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Marta Bańbura
Elena Bobeica

PCCI – a data-rich measure of underlying inflation in the euro area

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Contents

Abstract

This paper details the rationale and methodology behind the construction of the Persistent and Common Component of Inflation (PCCI), a measure of underlying inflation in the euro area. The PCCI reflects the view that underlying inflation captures widespread developments across the Harmonised Index of Consumer Prices (HICP) basket and that it is the persistent component of inflation. Methodologically, it relies on a generalised dynamic factor model estimated on a large set of disaggregated HICP inflation rates for 12 euro area countries. For each individual inflation rate, we estimate a low-frequency common component, i.e. a component driven by shocks or factors that are relevant for all inflation series and capturing cycles longer than three years. The PCCI is a weighted average of these common components. It is an alternative to the typical exclusion-based measures used to gauge underlying inflation (e.g. HICP excluding food and energy), as it does not a priori exclude any HICP items. It exhibits a set of desirable properties as a measure of underlying inflation, and it is a good tracker of more lasting inflationary developments (judging by smoothness and bias). Furthermore, it is timely and signals turning points with some lead, while acting as an attractor for headline inflation.

Keywords: Underlying (core) inflation, dynamic factor model, frequency domain

JEL Codes: C32, E31, E32, E52

Non-technical summary

This paper describes the methodology behind the Persistent and Common Component of Inflation (PCCI), which is one of the measures of underlying inflation that is monitored by the European Central Bank (ECB). The paper also discusses why the PCCI is a useful indicator as part of the ECB's toolkit for assessing past and future inflationary pressures. Timely estimates of PCCI are published in the ECB Statistical Data Warehouse.

Conceptually, the PCCI reflects the view that underlying inflation captures widespread or generalised developments across consumer prices for different items, and that it is the persistent part of inflation. Methodologically, it relies on the generalised dynamic factor model proposed by Forni et al. (2000, 2005) and adopted for underlying inflation by Cristadoro et al. (2005).

The model explores the rich dataset in the Harmonised Index of Consumer Prices (HICP), covering the four-digit ECOICOP (European Classification of Individual Consumption according to Purpose) classes for 12 euro area countries and amounting to around 1,000 monthly time series in total. It incorporates approximately 97% of the euro area HICP basket. In contrast to Cristadoro et al. (2005) we rely only on the information contained in the HICP and we use country as opposed to aggregate euro area data. The goal of this indicator is thus to capture the underlying inflationary pressures that are common across euro area countries. This is particularly policy-relevant given the special architecture of the euro area, in which the single one monetary policy should be fit for many participating countries.

The main idea behind the model is that the inflation rate of each item can be decomposed into two orthogonal components: a common one, driven by shocks relevant for all inflation series and capturing the bulk of cross-sectional correlation; and an idiosyncratic one, driven by measurement errors and sector and country-specific items. The PCCI is defined as a weighted average of common components of a large set of inflation rates. This is different from the approach of Cristadoro et al. (2005) and facilitates, among other things, an understanding of the drivers of the PCCI, and the derivation of low-frequency common components for sub-aggregates such as HICP excluding energy and food. Apart from commonality, the model also imposes persistence, as it excludes high-frequency fluctuations from the common components (defined as cycles shorter than three years). As a result, the PCCI should be free from idiosyncratic and transient elements.

Estimation is based on dynamic and generalised principal components. In order to hedge against the uncertainty related to the number of (dynamic and static) factors, the PCCI is calculated as the average of estimates based on a range of values. The methodology makes it possible to simultaneously combine both the information from the cross-sectional distribution of prices and their time series properties in a unified framework. Therefore, in contrast to univariate filtering techniques, it can exploit leading properties of certain (sectoral price) indices in the panel and produce a timely estimate of more lasting developments in inflation, as well as its turning points.

The PCCI proves to be a valuable complementary tool to understand past inflation developments and assess future inflationary pressures. It fares well as a measure of underlying inflation, in particular by comparison with exclusion-based measures, such as HICP excluding energy (and food). The PCCI is also a good tracker of more lasting inflationary developments (judging by smoothness and bias), and it is timely, signalling turning points in annual headline inflation with some lead, while acting as an attractor for headline inflation.

1 Introduction

The prolonged period of low inflation in the euro area in the aftermath of the Great Recession calls for an in-depth examination as to whether these developments reflect a secular trend or are mostly a result of transitory shocks, likely to fade away in the near future. Information on more lasting inflation developments is a crucial input into monetary policy decision-making, as policymakers need to see through transitory shocks and concentrate on medium and long-term inflation trends. This is also due to the fact that monetary policy affects economic variables such as inflation only with a considerable delay. It was reflected, for instance, in the introductory statement of former ECB President Mario Draghi to the ECB's press conference of 15 April 2015: "*When carrying out its assessment, the Governing Council will follow its monetary policy strategy and concentrate on trends in inflation, looking through unexpected outcomes in measured inflation in either direction if judged to be transient and to have no implication for the medium-term outlook for price stability*" (see Draghi, 2015). For these reasons, measures of underlying inflation, which are ideally free from the transient shocks reflected in headline inflation, are often constructed and used by central banks.

This paper details the rationale and methodology behind the construction of one of the underlying inflation measures monitored by the ECB, namely the Persistent and Common Component of Inflation (PCCI). The PCCI is a measure based on a dynamic factor model, exploiting disaggregated information from the HICP for a wide range of items from a large set of euro area countries. Real-time estimates of the PCCI are published in the ECB Statistical Data Warehouse.[1]

As important as it is, underlying inflation is an unobservable variable that is hard to grasp. While it is generally believed that it should capture the persistent component of inflation and provide timely signals for future inflation developments, there is neither a unanimously accepted definition of underlying or core inflation, nor a set of criteria it should satisfy (see, for example, Clark, 2001; Rich and Steindel, 2007; Wynne, 2008). Consequently, even with the benefit of hindsight, the decomposition of inflation into persistent and transitory developments is model-specific and surrounded by considerable uncertainty.

In order to ensure a robust assessment, a wide range of underlying inflation measures are often considered, including at the ECB (see, for instance, ECB, 2001, 2013; Ehrmann et al., 2018; Nickel and O'Brien, 2018). The ECB's Economic Bulletin routinely shows the path of the monitored measures of underlying inflation, and the President's introductory statement to the press conference regularly makes references to them.[2] Perhaps the most popular underlying inflation measures are the permanent exclusion-based measures. Such measures are derived by excluding a certain fixed set of items, considered as volatile and noisy, from the overall consumer

[1] The PCCI series can be found in the Statistical Data Warehouse with the code ICP.M.U2.N.PCCI00.3.3MM.

[2] See for instance ECB (2020) and Lagarde (2020), respectively.

price index. The most prominent indicators monitored by the ECB in this category include: HICP excluding energy; HICP excluding energy and unprocessed food; HICP excluding energy and food; and HICP excluding energy, food, travel-related items and clothing. Temporary exclusion-based measures also form part of the ECB toolkit. In this case, the items to be excluded are selected at a given point in time depending on their relative volatility. These measures offer more flexibility than the permanent exclusion-based measures, as they can also abstract from large one-off price changes in items that are typically less volatile. The examples include the 10% trimmed mean, the 30% trimmed mean or the weighted median of the HICP inflation items.

The main drawback of all exclusion-based measures is that the resulting indicators may still not be free of temporary shocks that have no implication for price stability over the medium term (e.g. temporary movements in commodity prices, changes in administered prices and indirect taxes, and calendar effects).[3] Also, the components considered to be volatile and thus excluded, such as energy and food, can exhibit very persistent movements that have implications for price stability in the medium term. This is also because they may trigger second-round effects, which will only show up with a delay in the exclusion-based measure. Moreover, in the euro area, exclusion-based measures can reflect idiosyncratic developments in a particular (large) member state, with limited relevance for the single monetary policy. This is why central banks complement exclusion-based measures with those based on more sophisticated statistical techniques, among which factor models feature prominently (see, for example, Kirker, 2010; Machado et al., 2001; Amstad et al., 2014). The PCCI, constructed at the ECB, is one such measure.[4]

Conceptually, the PCCI reflects the view that underlying inflation captures widespread or generalised developments across consumer prices of different items – as supported by Bryan and Cecchetti, 1993 – and that it is the persistent part of inflation (Eckstein, 1981; Blinder, 1997). Methodologically, it relies on the generalised dynamic factor model proposed by Forni et al. (2000, 2005) and adopted for underlying inflation by Cristadoro et al. (2005). A common component is estimated for all inflation series, reflecting the shocks or factors relevant across the items in the HICP basket. The PCCI is the weighted average across these common components, and reflects, apart from commonality, medium and long-run movements in inflation as it excludes high-frequency fluctuations from the common components (cycles shorter than three years). As a result, PCCI should be free – up to the estimation error – from idiosyncratic (e.g. sector or country-specific) and transient elements. The methodology makes it possible to simultaneously combine both the information from the cross-sectional distribution of prices and their time series properties in a unified framework. Therefore, in contrast to univariate filtering techniques, it can exploit leading properties of certain (sectoral price) indices in the panel and produce a timely estimate of more lasting headline inflation dynamics and its turning points.[5]

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[3] Measures of inflation that exclude the impact of changes in taxes on products (e.g. value added tax, excise duties) are also assessed by the ECB. See, for example, ECB (2007).

[4] The ECB also monitors the so-called Supercore measure, which is based on those items in the HICP excluding energy and food that co-move with the business cycle, in a similar vein to Stock and Watson (2019a).

[5] Univariate low-pass filters typically introduce a phase shift, meaning that turning points in the filtered series occur at a later point than in the original series.

In contrast to Cristadoro et al. (2005) we rely only on the information contained in the HICP[6] and we use country as opposed to aggregate euro area data. Another difference is that Cristadoro et al. (2005) define core inflation directly as the common component of euro area headline HICP, whereas we derive it from the common components of country and sector HICP inflation rates. Our approach is motivated by a number of considerations. First, it allows us to better disentangle aggregate euro area from country-specific developments. Second, we can obtain insights into whether the trends at the aggregate level are shared across countries or hide highly heterogeneous country developments. Furthermore, it also allows us to pinpoint which countries, and also which items, account for the deviation of euro area headline inflation from its underlying level.

The PCCI fares well in satisfying some criteria for a desirable measure of underlying inflation. It is a good tracker of more lasting inflationary developments (judging by smoothness and bias), it is timely, signalling turning points in annual headline inflation with some lead, and it acts as an attractor for headline inflation, indicating the direction in which headline inflation will head.

It is important to stress that the model underlying the PCCI relies on the stationarity of inflation rates. One element of such an assumption is that the long-term averages (unconditional means) of inflation rates do not change over time. Consequently, even if it can be persistent, the deviation of the PCCI from the long-term average of headline inflation is by construction temporary. This is conceptually different from some recent models, which allow trend or core inflation to be driven by shocks of a permanent nature.[7] Some of these models further incorporate survey-based inflation expectations as potential proxies for the degree of anchoring of inflation expectations and credibility of monetary policy. This is in order to pin down the unobserved inflation trend. While we find them insightful, we do not explore these avenues in this paper.

The rest of the paper is organised as follows: Section 2 provides the methodological details on the estimation of the PCCI and the data used, Section 3 explains why this indicator is useful, and Section 4 presents the conclusion.

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6 Stock and Watson (2019b) extend the multivariate unobserved component models with the stochastic volatility of Stock and Watson (2016) to estimate euro area trend inflation based on 13 sectoral price indices only. Approaches that also consider other economic variables, with the aim of relating shifts in inflation to the evolution of real activity or monetary policy, include Cogley and Sargent (2005) and Cogley et al. (2010), who define trend inflation as the time-varying steady-state level of inflation in a small VAR model, or Andrle et al. (2013) who construct a trimmed mean measure of underlying inflation using the correlation with output at business cycle frequencies as a criterion. Extensions of our model considering a vast set of real, financial and external variables have been explored, but the results are similar overall to the results obtained using price data only.

7 See, for example, Garnier et al. (2015), Mertens (2016) and Chan et al. (2018), where inflation trends evolve as random walks. The changes in trend (steady-state) inflation are also permanent in the models of Cogley and Sargent (2005) and Cogley et al. (2010).

2 Methodology

The methodology closely follows Cristadoro et al. (2005) with some differences in the implementation, which will be described in detail later in the text. It relies on the generalised dynamic factor model proposed by Forni et al. (2000), with (one-sided) estimation based on generalised principal components, as detailed in Forni et al. (2005).

The econometric model

The model rests on the assumption that the inflation rate of each item in the HICP basket can be decomposed into two orthogonal components: a common one, driven by shocks relevant for all inflation series and capturing the bulk of cross-sectional correlation, and an idiosyncratic one, driven by measurement errors and sector and country-specific shocks. For each item i and country j, it is assumed that the monthly inflation rate at time t, $x_{ij,t}$ can be decomposed into two stationary and orthogonal unobserved components, namely the common component $\chi_{ij,t}$ and an idiosyncratic component $\xi_{ij,t}$:

$$x_{ij,t} = \chi_{ij,t} + \xi_{ij,t}$$

Furthermore, it is assumed that the common component is a linear combination of current and past values of q dynamic factors, f_t:

$$\chi_{ij,t} = \lambda_{ij,1}(L) f_{1,t} + \cdots + \lambda_{ij,q}(L) f_{q,t},$$

which are driven by q common shocks, u_t:

$$A(L) f_t = u_t, \qquad f_t = (f_{1,t}, \cdots, f_{q,t})',$$

see Forni et al. (2005) for details.

We are interested in the part of the common component that abstracts from high-frequency fluctuations in order to distil the medium and long-term movements in inflation. Using spectral domain techniques, the common component can be decomposed into low and high-frequency parts:

$$\chi_{ij,t} = \chi_{ij,t}^{L} + \chi_{ij,t}^{F}$$

where $\chi_{ij,t}^{L}$ would capture the commonalities with frequencies below a certain threshold (or, equivalently, periodicities/cycles above a certain threshold).[8]

8 Spectral domain techniques rely on the fact that a stationary time series is an aggregation (over frequencies) of waves with random amplitudes.

Definition of PCCI

We define the PCCI as the weighted average of the low-frequency common components of the individual sectoral and country inflation rates:

$$PCCI_t = \sum_j w_{j,t} \sum_i \omega_{ij,t} \chi_{ij,t}^L$$

where $w_{j,t}$ refers to the weight of country j in the euro area (HICP) and $\omega_{ij,t}$ is the weight of item i in the consumption basket of country j (at time t). The sum of the weights is equal to one; the original weights have been adjusted to account for the fact that, for reasons of data availability, not all the countries and not all the items are included. For more information, see the "Data" subsection.

Note that our approach is somewhat different from that of Cristadoro et al. (2005) who define the core measure as the (low-frequency) common component of the headline inflation rate.[9] With our bottom-up approach it is straightforward to derive low-frequency common components for euro area or country sub-aggregates, such as HICP excluding energy and food, which are consistent with exclusion-based measures of underlying inflation monitored by the ECB. This can be done by applying the above formula to a subset of items and adjusting the weights. In the same way, we can decompose the difference between the headline inflation and the underlying inflation measure into contributions of individual items, and therefore gain insights into which countries or items account for the deviation. Finally, we want to avoid a disproportionate contribution from items with a low weight in the euro area headline inflation.

Estimation

As explained in Forni et al. (2005) and Cristadoro et al. (2005), the low-frequency common components can be estimated by projecting $\chi_t^L = (\chi_{11,t}^L, \cdots, \chi_{IJ,t}^L)'$ on the space spanned by the common shocks/factors.

In what follows, we denote $\hat{x}$ to be the estimate of x. It can be shown (see Forni et al., 2005) that the projection, and thus the estimate of the low-frequency component, is the product of the estimates of the projection coefficients and of the common factors as follows:

$$\hat{\chi}_t^L = \hat{\Gamma}^L \hat{Z}' (\hat{Z} \hat{\Gamma} \hat{Z}')^{-1} \hat{F}_t = \hat{\Gamma}^L \hat{Z}' (\hat{Z} \hat{\Gamma} \hat{Z}')^{-1} (\hat{Z} x_t).$$

Γ and Γ^L denote the covariance matrices of the vector of inflation rates, $x_t = (x_{11,t}, \cdots, x_{IJ,t})'$, and of χ_t^L, respectively. The latter covariance matrix is estimated using the dynamic principal components.[10] F_t is a vector of r static factors, collecting the

[9] They include the headline inflation rate in the dataset.

[10] Dynamic principal components operate on spectral densities (in the frequency domain). The covariance matrices of the common components are estimated by aggregating the "common" part of the spectral densities (which are restricted to having a rank q, reflecting the assumed number of dynamic factors) over frequencies. For the covariance matrix of the low-frequency common component, only the frequencies below a certain threshold are included in the aggregation.

contemporaneous and lagged dynamic factors, f_t. It is estimated via the generalised principal components: $\hat{F}_t = \hat{Z}x_t$, where $\hat{Z} = (\hat{Z}_1', \cdots, \hat{Z}_r')'$ and

$$\hat{Z}_j = \arg\max_a a\hat{\Gamma}^\chi a' \quad s.t. \quad a\hat{\Gamma}^\xi a' = 1 \quad and \quad a\hat{\Gamma}^\xi \hat{Z}_m' = 0, \;\; 1 \leq m \leq j-1, \;\; j = 1, \cdots, r.$$

Γ^χ and Γ^ξ denote the covariance matrices of the common and idiosyncratic components respectively. The maximisation searches for linear combinations that give a large weight to series with a high percentage of variance explained by common sources of fluctuations, subject to orthogonality constraints. See Forni et al. (2005) and Cristadoro et al. (2005) for a detailed explanation.

Data

The model explores a rich dataset of inflation rates from 12 euro area countries, as shown in Table 1. The data covers the ECOICOP four-digit classes, approximately 1,000 monthly time series in total.[11] The precise number of series can change, reflecting data availability at the country level for a given update. Series which are not available for the full period are eliminated and the weights are readjusted accordingly. This still ensures that for virtually every included country, almost all of the consumption basket is accounted for. In terms of coverage at the euro area level, the dataset incorporates 97% of the euro area HICP basket.

The inflation rates are expressed as annualised monthly inflation rates to ensure stationarity and are seasonally adjusted using the Census X-12-ARIMA method. Outliers are also removed prior to estimation. Owing to the data availability at this very disaggregated level, the sample starts in April 2001. The end date of the sample for the analysis in this paper is December 2018.

Table 1

Data coverage per country

(number, percentage)

Country	BE	DE	IE	GR	ES	FR	IT	LU	NL	AT	PT	FI	Total
Number of inflation rates	83	92	87	88	86	89	85	89	85	90	84	86	1,044
Weight in the national basket	98.3	99.9	99.9	96.1	99.9	96.1	99.6	99.4	99.7	100	98.5	99.9	-
Weight in the euro area basket	3.7	28.0	1.5	2.1	11.5	19.4	17.3	0.3	5.1	3.4	2.2	1.9	97

Implementation details

In order to estimate the common components, we need to select the number of static and dynamic factors, r and q respectively. We have experimented with a range of values. However, no single choice was found to be superior to another according to all possible criteria, which we set out below. To hedge against the uncertainty related to

[11] See the Eurostat's website for more information on the ECOICOP classification. The dataset does not include the methodological changes implemented by Eurostat on 22 January 2019.

this choice, the PCCI is the average of estimates based on two to eight dynamic factors and four to 16 static factors (under the restriction that the latter has to be larger or equal to the former) – 81 specifications in total.[12] It turns out that the estimates are relatively similar for a wide range of values for the number of factors, with a slight increase in uncertainty during the global financial crisis (see Chart A in the Annex).

Turning to the frequency threshold for the low-frequency common component, we keep the cycles with periodicities equal to or above three years and discard the others. Given the forecast horizon and the transmission lags of monetary policy, we deem this choice reasonable. We have also considered thresholds of two and six years. This is illustrated in Chart B in the Annex, which shows that the longer the considered cut-off periodicity, the smoother the estimated underlying inflation indicator. However, the results are qualitatively similar, for instance in terms of turning points.

An additional smoothing of the estimated component is performed ex post by taking the three-month moving average of the model output. This choice helps to achieve a satisfactory degree of smoothing which would otherwise not be obtained by exploiting the multivariate information, with a cost in terms of timeliness of the indicator.[13]

To sum up, the PCCI is estimated by means of a weighted average of the disaggregated inflation data. The weights attach more importance to series driven by common – as opposed to idiosyncratic – sources of fluctuations. Moreover, by exploiting the low-frequency covariance matrices, only more persistent movements of HICP inflation rates are retained. This permits the aggregation of all potentially leading, coincident and lagging information contained in the panel. Thus a measure is constructed that is coincident with month-on-month HICP inflation but is at least as smooth as year-on-year inflation without requiring, unlike centred moving averages, knowledge of unavailable future inflation rates.

[12] Automatic selection criteria for the number of common factors have also been applied, such as those proposed by Bai and Ng (2002), who argue that the optimum number of factors can be determined in a usual model selection framework, where there is a trade-off between good fit and parsimony. However, this procedure did not yield estimates of the common component that were superior in terms of smoothness, leading power for inflation or stability in the face of revisions.

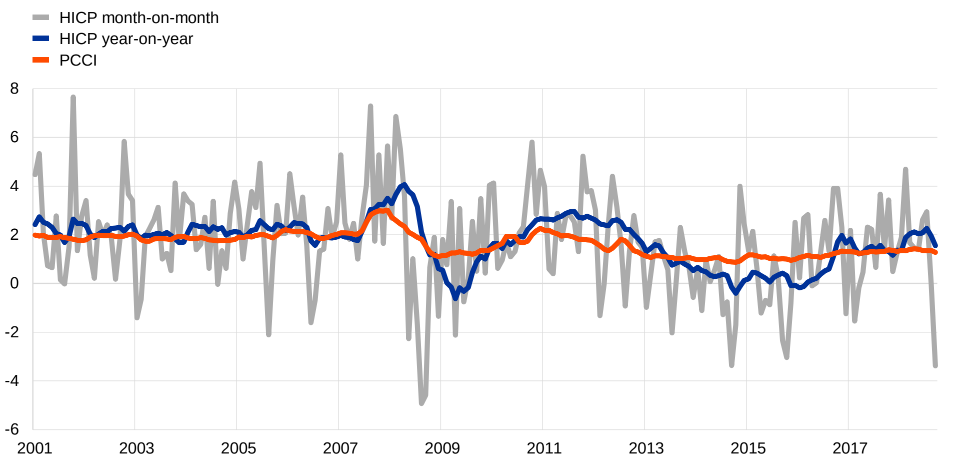
[13] This helps to smooth out several spikes that "leak" through the cross-sectional filter.

3 The PCCI – why is it useful?

Chart 1 shows the estimated PCCI and the annual and annualised monthly headline inflation rates for the euro area. The annual headline inflation rate is much smoother than the annualised monthly rate, but it is lagging. This is because it is essentially the result of a one-sided filter over 12 months. By contrast, the PCCI mainly relies on a "cross-sectional" filter and reduces the volatility of the annualised monthly inflation while not losing the timeliness. Overall, it appears to be a timely and smooth measure of more lasting inflationary developments. The next subsections evaluate these features more formally, also comparing them with the performance of the HICP excluding energy and the HICP excluding energy and food, which are frequently used to assess more persistent inflation developments (see, for example, ECB, 2013; Ehrmann et al., 2018).

Chart 1
The PCCI and headline HICP inflation in the euro area

(annualised monthly percentage changes, annual percentage changes)



Notes: HICP month-on-month is the annualised monthly headline HICP inflation rate, seasonally and working day-adjusted; its unit of measure is annualised monthly percentage changes. HICP year-on-year is the annual headline HICP inflation rate; its unit of measure is annual percentage changes, the same as for the PCCI.

3.1 Ability to track more lasting inflationary developments

In this subsection we present a number of statistics evaluating how well three measures of underlying inflation (the PCCI, the HICP excluding energy and the HICP excluding energy and food) perform in tracking low-frequency developments in headline inflation. We look at their volatility, long-term mean and closeness to a proxy for more lasting inflationary developments (see Table 2).[14] The latter is obtained as a three-year centred moving average of headline inflation and is therefore not a useful "real-time" measure, as it is not available for the most recent months.

[14] The statistics presented in Tables 1 and 2 are discussed in more detail in Clark (2001) and ECB (2013).

The PCCI fares well across these statistics when compared with the exclusion-based measures. First, it provides a less biased estimate of underlying inflation developments, as the long-term average of headline inflation is closer to the mean of the PCCI than to that of HICP inflation excluding energy and food or HICP inflation excluding energy. Second, the PCCI is a more precise real-time indicator of the more lasting developments in headline inflation, as its root mean squared error (RMSE) with respect to the centred moving average is smaller than that of the exclusion-based measures. Finally, it is less volatile than the exclusion-based measures and much less than annual headline HICP inflation.

Table 2

Volatility and ability to track more lasting headline inflation developments

	Tracking of more lasting inflation developments		Volatility		
	Average inflation rate (percentage)	RMSE vis-à-vis the three-year centred moving average of headline inflation	Standard deviation	Coefficient of variation	Mean absolute change
Headline HICP	1.74	0.63	0.96	0.55	0.20
HICP excluding energy and food	1.40	0.54	0.45	0.32	0.12
HICP excluding energy	1.59	0.47	0.58	0.36	0.12
PCCI	1.63	0.41	0.46	0.28	0.06
Three-year centred moving average	1.73	-	0.65	0.37	0.03

Notes: Based on monthly year-on-year growth rates; sample 2001-18. The coefficient of variation is the standard deviation divided by the mean. The mean absolute change is the average of the absolute value of the first difference of each inflation measure. The RMSE is the square root of the average squared difference between each underlying inflation measure and the three-year centred moving average of headline inflation, which is the proxy chosen for more lasting headline inflation developments.

3.2 Leading properties of the PCCI

The PCCI outperforms exclusion-based measures of underlying inflation in terms of leading properties with respect to headline inflation. It is highly correlated with annual headline inflation and tends to lead it by two months. Whereas the absolute correlation of the PCCI with headline inflation is highest at a two-month lead, that of HICP inflation excluding energy and food is highest at a six-month lag, and that of HICP inflation excluding energy is highest at a two-month lag (see Table 3). The PCCI also has a lower RMSE for headline inflation for various near-term forecast horizons than the exclusion-based measures.

All considered measures of underlying inflation exhibit “attractor” properties for headline inflation, i.e. when there is a gap between the headline rate and an underlying inflation measure, headline inflation is more likely to converge towards the underlying measure than vice versa. Moreover, on the basis of R^2, a significant amount of variation of future changes in headline inflation is explained by this reversion process, and more with the PCCI than when an exclusion-based measure of underlying inflation is used.

Table 3

Leading properties with respect to headline inflation

(based on monthly year-on-year growth rates)

Inflation measure	Correlation		RMSE vis-à-vis future headline inflation			Attractor properties		
	Maximum	Lead	Three months ahead	Six months ahead	12 months ahead	R^2	Intercept	Slope
HICP excluding energy and food	0.65	-6	0.89	0.91	0.95	0.38	0.25***	0.92
HICP excluding energy	0.77	-2	0.77	0.85	1.01	0.24	0.08	0.90
PCCI	0.85	2	0.70	0.71	0.90	0.47	0.06	1.26***

Notes: "Lead" refers to a shift in months at which the correlation with headline inflation is the highest. A positive number means that the measure leads the headline rate. The RMSE is the square root of the average squared difference vis-à-vis the future headline rate. "Intercept" and "slope" refer to α and β from the regression respectively: $\pi_{t+h} - \pi_t = \alpha + \beta(\pi_t^u - \pi_t) + \varepsilon_{t+h}$, where π_t and π_t^u refer to headline and underlying inflation rates and h stands for 12 months. Asterisks denote a significant difference from 0 for the intercept and from 1 for the slope, with 3, 2 and 1 asterisk(s) denoting the 1%, 5% and 10% confidence levels respectively; the lack of asterisk shows that the null hypothesis of the intercept being equal to 0 or the slope being equal to 1 cannot be rejected.

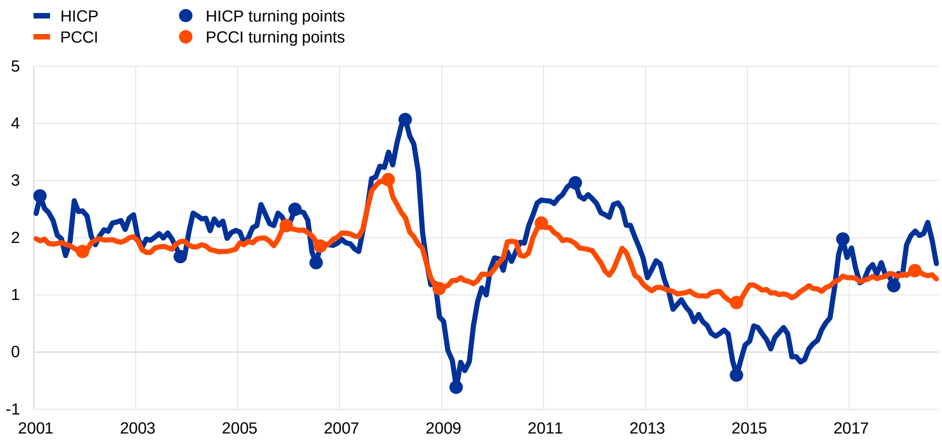
Finally, the PCCI can provide early signals on the turning points in annual headline HICP. The turning points identified over the historical sample typically occur a couple of months earlier in the case of the PCCI than in the case of the headline HICP. Chart 2 illustrates this point by applying the Bry and Boschan (1971) algorithm to identify the turning points in the PCCI and headline inflation. This statistical univariate procedure also identifies some local troughs and peaks with little economic relevance, for example, the February 2004 trough in headline inflation. However, when it comes to the big turning points in inflation, such as those in July 2008, July 2009 and November 2011,[15] the PCCI seems to have led inflation by even more than two months, as indicated by the lead/lag correlation analysis. Nevertheless, the latter is an average of the entire sample and if we look at specific episodes, there might be some deviations from this average. Overall, different measures of the leading properties yield different results, but what is consistent is that there appears to be some leading power in the PCCI.

[15] These big turning points are also in line with the estimates of de Bondt et al. (2018), who present an estimated euro area headline inflation cycle using data over a long period of time.

Chart 2

Turning points

(annual percentage changes)



Note: The identification of the turning points is based on Bry and Boschan (1971).

3.3 Stability of the estimated underlying inflation to new observations

The PCCI, as any estimated variable, is subject to revisions when a new observation is added to the dataset. This is also common to other unobservable economic variables, such as the output gap or the non-accelerating inflation rate of unemployment.[16]

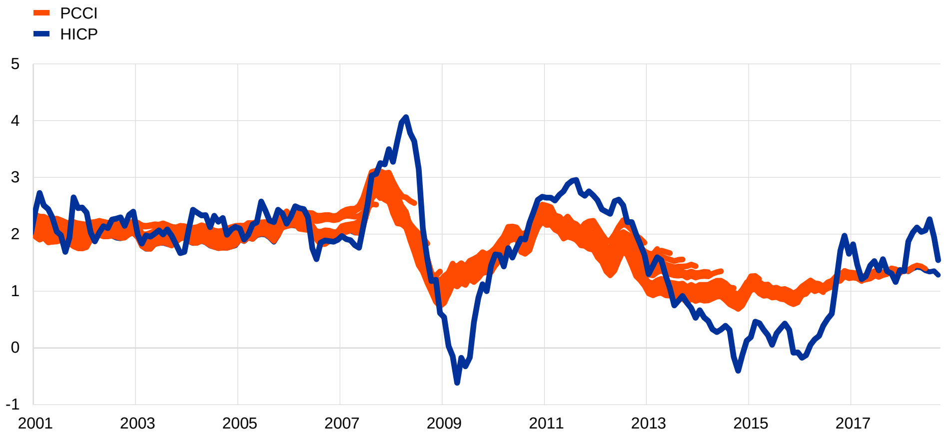
The PCCI is, overall, robust to new observations added to the sample, as shown in Chart 3. The chart presents the sequence of PCCIs estimated recursively over an expanding window (45 samples in total). Even when compared with an estimate based on a much shorter sample not covering the Great Recession period, the PCCI does not exhibit major revisions. The turning points in the underlying inflation measure are also estimated robustly, a necessary condition for ascertaining the ability of the PCCI to lead headline inflation. However, a sequence of downward revisions over recent years can be noted and potential structural breaks in inflation rates (e.g. in long-term averages) could be investigated.

[16] Recent analysis at the ECB of these unobservable variables can be found in ECB (2017) and Andersson et al. (2018).

Chart 3

Estimates of PCCI over different samples

(annual percentage changes)



Notes: Recursive estimates of the PCCI based on 45 expanding samples. The first sample starts in February 2001 and ends before the Great Recession in December 2007. The length of each subsequent sample increases by 3 months, with the 45th sample covering February 2001 to December 2018.

3.4 Degree of commonality across all inflation rates

The common shocks/factors account on average for almost 40% of the variability in the euro area inflation rates. Chart 4 shows the share of variance explained by the factors for different periodicities.[17] The share of the variability explained increases for higher periodicities (lower frequencies). This perhaps unsurprisingly suggests that the co-movement in inflation rates across items and countries increases after transitory shocks are removed.

It would be desirable for the common component as depicted by the PCCI to explain the bulk of the variability of inflation rates across items. The quite considerable share of the variability in the data that is not explained (by the common factors) suggests that there are sizeable idiosyncratic factors affecting the inflation rates of individual items. In other words, it appears that when it comes to the most disaggregated inflation data for the euro area, namely over 1,000 inflation series for 12 euro area countries, the degree of "commonality" is not extremely high; high-frequency and local/idiosyncratic noise characterise the data.[18] The PCCI does extract what is common from the cross-sectional information, but the considerable unexplained variability in the data might point to a limitation in this measure.

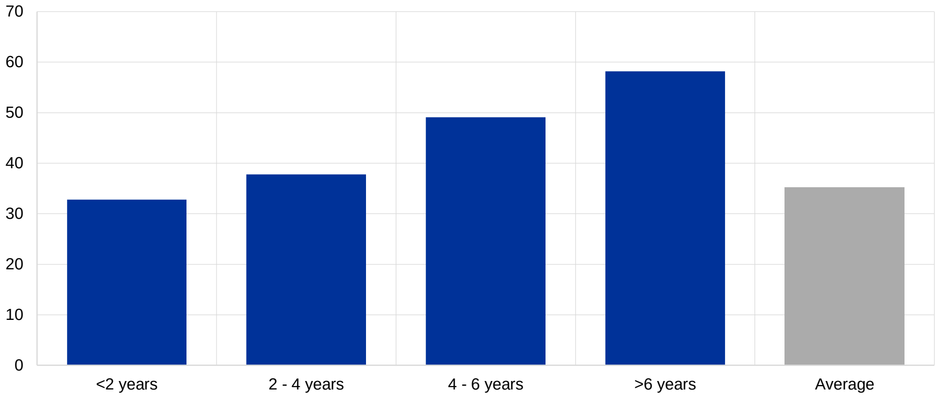
[17] Specifically, the degree of commonality is assessed by the ratio of the sum of the largest q dynamic eigenvalues (2 to 8, depending on the specification) of the spectral density matrix over the sum of all eigenvalues, in absolute terms. For instance, this share for periods of less than two years is computed by averaging the shares for the spectral density matrices over the frequencies corresponding to these periods.

[18] Using a similar model for the United States, Luciani (2020) finds that most of the fluctuations in core personal consumption expenditure prices observed since the Great Recession have been idiosyncratic in nature.

Chart 4

Share of variance explained by the common shocks

(percentage)



Notes: The share of variance is measures as the ratio of the sum of the largest q dynamic eigenvalues to the sum of all (dynamic) eigenvalues. The average value of the statistics for q between 2 and 8 is reported. “Average” refers to the average variability explained for all frequencies.

4 Conclusions

The model-based measure of underlying inflation described in this paper reflects the view that underlying inflation is the persistent part of inflation and that it captures widespread developments across HICP items. The PCCI captures commonalities among disaggregated HICP items in 12 euro area countries and abstracts from cycles shorter than three years. Exploiting lead-lag relationships among the HICP items, the PCCI is a timely and relatively smooth tracker of more lasting headline inflation developments.

For a judicious reading of the PCCI, the following considerations are noteworthy.

- It is derived on the basis of a fairly complicated model and the result depends on the choice of several parameters (e.g. the number of static and dynamic factors, the frequency of cycles to be eliminated, the lags and frequency grid for computing the covariance matrices, the number of months for the ex post computation of the moving average.).
- The degree of commonality explained is not overwhelming, suggesting a high degree of heterogeneity in the underlying data.
- The measure is subject to revisions when new observations are added to the sample.
- Its ability to forecast year-on-year inflation stems mainly from its exploitation of the lead-lag relationships of individual inflation rates, whereas a proper forecasting model would take into account a much wider dataset than only price series, thus incorporating more leading information.[19]
- Potential structural breaks (e.g. in long-term averages of inflation rates) are not accounted for in the estimation.
- The PCCI is only one of the measures of underlying inflation monitored by the ECB and, like others, has its own advantages and drawbacks. This justifies the current practice of monitoring a larger set of measures and, importantly, complementing the analysis with more structural examinations of the inflation drivers in order to better grasp (future) inflationary developments.

[19] See, for example, Peach et al. (2013).

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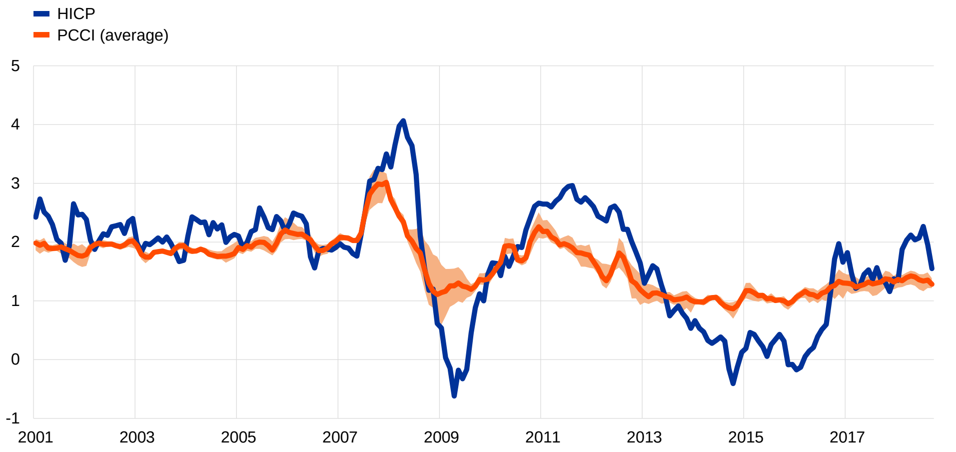
Annex: Sensitivity to some parameter choices

Chart A

Sensitivity to the choice of the number of factors

(annual percentage changes)

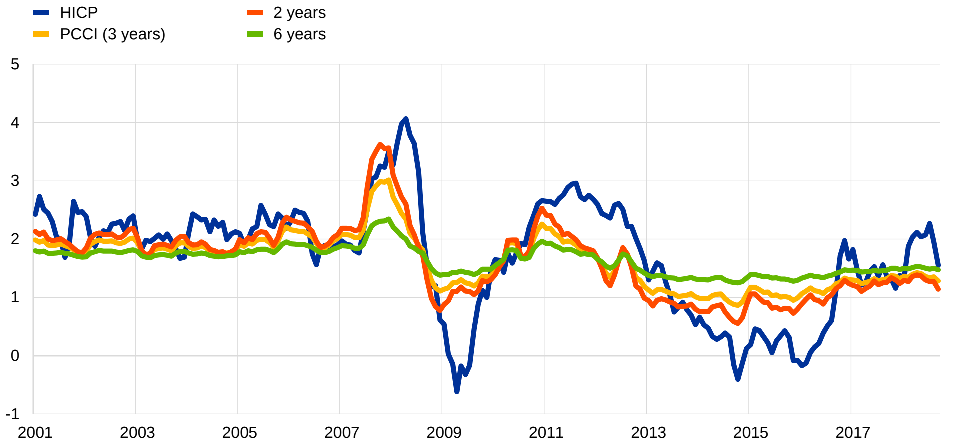


Note: The shaded area indicates the range of estimates based on two to eight dynamic factors and four to 16 static factors (under the restriction that the latter has to be larger or equal to the former) – 81 specifications in total.

Chart B

Sensitivity to the choice of the threshold cycle length

(annual percentage changes)



Note: The last two lines are based on common components for which the cycles shorter than two and six years respectively have been filtered out.

Abbreviations

Countries

BE	Belgium	**FR**	France	**PT**	Portugal
DE	Germany	**IT**	Italy	**FI**	Finland
IE	Ireland	**LU**	Luxembourg		
GR	Greece	**NL**	Netherlands		
ES	Spain	**AT**	Austria		

In accordance with EU practice, the euro area Member States are listed in this report using the alphabetical order of the country names in the national languages.

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Marta Bańbura
European Central Bank; email: Marta.Banbura@ecb.europa.eu

Elena Bobeica
European Central Bank; email: Elena.Bobeica@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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