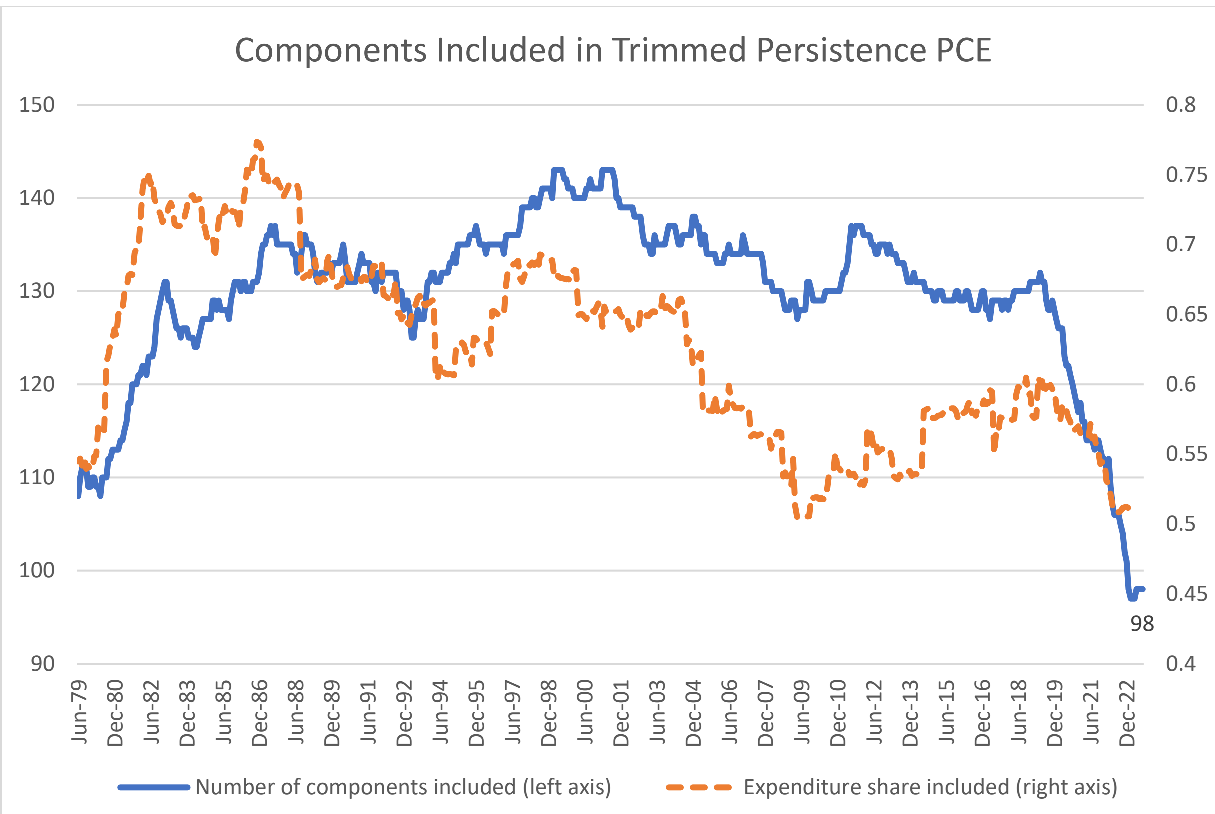
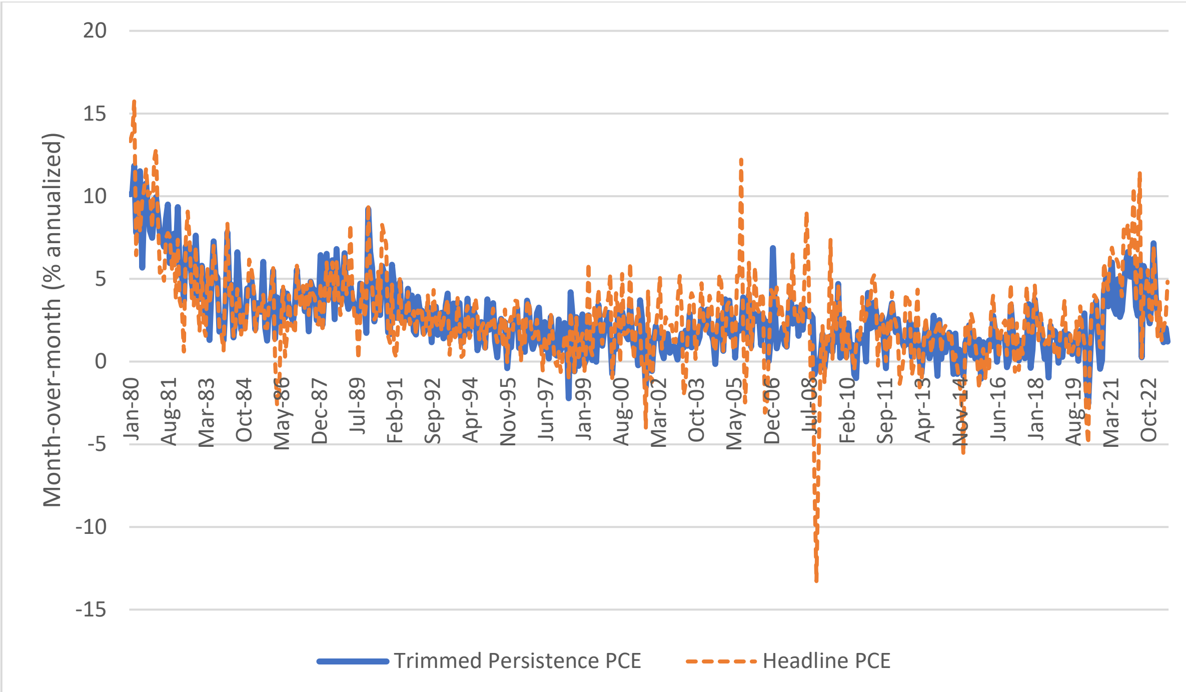
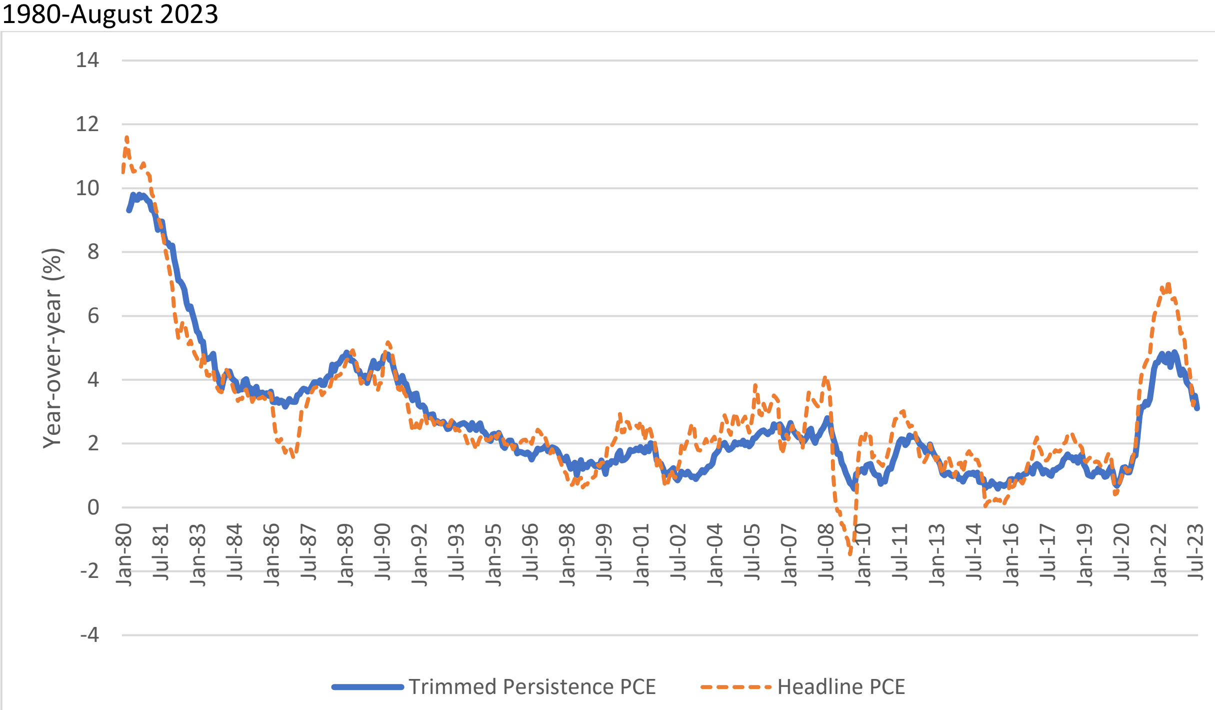


Figure 4 Count and expenditure share of components included in trimmed persistence PCE

Figure 5 plots the final result. The first panel of Figure 5 compares month-over-month annualized growth rates of the trimmed persistence PCE index to those of the headline PCE price index. The second panel plots year-over-year inflation rates of the trimmed persistence PCE and headline PCE price indices.



Month-over-month annualized change in headline and trimmed persistence PCE price indices, January 1980-August 2023

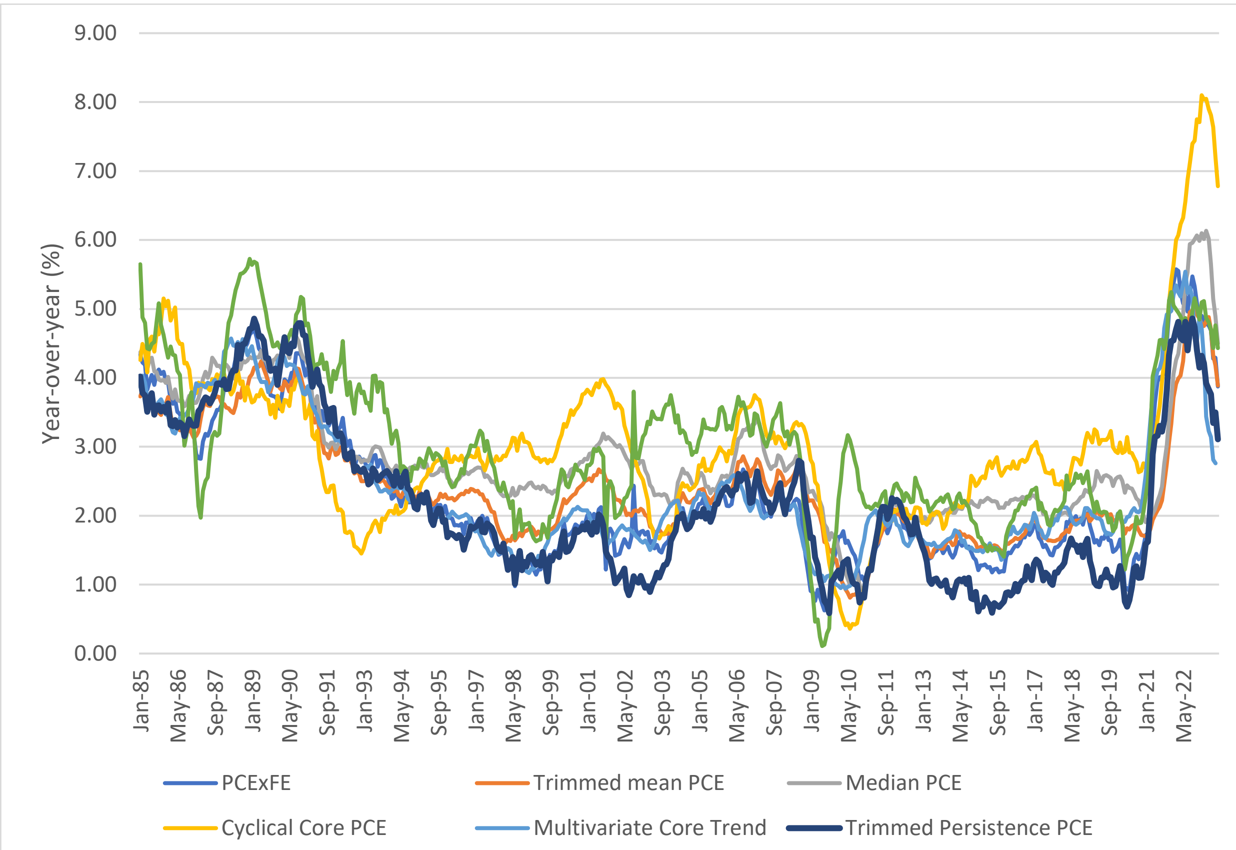


Year-over-year headline and trimmed persistence PCE inflation rates, January 1980-August 2023

Figure 5 Headline and trimmed persistence PCE inflation, January 1980-August 2023

V. The post-COVID-19 inflation

Figure 6 compares year-over-year trimmed persistence PCE inflation to year-over-year PCExFE, trimmed mean PCE, median PCE, cyclical core PCE inflation, and multivariate core trend inflation. Year-over-year trimmed persistence PCE inflation as of August 2023 was 3.1 percent—1.8 percentage points from its February 2020 level. In comparison, year-over-year PCExFE inflation in August 2023 was 2.2 percentage points from its February 2020 level, while trimmed mean and median inflation were both 1.9 percentage points from their February 2020 reading.



Comparison of core inflation proxy measures, 1980-present

Figure 6 Trimmed persistence PCE inflation versus other core inflation measures

Typically, authors introducing new core inflation measures use their new index to perform some kind of forecasting exercise. These exercises typically take the form of a horse race pitting the new core inflation measure against other alternatives in a forecasting regression, or against some rule of thumb such as a random walk forecast of inflation computed as the average of the previous four quarters of inflation (Atkeson & Ohanian, 2001). I skip this step for two reasons.

First, previous authors have found that out-of-sample predictive power is similar across alternative measures of core inflation: Dolmas and Koenig (2019) find that trimmed mean PCE does not dominate PCExFE inflation in terms of forecast performance; Carroll and Verbrugge (2019) find that median PCE inflation performs comparably to other trend inflation estimators such as trimmed mean PCE; and Bryan and Meyer (2010) find similar out-of-sample forecasting accuracy of sticky CPI, core sticky CPI, and CPI ex food and energy.

Second, sticking the trimmed persistence PCE in a forecasting model to generate unconditional forecasts of inflation may not be the best use of this measure. If a central bank is credible in its ability to influence the price level, then any forecast for inflation should be conditioned on the forecaster's assumptions about the future path of monetary policy. As evident in the FOMC Summary of Economic Projections from March 2022 (see Figure 7), intelligent people armed with the same information on realized inflation, economic fundamentals, and even inside knowledge of FOMC deliberations might still disagree on the path of inflation if their views of the appropriate future path of policy differ.

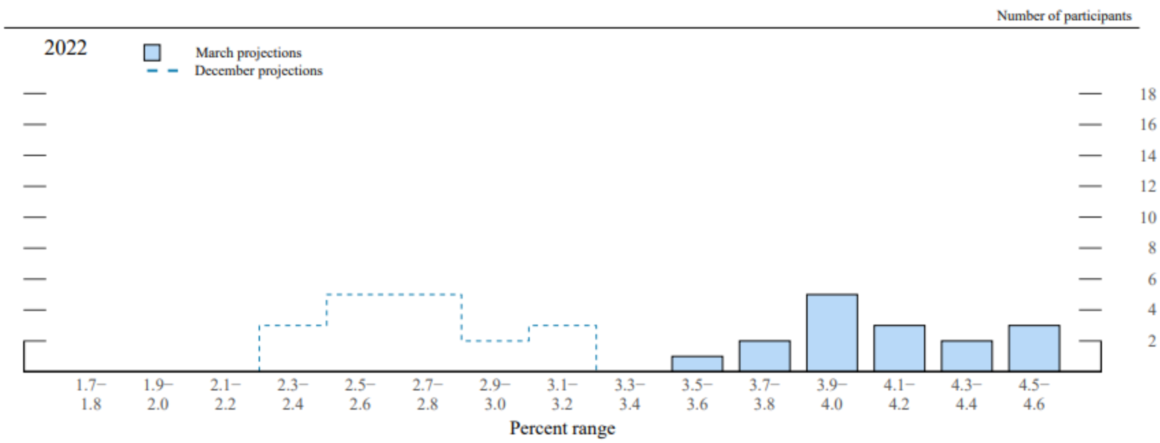


Figure 7 Distribution of FOMC projections for 2022 full-year core PCE inflation, March 2022

Source: Board of Governors, 16 March 2022. https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20220316.pdf}. Accessed 17 Dec. 2022.

Instead, the best use of the trimmed persistence PCE may be to serve as an additional signal about underlying inflationary pressures when incoming inflation readings are mixed. The COVID-19-era inflation spotlighted a number of challenges identifying and interpreting inflation data in an environment of mixed shocks to aggregate demand and supply. Ball et al. (2022) show that narratives explaining the trajectory of underlying inflation can be sensitive to the choice of core inflation metric used. Schmitt-Grohé and Uribe (2022) find that narratives explaining the rise in inflation during the pandemic can also be sensitive to the length of the historical sample used in the supporting empirical analysis. As discussed in Section I, Leigh et al. (2021) find that fixed-exclusion and outlier-exclusion measures of inflation can offer different perspectives on the trajectory of inflation.

The trimmed persistence PCE is neither a fixed-exclusion measure, as it does not omit changes in a fixed group of components, nor an outlier-exclusion measure, as it does not necessarily omit all large component-level price changes. This is clearly seen in Table 3, which lists the first ten items of all 180 PCE expenditure categories, sorted in ascending order by month-over-month price change for September 2022. Focusing on these ten categories with the largest monthly annualized price decreases reveals that some of the categories in the top ten, such as window coverings and spectator sports, are retained in the trimmed persistence PCE index whereas they would be excluded from trimmed mean and median PCE. Additionally, the price index for eggs is retained in the index in that month's trimmed persistence PCE reading, in contrast to PCExFE.

	Category	Price change (% MoM ann.)	AR1 coefficient	Included?
1	Gasoline & Other Motor Fuel	-49.92	0.25	No
2	Eggs	-42.55	0.22	Yes
3	Window Coverings	-41.31	-0.17	Yes
4	Calculators/Typewriters/Other Info Processing Eqpt	-37.49	0.33	No
5	Telephone and Related Communication Equipment	-37.48	0.33	No
6	Spectator Sports	-34.69	0.17	Yes
7	Fuel Oil	-32.34	0.3	No
8	Other Recreational Vehicles	-30.7	-0.29	No
9	Bicycles & Accessories	-30.69	-0.11	Yes
10	Pleasure Boats	-30.69	-0.29	No

Table 3 Top 10 PCE price changes and inclusion in trimmed persistence PCE, in ascending order (Sep. 2022)

Because it retains information from a subset of components with large relative price changes, the trimmed persistence PCE displays higher month-to-month volatility compared to other measures of core inflation. From January 1988 through July 2023, the standard deviation of month-over-month annualized changes in trimmed persistence PCE was 1.7, compared to 1.6 for PCE ex food and energy, 1.1 for median PCE, and 1.0 for trimmed mean PCE.

However, the relative performance of core inflation measures in terms of volatility can vary depending on the sample window. Figure 8 shows the standard deviation of monthly annualized inflation across various measures of inflation following the pandemic recession (May 2020-July 2023). Over this period, volatility of the trimmed persistence PCE has fallen between that of median PCE and PCExFE, suggesting that trimmed persistence inflation has performed comparably to other measures of core inflation during a period of elevated inflation and uncertainty.

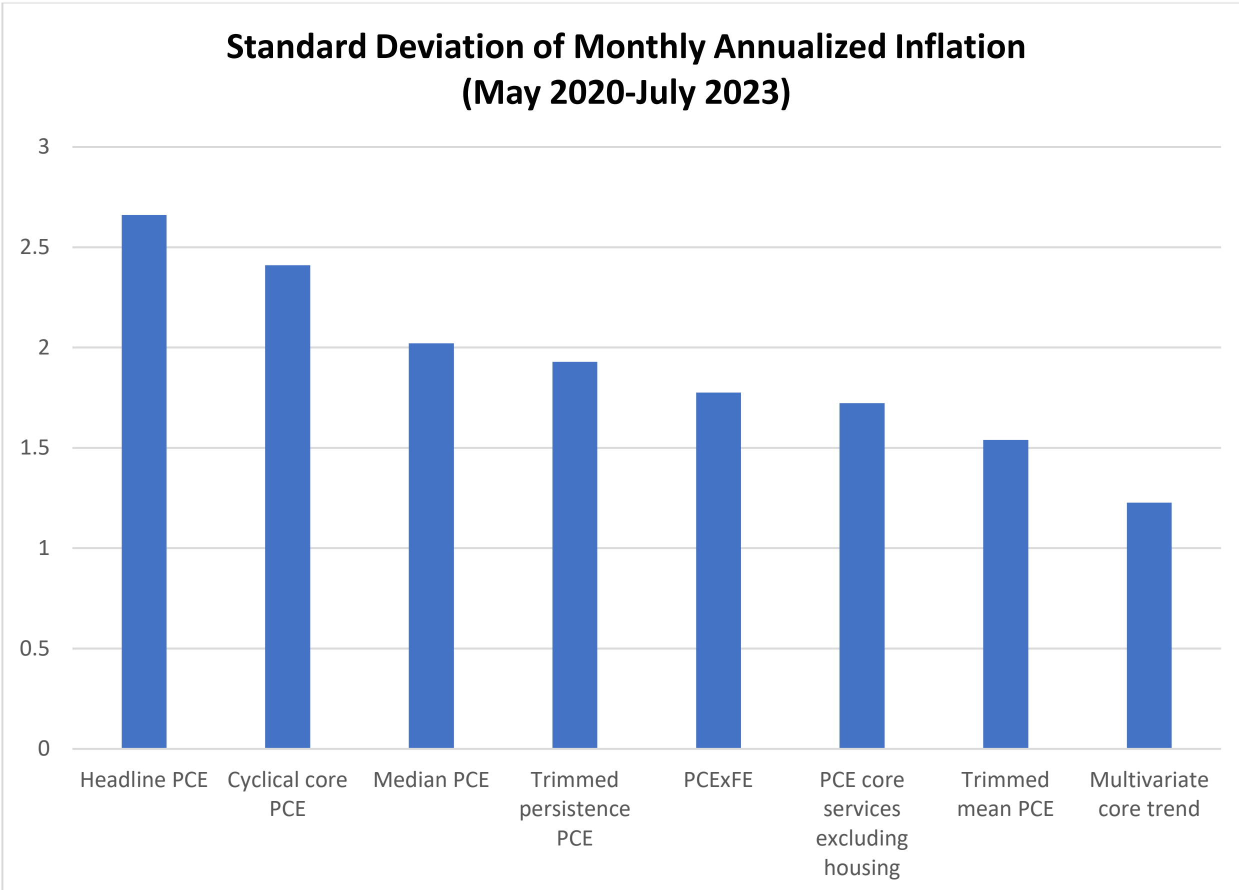


Figure 8 Volatility of monthly annualized inflation, May 2020-July 2023 (standard deviation, percentage points)

In terms of the relationship between inflation and economic slack, the trimmed persistence PCE compares favorably against the alternative core inflation measures examined in this article. I follow Leigh et al. (2021), who assess comovement between inflation measures and economic slack as measured by the twelve-month average gap between the unemployment rate and the Congressional Budget Office's estimate of the natural rate.

Figure 9 shows the estimated coefficient in a regression of twelve-month inflation against the average unemployment gap following the pandemic recession, with larger absolute magnitudes indicating a greater degree of negative comovement between inflation and slack. Based on this measure, the trimmed persistence PCE displays a similar degree of comovement with slack as median PCE, performing favorably in comparison to trimmed mean and multivariate core trend inflation.

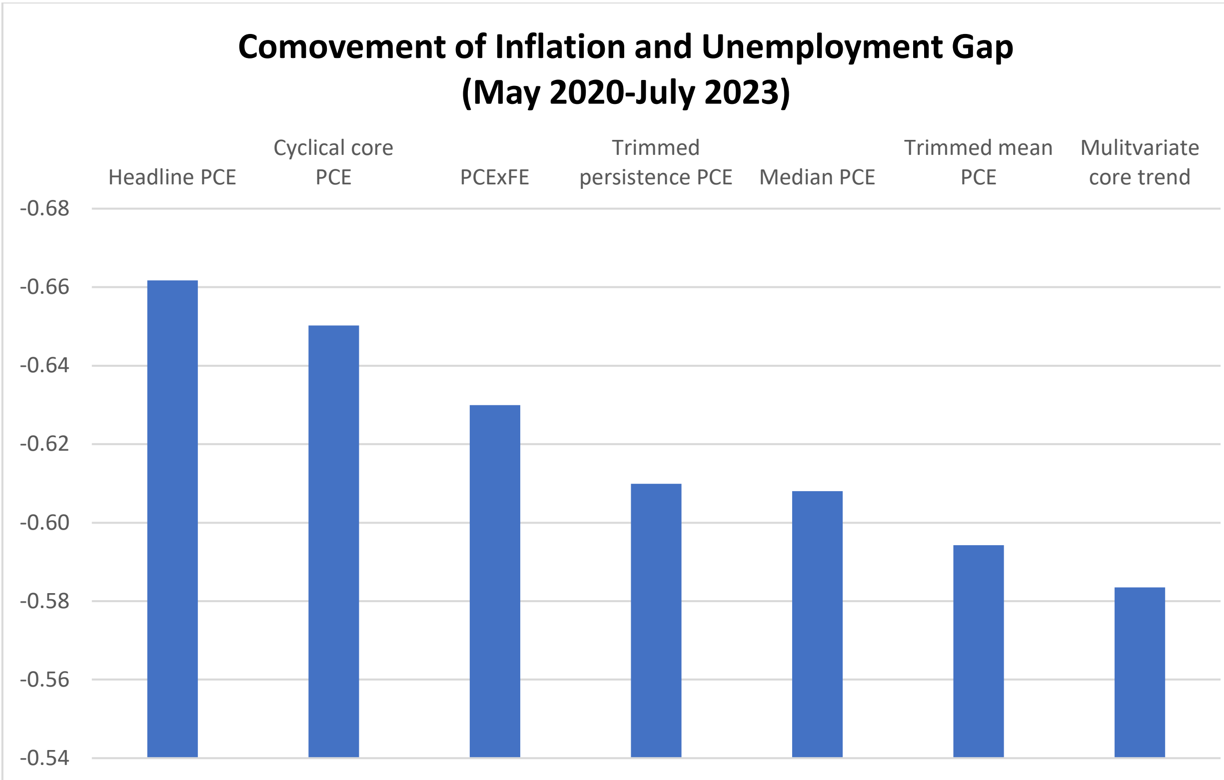


Figure 9 Comovement of inflation and unemployment gap (May 2020-May 2023)

Given the comparability of trimmed persistence inflation to other core inflation proxies in terms of volatility and correlation with economic slack, it would be reasonable to question whether the trimmed persistence PCE contributes any additional information to a forecaster's information set over pre-existing core inflation measures. I allow the data to decide, estimating inflation forecasting regression equations of the form:

$$\pi_{(\{t+h\},\{t+h\}-12)} = \alpha + \beta\pi^{c}_{(t,t-12)} + \epsilon^{(h)}_{t}, \qquad (14)$$

where $\pi_{(\{t+h\},\{t+h\}-12)}$ represents h-month ahead, year-over-year headline PCE inflation, and $\pi^{c}_{(t,t-12)}$ represents a vector of core inflation proxies measured as year-over-year inflation rates at month t. I look at horizons of $h \in \{6, 12, 18, 24, 30, 36\}$ months ahead. π^{c} contains some subset of the core inflation proxies displayed in Figure 9 .

I use statistical variable selection procedures to let the data decide which subset of the core inflation measures to retain in equation (14). These are tools designed to simplify models and tackle issues of collinearity that can arise when correlations between regressor variables (i.e., multicollinearity) are high. I consider three such procedures:

1. Forward stepwise regression, which starts from a model with no variables and individually tests each candidate variable according to a model fit criterion, selecting the best variable and repeating the process until no remaining variable results in an improvement in the fit;

2. Backward stepwise regression, which starts from a model that contains all candidate predictor variables and tests the deletion of each variable using a model fit criterion, removing the variable that results in the best improvement in the fit criterion and repeating the process until no variable can be deleted without a deterioration in model fit; and
3. LASSO (least absolute shrinkage and selection operator) regression, which selects a subset of known covariates in a model by shrinking coefficients toward and setting some coefficients equal to zero.

For the two stepwise regressions, I use the standard choice of Akaike's information criterion (AIC) as a measure of model fit.

Results for the model selection procedure are presented in Table 4. Trimmed persistence PCE is retained as a predictor variable in forecasting headline inflation at every horizon across all three model selection algorithms, with the exception of the six-month ahead inflation forecasting model selected via backward stepwise selection. Notably, trimmed persistence inflation is retained under every model selected via LASSO regression, which has been found to outperform stepwise selection procedures in out-of-sample forecast accuracy.

Forward stepwise selection	Multivariate core PCE, Median PCE, Headline PCE, **Trimmed persistence PCE**, Cyclical core PCE, PCExFE, Trimmed mean PCE	Multivariate core PCE, Trimmed mean PCE, Headline PCE, PCExFE, **Trimmed persistence PCE**	Multivariate core PCE, PCExFE, Trimmed mean PCE, Median PCE, **Trimmed persistence PCE**	Multivariate core PCE, PCExFE, Headline PCE, **Trimmed persistence PCE**, Median PCE	Multivariate core PCE, **Trimmed persistence PCE**, Median PCE, Headline PCE, Cyclical core PCE	Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**, Trimmed mean PCE, PCExFE
Backward stepwise selection	Headline PCE, PCExFE, Trimmed mean PCE, Cyclical core PCE, Multivariate core PCE	Headline PCE, PCExFE, Trimmed mean PCE, Multivariate core PCE, **Trimmed persistence PCE**	PCExFE, Trimmed mean PCE, Median PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, PCExFE, Median PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, Trimmed mean PCE, Multivariate core PCE, **Trimmed persistence PCE**	PCExFE, Trimmed mean PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**
LASSO	Headline PCE, PCExFE, Trimmed mean PCE, Median PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, PCExFE, Trimmed mean PCE, Median PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, PCExFE, Trimmed mean PCE, Median PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, PCExFE, Trimmed mean PCE, Median PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, PCExFE, Trimmed mean PCE, Median PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**	Headline PCE, PCExFE, Trimmed mean PCE, Cyclical core PCE, Multivariate core PCE, **Trimmed persistence PCE**
Forecast Horizon	**6**	**12**	**18**	**24**	**30**	**36**

Table 4 Inflation forecasting at various horizons: Model selection results

The alternative signal about true core inflation provided by the trimmed persistence PCE may be useful to monetary policymakers assessing the appropriate level of the policy rate through the framework of policy rules such as the Taylor (1993) rule. For example, former Richmond Fed president Jeffrey Lacker and Philadelphia Fed president Charles Plosser argued in 2022 that the Fed should routinely make reference to the implications of systematic monetary policy rules when discussing the likely future path of interest rates (Lacker & Plosser, 2022). The policy prescriptions of such rules can be sensitive to the choice of inflation metric used in the calculation (Dhawan & Jeske, 2007; Mehra & Sawhney, 2010; Garciga, Knotek, & Verbrugge, 2016). During the pandemic inflation, St. Louis Fed president James Bullard suggested using different measures of core inflation, including trimmed mean PCE and PCExFE, along with different calibrations of a Taylor-type rule to derive upper and lower bounds for the recommended level of the federal funds rate (Bullard, 2022).

To illustrate this application of the trimmed persistence PCE, I compare policy rule prescriptions obtained from using different measures of inflation in a generalized version of the Taylor rule, described in the Atlanta Fed's online Taylor Rule Utility (Higgins, 2016). The policy prescription $\widehat{FFR_t}$ given by the rule is calculated via the formula:

$$\widehat{FFR_t} = \rho FFR_{t-1} + (1-\rho)[(r_t^* + \pi_t^*) + 1.5(\pi_t - \pi_t^*) + \beta gap_t], \qquad (15)$$

where FFR_t denotes the fed funds target rate at the end of month t, π_t denotes inflation, π_t^* denotes the inflation target (set to 2.0 percent), r_t^* denotes the natural (real) interest rate (set to 1.0 percent), and gap_t is a measure of resource gap in the economy. Various measures of the resource gap are commonly used, but here I use a measure based on the difference between the unemployment rate in month t and the Congressional Budget Office's estimate of the natural rate of unemployment for the corresponding period. ρ in Equation (15) refers to the interest-rate smoothing parameter, which I set to 0.85 in line with the inertial Taylor rule in the Federal Reserve Board's FRB/US model of the U.S. economy, and β refers to the weight on the resource gap which is set to 0.5.

Table 5 shows that as of July 2023, the actual federal funds rate (FFR) of 5.375 was within the range of prescribed values obtained by incorporating various core inflation measures into the Taylor rule described in equation (15). However, the Taylor rule prescription under trimmed persistence PCE inflation was on the lower end of the range of prescriptions, suggesting the FFR setting may have been more restrictive than suggested by formulations of the policy rule using other inflation metrics.

Inflation Measure	Taylor Rule Prescription
Headline PCE	5.25
PCExFE	5.44
Trimmed Mean PCE	5.43
Median PCE	5.59
Cyclical Core PCE	6.12
Multivariate Core Trend	5.12
Trimmed Persistence PCE	5.21
Actual Fed Funds Rate	5.38

Table 5 Taylor rule prescriptions for fed funds rate (July 2023)

Figure 10 plots the actual FFR versus the prescribed rate from the trimmed persistence PCE-based Taylor rule. The gray shaded region indicates the range of rate prescriptions obtained from incorporating the alternative inflation measures listed in Table 5 into the specified rule. The figure shows that prior to the pandemic recession, the trimmed persistence PCE-based rule characterized the FOMC's setting for the FFR reasonably well, despite a notable period from 2009-2013 when the effective lower bound (ELB) was a binding constraint, with the rule recommending levels at or below zero.

During the early phase of the pandemic, the ELB once again became binding as the Taylor rule recommended negative rates from April through October 2020. The situation quickly reversed when inflation began to rise in March 2021; the rule-prescribed FFR was over 100 basis points higher than the actual FFR by the end of 2021.

With historically rapid policy tightening beginning in March 2022, including a string of four consecutive 75 basis point hikes, the gap between the actual FFR and the prescribed value narrowed rapidly. While the prescribed rate remained above the actual FFR through the first ten months of 2022, the gap between the two series was eliminated with a large 75 basis point FFR hike in November 2022, bringing the funds rate to 3.875 versus the rule-based prescription of 3.76. Thus, from the perspective of this particular specification of the Taylor rule, steep rate hikes by the FOMC were successful in bringing policy close to “appropriate” levels as quickly as the fourth quarter of 2022—though the rule-based prescription continued to rise in following months with ongoing elevated inflation, indicating further adjustment remained necessary. Still, taken as a whole, aggressive FFR normalization may have contributed to signs of progress for overall PCE inflation in the fourth quarter of 2022. This in turn may have allowed the FOMC to slow the pace of its rate hikes beginning in December 2022 as policy overshooting risks became more relevant.

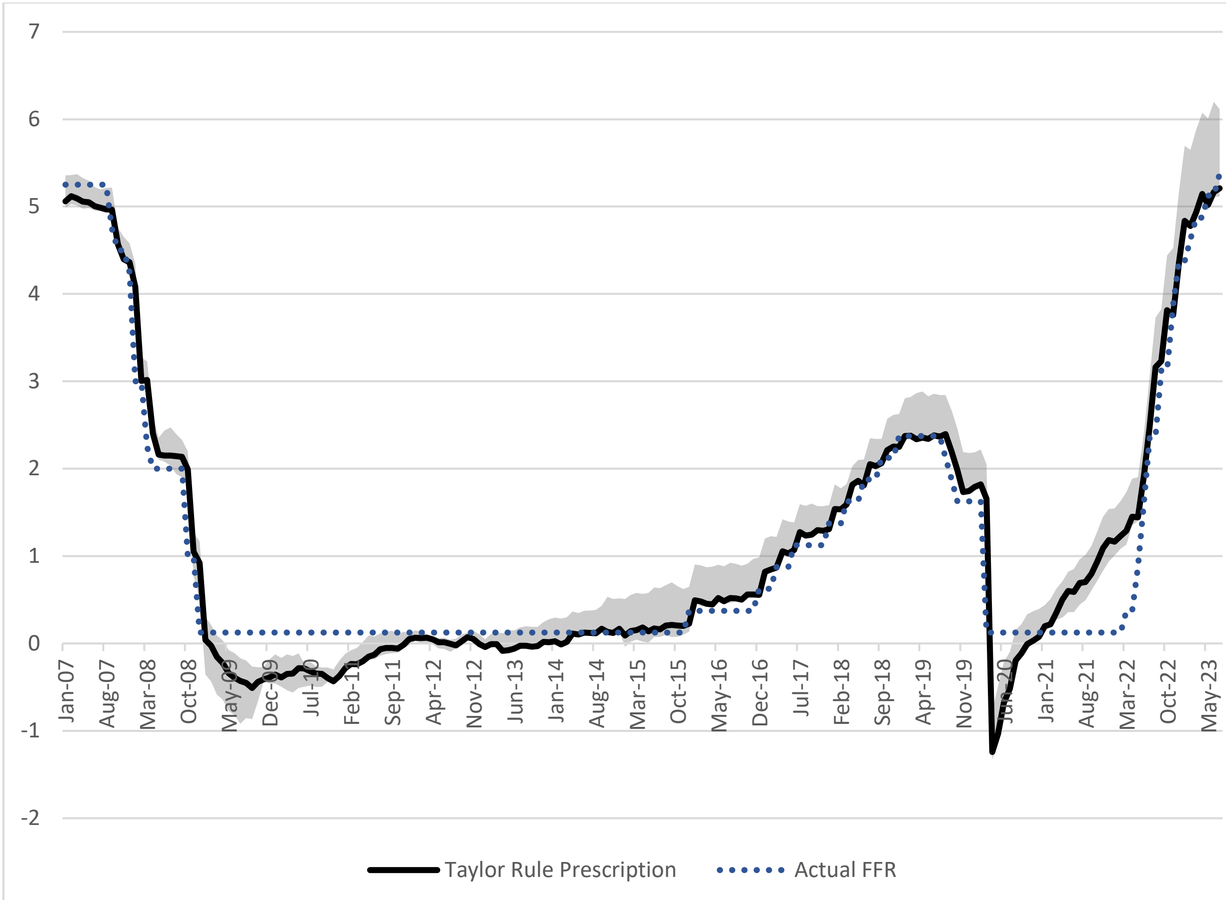


Figure 10 Fed funds rate versus prescription of trimmed persistence PCE-based Taylor rule, 2007-present

VI. Conclusion

I introduced an alternative measure of core inflation called the trimmed persistence PCE in which expenditure categories are weighted according to the time-varying persistence of their corresponding price changes. Excluding categories associated with more persistent price changes yields an inflation measure that is less volatile than headline PCE inflation. Additionally, because the underlying components of trimmed persistence inflation display less tendency to mechanically pass-through the prior period's level to the current period, the contemporaneous influence of fundamental drivers of inflation such as real supply and demand effects and the cumulative impact of monetary policy actions are likely to be more visible in recent trimmed persistence PCE inflation compared to the headline measure.

In contrast to other popular measures of core inflation, the trimmed persistence PCE is neither a fixed-exclusion measure omitting pre-specified expenditure categories such as food, energy, or “sticky price” categories, nor is it an outlier-exclusion measure that automatically strips out expenditure categories that experience outsized monthly price changes. Because it retains some information from expenditure categories with large price changes, the trimmed persistence PCE can be a more volatile measure of core inflation than trimmed mean or median PCE. However, following the pandemic recession, the trimmed persistence PCE performed favorably versus other measures of core inflation, with a standard deviation of monthly annualized inflation falling between that of median PCE and PCExFE.

Additionally, the trimmed persistence PCE performs comparably to other core inflation proxies in terms of relationship with economic slack. In the aftermath of the COVID-19 recession, trimmed persistence PCE displayed a stronger negative relationship with the unemployment gap than trimmed mean and multivariate core inflation, with the degree of comovement with slack similar to median PCE. In variable selection procedures pitting trimmed persistence PCE against other inflation measures, trimmed persistence PCE is shown to contribute to the predictive fit of regression-based inflation forecasting models for horizons up to three years ahead.

The trimmed persistence PCE can provide a helpful alternative signal of underlying inflation pressure. By relying on alternative weighting and exclusion criteria compared to other core inflation proxies, it contributes to policy debates about how, if at all, to take signals about aggregate inflation from disaggregated, expenditure category-level data. Additionally, for policymakers and economic forecasters judging the appropriate level of the benchmark policy rate through the framework of Taylor-type rules, incorporating trimmed persistence PCE inflation into such rules may provide additional context about the possible range of appropriate settings for the FFR. Using trimmed persistence PCE inflation in a Taylor-type rule calibrated to fit data observed prior to the pandemic shows a considerable deviation between the actual FFR and levels prescribed by the rule at the end of 2021, while aggressive rate hiking in 2022 may have returned policy to appropriate levels—as indicated by the rule—by the fourth quarter of that year.

This study also opens further avenues for additional research. For example, I estimated a simple time-varying AR(1) process for component-level price indices; further research could explore whether having richer specifications that include more autoregressive lags, or allowing for moving-average terms could improve the performance of the index. Another simplifying step used in this paper was a Divisia approximation to construct the trimmed persistence price index; further work could be done to move toward the Fisher ideal index construction. Additionally, I use a simple rule to determine whether an expenditure component is included at any given period; further work could explore alternative inclusion criteria relating each components' weight in the aggregate index to their estimated persistence coefficient. Future research could also explore whether other methods of estimating time-varying inflation dynamics, different from the generalized additive approach used in this paper, might yield superior results.

VII. Appendices

A. Appendix 1: List of PCE components used in calculation

Component	Description	Start Date
1	New Domestic Autos	1959-01-31
2	New Foreign Autos	1959-01-31
3	New Light Trucks	1959-01-31
4	Used Autos	1959-01-31

Component	Description	Start Date
5	Used Light Trucks	1959-01-31
6	Tires	1959-01-31
7	Accessories & Parts	1959-01-31
8	Furniture	1959-01-31
9	Clock/Lamp/Lighting Fixture/Other HH Decorative Item	1959-01-31
10	Carpets & Other Floor Coverings	1959-01-31
11	Window Coverings	1959-01-31
12	Major Household Appliances	1959-01-31
13	Small Elec Household Appliances	1959-01-31
14	Dishes and Flatware	1959-01-31
15	Nonelectric Cookware & Tableware	1959-01-31
16	Tools, Hardware & Supplies	1959-01-31
17	Outdoor Equipment & Supplies	1959-01-31
18	Televisions	1959-01-31
19	Other Video Equip	1959-01-31
20	Audio Equipment	1959-01-31
21	Audio Discs/Tapes/Vinyl/Permanent Digital Downloads	1959-01-31
22	Video Discs, Tapes & Permanent Digital Downloads	1977-01-31
23	Photographic Equip	1959-01-31
24	Personal Computers/Tablets & Peripheral Equipment	1977-01-31
25	Computer Software & Accessories	1977-01-31
26	Calculators/Typewriters/Other Info Processing Eqpt	1959-01-31
27	Sporting Equip, Supplies, Guns & Ammunition	1959-01-31
28	Motorcycles	1959-01-31
29	Bicycles & Accessories	1959-01-31
30	Pleasure Boats	1959-01-31
31	Pleasure Aircraft	1959-01-31
32	Other Recreational Vehicles	1959-01-31
33	Recreational Books	1959-01-31
34	Musical Instruments	1959-01-31
35	Jewelry	1959-01-31
36	Watches	1959-01-31
37	Therapeutic Medical Equip	1959-01-31
38	Corrective Eyeglasses & Contact Lenses	1959-01-31
39	Educational Books	1959-01-31
40	Luggage & Similar Personal Items	1959-01-31
41	Telephone and Related Communication Equipment	1959-01-31
42	Cereals	1959-01-31
43	Bakery Products	1959-01-31
44	Beef and Veal	1959-01-31
45	Pork	1959-01-31
46	Other Meats	1959-01-31
47	Poultry	1959-01-31

Component	Description	Start Date
48	Fish and Seafood	1959-01-31
49	Fresh Milk	1959-01-31
50	Processed Dairy Products	1959-01-31
51	Eggs	1959-01-31
52	Fats and Oils	1959-01-31
53	Fresh Fruit	1959-01-31
54	Fresh Vegetables	1959-01-31
55	Processed Fruits & Vegetables	1959-01-31
56	Sugar and Sweets	1959-01-31
57	Food Products, Not Elsewhere Classified	1959-01-31
58	Coffee, Tea & Other Beverage Mtls	1959-01-31
59	Mineral Waters, Soft Drinks & Vegetable Juices	1959-01-31
60	Spirits	1959-01-31
61	Wine	1959-01-31
62	Beer	1959-01-31
63	Food Produced & Consumed on Farms	1959-01-31
64	Women's & Girls' Clothing	1959-01-31
65	Men's & Boys' Clothing	1959-01-31
66	Children's & Infants' Clothing	1959-01-31
67	Clothing Materials	1959-01-31
68	Standard Clothing Issued to Military Personnel	1959-01-31
69	Shoes & Other Footwear	1959-01-31
70	Gasoline & Other Motor Fuel	1959-01-31
71	Lubricants & Fluids	1959-01-31
72	Fuel Oil	1959-01-31
73	Other Fuels	1959-01-31
74	Prescription Drugs	1959-01-31
75	Nonprescription Drugs	1959-01-31
76	Other Medical Products	1959-01-31
77	Games, Toys & Hobbies	1959-01-31
78	Pets & Related Products	1959-01-31
79	Flowers, Seeds & Potted Plants	1959-01-31
80	Film & Photographic Supplies	1959-01-31
81	Household Cleaning Products	1959-01-31
82	Household Paper Products	1959-01-31
83	Household Linens	1959-01-31
84	Sewing Items	1959-01-31
85	Misc Household Products	1959-01-31
86	Hair/Dental/Shave/Misc Pers Care Prods ex Elec Prod	1959-01-31
87	Cosmetic/Perfumes/Bath/Nail Preparatns & Implements	1959-01-31
88	Elec Appliances for Personal Care	1959-01-31
89	Tobacco	1959-01-31
90	Newspapers & Periodicals	1959-01-31

Component	Description	Start Date
91	Stationery & Misc Printed Materials	1959-01-31
92	Expenditures Abroad by U.S. Residents	1959-01-31
93	Less: Personal Remittances in Kind to Nonresidents	1959-01-31
94	Rental of Tenant-Occupied Nonfarm Housing	1959-01-31
95	Owner-Occupied Mobile Homes	1959-01-31
96	Owner-Occupied Stationary Homes	1959-01-31
97	Rental Value of Farm Dwellings	1959-01-31
98	Group Housing	1959-01-31
99	Water Supply & Sewage Maintenance	1959-01-31
100	Garbage & Trash Collection	1959-01-31
101	Electricity	1959-01-31
102	Natural Gas	1959-01-31
103	Physician Services	1959-01-31
104	Dental Services	1959-01-31
105	Paramedical Services	1959-01-31
106	Nonprofit Hospitals' Services to HHs	1959-01-31
107	Proprietary Hospitals	1959-01-31
108	Govt Hospitals	1959-01-31
109	Nursing Homes	1959-01-31
110	Motor Vehicle Maintenance & Repair	1959-01-31
111	Motor Vehicle Leasing	1973-01-31
112	Motor Vehicle Rental	1959-01-31
113	Parking Fees & Tolls	1959-01-31
114	Railway Transportation	1959-01-31
115	Intercity Buses	1959-01-31
116	Taxicabs and Ride Sharing Services	1959-01-31
117	Intracity Mass Transit	1959-01-31
118	Other Road Transportation Service	1959-01-31
119	Air Transportation	1959-01-31
120	Water Transportation	1959-01-31
121	Membership Clubs/Participant Sports Centers	1959-01-31
122	Amusement Parks/Campgrounds/Rel Recral Svcs	1959-01-31
123	Motion Picture Theaters	1959-01-31
124	Live Entertainment, ex Sports	1959-01-31
125	Spectator Sports	1959-01-31
126	Museums & Libraries	1959-01-31
127	Audio-Video, Photographic/Info Process Svcs	1959-01-31
128	Casino Gambling	1959-01-31
129	Lotteries	1959-01-31
130	Pari-Mutuel Net Receipts	1959-01-31
131	Veterinary & Other Services for Pets	1959-01-31
132	Package Tours	1959-01-31
133	Maint/Repair of Rec Vehicles/Sports Eqpt	1959-01-31

Component	Description	Start Date
134	Elementary & Secondary School Lunches	1959-01-31
135	Higher Education School Lunches	1959-01-31
136	Other Purchased Meals	1959-01-31
137	Alcohol in Purchased Meals	1959-01-31
138	Food Supplied to Civilians	1959-01-31
139	Food Supplied to Military	1959-01-31
140	Hotels and Motels	1959-01-31
141	Housing at Schools	1959-01-31
142	Commercial Banks	1959-01-31
143	Other Dep Instns/Regulated Invest Companies	1959-01-31
144	Pension Funds	1959-01-31
145	Financial Service Charges, Fees/Commissions	1959-01-31
146	Life Insurance	1959-01-31
147	Net Household Insurance	1959-01-31
148	Net Health Insurance	1959-01-31
149	Net Motor Vehicle/Oth Transportation Insur	1959-01-31
150	Communication	1959-01-31
151	Proprietary & Public Higher Education	1959-01-31
152	Nonprofit Pvt Higher Education Svcs to HHs	1959-01-31
153	Elementary & Secondary Schools	1959-01-31
154	Day Care & Nursery Schools	1959-01-31
155	Commercial & Vocational Schools	1959-01-31
156	Legal Services	1959-01-31
157	Tax Preparation & Other Rel Services	1959-01-31
158	Employment Agcy Services	1959-01-31
159	Other HH Business Services	1959-01-31
160	Labor Organization Dues	1959-01-31
161	Prof Assn Dues	1959-01-31
162	Funeral & Burial Services	1959-01-31
163	Hairdressing Salons & HH Grooming Establishments	1959-01-31
164	Misc HH Care Services	1959-01-31
165	Laundry & Dry Cleaning Services	1959-01-31
166	Clothing Repair, Rental & Alterations	1959-01-31
167	Repair & Hire of Footwear	1959-01-31
168	Child Care	1959-01-31
169	Social Assistance	1959-01-31
170	Social Advocacy/Civic/Social Organizations	1959-01-31
171	Religious Organizations' Services to HHs	1959-01-31
172	Sales Receipts: Foundatns/Grant Making/Giving Svcs to HH	1959-01-31
173	Domestic Services	1959-01-31
174	Moving, Storage & Freight Services	1959-01-31
175	Repair of Furn, Furnishings/Floor Coverings	1959-01-31
176	Repair of HH Appliances	1959-01-31

Component	Description	Start Date
177	Other Household Services	1959-01-31
178	Foreign Travel by U.S. Residents	1959-01-31
179	Less: Exps in the US by Nonresidents	1959-01-31
180	Final Consumptn Exps of Nonprofit Instns Serving HH	1959-01-31

Appendix Table 1 PCE components used in calculating trimmed persistence PCE

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