BANCA D'ITALIA
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Questioni di Economia e Finanza
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The series is available online at www.bancaditalia.it .

ISSN 1972-6643 (online)

Designed by the Printing and Publishing Division of the Bank of Italy

UNDERLYING COMPOSITE INFLATION (UCI): A NOVEL INDICATOR TO TRACK INFLATION DEVELOPMENTS

by Valentina Aprigliano* and Francesco Corsello*

Abstract

This paper introduces the Underlying Composite Inflation (UCI), a novel model-based indicator designed to enhance the measurement of underlying inflation in the euro area. UCI is estimated by a dynamic factor model in the frequency domain to capture the persistent component of inflation. We also provide a probabilistic evaluation of the underlying inflation dynamics, additional insights into cross-country inflation dynamics and address the challenges posed by short-term volatility and idiosyncratic factors. UCI not only offers a more stable and refined signal of underlying inflation but also exhibits superior out-of-sample forecasting performance compared to both exclusion-based and model-based alternatives. These findings underscore the potential of UCI as a valuable tool for monetary policy, inflation monitoring, and risk assessment.

JEL Classification: C22, C53, C55, E31, E37.

Keywords: underlying inflation, inflation trend, dynamic factor model, frequency domain analysis.

DOI: 10.32057/0.QEF.2025.928

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1 Introduction*

The ECB's monetary policy framework is oriented toward medium-term inflation stability. However, short-term volatility and transitory shocks can blur the signals of medium-term inflationary pressures (Lane, 2023). Disentangling the transitory from the persistent inflationary pressures is therefore of crucial importance for monetary policy.

To address this challenge, particularly during periods of heightened uncertainty (Kamps, 2024), the Eurosystem monitors various measures of underlying inflation in the euro area (EA). The most popular and simple approach is to exclude the most volatile components, either with a fixed selection, as in the case of removing energy and food prices for core inflation (HICPX), or through a selective process, for instance based on the percentiles of price growth recorded each month (trimmed mean or weighted median inflation). In 2020, the ECB published the Persistent and Common Component of Inflation (PCCI), a data-rich and model-based measure of underlying inflation.

In the same vein, this paper introduces the Underlying Composite Inflation (UCI), a novel indicator that estimates the inflation trend through a frequency-domain analysis of the comovement among HICP components. Unlike PCCI, UCI exploits the dynamic relationships between HICP components to produce more stable estimates of the latent medium- to long-term component of annual HICP variation. Furthermore, we employ the bootstrap methodology outlined in Giovannelli et al. (2023) to illustrate the uncertainty surrounding our UCI estimates.

The UCI methodology is applied at both the euro area and member state levels, offering novel insights into the recent inflationary cycle's cross-country dynamics. Measuring underlying inflation at the individual country level presents additional challenges due to the larger role of idiosyncratic factors. As illustrated in Figure 1b, core inflation rates in major euro area economies exhibit greater short-term volatility compared to the aggregate EA measure. By applying the UCI methodology at both the EA and national levels, this study aims to provide a more accurate assessment of inflation persistence and commonality across member states.

Unravelling the underlying dynamics of inflation has proved to be particularly challenging during the inflationary cycle observed since the pandemic outbreak, marked by exceptional volatility which makes it difficult to disentangle persistent inflation trends from temporary shocks. As illustrated in Figure 1, headline and core inflation rates have exhibited increased short-term noise and cross-country dispersion. Several factors have contributed to this volatility. The heterogeneous transmission of cost-push shocks has caused the pass-through of external price shocks to headline and core inflation to vary across member states. Fiscal and tax policies, being country-specific, can

*The views expressed are those of the authors and do not necessarily reflect those of the Bank of Italy or the Eurosystem. We are thankful to Fabio Busetti, Cristina Conflitti, Stefano Neri, Marianna Riggi, Alessandro Secchi, Fabrizio Venditti, Giovanni Veronese, Giordano Zevi and Roberta Zizza for useful comments and suggestions.

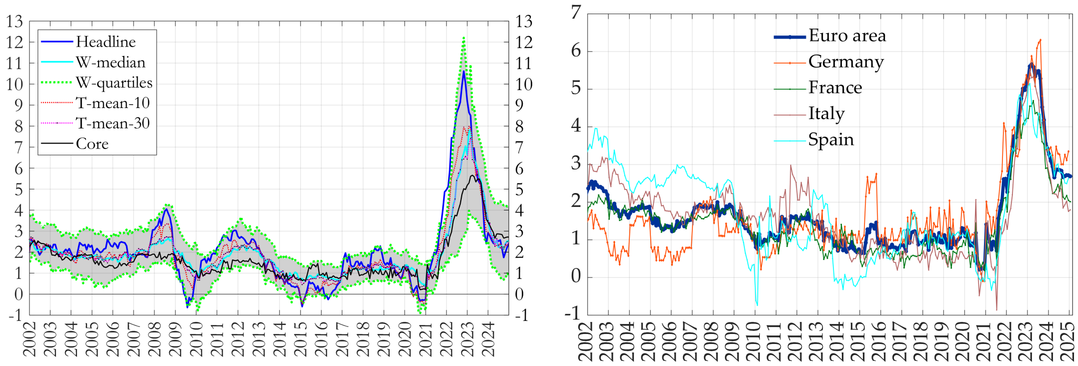
introduce short-term distortions in inflation data. Seasonal and technical factors, including changes in seasonal patterns and adjustments to HICP weights, have affected inflation measurements, potentially introducing temporary biases.

Given this plethora of one-off and sector-specific factors, exclusion-based measures may still be contaminated by transitory effects, failing to isolate medium-term inflation signals. While trimmed inflation indicators offer some respite to this issue by selectively excluding certain components, their effectiveness depends on period-specific selection criteria. This underscores the need for a robust model-based approach that takes advantage of the full sectoral breakdown of HICP to gauge underlying inflation.

We show that the UCI is a reliable indicator of underlying inflation, as its real-time estimates are minimally revised backward. Finally, the UCI has a good out-of-sample performance as a leading indicator of future headline inflation at several horizons, not only with respect to the exclusion-based indicators, but also with respect to the model-based PCCI indicator, which typically has very good leading properties.

Figure 1: Exclusion-based measures of underlying inflation

(a) distribution-based measures in the EA (b) core inflation in EA and main countries



Note: Calculations based on Eurostat data. The left-hand panel shows some distribution-based measures of underlying inflation, with the gray band indicating the range between the first and third weighted quartiles. The right-hand panel shows the y-o-y rates of core inflation in the euro area and in the major countries.

2 Data and methodology

We estimate UCI for both the EA and its major countries (Germany, France, Italy and Spain), by using the headline price index (HICP) and its detailed breakdown based on 4-digit ECOICOP components.[1] The estimation sample runs from January 2001 to December 2024. All the price indices are pre-treated to remove seasonal patterns and outliers and then transformed into annualized monthly growth rates.

HICP is the weighted sum of price sub-indices related to a representative consumption basket. A smooth common trend drives all price indices and originates from aggregated shocks plus idiosyncratic shocks. The latter hit the single price component

[1]We also use 3-digit ECOICOP when a finer breakdown is not available as of 2001.

and then propagate through the rest of the basket, with more or less dampened effects and with different lags. We use the Generalized Dynamic Factor Model (GDFM) as in Forni et al. (2005) to estimate the underlying signal of price inflation, interpreted as the smoothed common trend between HICP and its components' development.

The factor model splits the information carried by the observable variables x_{it}'s, $i = 1, \dots, N$, into two orthogonal processes:

$$x_{it} = \chi_{it} + \xi_{it} \tag{1}$$

i.e., the common χ_{it} and the idiosyncratic ξ_{it} components. χ_{it} is driven by a q-dimensional vector of common factors, with different loadings and lags:

$$\chi_{it} = b_{i1}(L)f_{1t} + \cdots b_{iq}(L)f_{qt} \tag{2}$$

and $\mathbf{f}_t = (f_{1t}, \dots, f_{qt})$ behave as autoregressive processes $A(L)\mathbf{f}_t = \mathbf{u}_t$. Equation (2) can be written in the static form:

$$\chi_{it} = c_{i1}F_{1t} + \cdots + c_{ir}F_{rt} \tag{3}$$

given $\mathbf{F}_t = (\mathbf{f}'_t, \mathbf{f}'_{t-1}, \dots, \mathbf{f}'_{t-s})$. The χ_{it}s can be further split into low- and high-frequency components:

$$\chi_{it} = \chi^{\phi}_{it} + \chi^{\psi}_{it} \tag{4}$$

with corresponding spectral matrices $\Sigma_\chi(\theta)$, $\Sigma_\phi(\theta)$ and $\Sigma_\psi(\theta)$ and covariance matrices Γ_χ, Γ_ϕ and Γ_ψ.

The UCI aims to track the smooth underlying trend of the price evolution. More formally, given the decomposition of HICP into two orthogonal low- (c_t) and high-frequency components (s_t):

$$HICP_t = c_t + s_t \tag{5}$$

The UCI is obtained as the projection of the target c_t on the smoothed approximation of the factor space $G_\phi(F_t)$:

$$UCI_t = Proj(c_t | G_\phi(F_t)) \tag{6}$$

Following Forni et al. (2000) and Brillinger (1981), we estimate the spectral matrices $\hat{\Sigma}_\phi(\theta)$ and $\hat{\Sigma}_\xi(\theta)$.[2] The corresponding covariance matrices $\hat{\Gamma}_\phi$ and $\hat{\Gamma}_\xi$ are computed by integrating over the frequency band $[-\pi/6, \pi/6]$.[3] Then we take the eigenvectors corresponding to the largest r eigenvalues of the pair of matrices $(\hat{\Gamma}_\phi, \hat{\Gamma}_x)$ to estimate $G_\phi(F_t)$ by principal components. We refer to Altissimo et al. (2010) to estimate (6).

The UCI is reported in both year-on-year changes and 3-month annualized (UCI-

[2]Using a Bartlett lag-window estimator.
[3]The frequency components with periodicity lower than one year are filtered out.

3m).[4] The latter transformation accounts for the short-term evolution of inflation without blurring the signal with excessive short-run volatility.

Measuring underlying inflation with model-based approaches has a long tradition, renewed during the recent years of price upsurges. Cristadoro et al. (2005) estimated a GDFM on a large panel of real and nominal macroeconomic indicators. This approach may encounter difficulty when the relationship between real and nominal variables breaks, as may happen in the aftermath of an inflation regime shift. In this respect, our model based only on nominal variables, i.e. a fine breakdown of HICP, is less affected by the instability of the estimates implied by the time-varying correlations between nominal and real indicators.

Our methodology also differs from Conflitti (2020), in that the UCI is entirely estimated in the frequency domain (in order to exploit the full dynamic covariance structure of the dataset) and it is based only on the smoothest approximation of the common factors' space.[5]

The closest competitor is the Persistent and Common Component of Inflation (PCCI), introduced in Bańbura and Bobeica (2020), that adds to the ECB's toolbox for tracking the underlying trend of inflation, in the spirit of Lane (2023): "There are no short cuts in the analysis of underlying inflation, which requires a comprehensive multi-variate and multi-method assessment." PCCI is the weighted sum of the low-frequency common components,[6] which are estimated from a large dataset of HICP's four-digit ECOICOP classes from 12 EA countries. The weights are those provided by Eurostat for each item in the HICP's consumption basket and for each country in the EA HICP. UCI is instead the projection of the (unobservable) medium- to long term component of HICP on the space spanned by the aggregated common shocks, that explains the comovement of the HICP items in a specific low frequency band, as in (6). Therefore, the UCI sticks to the path of the HICP, and this is the reason why our indicator displays some valuable properties in terms of reliability of the real-time estimates and forecasting ability, as shown in the following sections.

3 Results

3.1 Estimates for EA and major countries.

The UCI is estimated for both the headline (HICP) and the core price index (HICPX)[7] of the EA and its four major countries.

[4] The 3-month annualized inflation rate is computed as the annualized rate of price change between the t and $t-3$, where t is the current month.

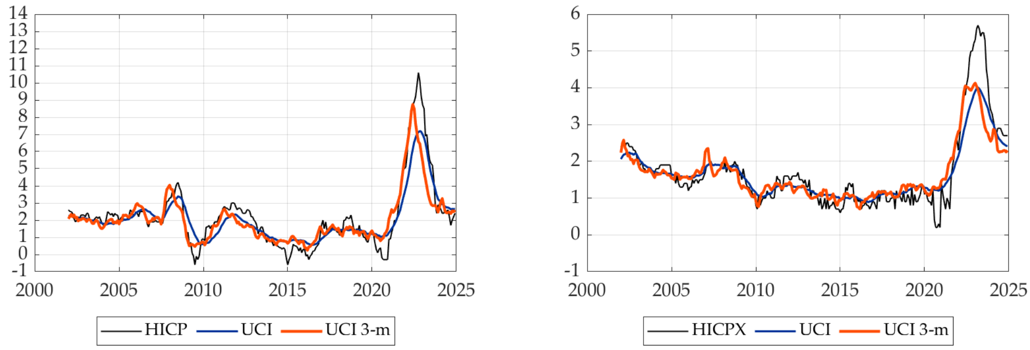
[5] Conflitti (2020) proposes an additional measure of underlying inflation for the euro area (core cycle measure), that exploits the Phillips curve setting to distinguish between inflation components more linked to the economic cycle from other components driven by category-specific developments.

[6] With periodicity greater than 3 years.

[7] HICPX defined as all items except for energy and food components, i.e. the core components.

Figure 2: Trend inflation for EA: UCI y-o-y and 3-month annualized

(a) all items (b) core



Note: UCI 3-month annualized is the annualized rate of price change between t and $t-3$, where t is the current month.

Figure 2 presents the results that refer to UCI for the EA only. UCI year-on-year growth (UCI y-o-y, blue line) smooths HICP y-o-y effectively and provides a coincident estimate of the underlying inflation. The smoothing effect is even more pronounced with respect to the HICPX y-o-y (black line). In fact, the latter is quite volatile despite removing energy and food components. UCI 3-month annualized (UCI 3m; red line) exhibits a slightly coarser shape than UCI y-o-y, still it is less noisy than HICP(X) y-o-y and somewhat leads the inflation trend. This property turns out to be suitable for forecasting price evolution (see Section 4). Focusing on the period since 2020, UCI indicators reveal that the onset of the pandemic had a negligible impact on inflation trends. Throughout 2020, there were no significant shifts in underlying inflation, as most fluctuations proved to be transitory. However, the picture changes in 2021 when energy prices surged notably, and supply-chain bottlenecks affected industrial production and logistics. The combined impact of these shocks swiftly impacted headline inflation in the euro area, with core inflation experiencing a more gradual increase. Throughout 2022, UCI indicators continued to rise in the EA, influenced by the persistent and widespread impact of energy shocks on the core components, peaking in Q1:2023 and then starting to decrease gradually.

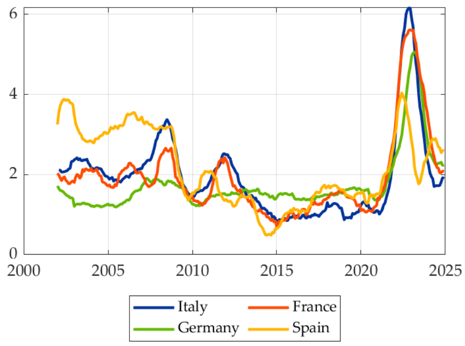
It is worth looking at the UCI for Germany, France, Italy and Spain as well, to get a sense of the synchronicity of the inflation trends across countries accounting for 75% of total EA HICP.

After a prolonged period of low inflation from 2013 to 2020 in most countries, UCI indicators in the EA and its major economies began to rise from 2021 onward, peaking in late 2022 and early 2023 before declining steadily thereafter. In Italy, France, Spain, and the euro area as a whole, the cyclical pattern of UCI indicators has followed a broadly similar trajectory in recent years, albeit with differences in peak levels, particularly for all-items indicators, which include the heterogeneous fluctuations in energy and food inflation.[8]

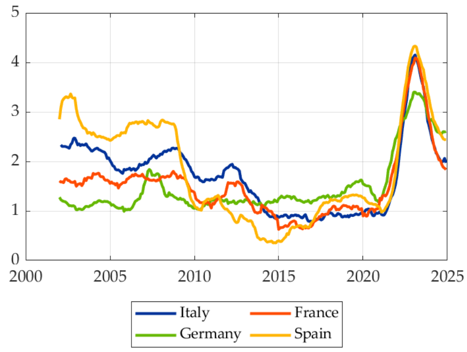
Germany, however, has exhibited a distinct pattern: while the core UCI indicator increased at a faster pace, it reached a lower peak. Price dynamics in Germany in recent years have been heavily influenced by specific and temporary factors, such as government interventions to reduce transport service prices.[9] As a result, a significant divergence emerged between the underlying inflationary pressures measured by the UCI indicator and the official core inflation series.

Figure 3: Trend inflation for EA major countries: UCI y-o-y

(a) all items



(b) core



3.2 In-sample assessment

Through an in-sample analysis and using the ECB's PCCI as a benchmark, we assess the UCI's goodness of fit with respect to the target, i.e. the (unobservable) underlying trend of inflationary pressures, its "attractor" properties for HICP(X) and the reliability of its real-time estimates.

The optimal estimate of the target is the unfeasible infinite centered moving average of HICP:

$$c_t = \sum_{k=-\infty}^{k=\infty} \gamma_k y_{t-k}, \quad \gamma_k = \begin{cases} \frac{\sin(k\pi/6)}{k\pi}, & k \neq 0 \\ 1/6, & k = 0 \end{cases} \tag{7}$$

The best finite-sample approximation of this ideal band-pass filter was proposed in Baxter and King (1999), but the truncation entails poor estimates at the endpoints of the sample. Therefore, we can only use the in-sample estimate of the band-passed HICP,

[8]Idiosyncratic volatility has a stronger impact on overall price developments in individual countries, as they are more exposed to transitory factors (e.g., the effects of fiscal measures). By contrast, its influence on euro-area inflation is smaller, given that the latter results from a weighted aggregation of national price indices.

[9]For example, in the summer of 2023, services inflation in Germany surged due to substantial base effects. Between June and August 2022, public transport prices had been significantly lowered under the government's "9-Euro Ticket" initiative, aimed at alleviating inflationary pressures on households. Furthermore, in response to the COVID-19 pandemic, the German government temporarily reduced indirect taxes on certain goods and services, such as restaurant services, leading to short-term distortions in core inflation.

i.e. $\hat{c}_t$, as a benchmark to evaluate the goodness of fit of UCI with respect to the target. The estimates from the following regression:

$$UCI_t = \alpha + \beta \hat{c}_t + \epsilon_t \tag{8}$$

prove a statistically significant and tight relation between UCI and the target (see Table 1), in that a unit variation in the latter translates into a change of 0.7 in UCI headline and 0.9 in UCI core. The relation with the target explains approximately 70% and 90% of the variance of UCI and UCI core, respectively.

Measuring the ability to attract inflation adds to the validation of UCI as a proper indicator of underlying trend. According to the following relation (as used also by Bańbura and Bobeica (2020)):

$$\pi_{t+h} - \pi_t = \alpha + \beta(\pi_t^u - \pi_t) + \epsilon_{t+h} \tag{9}$$

the inflation rate, π_t, tends to revert to its underlying trend at time $t+h$. As shown in Table 1, UCI behaves well as an attractor of inflation, notably the UCI-3m transformation, which outperforms PCCI for both headline and core inflation. Indeed, UCI-3m turns out to be the best predictor of inflation, as we will discuss in Section 4. Overall, these results support UCI as an early indicator of the inflation trajectory, which is particularly desirable during periods of high volatility when it is more difficult to understand where inflation is headed.

For the UCI to be employed as a reliable tool for the conjunctural assessment of price dynamics, its real-time estimates should be stable and not revised much backward as new information enters the dataset. Figures 4 and 5 show the real-time estimates of UCI y-o-y and of PCCI from November 2018 until December 2024. The "tentacles" in UCI's plot are quite close to each other, while the profile of PCCI instead tends to be revised backward significantly. The real-time estimates of PCCI were adjusted largely during the surge of inflation after 2020. The average revision of PCCI peaked in 2022 at 0.1 percentage points against the negligible average revision of the UCI.

Figure 4: Real time estimates of UCI y-o-y for Euro Area

(a) all items (b) core

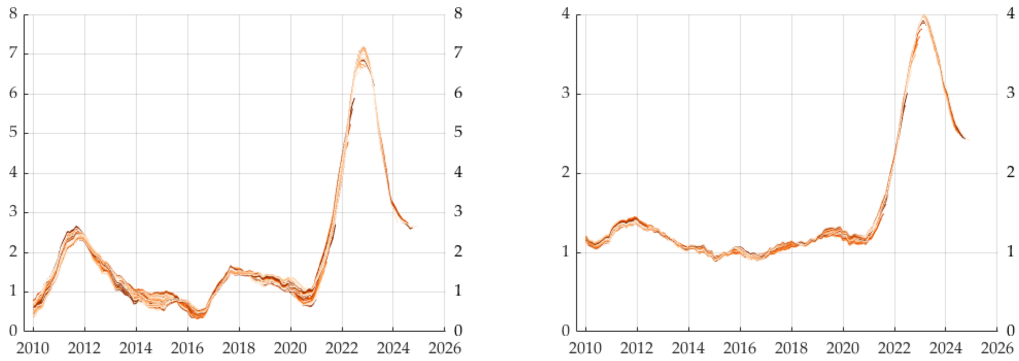
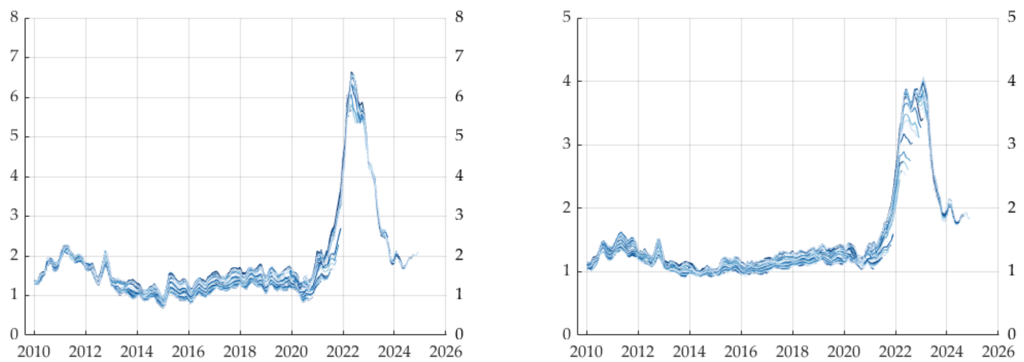


Figure 5: Real time estimates of PCCI for Euro Area

(a) all items (b) core



Note: PCCI is computed as 3-month moving average of the annualized m-o-m changes.

Table 1: In-sample sssessment of UCI

	Attractor properties (1)		**Goodness of fit** (2)		**Revisions** (3)
Indicator	α	β	R^2	β	[min, max]
UCI	0.29	1.11	0.81	0.83	-0.20, 0.35
UCI core	0.52	0.71	0.76	0.89	-0.07, 0.10
UCI 3m	0.20	2.03	0.78	0.85	-0.43, 0.91
UCI core 3m	0.56	0.86	0.68	0.89	-0.11, 0.25
PCCI	0.18	1.15	0.40	0.55	-0.28, 0.45
PCCI core	0.50	0.76	0.40	1.11	-0.17, 0.32
HICPX	0.57	0.76	-	-	-
HICPXX	0.62	0.83	-	-	-
Supercore	0.40	0.77	-	-	-

Note: (1) the displayed attractor properties are obtained by estimating equation 9 separately for each indicator π^u_t, using headline inflation π_t as the target and $h = 12$; (2) the target is the band-pass filtered y-o-y inflation with period higher than one year (corresponding to cut the fluctuations in the frequency band $[0, \pi/6]$, estimated as in Baxter and King (1999); (3) min and max of the revisions of each indicator $\pi^u_{t|t+1} - \pi^u_{t|t}$.

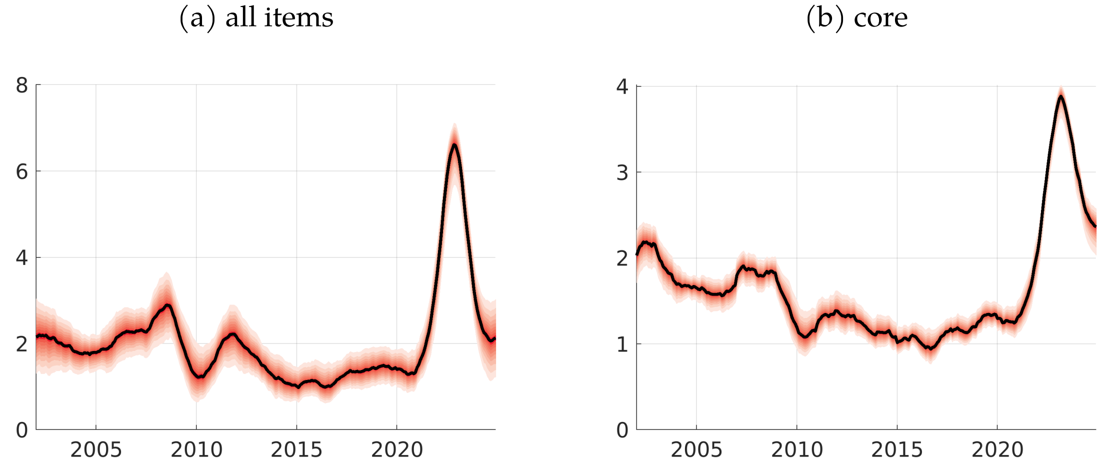
As reported in Table 1, EA UCI y-o-y's range of revisions is much narrower than PCCI's and spans between -0.2 and 0.3 for the headline and between 0.0 and 0.1 for the core ([-0.3,0.45] and [-0.2,0.3] for PCCI headline and core, respectively). The stability of the UCI real-time estimates is particularly remarkable for UCI core, and it is a striking improvement from the corresponding PCCI. In 2022, PCCI core tended to signal a turning point too early, when inflation had yet to peak.

3.3 Density estimates

This section presents a measure of uncertainty around the point-estimates of UCI, that translates into uncertainty surrounding our expectations on the inflation trajectory and our forecast of the price evolution.

As in Giovannelli et al. (2023), we run a bootstrap to estimate the sampling distribution of UCI. For each iteration, we draw the spectral density matrix from a complex Wishart distribution (see Brillinger, 1981) with $\nu = T/M_T * \log(M_T + 1)$ degrees of freedom, where M_T is the width of the Bartlett lag-window estimator of the spectral density, and scale matrix $\Sigma_\phi(\theta)/\nu$, i.e. $\hat{\Sigma}_\phi(\theta) \sim W_C(\nu, \Sigma_\phi(\theta)/\nu)$. Then we compute the corresponding covariance matrix Γ_ϕ and estimate UCI as in Section 2. Figure 6 shows the density estimates for UCI y-o-y headline and core. The former are more widespread, owing to the higher volatility of HICP compared to HICPX y-o-y. In general, the uncertainty band tends to enlarge at the turning points. It is thin around the steep increase of inflation in the aftermath of the pandemic, while it enlarged when HICP y-o-y peaked in October 2022 and was about to turn toward a descending path.

Figure 6: Density estimates of UCI y-o-y for Euro Area



Note: the red bands represent the 95% interval estimates for the UCI obtained using the bootstrap technique, while the black line denotes the median estimate.

4 Forecasting application

We conduct a (pseudo) real-time forecasting exercise using a direct forecast scheme to evaluate the predictive power of the UCI relative to a set of benchmark measures of underlying inflation across different forecast horizons.

We employ the following univariate regression models, without an intercept, for each specific horizon H:

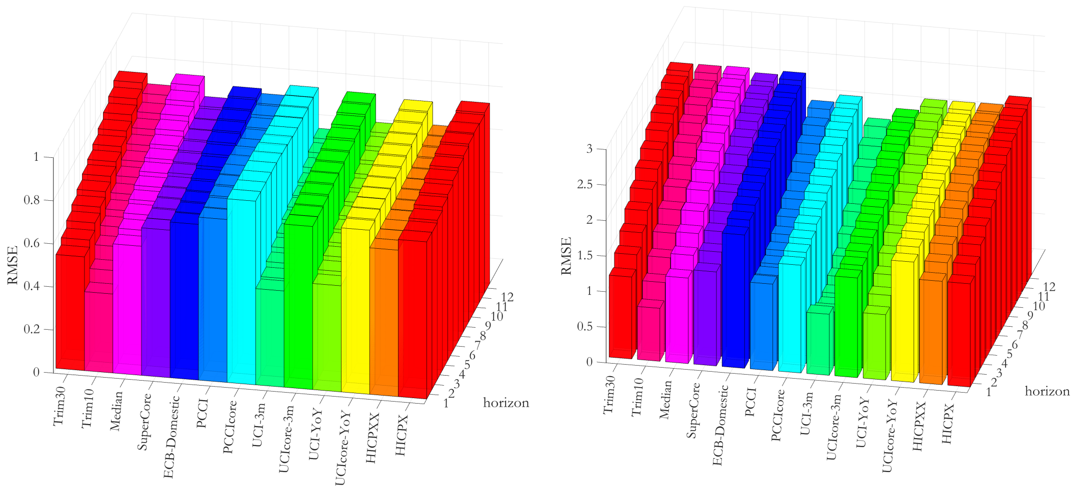
$$\pi_t = \beta(\pi^u_{t-H}) + \epsilon_t. \tag{10}$$

where π_t is headline inflation and π^u_{t-H} is a lagged indicator of underlying inflation. For a given H, we estimate these models using recursive (rolling) samples, starting in 2003, with the end of the sample (T) ranging from 2013 to 2024. For each sample ending in T, we predict headline inflation on the horizon $T + H$. We assess forecast accuracy using the root mean squared error (RMSE), a standard metric for point forecasting evaluation. We also conduct the exercise with a sample ending in 2019 to exclude the recent period of inflation fluctuations.

The results, shown in Figure 7 and Table 2, indicate that both UCI and UCI-3m consistently outperform alternative measures in terms of forecast accuracy. This advantage holds not only against exclusion-based measures, but also against model-based alternatives, such as the PCCI indicator. The UCI exhibits superior performance across all tested horizons, and the predictive accuracy of UCI-3m turns out to be outstanding as it yields the lowest RMSE. Notably, the UCI exhibits minimal revisions during the high inflation period of 2022-2023 (as shown in Section 3.2), while also showing significantly better predictive performance during that time. Moreover, the strong performance of the UCI persists even when using only the pre-COVID sample (Figure 7, left-hand panel and Table 3).

Figure 7: Root mean squared error

(a) 2003-2019 (b) 2003-2024



Note: root mean square errors, computed using the rolling forecasts produced by estimating equation 10 for headline inflation π_t, are reported on the z-axis, for each indicator π^u_t (x-axis) and each horizon h (y-axis).

Table 2: Root mean squared errors, 2003-2024

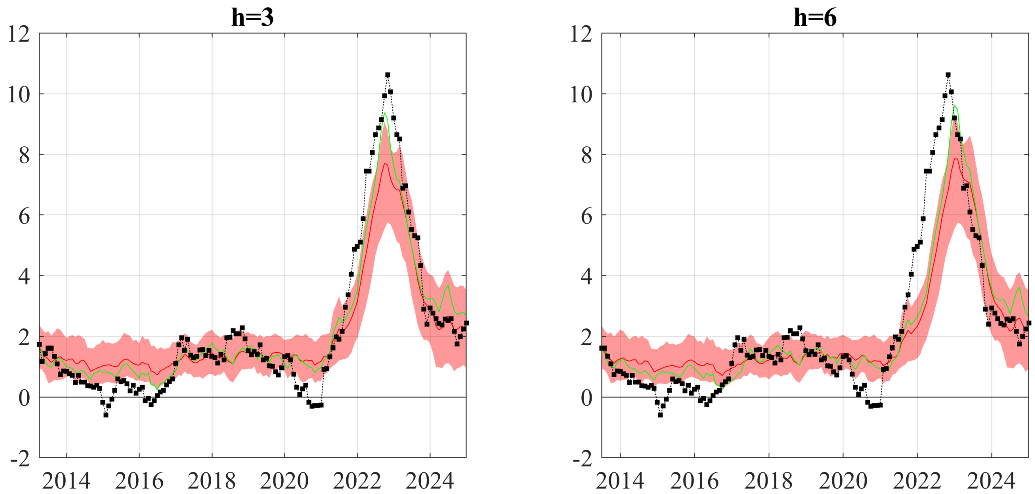
	HICP X	HICP XX	UCI core	UCI	UCI core 3m	UCI 3m	PCCI core	PCCI	Dom	Sup Core	Med	Trim 10	Trim 30
h=1	1.45	1.45	1.69	0.92	1.40	0.86	1.52	1.22	1.88	1.32	1.20	0.74	1.15
h=2	1.59	1.58	1.77	1.05	1.44	0.76	1.56	1.20	1.95	1.47	1.39	0.97	1.33
h=3	1.73	1.70	1.84	1.21	1.50	0.71	1.62	1.22	2.02	1.61	1.56	1.19	1.51
h=4	1.86	1.82	1.92	1.36	1.57	0.74	1.69	1.28	2.10	1.76	1.73	1.40	1.68
h=5	1.99	1.93	1.99	1.52	1.64	0.84	1.77	1.37	2.17	1.90	1.89	1.59	1.85
h=6	2.10	2.04	2.06	1.68	1.72	0.99	1.86	1.48	2.24	2.03	2.04	1.77	2.00
h=7	2.21	2.14	2.13	1.83	1.81	1.16	1.95	1.60	2.31	2.16	2.18	1.95	2.13
h=8	2.31	2.22	2.19	1.97	1.90	1.35	2.04	1.72	2.38	2.27	2.30	2.12	2.26
h=9	2.38	2.29	2.24	2.09	1.99	1.53	2.12	1.85	2.43	2.36	2.41	2.27	2.37
h=10	2.42	2.33	2.28	2.20	2.07	1.71	2.20	1.98	2.48	2.43	2.48	2.39	2.45
h=11	2.46	2.35	2.32	2.28	2.13	1.87	2.26	2.09	2.52	2.48	2.54	2.49	2.52
h=12	2.49	2.35	2.35	2.35	2.18	2.01	2.30	2.20	2.57	2.52	2.58	2.57	2.57

Table 3: Root mean squared errors, 2003-2019

	HICP X	HICP XX	UCI core	UCI	UCI core 3m	UCI 3m	PCCI core	PCCI	Dom	Sup Core	Med	Trim 10	Trim 30
h=1	0.73	0.68	0.76	0.49	0.76	0.45	0.85	0.76	0.72	0.69	0.60	0.37	0.53
h=2	0.73	0.68	0.77	0.51	0.76	0.46	0.85	0.76	0.73	0.69	0.63	0.43	0.56
h=3	0.74	0.68	0.77	0.53	0.76	0.48	0.85	0.77	0.73	0.69	0.65	0.49	0.60
h=4	0.76	0.68	0.77	0.55	0.77	0.51	0.85	0.78	0.74	0.70	0.67	0.54	0.62
h=5	0.77	0.68	0.78	0.57	0.78	0.53	0.85	0.78	0.75	0.70	0.69	0.57	0.65
h=6	0.79	0.69	0.78	0.59	0.78	0.54	0.85	0.78	0.76	0.72	0.71	0.60	0.68
h=7	0.80	0.69	0.79	0.60	0.79	0.56	0.84	0.77	0.77	0.72	0.73	0.64	0.70
h=8	0.82	0.69	0.79	0.63	0.79	0.57	0.83	0.77	0.79	0.73	0.75	0.67	0.73
h=9	0.83	0.70	0.80	0.65	0.80	0.58	0.83	0.76	0.79	0.74	0.78	0.70	0.75
h=10	0.83	0.70	0.81	0.66	0.82	0.61	0.84	0.77	0.80	0.74	0.80	0.72	0.78
h=11	0.83	0.71	0.81	0.68	0.83	0.63	0.84	0.79	0.81	0.75	0.82	0.75	0.81
h=12	0.84	0.71	0.82	0.70	0.84	0.65	0.84	0.79	0.82	0.76	0.85	0.80	0.84

As an additional exercise, we use the density estimates described in Section 3.3 to assess the uncertainty surrounding the predictive power of UCI-3m, which exhibits the strongest point forecasting performance among the underlying inflation indicators across multiple horizons. In this case as well, the forecasting design follows a rolling window approach and a direct forecasting strategy. We generate out-of-sample forecasts at 3- and 6-month horizons using 2,000 simulations of the UCI-3m density, computing the forecasts for each horizon and each simulation.

Figure 8: Density forecasting exercise using UCI-3m



Note: The black dotted line indicates the actual values of headline inflation. The red bands represent the 95% interval estimates for the hh-step-ahead forecasts of headline inflation, while the red line denotes the median forecast and the green line represents the forecast based on the UCI point estimate.

The results (Figure 8) indicate that even during periods of increased volatility, when the UCI point estimate loses predictive accuracy, the interval estimate remains effective in capturing the inflation evolution.[10]

These findings have important implications for monetary policymakers, as they highlight the value of the UCI in uncertain environments, when inflationary dynamics arise from overlapping demand and supply shocks.

5 Conclusion

This paper introduces the Underlying Composite Inflation (UCI), a novel model-based indicator that enhances the measurement of underlying inflation in the euro area. The UCI provides a more stable and reliable inflation signal compared to both exclusion-based and model-based alternatives, offering a clearer distinction between transitory and persistent inflationary pressures.

By applying the UCI methodology at both the euro area and the national level, we address the challenges posed by short-term fluctuations in inflation data and uncover new insights into cross-country inflation trends.

These results highlight the practical relevance of the UCI for real-time inflation monitoring and monetary policy decisions, with potential applications to improve inflation forecasting models and risk assessment frameworks.

[10]Bootstrap confidence intervals are consistent under more general assumptions (Gaussianity is not required). For such a reason, bootstrap prediction intervals are more effective in capturing skewness (Goncalves et al., 2017) and they are asymmetric around UCI indeed, notably during more volatile and uncertain periods.

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