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# Measurement and Theory of Core Inflation

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## Abstract

We discuss the concept of core inflation and its relevance for policymakers and then review a variety of approaches that have been pursued for the construction of informative core measures. After illustrating some empirical patterns displayed by U.S. inflation data and discussing conceptual issues around measurement, we provide a unified framework to interpret various widely used core measures and compare their relative properties.

JEL classification: E31, E32, E52
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## 1. Introduction

The term "core" inflation is typically associated with a particular inflation measure, the price changes for all items 'excluding food and energy' (xFE for short). In the U.S., this measure is reported in monthly releases of both the Consumer Price Index (CPI) [1] and the Personal Consumption Expenditure (PCE) Index[2] alongside the 'all items' (or headline) measure.

Core inflation is routinely featured in the press and in economic commentaries and is closely monitored by policymakers. Indeed, even though the FOMC longer-run inflation objective is defined in terms of the headline price index, projections for core PCE inflation are reported in the quarterly Summary of Economic Projections (SEP),[3] which collects four times a year FOMC participants' forecasts of output growth, inflation, and unemployment over the next three years. Most central banks around the world monitor similar "core" measures for the price index that defines their inflation objective, often together with a broader set of measures.[4]

Why is core inflation of interest? For a bit of history, the creation of the xFE index in the U.S. dates to the '70s, a period when elevated inflation was a major economic and policy issue. Among many factors at play behind the persistently high readings of inflation at that time, food and energy shocks appeared to be the largest contributors. The Bureau of Labor Statistics (BLS) had introduced a CPI index for "all items less food" back in 1957, due to high volatility in food prices owed to seasonal and weather-related factors. Following skyrocketing energy prices in the early '70s, the BLS introduced an index for "all items less food and energy" in April 1977, with a historical series extending back to 1957 [5]. The index came to be referred to as "core CPI," but as the BLS pointed out, this was an unofficial designation "created by the media and not the Bureau of Labor Statistics".[6]

This genesis indicates how the notion of core reflects the need of downweighing volatile and likely transitory factors that especially when large, make difficult the assessment of inflationary pressures. As such, measures of core inflation are of utmost relevance for central banks that, either with an explicit or an implicit inflation target (or target range), manage monetary policy to achieve that goal over time:[7] core inflation may help gauging the extent to which observed

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[1] See Concepts: Handbook of Methods: U.S. Bureau of Labor Statistics (bls.gov)

[2] See Personal Consumption Expenditures Price Index, Excluding Food and Energy | U.S. Bureau of Economic Analysis (BEA)

[3] See Summary of Economic Projections, December 13, 2023 (federalreserve.gov)

[4] See a brief discussion of measures tracked by other central banks in section 5.

[5] The index had been requested by the Cost of Living Council, the body established by President Nixon to implement a wage and price stabilization program (see Executive Order 11615—Providing for Stabilization of Prices, Rents, Wages, and Salaries | The American Presidency Project (ucsb.edu)

[6] For more on the origin of the so-called "core", see https://www.bls.gov/opub/btn/archive/the-so-called-core-index-history-and-uses-of-the-index-for-all-items-less-food-and-energy.pdf.

[7] For the Federal Reserve's goals and strategy, see Statement on Longer-Run Goals and Monetary Policy Strategy (federalreserve.gov)

departures of inflation from its stated objective are going to dissipate relatively quickly or are going to remain for some time.

The degree of persistence is the relevant issue for such evaluation: the more persistent are inflationary pressures, the higher is the risk that they become ingrained in consumers, businesses, and market expectations. In turn, de-anchoring of inflation expectations would make it harder for policymakers to maintain inflation control. A measure of core inflation that purges the headline measure of high frequency variations better capture the level at which inflation will likely settle over the medium term. Hence, even though core measures have not gained an official status in most central banks' inflation targets, they play an important role in their policy discussions and communications with the public.

Since the first creation of a 'core', researchers in academia and at central banks have developed alternative methods to separate transitory from persistent inflationary movements. These receive particular attention when there is a bout of high inflation readings, as it happened following the COVID-19 pandemic episode. As in the '70s, the question in focus in 2021 was whether the observed price spikes reflected purely temporary, idiosyncratic relative price movements, or were the beginning of a generalized and persistent increase in inflation. With economists engaged in heated public debates and aligned under 'team transitory' and 'team persistent' banners,[8] renewed attention was paid to a range of measures to pin down core inflation.

In this chapter, we set a framework to organize the definition and the measurement of core inflation as an indicator of inflation persistence and discuss the relation among different ways to approach its measurement. Although the term 'core' inflation is often used interchangeably with 'underlying' inflation in the literature, here we refrain from using the latter term, as it doesn't seem to have a uniquely understood definition. In some jurisdictions, the term underlying inflation conceptually "reflects medium-term inflation developments linked to the business cycle," and the set of measures to track it encompasses many of the core measures we discuss here (Banbura et al., 2023). In others instead, the term underlying inflation is used to indicate the level of inflation that would prevail "in the absence of economic slack, supply shocks, idiosyncratic relative price changes, or other disturbances." (Rudd, 2020) The latter would be a notion of longer-run trend, or steady state inflation, that is deeper than the one analyzed here and one for which estimation generally requires considering other macro variables; it is therefore outside the scope of the current analysis.[9]

Our focus is on U.S. price indexes. In what follows, section 2 addresses conceptual issues around the measurement of core inflation, and section 3 reviews several approaches to constructing such measures. Section 4 discusses comparisons of core measures and conducts an evaluation of their relative ability to predict future inflation using a sample that includes the post-

[8] For a recent retrospective on the debate, see Has Team Transitory really won America's inflation debate? (economist.com). Recent work by Bernanke and Blanchard (2024) assigns partial victory to each side.

[9] For some estimates of long-run trend inflation in macro models see Cogley and Sbordone (2008) and Cogley et al. (2010).

pandemic period. Section 5 briefly reviews other central banks' measures and section 6 concludes.

## 2. Conceptual issues around the measurement of core inflation

Any measure of core inflation must separate the 'signal' from the noise in inflation data. This involves making decisions on how to weigh the various component of the price index in a way that reflects the strength of the signal that each component provides for overall inflation. Importantly, it should also account for whether and how much the prices of the various components move together.

The 'all items ex food and energy' index is an appealing core measure: first, it is transparent and easy to communicate. Importantly, it is based on the observation that food and energy prices are typically more volatile than other items in the price index and therefore likely constitute 'noise'. Moreover, their spikes and declines are generally less related to developments in the domestic economy: hence, also in this respect they may provide little signal. However, the automatic exclusion of certain components rests on some critical assumptions: first, that the prices of these components are those that are most often in the tails of the distribution of price changes, and second, that their removal implies no loss of relevant information for evaluating medium-term inflationary pressures. The latter is particularly critical, because the covariance of price changes matters for gauging at any point in time the strength of inflationary pressures.

Questioning these assumptions has led over time to the development of alternative core measures. As a background for the discussion of these measures in section 3, we look at the distributions of monthly price changes to illustrate some relevant features: the presence of asymmetries and large tails, and the co-movement of price changes across components.

We center our analysis on the PCE price index because the U.S. Federal Reserve has framed its objective of price stability in terms of this index; similar measures and relative analyses exist also for the CPI. The PCE price index is organized in seventeen main aggregates, which in turn are composed of several sub-aggregates of individual items or groups of items for a total of about 200 goods or services.[10] To illustrate some features of the distribution of price changes we consider a moderately disaggregated set of components, which includes 52 items (a 4$^{th}$ level of disaggregation).[11]

We start by displaying the cross-sectional distribution of inflation rates over the period beginning in January 1960 and ending in December 2023 in figure 1. We also display headline and core PCE monthly annualized inflation rates as a reference.

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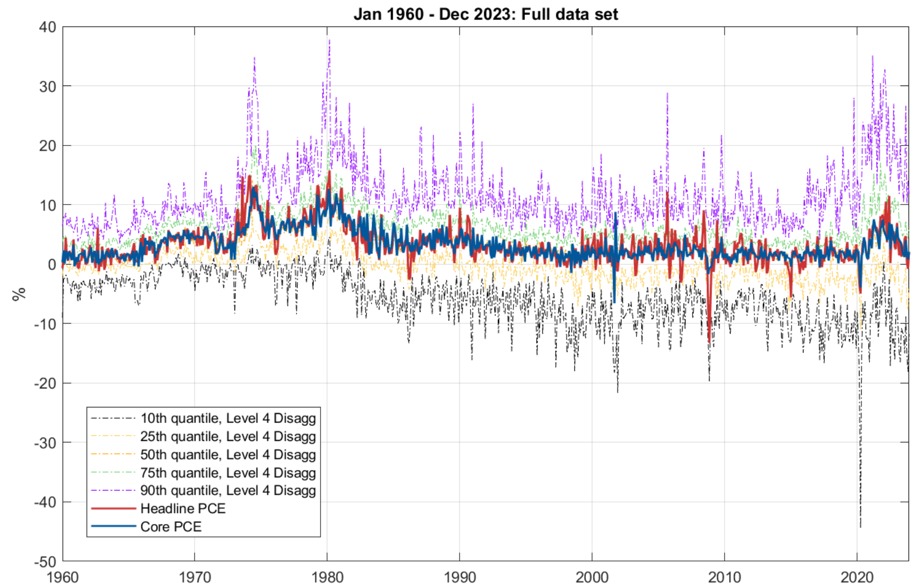
[10] Documentation on the PCE price index can be found in NIPA Handbook: Concepts and Methods of the U.S. National Income and Product Accounts.

[11] The 52 components can be read from Figure 5 below. Data on the more detailed components of the PCE index are found in tables 2.4.4U of the Underlying Detail Tables section of the BEA's website. Data at the chosen disaggregated level are available since 1960.

**FIGURE 1. Cross-sectional distribution of inflation rates**




The first thing to highlight is the large dispersion of individual price changes: it is not rare to see big price increases in some items in periods of low inflation and negative price changes in periods of relatively high inflation (note that the price changes reported in the figure are not literally individual price changes, but aggregates at low level. Individual prices will be even more dispersed.)

We next summarize some features of the distribution of price changes displaying statistics that provide evidence of changes over time in dispersion, asymmetry, and presence of heavy tails. These are illustrated in Figures 2-4 below. Because of the relatively small number of observations and the potential presence of outliers we rely on robust measures that are functions of the percentiles of the cross-sectional distribution (as opposed to moment-based measures).

Let $Q_t(p)$ be the $p$-th percentile of the distribution of item-wise inflation rates for month $t$. For illustrative purposes, we focus on the distribution of unweighted price changes although many of the observations we make extend to weighted price changes. We use the following measures:

$$Disp_t = Q_t(90) - Q_t(10)$$

$$Asym_t = \frac{\big(Q_t(90) - Q_t(50)\big) + \big(Q_t(10) - Q_t(50)\big)}{Q_t(90) - Q_t(10)}$$

$$Tails_t = \frac{Q_t(95) - Q_t(5)}{Q_t(90) - Q_t(10)}$$

The dispersion measure is like the interquartile range except that we compare the 10th and 90th percentile. The asymmetry measure (known as the Kelly's measure) compares the proportion of positive and negative realizations relative to the median: positive (negative) values indicate positive (negative) skewness, and its value is bounded between -1 and 1. Finally, Tails measures the size of extreme realizations (5th and 95th percentiles) relative to less extreme realizations (10th and 90th percentiles). For reference, a normally distributed random variable with standard deviation $\sigma$ has dispersion $2.56 \times \sigma$, zero asymmetry, and tails measure $1.28$.

Figure 2 shows the dispersion of monthly price changes measured by the difference between the 90th and 10th percentiles of the distribution: although periods of high inflation – the '70s and '80s -- present the highest level of dispersion, values are high throughout the period. Part of the observed changes over time in the dispersion are associated with the measurement of prices, as over time the increased availability of new sources has allowed the statistical offices to rely less on imputation methods.

Figure 3 presents evidence of significant asymmetries, with left skewed distributions more frequent in the low inflation periods and right skewed distribution present both in the inflation period of the '70s and the most recent pandemic episode.

**FIGURE 2. Dispersion of cross-sectional distribution of inflation rates**

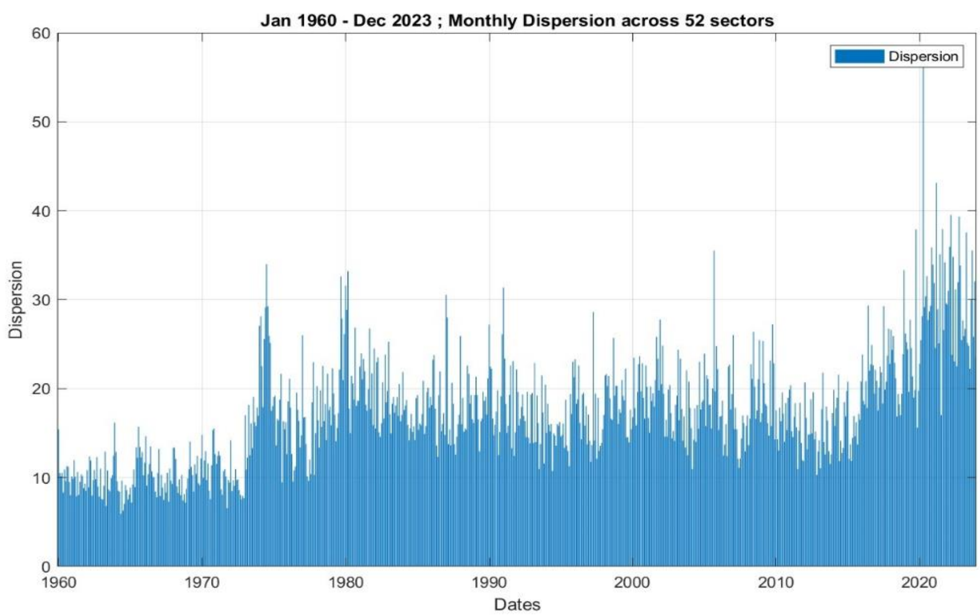
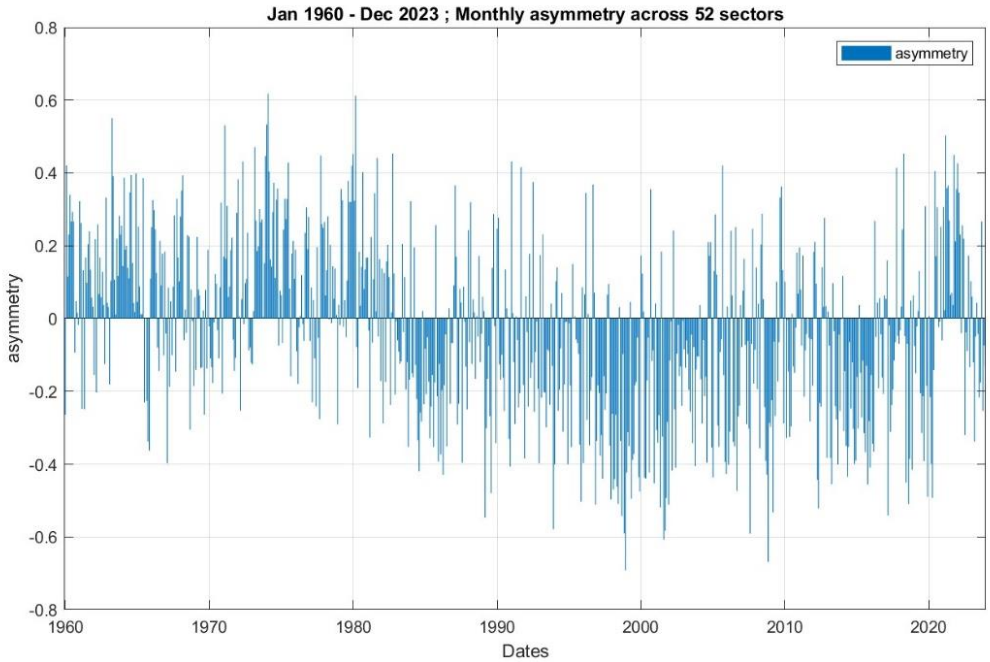
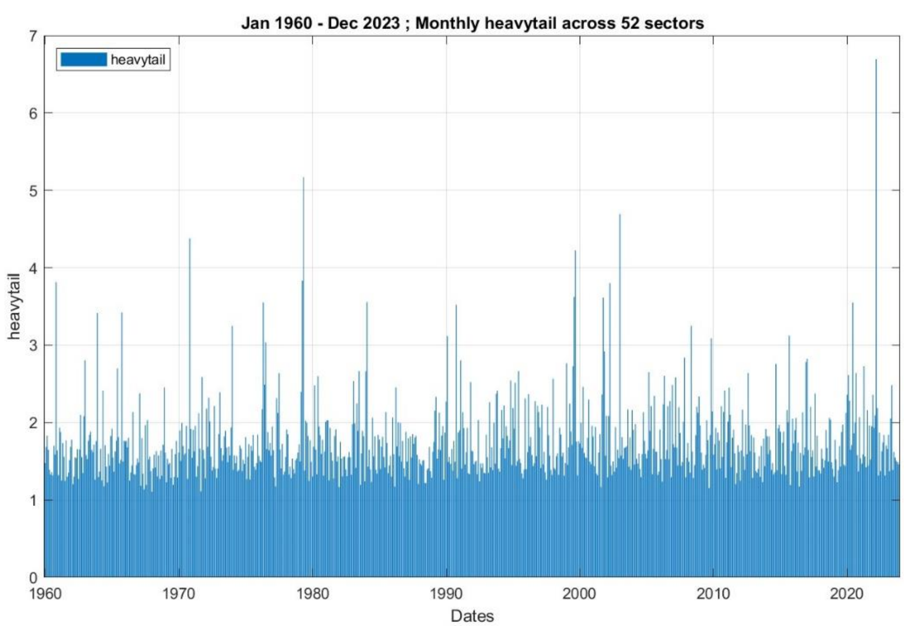


**FIGURE 3. Asymmetry of cross-sectional distribution of inflation rates**




Finally, Figure 4 illustrates the presence of heavy tails in the distributions. Most of the time, the size of the tails is not different from the reference value for the normal distribution (of around 1.3). In a few periods, however, we observe values of 3 or above which indicate substantial nonnormality in the distributions.

**FIGURE 4. Heavy tails in the cross-sectional distribution of inflation rates**



Next, to examine the covariance across component series we look at the correlation of each sector with the ex-food and energy measure and represent this with a heat map (see Figure 5), where we showcase the behavior across three subperiods that present different average values of inflation: there is significant co-movement of price changes across sectors and the strength of the co-movement varies over time.

**FIGURE 5. Correlation of sectors with Core PCE**

This evidence suggests that the removal of some predetermined categories to obtain a core index may not be an accurate measure of the true core, as it may remove important information while not necessarily removing all the noise. To improve on such measure, a variety of smoothing techniques have been explored using both the cross-sectional and the time series dimensions of the data.

Using only the sectoral dimension of the data, smoothing is obtained by constructing an index that downweighs those sectors in the headline index that have more volatile prices. The rationale is that volatile price movements are also less persistent, and therefore do not contribute to the assessment of core inflation. A negative relationship between volatility and persistence is intuitive, but its strength is of course an empirical question.[12] Exclusion measures (also referred to as limited-influence estimators) such as the xFE inflation are an example of this approach to smoothing.

Alternatively, smoothing can be obtained by exploiting the temporal dimension of the data. Time-series smoothing methods can be applied to extract the 'signal' either in aggregate inflation or in sectoral inflation data: univariate or multivariate dynamic factor models belong to this approach. We characterize these methods more precisely in the next section. [13]

## 3. The measurement of core inflation

To review approaches to constructing measures of core inflation from price (and expenditure share) data, we begin by introducing some notation. We use $\pi_{it}$ for the inflation rate of sector $i$ during period $t$, that is, the rate of change of the price level in sector $i$ between periods $t-1$ and $t$. We also use $s_{it}$ for the expenditure share of sector $i$ during time $t$. We denote by $N$ the number of sectors, noting that different measures rely on different levels of sectoral disaggregation and therefore $N$ is measure specific. The time unit $t$ is typically a month and occasionally a quarter.

Recalling that the PCE price index is a chain-type Fisher price index, the aggregate inflation rate during time $t$ is related to the sectoral inflation rates by the equation:

$$1+\pi_t = \sqrt{\frac{\sum_{i=1}^{N} s_{i,t-1}(1+\pi_{it})}{\sum_{i=1}^{N} s_{it}(1+\pi_{it})}}.$$

If sectoral inflation rates are small, we obtain the following approximation that we will exploit repeatedly in this section:

[12] For an example, see Ehrmann et al (2018) on the relation between volatility and persistence in the annual rate of growth of components of the euro area HICP.

[13] We adopt a parsimonious classification of different methods that encompasses a variety of measures as those listed by Luciani and Trezzi (2019): "exclusion indexes, central-tendency statistical measures, variance-weighted indexes, regression-weighted indexes, model-based trend inflation measures, and component-smoothing indexes." Wynne (2008) provides a review of the literature.

$$\pi_t \approx \sum_{i=1}^{N} \tilde{s}_{it}\pi_{it}$$

where the shares are $\tilde{s}_{it} = (s_{i,t-1} + s_{it})/2$. Inflation is sometimes expressed in annual rate, by setting for example $\pi_t^{AR} = (1+\pi_t)^{12} - 1 \approx 12\pi_t$ if $t$ is a month. This only affects the scale of inflation. Another transformation usually applied is to compute 12-month rates of change by doing $\pi_{12,t} = \prod_{r=1}^{12}(1+\pi_{t-r+1}) - 1 \approx \sum_{r=1}^{12}\pi_{t-r+1}$. This is a more substantive transformation as it affects the smoothness of the inflation series. Unless otherwise stated, we will focus on inflation data that are not temporally aggregated. The same applies to sectoral inflation rates.

We will use $\hat{\tau}_t$ to denote a measure of core inflation and $\tilde{\tau}_t$ to denote its target value (i.e., the value it would achieve in the absence of noise) in their multiple forms. We divide the different approaches in three classes. Cross-sectional approaches make $\hat{\tau}_t$ a function of the disaggregated data $\{\pi_{it}\}_{i=1}^{N}$ for the same period $t$. Time series approaches make $\hat{\tau}_t$ a function of the aggregated data $\{\pi_r\}_{r=1}^{T}$ for different periods (perhaps covering all the history). Finally, a third class of approaches exploits both the cross-section and the time series dimensions of the data by setting $\hat{\tau}_t$ as a function of $\{\{\pi_{it}\}_{i=1}^{N}\}_{t=1}^{T}$.

There are at least two questions we wish to ask about each approach to core inflation. First, what each method is designed to estimate. Second, what are the method's properties in the actual data when seen as an assessment of current and future inflationary pressures. We leave the second question to the next section. As for the first, we address it as we describe in turn the different approaches.

Of course, to be able to characterize the target of a given measure, we need to introduce some statistical assumptions. These will be motivated by the empirical patterns we reported in the previous section about the joint distribution of sectoral inflation rates.

The starting point is the following decomposition:

$$\pi_{it} = \tau_{it} + \varepsilon_{it},$$

where $\tau_{it}$ is the trend (or persistent) component and $\varepsilon_{it}$ is the noise (or transitory) component of the sectoral inflation rate $\pi_{it}$. The persistent component is intended to capture movements in inflation that are long-lasting, reflecting aggregate and sectoral shocks that propagate over many periods. The noise component, on the other hand, represents a combination of pure transitory shocks and measurement error or outliers.[14]

It is reasonable to assume that core components are uncorrelated with the noise components for each sector and period. Based on the properties of inflation data we documented before, one should expect (i) cross-sectional correlation in both $\tau_{it}$ and $\varepsilon_{it}$, (ii) strong serial correlation in the core components, and (iii) non-normality in the noise components. Finally, defining the

[14] As discussed in the previous chapter of the *Handbook*, the measurement of inflation is a challenging task that relies on surveying a vast number of price-setting units. Moreover, imputation rules are applied for some items that are inherently difficult to measure. It is therefore natural to expect that part of the quarter-to-quarter or month-to-month variations we observe in inflation is the result of measurement error.

aggregate core and noise components as $\tau_t = \sum_{i=1}^{N} \tilde{s}_{it}\tau_{it}$ and $\varepsilon_t = \sum_{i=1}^{N} \tilde{s}_{it}\varepsilon_{it}$ and using the approximate aggregation formula, we have

$$\pi_t = \tau_t + \varepsilon_t.$$

The goal of any measure of core inflation is to capture $\tau_t$ and eliminate $\varepsilon_t$. However, as will become clear below, a given measure $\hat{\tau}_t$ may have a target value $\tilde{\tau}_t$ that is not necessarily equal to the aggregate core component $\tau_t$. This is because in practice, to reduce the role of the noise component, $\hat{\tau}_t$ typically needs to exclude or downweigh a subset of sectors with low signal value. As an example, food and energy contribute to the persistent component of aggregate inflation $\tau_t$ but PCE inflation excluding food and energy targets a different weighted average of persistent components, $\tilde{\tau}_t$. Hence the need to maintain a notational distinction between $\tau_t$ and $\tilde{\tau}_t$.

### 3.1. Cross-sectional approaches

The simplest form of cross-sectoral smoothing is obtained by removing certain components from the aggregate index, as the already mentioned xFE index, or indexes excluding other items. These indexes are defined by permanent exclusions. Two other popular measures under this heading are defined by temporary exclusions.

The *trimmed mean* measure removes at any time $t$ only those components that experience the largest positive or negative rates of change. The *weighted median*, also an exclusion measure, defines instead the core as the median price change at each time $t$. Both measures are motivated by the statistical case for using robust central-tendency measures when the distribution of price changes has heavy tails.

These measures can be represented as follows. Let $I_t$ be the subset of cross-sectoral indexes $\{1, \dots, N\}$ to be included in the calculation for month $t$. The corresponding estimate of core inflation is:

$$\hat{\tau}_t = \frac{\sum_{i\in I_t} \tilde{s}_{it}\pi_{it}}{\sum_{i\in I_t} \tilde{s}_{it}} = \frac{\sum_{i\in I_t} \tilde{s}_{it}\tau_{it}}{\sum_{i\in I_t} \tilde{s}_{it}} + \frac{\sum_{i\in I_t} \tilde{s}_{it}\varepsilon_{it}}{\sum_{i\in I_t} \tilde{s}_{it}}$$

which targets the quantity:

$$\tilde{\tau}_t = \frac{\sum_{i\in I_t} \tilde{s}_{it}\tau_{it}}{\sum_{i\in I_t} \tilde{s}_{it}}.$$

For PCE inflation excluding food and energy, $I_t$ is the same set over time and contains precisely all the components of PCE that do not belong in the food or energy categories. For the trimmed mean inflation rate, the set $I_t$ changes over time and is obtained by excluding a fraction $\phi_l$ of the price changes at the lower end of the distribution and another fraction $\phi_u$ of the price changes at the higher end. Finally, for the median inflation rate, $I_t$ consists of a single index – the one in the middle of the distribution of price changes.

This calculation makes clear what the target and the estimation error of $\hat{\tau}_t$ are – they are weighted averages of sectoral persistent and noise components. Removing the most volatile components helps to reduce the variance of the error term:

$$\hat{\tau}_t - \tilde{\tau}_t = \frac{\sum_{i \in I_t} \tilde{s}_{it} \varepsilon_{it}}{\sum_{i \in I_t} \tilde{s}_{it}}.$$

In general, however, averaging and removing volatile sectors does not eliminate the estimation error completely. One possible explanation is the presence of cross-sectional correlation in the noise components. For example, suppose $\varepsilon_{it} = \alpha_{\varepsilon,i} \bar{\varepsilon}_{ct} + \bar{\varepsilon}_{it}$ where the common component $\bar{\varepsilon}_{ct}$ and the sector-specific component $\bar{\varepsilon}_{it}$ have zero mean and are independent of each other. We obtain the following:

$$\hat{\tau}_t - \tilde{\tau}_t = \left( \frac{\sum_{i \in I_t} \tilde{s}_{it} \alpha_{\varepsilon,i}}{\sum_{i \in I_t} \tilde{s}_{it}} \right) \bar{\varepsilon}_{ct} + \frac{\sum_{i \in I_t} \tilde{s}_{it} \bar{\varepsilon}_{it}}{\sum_{i \in I_t} \tilde{s}_{it}}.$$

So, even if the second term is small (it is an average of independent zero mean random variables), the first term need not be. To mitigate this problem, it is customary to use time series averages of $\hat{\tau}_t$, either by computing 6-month or 12-month measures or by exploiting the filtering techniques we discuss in subsequent sections.

We now discuss in more detail the construction of trimmed mean and weighted median measures of core inflation for the US.

*a. Trimmed-mean measures.*

The trimmed-mean PCE inflation is one of the core measures routinely monitored for the U.S. It was introduced by Dolmas (2005), applying to the Fed's preferred inflation gauge previous research on the CPI price index.[15] While the rationale to consider a trimmed-mean measure was intuitive: "simply excluding all food and energy items [….] fails to exclude some highly volatile items, while potentially throwing out some useful information" (Dolmas, 2005, p. 3), from a statistical point of view, Dolmas noted, a trimmed mean is a robust measure of location.[16]

The trimmed-mean PCE inflation is published by the Federal Reserve Bank of Dallas, with series for the 1-month and 6-month (annualized) and 12-month measures starting from 1977. This measure is constructed as a weighted average of the rate of change in the prices of a subset of the PCE index, determined by discarding a certain fraction of the most extreme observations at both ends of the distribution. The trimmed-mean inflation rate is then calculated as a weighted average of the remaining components with appropriately renormalized weights. In terms of the notation we established, the fractions of price changes $\phi_l$ and $\phi_u$ that are dropped from the lower

[15] See Bryan and Cecchetti, 1994; Cecchetti, 1997.

[16] Ball and Mankiw (1995) show that the observed feature of the distribution of price changes are easily generated in models with costs of price adjustments. In such models, relative-price changes matter for aggregate inflation only if they are unusually large. A tail of unusually large relative price increases skews the distribution to the right, hence raising aggregate inflation, while a tail of unusually large price declines skews it to the left, lowering aggregate inflation.

and upper tails are 24 and 31 percent, respectively.[17] These cut-off points have been determined as those that produce the 'best fit' in the sense of minimizing the distance of the trimmed-mean from an ideal underlying trend.[18] The intuition for why an optimal trimming is asymmetric rests on the asymmetry of the distribution of monthly price changes. If this distribution across PCE categories has negative skewness (or a fat left tail), a trimming that removes more observations from the top of the distribution corrects for the potential bias that would result from removing too much of the influence of the lower tail. As we have documented in figure 2, there are strong asymmetries in the distributions of price changes, at least for the sectors and the sample we considered; however, the extent of these asymmetries varies over time, so it is not clear that the same asymmetric trim is optimal across periods. Compared to permanent exclusion indexes, the items excluded from the trimmed-mean index vary over time and are not limited to, nor include all food and energy items.

*b. Median PCE Inflation*

In the same spirit of the trimmed-mean measure, also the median PCE inflation, developed from an original suggestion of Bryan and Pike (1991), intends to be less sensitive to observations in the tails. It could be considered as an extreme trimming measure, where all observations in both tails except the price change in the middle are trimmed.

The median PCE inflation measure, published by the Federal Reserve Bank of Cleveland, is defined as the one-month inflation rate of the component whose expenditure weight is in the 50$^{th}$ percentile of price changes. The measure is constructed using all 200 components in the BEA index, similarly to the trimmed mean PCE inflation, and is tracked for both monthly and 12-month rates. Details of its computation are found on the Cleveland Fed's website. The website reports also a median CPI inflation, computed on 44 CPI components with the same methodology. [19]

## 3.2. Time series smoothing approaches

As we mentioned, forming time series averages is an attractive way of filtering out the noise component to obtain measures of core inflation. In this section, we discuss the basic principle of

[17] These cut-offs were adjusted in 2009 after the BEA release of the comprehensive revision to the US national income and product account, that included a reorganization of underlying data on component-level PCE prices and quantities (see The 2009 revision to the trimmed mean PCE inflation series PCE inflation series - FRB Dallas (dallasfed.org).

[18] Since this trend is unobservable, Dolmas (2005) documents robustness of the measure to different candidate choices for the underlying trend.

[19] See Median PCE Inflation (clevelandfed.org). The weighted CPI median was first introduced by Bryan and Cecchetti (1994).

time series filtering abstracting from the cross-sectional dimension we discussed above. We turn to approaches that combine both dimensions in the next section.

We focus here on aggregate inflation data $\pi_t$ observed over time. This may be headline PCE inflation or PCE inflation excluding food and energy. Recall the decomposition of the inflation rate $\pi_t$ into a persistent and a noise component,

$$\pi_t = \tau_t + \varepsilon_t.$$

The idea of decomposing a time series into persistent and transitory components has a long tradition in economics. It has been used, for example, in the analysis of rational expectations (Muth, 1961) or the empirics of life-cycle earnings (MaCurdy, 1981).[20] The question is how to transform data $\{\pi_t\}$ into estimates of the unobserved persistent component $\{\tau_t\}$. When only the time series dimension can be exploited, assumptions on the dynamics of $\tau_t$ and $\varepsilon_t$ are needed to achieve this.

To illustrate the point, let us assume the following simple model for the persistent and the noise components:

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau}\eta_{\Delta\tau,t},$$
$$\varepsilon_t = \sigma_\varepsilon\eta_{\varepsilon,t},$$

where the shocks $\eta_{\Delta\tau,t}$ and $\eta_{\varepsilon,t}$ are mutually and serially independent $N(0,1)$ random variables, and the initial condition is $\tau_0 \sim N(\mu_0, \sigma_0^2)$, independent of $\{\eta_{\Delta\tau,t}, \eta_{\varepsilon,t}\}$. The parameters are the volatilities of the persistent and the transitory shocks, $\sigma_{\Delta\tau}$ and $\sigma_\varepsilon$, which govern the proportion of signal-to-noise in inflation. This model is usually referred to as the local-level model since $\tau_t$ acts as a time-varying level of inflation.

This specification implies that $\Delta\pi_t$ is an MA(1) process (or, equivalently, $\pi_t$ is an IMA(1, 1) process). That is, changes in inflation should not be correlated beyond a single period. Moreover, the first-order autocorrelation of $\Delta\pi_t$ should be negative since

$$Cov(\Delta\pi_t, \Delta\pi_{t-1}) = -\sigma_\varepsilon^2 < 0.$$

Hence, checking the autocorrelation patterns of $\Delta\pi_t$ provides a quick diagnostic of the restrictions imposed by this model.

Turning to the estimation of $\{\tau_t\}$, we assume for now that we know $(\sigma_{\Delta\tau}, \sigma_\varepsilon)$.[21] The model is a particular case of a linear state-space model (see, e.g., Hamilton, 1994, Durbin and Koopman, 2012) and, therefore, we can apply the Kalman filter to learn about the latent state $\{\tau_t\}$. Specifically, letting $\pi = (\pi_1, \ldots, \pi_T)'$ and $\tau = (\tau_1, \ldots, \tau_T)'$, we have

$$\tau|\pi \sim N(\mu_\tau, \Sigma_\tau),$$

[20] In the context of life-cycle earnings, the importance of distinguishing between permanent and temporary income shocks was originally motivated by the permanent income hypothesis that predicts different consumption effects of shocks of different durability (Friedman, 1957, Hall and Mishkin, 1982).

[21] Of course, to implement the approaches we discuss below, we need estimates of $(\sigma_{\Delta\tau}, \sigma_\varepsilon)$. Pseudo-maximum likelihood (PML) estimates are straightforward to obtain using the Kalman filter to evaluate the log-likelihood function of the data $\{\pi_t\}_{t=1}^T$. See, e.g., Hamilton (1994) or Durbin and Koopman (2012).

where the mean vector $\mu_\tau$ and the covariance matrix $\Sigma_\tau$ come from the Kalman recursions.[22] The point estimate for the persistent component of inflation is then given by $\hat{\tau} = (\hat{\tau}_1, \dots, \hat{\tau}_T)' = \mu_\tau$.

To gain some intuition, it is useful to connect the Kalman filter estimate with the exponentially weighted moving average (EWMA) obtained when we apply the so-called steady state filter.[23] Allowing ourselves to use infinitely many past observations $\{\pi_s\}_{s=-\infty}^{T}$, we obtain

$$\hat{\tau}_T \approx \sum_{\ell=0}^{\infty} (1-\kappa)^\ell \kappa \pi_{T-\ell},$$

where, having defined the signal-to-noise ratio $q = \sigma_{\Delta\tau}^2 / \sigma_\varepsilon^2$, $\kappa$ is:

$$\kappa = \left(1 + \frac{2/\mathrm{q}}{1+\sqrt{1+4/q}}\right)^{-1}.$$

The trend estimate $\hat{\tau}_T$ is a weighted average of all available data with weights that sum to one (since $\sum_{\ell=0}^{\infty}(1-\kappa)^\ell = 1/\kappa$). It discounts past data more heavily ($\kappa$ is closer to 1) when the signal-to-noise ratio $q$ is high, while it tends to be more backward-looking when $q$ is low. This is to be compared with the usual practice of computing 3-, 6- and 12-month inflation rates, that are equivalent to constant weights within a fixed window. In other words, time series smoothing adjusts the weight that $\hat{\tau}_T$ gives to past data as a function of the relative importance of persistent versus transitory shocks.

This basic model can be enriched in many ways. An empirically important extension is allowing the volatilities of persistent and transitory shocks (and, therefore, the signal-to-noise ratio) to evolve over time as in Stock and Watson (2007, 2008). Namely, one can assume:

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t}\eta_{\Delta\tau,t},$$
$$\varepsilon_t = \sigma_{\varepsilon,t}\eta_{\varepsilon,t},$$

and let the volatility processes to evolve as in Kim, Shephard, and Chib (1998):

$$\Delta \ln \sigma_{\Delta\tau,\mathrm{t}} = \gamma_{\Delta\tau}\, \nu_{\Delta\tau,\mathrm{t}},$$
$$\Delta \ln \sigma_{\varepsilon,\mathrm{t}} = \gamma_{\varepsilon}\, \nu_{\varepsilon,\mathrm{t}},$$

where the innovations $\nu_{\Delta\tau,t}$ and $\nu_{\varepsilon,t}$ are mutually and serially independent $N(0,1)$ random variables, independent of $\{\eta_{\Delta\tau,t}, \eta_{\varepsilon,t}\}$ and $\tau_0$. Allowing for time-varying parameters is particularly important when analyzing long datasets as the properties of persistent and transitory shocks are likely to change over time.

---

[22] The conditional distribution of $\tau$ given $\pi$ is normal because we assumed normality of the initial condition $\tau_0$ and the shocks $\{\eta_{\Delta\tau,\mathrm{t}}, \eta_{\varepsilon,t}\}$. Without that, $\mu_\tau$ and $\Sigma_\tau$ can still be interpreted as the best linear predictor of $\tau$ given $\pi$ and its mean-square error matrix, respectively.

[23] The connection between the local-level model and exponential smoothing was noted by Muth (1960). See, e.g., Durbin and Koopman (2012) for a detailed discussion.

### 3.3. Combining cross-sectional and time series approaches

To summarize, cross-sectional approaches assign weights to components of PCE inflation as a function of their variability. Time series approaches, on the other hand, assign weights not to specific components but to different periods as a function of the noisiness of the series. Both dimensions are potentially informative to extract the core inflation concept we are after in this chapter. In this section, we explore approaches that combine them. The technique of choice is that of dynamic factor models.[24]

We start from the decomposition of the inflation rate $\pi_{it}$ of sector $i$ during time $t$ that we outlined at the beginning of the section:

$$\pi_{it} = \tau_{it} + \varepsilon_{it}.$$

Recall that our target is the persistent component of aggregate inflation,

$$\tau_t = \sum_{i=1}^{N} \tilde{s}_{it}\tau_{it}$$

and our goal is to estimate $\tau_t$ from data $\{\{\pi_{it}\}_{i=1}^{N}\}_{t=1}^{T}$.

A first question is how to model the correlation of persistent and transitory shocks across sectors. Defining the $N$-vectors $\vec{\tau}_t = (\tau_{1t}, \dots, \tau_{Nt})'$ and $\vec{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})'$, we assume the following:

$$\Delta\vec{\tau}_t \sim i.i.d.N(0_{N\times 1}, \Sigma_{\Delta\tau}),$$
$$\vec{\varepsilon}_t \sim i.i.d.N(0_{N\times 1}, \Sigma_{\varepsilon}),$$

and also assume that $\Delta\vec{\tau}_t$ and $\vec{\varepsilon}_t$ are mutually independent and independent of the initial condition $\vec{\tau}_0 \sim N(\mu_0, \Sigma_0)$. To begin, we leave the covariance matrices $\Sigma_{\Delta\tau}$ and $\Sigma_{\varepsilon}$ unrestricted. If we let $\vec{\pi}_t = (\pi_{1t}, \dots, \pi_{Nt})'$, the measurement equation becomes: $\vec{\pi}_t = \vec{\tau}_t + \vec{\varepsilon}_t$.

As before, this is a linear state-space model: we can use the Kalman filter to characterize the conditional distribution of $\{\vec{\tau}_t\}_{t=1}^{T}$ given $\{\vec{\pi}_t\}_{t=1}^{T}$ and obtain:

$$\vec{\tau}_t|\{\vec{\pi}_t\}_{t=1}^{T} \sim N\left(\mu_{(\tau,\, t|T)}, \Sigma_{(\tau,\, t|T)}\right).$$

The point estimate of the persistent component of aggregate inflation is given by:

$$\hat{\tau}_t = \vec{s}_t'\, \mu_{(\tau,\, t|T)}$$

where $\vec{s}_t = (\tilde{s}_{1t}, \dots, \tilde{s}_{Nt})'$ is the vector of expenditure shares used in the construction of the price index.

We note that in the absence of cross-sectional correlation (i.e., if $\Sigma_{\Delta\tau}$ and $\Sigma_{\varepsilon}$ are diagonal), $\mu_{(\tau,\, t|T)}$ reduces to a vector with each entry given by the univariate model formula discussed in the previous section. In that case, each sector will contribute to the trend estimate in proportion to (i) its expenditure share and (ii) its individual signal-to-noise ratio. In general, however, one

[24] An early estimate of a core measure using a dynamic factor index model, applied to the CPI index, is Cecchetti (1997), based on Stock-Watson (1991).

should expect correlation across sectors: a parsimonious way of introducing correlation is through a common factor structure. To be specific, let

$$\tau_{it} = \alpha_{\tau,i}\, \bar{\tau}_{ct} + \bar{\tau}_{it}, \qquad i = 1, \dots, N,$$
$$\varepsilon_{it} = \alpha_{\varepsilon,i}\, \bar{\varepsilon}_{ct} + \bar{\varepsilon}_{it}, \qquad i = 1, \dots, N,$$

where the persistent components are

$$\bar{\tau}_{ct} = \bar{\tau}_{c,t-1} + \sigma_{\Delta\tau,c}\, \eta_{\Delta\tau,ct},$$
$$\bar{\tau}_{it} = \bar{\tau}_{i,t-1} + \sigma_{\Delta\tau,i}\, \eta_{\Delta\tau,it},$$

and the transitory components are

$$\bar{\varepsilon}_{ct} = \sigma_{\varepsilon,c}\, \eta_{\varepsilon,ct},$$
$$\bar{\varepsilon}_{it} = \sigma_{\varepsilon,i}\, \eta_{\varepsilon,it}.$$

The innovations $\eta$ are mutually and serially uncorrelated $N(0, 1)$ random variables. The terms $\bar{\tau}_{ct}$ and $\bar{\varepsilon}_{ct}$ are common components, while $\bar{\tau}_{it}$ and $\bar{\varepsilon}_{it}$ are their sector-specific counterparts. This is a particular case of the unrestricted model we discussed before and therefore can be estimated with linear state-space model techniques as well. In fact,

$$\Sigma_{\Delta\tau} = \sigma^2_{\Delta\tau,c}\vec{\alpha}_\tau\vec{\alpha}'_\tau + \ diag(\vec{\sigma}^2_{\Delta\tau}),$$
$$\Sigma_{\varepsilon} = \sigma^2_{\varepsilon,c}\vec{\alpha}_\varepsilon\vec{\alpha}'_\varepsilon + \ diag(\vec{\sigma}^2_{\varepsilon}),$$

where we have defined vectors $\vec{\alpha}_\tau = \ (\alpha_{\tau,1}, \dots, \alpha_{\tau,N})'$, $\vec{\alpha}_\varepsilon = \ (\alpha_{\varepsilon,1}, \dots, \alpha_{\varepsilon,N})'$, $\vec{\sigma}^2_{\Delta\tau} = (\sigma^2_{\Delta\tau,1}, \dots, \sigma^2_{\Delta\tau,N})'$ and $\vec{\sigma}^2_\varepsilon = \ (\sigma^2_{\varepsilon,1}, \dots, \sigma^2_{\varepsilon,N})'$.

As before, we can use the Kalman filter to estimate $\tau_{it}$ and its common and sector-specific subcomponents, $\bar{\tau}_{ct}$ and $\bar{\tau}_{it}$. From these, we derive the common and sector-specific constituents of the persistent component of *aggregate* inflation $\tau_t$ as

$$\tau_{c,t} = \sum_{i=1}^{N} \tilde{s}_{it}\alpha_{\tau,i}\bar{\tau}_{ct},$$
$$\tau_{ss,t} = \sum_{i=1}^{N} \tilde{s}_{it}\bar{\tau}_{it}$$

An important comment is due about identification. If we let the parameters $\vec{\alpha}_\tau, \vec{\sigma}_{\Delta\tau,c}, \vec{\alpha}_\varepsilon, \vec{\sigma}_{\varepsilon,c}$ unrestricted, they are not point identified from the autocovariance structure of the data. This is because we can multiply the loadings by a constant $k$ and divide $\bar{\tau}_{ct}, \bar{\varepsilon}_{ct}$ (and therefore the volatilities $\vec{\sigma}_{\Delta\tau,c}, \vec{\sigma}_{\varepsilon,c}$) by $k$ without altering the data. In a similar vein, we can add a constant $k$ to $\alpha_{\tau,i}\bar{\tau}_{ct}$ and subtract the same constant from $\bar{\tau}_{it}$ without affecting the data. Hence, the levels of the common and sector-specific components are not pinned down (although their changes over time are).

Finally, when analyzing a long dataset, it is important to allow loadings and volatilities to change over time. Moreover, when using disaggregated inflation data, one needs to be aware of the presence of outliers. This motivated Stock and Watson (2016) to extend the model to incorporate both time-varying parameters and outliers. Specifically, they augment the common factor structure introduced above:

$$\tau_{it} = \alpha_{\tau,it}\,\bar{\tau}_{ct} + \bar{\tau}_{it}, \qquad i = 1, \ldots, N,$$
$$\varepsilon_{it} = \alpha_{\varepsilon,it}\,\bar{\varepsilon}_{ct} + \bar{\varepsilon}_{it}, \qquad i = 1, \ldots, N,$$

by including stochastic volatility in the persistent components

$$\bar{\tau}_{ct} = \bar{\tau}_{c,t-1} + \sigma_{\Delta\tau,ct}\,\eta_{\Delta\tau,ct},$$
$$\bar{\tau}_{it} = \bar{\tau}_{i,t-1} + \sigma_{\Delta\tau,it}\,\eta_{\Delta\tau,it},$$

and modeling the transitory components as:

$$\bar{\varepsilon}_{ct} = \sigma_{\varepsilon,ct}\,o_{\varepsilon,ct}\,\eta_{\varepsilon,ct},$$
$$\bar{\varepsilon}_{it} = \sigma_{\varepsilon,it}\,o_{\varepsilon,it}\,\eta_{\varepsilon,it},$$

where $o_{\varepsilon,ct}$ and $o_{\varepsilon,it}$ are outlier indicators in the common and the sector-specific transitory components, respectively. The time-varying parameters are modeled as

$$\Delta\alpha_{\tau,it} = \lambda_{\tau,i}\,\upsilon_{\tau,it},$$
$$\Delta \ln \sigma_{\Delta\tau,\mathrm{ct}} = \gamma_{\Delta\tau,\mathrm{c}}\,\nu_{\Delta\tau,\mathrm{ct}},$$
$$\Delta \ln \sigma_{\Delta\tau,\mathrm{it}} = \gamma_{\Delta\tau,\mathrm{i}}\,\nu_{\Delta\tau,\mathrm{it}},$$
$$\Delta\alpha_{\varepsilon,it} = \lambda_{\varepsilon,i}\,\upsilon_{\varepsilon,it},$$
$$\Delta \ln \sigma_{\varepsilon,\mathrm{ct}} = \gamma_{\varepsilon,\mathrm{c}}\,\nu_{\varepsilon,\mathrm{ct}},$$
$$\Delta \ln \sigma_{\varepsilon,\mathrm{it}} = \gamma_{\varepsilon,\mathrm{i}}\,\nu_{\varepsilon,\mathrm{it}}.$$

The innovations $\upsilon$ and $\nu$ are mutually and serially uncorrelated $N(0,1)$ random variables. The outlier indicators, on the other hand, are modeled as $o_{\varepsilon,ct} = 1$ with probability $p_c$ and $o_{\varepsilon,ct} \sim U[1,\bar{s}]$ with probability $1 - p_c$, and similarly for $o_{\varepsilon,it}$.

A further extension allows the transitory component to display moving average dynamics,

$$\bar{\varepsilon}_{ct} = \left(1 + \theta_{c1}L + \cdots + \theta_{cp}L^p\right)\sigma_{\varepsilon,ct}\,o_{\varepsilon,ct}\,\eta_{\varepsilon,ct},$$
$$\bar{\varepsilon}_{it} = \left(1 + \theta_{i1}L + \cdots + \theta_{ip}L^p\right)\sigma_{\varepsilon,it}\,o_{\varepsilon,it}\,\eta_{\varepsilon,it}.$$

where $L$ is the lag operator. This is particularly important when applying the model to monthly data because it allows for some prolonged effect of the shocks. This is the approach taken by the Multivariate Core Trend (MCT) inflation measure developed at the New York Fed for the PCE price index and updated regularly on its website after every official PCE price releases.[25]

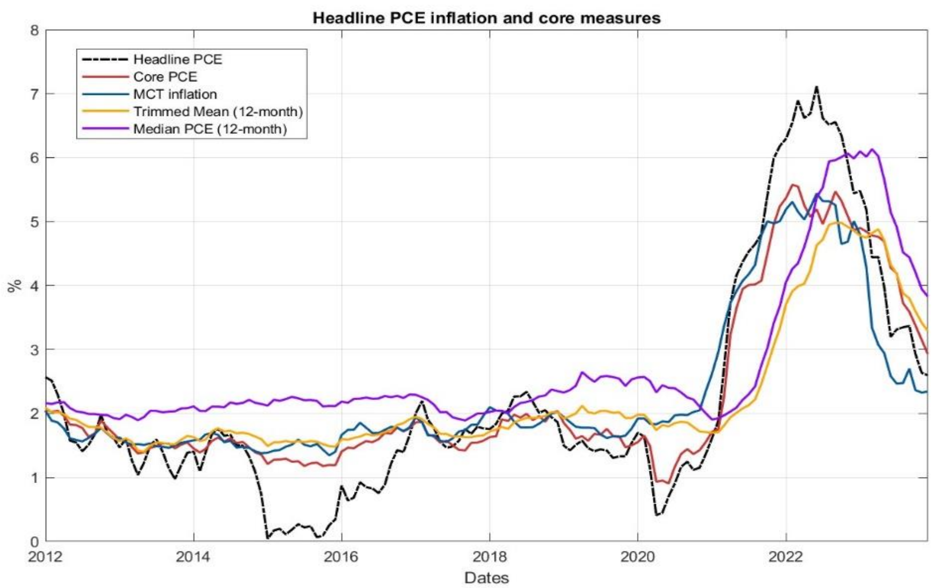
## 4. Comparing measures

Figure 6 depicts the three cross-sectional smoothing measures (their 12-month version) and the MCT measure, constructed, as discussed, following an approach that combines both cross-sectional and time series smoothing to estimate core inflation. They are all plotted against 12-month headline PCE inflation. While all measures broadly move together, the figure shows notable differences in their dynamics. For example, the rise of the trimmed mean and the median in 2021 lag core PCE inflation, while the MCT measure leads the surge. Also, the median tends to be higher than the other measures in the low inflation period preceding the pandemic.

[25] See Multivariate Core Trend Inflation - FEDERAL RESERVE BANK of NEW YORK (newyorkfed.org)

A set of metrics have been used in the literature to compare different measures of core inflation, based on properties that are generally desirable for such a measure. Some metrics are qualitative in nature, such as the simplicity to compute or explain to a broader audience. Other are quantitative, as for example the bias, the degree of smoothness, the ability to track the long-run trend of headline inflation, or the ability to predict future values of inflation.[26]

**FIGURE 6: Measures of core inflation**




Ideally, one would like to quantify the error in tracking the trend component of inflation. The difficulty is that this trend component is unobservable, so researchers typically use for an approximation two-sided moving average filters of headline inflation with weights that reflect the choice between a medium-run and a very long-run notion of trend inflation.

Alternative measures are generally evaluated against the benchmark of the PCE index excluding food and energy. For example, Luciani and Trezzi (2019) compare trimmed-mean PCE inflation and PCExFE measure over the 1977-2018 period. They document that both indexes can reduce the variance of inflation, although the trimmed mean is better than the xFE index at smoothing across large idiosyncratic episodes. On the other hand, the trimmed mean appears to have been consistently higher than the xFE measure since the 1990s, as it can be seen

[26] For an earlier proposal of different metrics for comparing core measures for the CPI price index see Clark (2001).

also in figure 6 above; that suggests caution when interpreting current core levels.[27] To further assess the relative performance of the two measures, the authors run a real-time forecasting exercise. They compare root mean-squared forecast errors (RMSEs) for various horizons and using the core measure defined over alternative monthly intervals. The message is that both measures are better forecast of headline inflation than headline itself, but there is no clear winner. Another dimension investigated by Luciani and Trezzi is the sensitivity to data revisions, measured as the difference between current vintage estimates and real time estimates. On this, they found that revisions for the trimmed mean are both smaller and less volatile.

As for the median inflation as a core measure, its properties have been recently discussed by Ball and Mazumder (2019) relative to the standard core measure, and by Carroll and Verbrugge (2019) in a three-way comparison also including the trimmed mean.

The latter analysis is conducted over a sample covering 1984 to 2016 and its main results can be summarized as follows. All three measures are simple to compute and relatively easy to explain (except for the rationale for the asymmetric trimming). Both trimmed mean and median are smoother measures than standard core and are all significantly less volatile than headline. Trimmed mean and median inflation present some modest upward bias – measured as the difference from the average headline measure, but such bias is stable, while standard core exhibits an unstable bias over time.

As for each measure's ability to track inflation trend historically, where for a measure of historical trend they use a 2-stage centered moving average trend (2SMA),[28] the results appear sensitive to whether one considers monthly versus 12-month movements. The trimmed mean provides a best tracking of trend on a monthly basis, while the xFE core is more accurate as a year over year measure.

Carroll and Verbrugge (2019) also compare the relative forecasting ability of the three measures: they evaluate out-of-sample predictability of headline PCE on horizons of 6, 12 and 24 months via rolling-window regressions. In this exercise, the median PCE inflation has better forecasting ability at longer horizons before mid-2007, but xFE core does better post mid-2007, at all horizons.

Overall, these results point out that it is difficult to systematically improve upon simple core measures: however, there are differences in performance depending on time aggregation (i.e., whether a 6-month or a 12-month average is a better choice), on the sample period and on the measure.

The comparative studies discussed so far evaluate only cross-sectional core measures and cover pre-pandemic samples. We next conduct our own comparison of all the core measures discussed in this chapter using a long sample and focusing on these measures' ability to predict future inflation.

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[27] In a similar comparison, Dolmas and Koenig (2019) find that mean inflation rates computed from first-releases of the two measures against the mean headline PCE figure (computed from the latest-vintage) show a small downward bias of the PCExFE.

[28] This measure was one of those considered in Higgins and Verbrugge (2015).

### 4.1. A new comparison of core measures including the COVID-19 pandemic

The sample we use for this analysis begins in January 1978 (the earliest date for which all the measures are available) and ends in December 2023. Importantly, our sample includes the COVID-19 pandemic and the subsequent inflation surge, in addition to cover the high-inflation period of the late 70s as well as periods of more stable prices.

To illustrate the impact of the inflation regime on the properties of the measures, we also report comparisons based on three subsamples. These are (i) a Great Moderation sample (from January 1984 to December 2007), (ii) a pre-pandemic sample (from January 1984 to December 2019), and (iii) a high-inflation sample (from January 1978 to December 1983 and from January 2020 to December 2023).

As metric for comparison, we look at the ability of different measures of core inflation to predict future inflation in real time. To understand why this is informative, consider again our decomposition of observed aggregate inflation into its persistent and noise components:

$$\pi_t = \tau_t + \varepsilon_t.$$

We are interested in comparing the estimate of core inflation at the end of the sample $\hat{\tau}_T$ with the out-of-sample average inflation for some horizon $H$,

$$\bar{\pi}_T(H) = \frac{1}{H}\sum_{h=1}^{H} \pi_{T+h} = \frac{1}{H}\sum_{h=1}^{H} \tau_{T+h} + \frac{1}{H}\sum_{h=1}^{H} \varepsilon_{T+h}.$$

Since $\tau_t$ is persistent and $\varepsilon_t$ is not, $\bar{\pi}_T(H)$ should be close to true core inflation at the end of the sample $\tau_T$ for moderate-to-large $H$. The choice of $H$ is non-trivial. Higher values reduce the role of the noise components (thanks to their averaging out to their zero mean) but increases the probability of shocks that affect out-of-sample values of $\tau_t$. Below, we look at horizons of $H = 6$, 12 and 24 month out of the sample.

For the cross-sectional measures, as mentioned before, an important choice is the level of time aggregation. To explore the consequences of this choice, we will use 1-month, 6-month and 12-month rates for PCE inflation excluding food and energy (PCExFE) and trimmed-mean PCE inflation. For the median PCE inflation rate, since it has no official 6-month version we report only 1-month and 12-month rates.

In addition to the cross-sectional measures, we report results for the MCT inflation estimate computed by the New York Fed. As we said before, this measure belongs to the approach that combines both cross-sectional and time series smoothing to estimate core inflation. All measures are compared by means of the root mean-square error (RMSE).

The results are organized as follows: Full sample RMSEs are in table 1, while those for the three subsamples are respectively in table 2 (Great Moderation); table 3 (Pre-pandemic period); and table 4 (High-inflation sample).

A summary of the patterns we find is as follows:

(i) The predictability of inflation (measured by the minimum RMSE) changes significantly across sub-periods, with inflation being more predictable in the Great Moderation sample and less predictable in the High-inflation sample.

(ii) The optimal level of time aggregation for the cross-sectional measures varies across sub-periods. In the Great Moderation sample, for instance, 12-month or 6-month cross-sectional measures tend to perform better than the 1-month measures. In the High-inflation sample instead, for some of the cross-sectional measures the 1-month rate dominates.[29] This suggests that in periods of high inflation, compared to periods of price stability, the variance of shocks to the core component of inflation tends to be higher relative to the noise component.

(iii) Trimmed mean and PCExFE inflation rates tend to outperform the median PCE.

(iv) Time series smoothing usually achieves the best performance in all the subsamples. This suggests that weighting the data as a function of their signal-to-noise ratio is generally a good idea.

**TABLE 1. Full sample (Jan1978-Dec2023)**

| MEASURE | $H = 6$ | $H = 12$ | $H = 24$ |
|---|---|---|---|
| PCExFE | | | |
| • 1-month | • 1.82 | • 1.72 | • 1.77 |
| • 6-month | • 1.44 | • 1.36 | • 1.39 |
| • 12-month | • 1.54 | • 1.44 | • 1.45 |
| Trimmed-mean PCE | | | |
| • 1-month | • 1.52 | • 1.38 | • 1.33 |
| • 6-month | • 1.48 | • 1.34 | • 1.28 |
| • 12-month | • 1.55 | • 1.41 | • 1.34 |
| Median PCE | | | |
| • 1-month | • 1.63 | • 1.49 | • 1.41 |
| • 12-month | • 1.65 | • 1.50 | • 1.42 |
| MCT inflation | • 1.46 | • 1.35 | • 1.35 |

[29] This result is consistent with the result of McCraken and Ngan (2024) on the 'content horizon' of core PCE inflation as forecast of headline PCE inflation. They find that the forecast accuracy of core PCE is high at shorter time horizons, and increased in the post 2021 period, when inflation started to accelerate.

**TABLE 2. Great Moderation (Jan1984-Dec2007)**

| MEASURE | $H = 6$ | $H = 12$ | $H = 24$ |
|---|---|---|---|
| PCExFE | | | |
| • 1-month | • 1.57 | • 1.51 | • 1.47 |
| • 6-month | • 1.00 | • 0.92 | • 0.81 |
| • 12-month | • 1.02 | • 0.90 | • 0.81 |
| Trimmed-mean PCE | | | |
| • 1-month | • 1.08 | • 0.98 | • 0.90 |
| • 6-month | • 0.93 | • 0.82 | • 0.70 |
| • 12-month | • 0.94 | • 0.81 | • 0.72 |
| Median PCE | | | |
| • 1-month | • 1.21 | • 1.11 | • 1.04 |
| • 12-month | • 1.08 | • 0.96 | • 0.91 |
| MCT inflation | • 0.99 | • 0.90 | • 0.75 |

**TABLE 3. Pre-pandemic period (Jan1984-Dec2019)**

| MEASURE | $H = 6$ | $H = 12$ | $H = 24$ |
|---|---|---|---|
| PCExFE | | | |
| • 1-month | • 1.60 | • 1.43 | • 1.36 |
| • 6-month | • 1.22 | • 0.99 | • 0.84 |
| • 12-month | • 1.23 | • 0.94 | • 0.82 |
| Trimmed-mean PCE | | | |
| • 1-month | • 1.30 | • 1.05 | • 0.92 |
| • 6-month | • 1.21 | • 0.95 | • 0.77 |
| • 12-month | • 1.22 | • 0.94 | • 0.77 |
| Median PCE | | | |
| • 1-month | • 1.43 | • 1.20 | • 1.06 |
| • 12-month | • 1.36 | • 1.10 | • 0.94 |
| MCT inflation | • 1.22 | • 0.95 | • 0.79 |

**TABLE 4. High-inflation sample (Jan1978-Dec1983 & Jan2020-Dec2023)**

| MEASURE | $H = 6$ | $H = 12$ | $H = 24$ |
|---|---|---|---|
| PCExFE | | | |
| • 1-month | • 2.47 | • 2.57 | • 2.99 |
| • 6-month | • 2.08 | • 2.31 | • 2.73 |
| • 12-month | • 2.37 | • 2.60 | • 2.92 |
| Trimmed-mean PCE | | | |
| • 1-month | • 2.18 | • 2.27 | • 2.44 |
| • 6-month | • 2.21 | • 2.32 | • 2.50 |
| • 12-month | • 2.43 | • 2.53 | • 2.69 |
| Median PCE | | | |
| • 1-month | • 2.21 | • 2.31 | • 2.42 |
| • 12-month | • 2.45 | • 2.52 | • 2.67 |
| MCT inflation | • 2.14 | • 2.34 | • 2.69 |

## 5. Core measures tracked in other jurisdictions

Central banks in most advanced economies also rely on a variety of core measures to assess the persistence of inflationary pressures building into their targeted price index. The type of measures, as well as the frequency by which these measures feature in official communications varies.

As in the U.S., core measures in other economies often include both exclusion-based measures and model-based measures. The European Central Bank (ECB) for example, where the inflation objective is stated in terms of the Harmonized Index of Consumer Prices (HICP), uses several 'underlying' inflation measures (a term they use as more general than core to indicate measures of persistent pressures) for its comprehensive assessment of inflation.[30] In addition to variants of the standard ex-food and energy measure (such as excluding only energy, only energy and unprocessed food), other measures monitored by the ECB follow either a cross-sectional smoothing approach, such as trimmed-means and weighted medians, or a model-based approach to provide a more solid theoretical ground for the assessment of persistence.

Two measures of the latter kind are the Persistent and Common Component of Inflation (PCCI) and the Supercore. The PCCI is a measure derived from a dynamic factor model

[30] The term underlying inflation is recurrent and well-defined in ECB public communication: see for example Lane, 2023.

estimated on a large set of HICP items from twelve euro area countries: the model extracts common and persistent components from this set and aggregates them using HICP weights. A version of the PCCI that excludes energy is also computed. The PCCI is based only on price data and its theoretical framework is similar to that of the MCT model we discussed for the U.S. The Supercore belongs instead to a class of measures that include more than just price components for their construction: based on models that link inflationary pressures to domestic demand, the Supercore is obtained by aggregating core HICP items that are sensitive to economic slack.

The metrics used by ECB staff for evaluating the measures' performance are also similar to those discussed for the U.S. Overall, while most measures provide useful signal for assessing euro area inflation over the medium term, their relative forecasting performance varies over time. Importantly, recent assessments covering the pandemic-related inflation episode find that more slowly reverting transitory element can cloud the readings of underlying inflation measures.[31]

A range of exclusion-based measures is also tracked by the Bank of England[32] and the Norges Bank for CPI inflation,[33] and by the Riksbank for the CPIF (CPI with fixed interest rate); they are either variously reported in official publications of the central banks, or regularly published on their websites.

Interestingly, only the Bank of Canada indicates explicitly the use of core inflation measures as operational guides for its inflation-control strategy.[34]

## 6. Concluding remarks

In this chapter we introduce the concept of core inflation and discuss issues around its measurement. We provide a unified framework to interpret some widely used core measures in the U.S. and elsewhere and compare their relative properties.

Our analysis of core measures for the U.S. PCE inflation over a sample covering the pandemic inflation episode suggests that weighting the data as a function of the signal-to-noise ratio provides a good core measure.

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[31] Banbura et al (2023) provides a recent discussion of underlying inflation measures for the euro area. For more detail on the various measures, see Ehrmann et al. (2018).

[32] See Monetary Policy Report - February 2024 | Bank of England

[33] An important underlying inflation indicator used by the Norges Bank in its inflation assessment is the CPI adjusted for tax changes and excluding energy products (CPI-ATE), see Norges Bank's monetary policy strategy statement (norges-bank.no)

[34] "The Bank's two "preferred measures of core inflation are the CPI-trim, which excludes CPI components whose rates of change in a given month are the most extreme, and CPI-median, which corresponds to the price change located at the 50th percentile (in terms of basket weight) of the distribution of price changes." Canada's inflation-control strategy in Monetary Policy Report - January 2024 (bankofcanada.ca)

## References

Ball, Laurence, and N. Gregory Mankiw. 1995. "Relative-Price Changes as Aggregate Supply Shocks," *Quarterly Journal of Economics*, pp. 161-93.

Ball, Laurence and Sandeep Mazumder, 2019. "The nonpuzzling behavior of median inflation, NBER wp 25512.

Banbura, Marta, Elena Bobeica, Katalin Bodnar, Bruno Fagandini, Peter Healy and Joan Paredes. 2023. "Underlying inflation measures: an analytical guide for the euro area." Published as part of the ECB Economic Bulletin, Issue 5/2023.

Bernanke, Ben and Olivier Blanchard. 2024. "An Analysis of Pandemic-Era Inflation in 11 Economies," PIIE working paper 24-11.

Bryan, Michael and Christopher Pike, 1991 "Median Price Changes: An Alternative Approach to Measuring Current Monetary Inflation." Federal Reserve Bank of Cleveland, Economic Commentary 12/1/1991. https://doi.org/10.26509/frbc-ec-19911201

Bryan, Michael F. and Stephen Cecchetti, 1994. "Measuring Core Inflation" in N. Gregory Mankiw (ed.) 'Monetary Policy' NBER volume.[working paper version]

Carroll, Daniel and Randal J. Verbrugge 2019. "Behavior of a New Median PCE Measure: A Tale of Tails" Economic Commentary, Economic Commentary, Federal Reserve Bank of Cleveland Behavior of a New Median PCE Measure: A Tale of Tails (clevelandfed.org)

Cecchetti, Sthephen G. 1997. "Measuring Short-Run Inflation for Central Bankers" Federal Reserve Bank of St. Louis, May/June.

Clark, Todd E. 2001. "Comparing Measures of Core Inflation", *Economic Review, Federal Reserve Bank of Kansas City*.

Cogley, Timothy and Argia M. Sbordone. 2008. "Trend Inflation, Indexation, and Inflation Persistence in the New Keynesian Phillips Curve.' *American Economic Review* 98"5, 2101-26.

Cogley, Timothy, Giorgio E. Primiceri and Thomas J. Sargent. 2010. "Inflation Gap Persistence in the US," *American Economic Journal: Macroeconomics*, 2:1, 43-69.

Dolmas, Jim, 2005. "Trimmed mean PCE inflation", Federal Reserve Bank of Dallas, wp 0506.

Dolmas, Jim and Evan F. Koenig, 2019 Two Measures of Core Inflation: A Comparison – Research Dept. Working Paper No. 1903 – Dallas Fed

Durbin, James and Siem Jan Koopman. 2012. "Time Series Analysis by State Space Methods," OUP Catalogue, Oxford University Press, edition 2, number 9780199641178.

Ehrmann, Michael, Gianluigi Ferruzzi, Michele Lenza and Derry O'Brien. 2018. "Measures of Underlying inflation for the euro area" published as part of the ECB Economic Bulletin, Issue 4/2018.

Friedman, Milton, 1957. Theory of the Consumption Function. Princeton University Press.

Hall, Robert E., and Frederic S. Mishkin, 1982. "The Sensitivity of Consumption to Transitory Income: Estimates from Panel Data on Households." *Econometrica* 50 (2): 461–81.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press.

Higgins, Amy, and Randal J. Verbrugge. 2015. "Is a Non-seasonally Adjusted Median CPI a Useful Signal of Trend Inflation?" Federal Reserve Bank of Cleveland, Economic Commentary 2015-13. https://doi.org/10.26509/frbc-ec-201513

Kim, Sangjoon, Shephard, Neil and Siddhartha Chib. 1998. "Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models," *Review of Economic Studies* 65, pp.361-393.

Lane, Philip, 2023. "Underlying Inflation", lecture at the Trinity College in Dublin, March.

Luciani, Matteo, and Riccardo Trezzi. 2019. The Fed - Comparing Two Measures of Core Inflation: PCE Excluding Food & Energy vs. the Trimmed Mean PCE Index (federalreserve.gov) FEDS Notes. Washington: Board of Governors of the Federal Reserve System, August 2, 2019.

MaCurdy, Thomas E. 1981. "An Empirical Model of Labor Supply in a Life-Cycle Setting." *Journal of Political Economy*, vol. 89 (6) pp. 1059–85.

McCraken, Michael and Tran Khanh Ngan. 2024. "Core Inflation Revisited: Forecast Accuracy Across Horizons." Federal Reserve Bank of St. Louis, February. Core Inflation Revisited: Forecast Accuracy across Horizons | St. Louis Fed (stlouisfed.org).

Muth, John F., 1960. "Optimal Properties of Exponentially Weighted Forecasts." Journal of the American Statistical Association, vol. 55, no. 290: 299–306.

Muth, John F., 1961. "Rational Expectations and the Theory of Price Movements." *Econometrica,* vol. 29 (3): 315–35.

Rudd, Jeremy B. 2020. [“Underlying Inflation: Its Measurement and Significance.” FEDS Notes].

Stock, James H. and Mark W. Watson, 1991. “A Probability Model of the Coincident Economic Indicators,” in Leading Economic Indicators: New Approaches and Forecasting Records, K. Lahiri and G. H. Moore, eds., Cambridge University Press, 1991, pp. 63-89.

Stock, James H. and Mark W. Watson, 2007. “Why Has U.S. Inflation Become Harder to Forecast?” *Journal of Money, Banking and Credit*, Vol. 39, No. 1.

Stock, James H. and Mark W. Watson, 2016. “Core Inflation and Trend Inflation” *Review of Economic and Statistics* 98(4): 770-784.

Wynne, Mark A., 2008. “Core Inflation: A review of Some Conceptual Issues” Federal Reserve Bank of St. Louis Review, 90, 3, Part 2, May/June 2008. Available online at http://research.stlouisfed.org/publications/review/08/05/part2/Wynne.pdf