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The analyses, opinions and findings of these papers represent the views of the authors, they are not necessarily those of the Banco de Portugal or the Eurosystem.

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Navigating with a compass: Charting the course of underlying inflation

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Abstract

We propose a novel tool to gauge price pressures resorting to circular statistics, the so-called inflation compass. We show that it provides a reliable indication on inflationary pressures in the euro area by focusing on key episodes of high and low inflation since the monetary union inception. Unlike most alternative measures of underlying inflation, the inflation compass does not exclude any subitems of inflation, ensuring that all disaggregated information is taken on board. Moreover, it is not subject to revisions, providing policymakers with real-time signals about the course of underlying inflation, while being easily understood and visually appealing. We also provide evidence of the usefulness of the inflation compass to forecast overall inflation up to 36 months ahead, even during periods of increased turbulence, such as those marked by the COVID-19 pandemic or the recent inflation surge. Our findings indicate that the inflation compass surpasses other widely used measures of underlying inflation for the euro area, leading to statistically significant improvements in forecast accuracy. Lastly, we show that our approach can handle large-dimensional data by leveraging on finer product-level and country-level data. In such environment, the inflation compass still exhibits higher accuracy, underscoring its robustness and reliability.

JEL: C53, C55, E31, E37.

Keywords: Inflation compass; Underlying inflation; Circular statistics; Large datasets; Forecasting.

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"Our compass is price stability. We will stay riveted to that compass as we fight inflation to deliver stable prices for people across Europe." Christine Lagarde, Brussels, September 26, 2022

"Underlying inflation is not a policy target, but measures of underlying inflation can serve as a complementary cross-check of our forecasting process." Christine Lagarde, Frankfurt am Main, March 22, 2023

1. Introduction

Central bank mandates vary in scope, encompassing the maintenance of price stability, the promotion of full employment, and the fostering of economic growth, among others. Nonetheless, a prevailing characteristic shared by central banks worldwide is the unwavering attention to monitoring inflation dynamics. In the recent past, this became even more evident as inflation recorded levels not seen for decades, triggering renewed discussions among inflation targeters, e.g., the US Federal Reserve, the European Central Bank (ECB), the Bank of Japan, the Bank of England, to name a few.

The growing interest by central banks in gauging the persistence of price changes in a timely manner has reinforced the development of new methods to filter incoming data on aggregate prices. Thus, several tools have been proposed in the literature to extract relevant information from granular data, leading to the construction of different underlying inflation measures aimed at discarding transitory price movements and capturing the subjacent trend in prices. By closely monitoring them, policymakers can anticipate shifts or rapid reversals in the overall pace of inflation, both in periods of upward and downward price pressures.

Despite their value to guide monetary policy decisions, the lack of a consensus on a preferred instrument to track price pressures still persists. However, it is widely acknowledged that these measures ought to have desirable properties, such as the accuracy in tracking overall inflationary pressures, the ability to be computed in real-time, the lack of revisions, or the forecasting performance within a regression framework. Previous work has examined some of these properties (see inter alia, Bryan and Cecchetti (1994); Bryan *et al.* (1997); Bakhsi and Yates (1999) and Dolmas (2005)). See also Clark (2001), Cogley (2002), Marques *et al.* (2003), Rich and Steindel (2007) or Wynne (2008) for the United States, Roger (1997) for New Zealand, Hogan *et al.* (2001) for Canada and Mankikar and Paisley (2002) for the United Kingdom. More recently, central banks have shown a renewed and heightened interest in this issue as illustrated by the resurgence of work along this line (for example, Luciani and Trezzi (2019) or Luciani (2020) for the United States and Pincheira-Brown *et al.* (2019) for Latin America countries).

In the euro area, the ECB has set as primary objective the maintenance of price stability, which entails keeping inflation at a low, stable, and predictable level around 2%. Monetary policy prescriptions have thus relied on the assessment of the

inflation outlook, considering incoming economic and financial data, the dynamics of inflation, and the effectiveness of monetary policy transmission. More than ever before, the recent surge in euro area inflation from 1% at the start of 2021 to 10% by the autumn of 2022 drew attention to the need of monitoring closely underlying inflation measures. Ehrmann *et al.* (2018) provide a comprehensive overview of the tools typically tracked by the ECB to monitor inflation developments. These include permanent-exclusion measures such as the Harmonised Index of Consumer Prices (HICP) excluding energy and unprocessed food, the HICP excluding energy and food, and the HICP excluding energy, food, travel-related items, clothing and footwear. Additionally, there are temporary-exclusion measures including trimmed means and the weighted median, as well as frequency-exclusion ones. Examples of the latter include the Supercore and the Permanent and Common Component of Inflation (PCCI).

We depart from the existing literature on underlying inflation measures by proposing a novel tool to gauge price pressures resorting to circular statistics, the socalled inflation compass. Even though the use of circular statistics is not recurrent in economics, recent work has evidenced their usefulness in inferring the business cycle stance, as shown in Lourenço and Rua (2023). Unlike previous literature on core inflation, we take a different perspective by bringing on board the information from every subitem of the HICP basket. In particular, we retain the inflation level and the change in the inflation rate corresponding to each subitem, and convert such information to angular data. By assigning the HICP weights to this granular data, we can determine an overall direction and gain insights into the underlying price pressures in the economy. That is, starting with the HICP elementary items, we extract an angle for each subitem, and subsequently determine a weighted mean direction that summarises the different price pressures in the consumption basket.

Such an approach leads to a compass representation, allowing to infer whether inflation is approaching the target as well as the directional change of price pressures, i.e., whether price pressures are accelerating or decelerating. In our application, we illustrate the compass for key episodes of high and low inflation in the euro area, showing that it provides informative signals on inflationary pressures since the monetary union inception. Unlike most alternative measures, the compass does not exclude any subitems of inflation, ensuring that all available information is used. On top of that, it is not subject to revisions, providing policymakers with a reliable real-time assessment. As a by-product, we take advantage of the properties of the inflation compass to shed light on the periods during which underlying inflation did not deviate from 2%, thus providing a characterisation of the full spectrum of price pressures in the euro area.

In addition to its qualitative informational content in gauging price pressures, we provide evidence of the usefulness of the inflation compass for forecasting overall inflation up to 36 months ahead. In particular, we assess the performance both insample and out-of-sample of several underlying inflation measures. To address this, we adopt the usual econometric specification relating future changes in inflation to the transitory component of price changes identified by the underlying inflation

measure. This regression framework not only has the advantage of being simple to interpret but is also flexible enough to incorporate alternative horizons into the analysis. Quantitatively, we find that the inflation compass outperforms the underlying inflation measures typically tracked in the euro area in a forecasting framework and that the accuracy gains are, in general, statistically significant.

As a robustness analysis, we provide evidence that the inflation compass delivers higher accuracy than the other measures, even during challenging and turbulent periods like the COVID-19 pandemic and the subsequent inflation surge. Furthermore, as our approach can handle straightforwardly large-dimensional data, we enlarge our initial dataset, which already comprises almost one hundred series, by considering two variants of data disaggregation. Firstly, we consider more detailed product-level data entailing nearly three hundred HICP subitems. Secondly, we consider country-level data, as opposed to aggregate euro area data, which enables us to consider more than one thousand HICP series. Notably, the inflation compass is robust to these data-rich environments as the results reaffirm its superior performance.

The remainder of the paper is organised as follows. Section 2 discusses the main building blocks behind the inflation compass representation. Section 3 describes the data. In Section 4, the empirical application is conducted. Section 5 evaluates the forecasting performance of the novel approach against other underlying inflation measures commonly tracked in the euro area and Section 6 provides a robustness analysis. Finally, Section 7 concludes.

2. The circular statistics approach

As alluded above, we depart from previous literature by addressing underlying inflation measurement from a different angle using literally angles. In fact, any point in the Cartesian coordinate plane defined as (x_i, y_i) can be displayed in the polar coordinate system by a distance from the origin r_i and an angle θ_i as illustrated in Figure 1.

These conversions are conducted using sine and cosine trigonometric functions, drawing on the relationships $\cos \theta_i = \frac{x_i}{r_i}$ and $\sin \theta_i = \frac{y_i}{r_i}$. The mathematical convention for angular measures in statistics typically uses the polar angle, where the angle is measured counterclockwise from the positive x-axis (pointing East) to the line segment connecting the origin to a given point. Naturally, a rotation in the opposite direction to the conventional results in a negative angle. In this case, negative angles are subtracted from 360° to convert them to the corresponding positive angles.



Figure 1: Angle reading example in the Cartesian plane.

Considering a sample of N angles, i.e., $\theta_1, \theta_2, ..., \theta_N$, we end up with N observations, each with a given direction. Sample moments can be derived from the distribution of the angles, however these require the use of methods tailored for circular data.¹ For instance, directions of 0° and 360° have the same meaning, but the sample mean computed in a linear scale would yield 180° , thus pointing in the opposite direction.² Hence, due to the geometrical properties of circular data, these cannot be treated in the same way as linear data. Whereas linear data can be represented on a straight line, the natural support to represent circular data is on the circumference of a unit circle. The unit circle can be divided into four quadrants, each of them representing a range of angles as depicted in Figure 2.

In our setting, we end up with an angle corresponding to every inflation subitem. In particular, the angle θ_i for item *i* can be determined by setting the value of x_i as the change in the inflation rate for item *i* and y_i as the observed inflation rate for item *i* subtracted to 2%. That is, θ_i corresponds to the Cartesian coordinates given by $\Delta \pi_i$ and π_i minus 2%, respectively. The rationale for the latter normalisation lies in the fact that the ECB's Governing Council, after concluding its strategy review in 2021, considered that price stability is best maintained by aiming for 2% inflation over the medium term. Therefore, this transformation allows for a more appealing interpretation of the directions pointing towards 0° or 180°, where inflation would be on target.³ This implies that the counterclockwise movements

^{1.} An overall treatment of circular statistics can be found, for example, in Fisher (1993), Mardia and Jupp (2000) and Jammalamadaka and SenGupta (2001).

^{2.} Note that circular data can be measured either in degrees, in the interval between 0° and 360° , or in radians, in the interval between 0 and 2π , where the relationship between both is given by $\frac{\theta_{degrees}}{360^{\circ}} = \frac{\theta_{radians}}{2\pi}$.

^{3.} For the sake of simplicity, throughout the paper, we refer to a 2% inflation target, even though we are aware of the previous quantitative definitions of price stability. These include the one in place after Dec-1998: "Price stability shall be defined as a year-on-year increase in the Harmonised Index of Consumer Prices (HICP) for the euro area of below 2%. Price stability is to be maintained over

around the unit circle can be interpreted as follows. In the first quadrant, lying in the upper right part of the circle, where the angle is between 0° and 90° , inflation is above the target. As we move along this quadrant, price pressures build-up with inflation increasing until it attains a local maximum denoted with the 90° angle. Transitioning into the second quadrant, which spans from 90° to 180° , inflation continues to remain above the target. However, prices start to decelerate as we progress along this quadrant until inflation reaches the target with the angle at 180° . Entering the third quadrant, which covers the range from 180° to 270° , inflation is below the target. Here, price pressures continue to decelerate as we move further along this quadrant until inflation hits a local minimum with the angle at 270° . Finally, in the fourth quadrant, spanning from 270° to 360° , prices are accelerating. As we rotate through this quadrant, inflation increases until it reaches the target again.



Figure 2: Inflation compass reading.

As our object of interest is not inflation at the granular level, but the underlying trend in overall inflation, we focus on the mean angle. Given that the headline inflation rate is a weighted average of subitems whose weights reflect the relative importance of each item in the consumption basket, we compute the weighted average of the angles of those subitems. More formally, for a sample of N angles, i.e., $\theta_1, \theta_2, ..., \theta_N$, the computation of the weighted mean angle $\overline{\theta}_{\omega}$ requires to compute the rectangular coordinates

$$\overline{X}_{\omega} = \frac{1}{N} \sum_{i=1}^{N} \omega_i \cos \theta_i \tag{1}$$

the medium term" and the ex-post clarification of the same definition in 2003 to "below, but close to 2% over the medium term."

$$\overline{Y}_{\omega} = \frac{1}{N} \sum_{i=1}^{N} \omega_i \sin \theta_i$$
⁽²⁾

and the resulting length of the mean vector

$$r = \sqrt{\overline{X}_{\omega}^2 + \overline{Y}_{\omega}^2} \tag{3}$$

where ω_i corresponds to the weight of item *i* in the computation of the headline inflation. The weighted average angle, $\overline{\theta}_{\omega}$, can be determined using the cosine and sine trigonometric functions, likewise mentioned before, using

$$\cos \overline{\theta}_{\omega} = \frac{\overline{X}_{\omega}}{r} \tag{4}$$

$$\sin\overline{\theta}_{\omega} = \frac{\overline{Y}_{\omega}}{r}.$$
(5)

To put it simply, $\overline{\theta}_{\omega}$ can be obtained as

$$\overline{\theta}_{\omega} = \operatorname{atan2}\left(\sum_{i=1}^{N} \omega_{i} \sin \theta_{i}, \sum_{i=1}^{N} \omega_{i} \cos \theta_{i}\right),$$
(6)

or alternatively, it can be computed as

$$\overline{\theta}_{\omega} = \arg\left(\sum_{i=1}^{N} \omega_i e^{i\theta_i}\right).$$
(7)

The resulting $\overline{\theta}_{\omega}$ measure provides the overall direction underlying all inflation subitems at each point in time. Hence, the rotation of the direction given by $\overline{\theta}_{\omega}$ around the unit circle provides insights on the evolving underlying inflationary pressures.

Given the statistical uncertainty surrounding any measure, it is important to evaluate its magnitude for a well-grounded inference. In fact, it can be extremely useful to provide a confidence interval for the measure of interest to allow for a better assessment of the current direction.

In the case of directional data, the most used distribution is the von Mises distribution, which assumes unimodality and symmetry. It is basically the circular analogue to normal distribution. As these conditions do not always hold, the pursuit for robust methods leads to nonparametric or distribution-free techniques. Note that whereas in linear inference one can justify an assumption of normality, for instance, when dealing with means of large samples, there is no analogue rationale for invoking the von Mises distribution in directional inference. Hence, it has been advocated the use of bootstrap methods for directional data as the distributions of the statistics commonly used for inference are frequently intractable (see Mardia and Jupp (2000) for details).

In fact, bootstrap methods have proved very effective in situations where distributional assumptions are kept to a minimum or when distributional results for the statistic of interest are not available. With bootstrapping, the distribution of a statistic of interest can be assessed by resampling, i.e., sampling from the observed data, and then evaluating the statistic of interest for each of the bootstrap samples with the variability of these values taken as an estimate of the variability of the statistic over the population (see for example, Efron and Tibshirani (1993)).

In particular, to obtain a $(1-\alpha)100\%$ confidence interval for $\overline{\theta}_{\omega}$ we proceed as follows. For the b^{th} bootstrap sample, we evaluate the corresponding weighted mean angle, $\overline{\theta}_{\omega}^{b}$. Then, we compute the circular distance between the weighted mean angle for the original sample and that of the b^{th} bootstrap sample as

$$\gamma_b = \overline{\theta}^b_\omega - \overline{\theta}_\omega, \ b = \{1, ..., B\},$$
(8)

with B denoting the number of bootstrap samples.⁴ We then determine the quantiles $\alpha/2$ and $1-\alpha/2$ of $\gamma_b,\,\gamma_b^{\alpha/2}$ and $\gamma_b^{1-\alpha/2}$ respectively. The $(1-\alpha)100\%$ confidence interval for $\overline{\theta}_\omega$ is given by

$$CI_{\overline{\theta}_{\omega}}^{1-\alpha} = \left[\overline{\theta}_{\omega} + \gamma_{b}^{\alpha/2}, \overline{\theta}_{\omega} + \gamma_{b}^{1-\alpha/2}\right].$$
(9)

With the above $(1 - \alpha)100\%$ confidence interval, we can also conduct an hypothesis test with a significance level α by simply not rejecting the null hypothesis that the weighted mean is equal to a value of interest $\overline{\theta}^0_{\omega}$ if $\overline{\theta}^0_{\omega}$ lies within the $(1 - \alpha)100\%$ confidence interval and rejecting the null hypothesis otherwise. For instance, given that directions of 0° and 180° correspond to a 2% inflation level, which is the ECB inflation target, we can assess if our measure $\overline{\theta}_{\omega}$ departs statistically from 0° and 180°. If 0° or 180° do not lie inside the confidence interval, then it signals that the underlying inflation is statistically different from the inflation target. Note that the bootstrap confidence interval is not necessarily symmetric around the point estimate as it relies on resampling from the original data, allowing for enhanced flexibility in the characterisation of the distribution.

3. Data

The HICP is the official index of consumer prices in the euro area, harmonised within member states and taken as reference for the purposes of monetary policy. It is used to assess price stability around the inflation target and price convergence required for entry into the European Monetary Union.

The empirical application that follows relies on the universe of subitems that compose the HICP in the euro area, according to the European classification

^{4.} In the empirical application that follows, the number of bootstrap samples is set to 10,000.

of individual consumption by purpose (ECOICOP) at the 4-digit level.⁵ This amounts to 93 series spanning the period from Jan-1996 to Dec-2022. Similarly, we collect data on the corresponding weights for each subitem in the reference consumption basket. Taken together, this information provides the building blocks for constructing the inflation compass. Data are neither seasonally nor working day adjusted and we compute year-on-year rates of change for each subitem.



Figure 3: Measures of underlying inflation | Year-on-year percentage change. Notes: The sample period for all measures starts in Jan-1997, except for the Supercore (Jan-2003) and PCCI (Apr-2001). The latest vintage of the PCCI is displayed (Dec-2022).

Figure 3 depicts several measures of underlying inflation commonly tracked in the euro area economy. As mentioned before, these can be grouped into three broad categories: i) permanent-exclusion measures, ii) temporary-exclusion measures, and iii) frequency-exclusion measures. The idea of the first group of measures is to abstract from typically volatile components (e.g., fluctuations in oil prices that affect energy goods inflation, or atypical weather which induces strong volatility in food price inflation). The second class consists of a temporary exclusion of subitems in line with a given statistical criteria. These include trimmed means (10%, 30%)or the weighted median. For example, the 10% trimmed mean removes 5% of the year-on-year rates of change from each tail of the distribution of all subitems and aggregates the remaining year-on-year rates of change by rescaling the weights. Note that the weighted median can be considered an extreme form of trimmed mean as it trims all price changes, except for the weight-based mid-point of the distribution. The third category, in turn, comprises model-based measures, built to filter out the transitory component of inflation and retain the persistent components of all subitems. Examples of these measures include the so-called Supercore and PCCI. The former relies solely on subitems that are deemed sensitive to slack, as

^{5.} Data are retrieved from the Eurostat database and can be accessed at https://ec.europa.eu/eurostat/web/hicp/database.

measured by the output gap in a Phillips curve regression framework, thus departing from purely statistical criteria.⁶ The latter draws on the estimation of a dynamic factor model to capture the persistent and common component of all subitems' inflation rates across 12 euro area countries, based on ECOICOP 4-digit classes, amounting to approximately 1,000 series. The estimation of the low-frequency component for each subitem entails the choice of a set of parameters, including the number of dynamic and static factors and the threshold for the minimum length of cycles allowed in the common component (see Bańbura and Bobeica (2020) for details). These measures are sourced from the ECB's Statistical Data Warehouse.

While HICP inflation has hovered around 2% for over 20 years in the euro area, with some periods falling below the target over the last decade, the recent surge in inflation has also been evident in all measures of underlying inflation. Although there were already some signs of easing towards the end of 2022, these remain at historically high levels.

4. The inflation compass for the euro area

In this section, we present the inflation compass for the euro area, focusing on key episodes of historically high and low inflation since the beginning of the monetary union. Figure 4 depicts such episodes, where the red (blue) dots denote the periods of high (low) inflation. Two episodes of high inflation emerge, occurring in Jul-2008 and Oct-2022, with inflation rates hovering around 4% and 10%, respectively. In contrast, in Jul-2009, Jan-2015, and Sep-2020, inflation in the euro area was marginally negative. We pick these episodes in order to illustrate the inflation compass for the euro area and to confirm its usefulness during such periods.

In Figure 5, the inflation compasses for the months of high or low inflation mentioned above are displayed in the centre of each row, along with the adjacent months on either side. In the compass, the needle in red denotes the weighted mean direction, whereas the arc in black around the compass depicts the corresponding 95% confidence interval. The compass reads as explained in detail in Section 2.

Starting with the episode of high inflation identified in Jul-2008, the compass needle in this month is pointing towards the North, i.e., in the 90° direction, with the confidence interval including this direction. This means that we would not reject that underlying inflation has attained a local maximum. In fact, we would reject the occurrence of an episode of high inflation in the preceding month (i.e., Jun-2008) as the 90° direction lies outside the confidence interval. Naturally, a wider confidence interval reflects a greater dispersion of the evolution of the subitems of the consumption basket, thus inducing higher uncertainty in the overall direction of price pressures. The rotation of the compass from Jun-2008 to Aug-2008 signals that price pressures in the euro area increased and hit a local maximum.

^{6.} See the box entitled "The Supercore measure of underlying inflation", *Economic Bulletin*, Issue 4, ECB, 2018.



Figure 4: Key episodes of high and low inflation in the euro area | Year-on-year percentage change.

The global financial crisis was also marked by periods of (marginally) negative inflation in the euro area. The inflation compasses in the second row of Figure 5 illustrate these events. Starting in Jun-2009, price pressures steadily decelerated as we moved further along the third quadrant until the compass needle pointed towards South, that is, in the 270° direction. In fact, in Aug-2009, one cannot reject that underlying inflation has reached a local minimum. The wider confidence intervals reflect the turbulent economic landscape experienced during these times, with repercussion in the elementary items of the overall consumer price index.

The two other periods of low inflation, in early 2015 and in the autumn of 2020, are depicted in the third and fourth rows of Figure 5, respectively. We observe that the compass needles for these episodes are pointing towards the South direction, with little dispersion around the mean direction. The narrower confidence interval in both episodes conveys smaller uncertainty, which can be explained by the greater synchronisation of the dynamics of the subitems of inflation during these periods.

Since then, inflation surged worldwide. When analysing the rotation of the compass needle between Oct-2020 and Sep-2022, we observe this build-up of inflationary pressures as the needle rotates smoothly from the South to the North direction. In the euro area, inflation reached double-digits at the start of the autumn 2022. The bottom row in the figure illustrates this idea. Departing from the first quadrant, price pressures gradually accelerated until underlying inflation reached a local maximum at 90° , notably in Nov-2022.



Figure 5: Inflation compasses during episodes of high and low inflation.

These results highlight that the inflation compass stands out for its appealing properties in tracking price pressures in the euro area. Unlike most existing tools, it does not exclude any subitems of inflation, whether temporarily or permanently, ensuring that all available information is used. This eliminates any ad-hoc selection of subitems, thus granting a comprehensive analysis of the whole range of price data. As the inflation compass is not subject to revisions, it allows for reliable real-time insights into price pressures. Furthermore, its transparency sets it apart from intricate underlying inflation measures like the PCCI and Supercore, providing clear and easily understandable information for policymakers and the wider public.

For the sake of tractability and to ease presentation, the analysis so far has focused on a few episodes of high and low inflation. However, we can also take advantage of the properties of the inflation compass to characterise the price pressures since the beginning of the monetary union. In particular, drawing on the confidence interval obtained by bootstrap methods, we can evaluate at each point in time whether the underlying inflation departs from the 2% inflation rate, i.e., if the confidence interval encompasses the directions of 0° or 180° . Therefore, we display in Figure 6 the periods in which underlying inflation in the euro area is not statistically different from the 2%.



Figure 6: HICP inflation | Year-on-year percentage change. Note: The shaded areas denote the periods in which underlying inflation is not statistically different from the 2% inflation rate with a 95% confidence level.

The gray shaded areas map the periods where the confidence interval of the compass needle includes the 0° or 180° directions, i.e., the East or the West directions. As alluded before, these are the directions where euro area inflation would be on target. These results convey two important remarks. Firstly, the episodes addressed before lie outside the shaded areas. In fact, these were periods of high (or very high) and (marginally) negative inflation in the euro area, thus differing from 2% in a statistical sense. Secondly, Figure 6 highlights that the

underlying trend in overall inflation in the euro area was pointing to the target for most of the time during the first decade of the 2000s and in the 2011-12 period. Overall, the 2008-2011 period was marked by initially rising inflation, followed by a period of disinflationary pressures, and later, a slow return to levels around 2%. Moreover, euro area inflation was persistently low from 2013 to 2019, with an average rate of 1.0% during this period, significantly below 2%. In fact, this low inflation environment can be attributed to a combination of interconnected factors, including the underestimation of the economic slack, a de-anchoring of longer-term inflation expectations, and the ongoing structural trends in the economy such as globalisation, digitalisation or demographic trends, as advocated by Koester et al. (2021). In the aftermath of the COVID-19 pandemic and the war in Ukraine, inflation surged from 1% in the beginning of 2021 to double-digits by the autumn of 2022, thus crossing 2%, as evidenced in Figure 6. Hence, this complementary analysis based on the the inflation compass offers valuable insights when monitoring price pressures within the euro area, by assessing whether underlying inflation deviates from 2%.

5. Predictive content of underlying inflation measures

Economists and policymakers usually resort to measures of underlying inflation to predict future changes in overall inflation. As such, an empirical evaluation of the information content delivered by the inflation compass to forecast headline inflation is conducted. To this end, we compare the suggested tool in a forecasting context exercise against the underlying inflation measures commonly used in monetary policy diagnostics in the euro area. Besides its qualitative allure, we show that the inflation compass holds considerable quantitative relevance in monitoring inflation, particularly within the context of forecasting up to 36 months ahead.

The predictive content is gauged from a regression equation that relates the change in overall inflation between the current month and a future time period to the current gap between the underlying inflation measure and the overall inflation rate. Formally, we assess the ability to predict future inflation by estimating the equation

$$\pi_{t+h} - \pi_t = \alpha_t + \beta_t (\pi_t^u - \pi_t) + \varepsilon_{t+h}$$
(10)

where π_{t+h} represents the year-on-year headline inflation rate *h*-months ahead; π_t denotes the year-on-year headline inflation rate in a given month; π_t^u denotes the underlying inflation measure in the same month; ε_t is a mean-zero random disturbance term and t indexes time.

This regression framework has been used in several studies that evaluate the ability of underlying inflation measures to forecast inflation (see inter alia, Clark (2001), Hogan *et al.* (2001), Cogley (2002), Rich and Steindel (2007) or Bańbura

and Bobeica (2020)).⁷ To address the inherent subjectivity introduced by the requirement to specify an econometric model, we employ a regression framework that links future inflation changes to the transitory component of price changes identified by the underlying inflation measures. Note that the use of differences in inflation rates for both dependent and independent variables ensures stationarity and avoids issues arising from the existence of unit roots. This framing offers the advantages of both interpretability and flexibility, as it not only simplifies the readability of the exercise, but also allows for the incorporation of alternative horizons in the analysis. As Clark (2001) and Rich and Steindel (2007) argue, this framework is also aligned with the common beliefs of central bankers who consider movements in underlying inflation, by themselves, as signals of future changes in inflation.

We estimate the regression model in (10) for several horizons, $h = \{12, 18, 24, 30, 36\}$, to examine the medium to long-run predictive content of the several underlying inflation measures. The emphasis on these horizons is motivated by conventional wisdom about the lags in the monetary policy transmission mechanism. In fact, many countries that implement inflation targeting typically establish an horizon at which monetary policy operates over the business cycle and central banks may effectively anchor expectations or maintain inflation at desirable levels.

5.1. In-sample evaluation

We start by presenting the results of the in-sample evaluation. For this purpose, we estimate equation (10) using all the available data for each underlying inflation measure. This means that the sample period starts in Feb-1997, except for the Supercore (Jan-2003) and the PCCI (Apr-2001). Table 1 reports the root-mean-squared error (RMSE) over the different horizons for the inflation compass relative to that of each underlying inflation measure. A reading below one indicates the inflation compass has greater in-sample ability to track headline inflation than the alternative measure.

^{7.} In the case of the inflation compass, as we have a circular predictor, we include both the sine and cosine of $\overline{\theta}_{\omega}$, and run a standard linear regression with these components. This corresponds to a linear-circular regression model where the response is a linear variable whereas at least one of the covariates is circular (see Johnson and Wehrly (1978)).

	Dependent variable: $\pi_{t+h} - \pi_t$				
Underlying inflation	h = 12	h = 18	h = 24	h = 30	h = 36
HICPX	0.928	0.898	0.902	0.952	0.966
HICPXX	0.944	0.921	0.904	0.955	0.970
HICPXXX	0.968	0.967	0.959	0.979	0.981
Trimmed mean (10%)	0.920	0.853	0.847	0.897	0.909
Trimmed mean (30%)	0.923	0.877	0.877	0.921	0.939
Weighted median	0.927	0.900	0.909	0.956	0.956
Supercore	0.835	0.809	0.819	0.862	0.864
PCCI	0.935	0.966	0.954	0.921	0.914

Notes: HICPX refers to the HICP excluding energy, HICPXX corresponds to the HICP excluding energy and food, and HICPXXX is the HICP excluding energy, food, travel-related items, clothing and footwear. The latest vintage of the PCCI is used (Dec-2022).

Table 1. In-sample relative RMSE across the different horizons.

We find that the inflation compass outperforms the measures of underlying inflation commonly followed in the euro area across all horizons. In other words, the in-sample estimates provide evidence of a stronger tracking ability between underlying and headline inflation when using the inflation compass. Despite the relatively minor improvements observed for most measures, the inflation compass exhibits sizable gains across various horizons when compared to the Supercore measure, and to a less extent relative to the trimmed means. In-sample analyses are commonly subject to criticism as they tend to deviate from real-time forecasting exercises and are susceptible to overfitting. To overcome these limitations, we proceed our analysis with an out-of-sample forecast evaluation.

5.2. Out-of-sample forecast evaluation

This subsection introduces the out-of-sample forecasting exercise. For each horizon h, we start by estimating equation (10) with data until Dec-2015 and produce an h-step ahead forecast. For example, when h = 12, the first forecast refers to Dec-2016. We proceed by estimating the forecasting equation recursively, expanding the estimation window at each time by one month. This yields a sequence of h-step ahead forecasts and forecast errors. The exercise is conducted in real-time using the actual vintages of data available at each point in time.⁸

^{8.} In particular, in the case of PCCI, we consider the corresponding real-time vintages kindly made available by the ECB to the authors.

	Forecast horizon				
Underlying inflation	h = 12	h = 18	h = 24	h = 30	h = 36
HICPX	0.958	0.929**	0.943*	0.982**	0.972*
HICPXX	0.968	0.935**	0.935*	0.969**	0.964*
HICPXXX	0.993	0.977*	0.984	0.988	0.974*
Trimmed mean (10%)	0.957*	0.897**	0.901**	0.949***	0.962**
Trimmed mean (30%)	0.937***	0.910**	0.924**	0.961**	0.973**
Weighted median	0.935**	0.928**	0.948*	0.984**	0.973*
Supercore	0.930**	0.916**	0.941*	0.972**	0.954**
PCCI	0.931	0.974*	0.999	0.979**	0.962**

Notes: ***, **, ** denote statistical significance at 1%, 5% and 10% significance levels, respectively. HICPX refers to the HICP excluding energy, HICPXX corresponds to the HICP excluding energy and food, and HICPXXX is the HICP excluding energy, food, travel-related items, clothing and footwear. The recursive out-of-sample forecasting exercise uses as starting estimation sample the period up to Dec-2015.

Table 2. Out-of-sample relative RMSFE across the different horizons.

To quantify the out-of-sample forecasting performance of each underlying inflation measure, we compute the root-mean-squared forecast error (RMSFE). In addition, we assess whether the forecast accuracy of the inflation compass significantly differs from that of other measures by employing the Clark and West (2007) test. These results are reported in Table 2.

The out-of-sample analysis shows that the inflation compass provides more accurate forecasts compared to other methods, given that the relative RMSFEs for different time horizons are below unity, indicating its superiority. When comparing the inflation compass with temporary-exclusion measures, it achieves an average gain of 6% reaching around 10% for the medium-term horizons, h = 18 and h = 24, vis-à-vis the trimmed means. Compared with the model-based measures, the average gain is close to 4%, being higher vis-à-vis the Supercore than against the PCCI. This is very clear in the case of the horizons h = 18 and h = 24. In turn, the accuracy gains are somewhat smaller vis-à-vis the permanent-exclusion measures, averaging slightly less than 4%. This is particularly visible against the HICPXXX where the gains are the lowest across all the alternative measures. Nevertheless, the gains are, in general, statistically significant according to the Clark and West (2007) test procedure, which corroborates the usefulness of the proposed tool. We find that the statistical significance of the differences in performance is more marked for horizons h = 18 and above.

6. Robustness analyses

6.1. The COVID-19 pandemic and the recent inflation surge

As a sensitivity analysis, we assess the forecasting performance of each measure over the last three years, a period during which the euro area economy was severely hit by the COVID-19 pandemic and, more recently, by an inflation surge. As Chahad *et al.* (2022) outlined, there has been a significant degradation in the precision of HICP forecasts since the outbreak of the pandemic, and particularly following the third quarter of 2021. The plunge in the accuracy of these projections is mainly ascribed to unforeseen fluctuations in energy prices. This factor, along with the consequences of the post-lockdown reopening of economies and the global supply chain bottlenecks, has spurred unprecedented surges in HICP inflation.

In the analysis that follows, we take the forecast errors from Jan-2020 until Dec-2022 for all horizons and proceed as before by computing the RMSFEs and employing the Clark and West (2007) test for equal forecast accuracy (Table 3).

	Forecast horizon				
Underlying inflation	h = 12	h = 18	h = 24	h = 30	h = 36
HICPX	0.962	0.930*	0.942	0.981	0.965*
HICPXX	0.969	0.934*	0.932	0.967*	0.957**
HICPXXX	0.994	0.977	0.980	0.984	0.968*
Trimmed mean (10%)	0.967	0.900**	0.905*	0.955*	0.957*
Trimmed mean (30%)	0.942**	0.912**	0.926*	0.964*	0.966**
Weighted median	0.939**	0.930**	0.948	0.984	0.966*
Supercore	0.930**	0.916*	0.940	0.970**	0.947**
PCCI	0.929	0.975	1.000	0.975*	0.955**

Notes: ***, **, ** denote statistical significance at 1%, 5% and 10% significance levels, respectively. HICPX refers to the HICP excluding energy, HICPXX corresponds to the HICP excluding energy and food, and HICPXXX is the HICP excluding energy, food, travel-related items, clothing and footwear. The forecast errors are computed for the period from Jan-2020 until Dec-2022.

Table 3. Out-of-sample relative RMSFE during the COVID-19 pandemic and the recent inflation surge.

The results reveal that, in general, the inflation compass delivers higher accuracy than alternative measures. Despite the gains being slightly larger than the ones obtained in the previous out-of-sample forecast evaluation, the key finding is that results are robust to the pandemic and inflation surge periods, during which monetary policy gained prominence.⁹ Throughout these periods, policymakers closely monitored a set of measures, while significant interest rate hikes were implemented. Notably, these results underscore the importance of the inflation compass in tracking overall inflation developments during times of disruption or structural change. The fact that it comprises all the information available, weighting the changes in all items of the consumption basket, allows the inflation compass to capture strong and unexpected fluctuations that are not predicted by other underlying inflation measures that exclude items, such as energy, or others that smooth swift movements in headline inflation.

6.2. Bringing on board more data

In this subsection, we investigate whether using more disaggregated data changes the reliability of the inflation compass and its forecast accuracy. To this end, we consider two dimensions of disaggregation: i) from ECOICOP4 to ECOICOP5 (product-level disaggregation); ii) and from ECOICOP4 at the product-level for the euro area to ECOICOP4 using data for 12 euro area countries, i.e., we use country as opposed to aggregate data (country-level disaggregation).¹⁰ One should note that the suggested approach is flexible enough to accommodate a time-varying composition of the input data and can handle straightforwardly large-dimensional data.

We illustrate the outcomes of these two levels of disaggregation by focusing on the two recent episodes of low and high inflation in the euro area experienced since 2020. In particular, Figure 7 reports the inflation compasses computed using the 5-digit classes data encompassing nearly 300 HICP subitems and corresponding weights.

We observe that the compass needles in the first row of Figure 7 are pointing towards the South direction, with little dispersion around the weighted mean direction as evidenced before. In addition, the bottom row in the figure reinforces the idea of gradually accelerating price pressures until inflation reached a local maximum around Nov-2022.

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^{9.} Note that the loss of statistical significance may be related with the lower number of observations used to perform the tests.

^{10.} The 5-digit ECOICOP classes are only available from Jan-2017 onwards and are retrieved from the Eurostat database outlined before. The country-level data refers to the eleven founding euro area Member States namely Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, The Netherlands, Portugal and Spain, plus Greece that joined the euro area in 2001.



Figure 7: Inflation compasses using 5-digit data.

Similarly, in Table 4 we benchmark the forecasting ability of the inflation compass computed using the 5-digit classes against the set of alternative underlying inflation measures.

	Forecast horizon				
Underlying inflation	h = 12	h = 18	h = 24	h = 30	h = 36
HICPX	0.964	0.930*	0.942	0.981	0.966*
HICPXX	0.971	0.934*	0.932	0.967*	0.958**
HICPXXX	0.996	0.977	0.980	0.984	0.969*
Trimmed mean (10%)	0.969	0.900**	0.905*	0.955*	0.958*
Trimmed mean (30%)	0.943**	0.912**	0.926*	0.964*	0.967**
Weighted median	0.940**	0.930**	0.948	0.984	0.966*
Supercore	0.931**	0.916*	0.939	0.970**	0.947**
PCCI	0.931	0.974	0.999	0.975*	0.956**
Inflation compass	1.002	1.000	1.000	1.000	1.001

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% significance levels, respectively. HICPX refers to the HICP excluding energy, HICPXX corresponds to the HICP excluding energy and food, and HICPXXX is the HICP excluding energy, food, travel-related items, clothing and footwear. The bottom row corresponds to the ratio between the RMSFE of the inflation compass computed from the 5-digit classes and the RMSFE using the 4-digit classes. The forecast errors are computed for the period from Jan-2020 until Dec-2022.

Table 4. Out-of-sample relative RMSFE using 5-digit data.

Navigating with a compass: Charting the course of underlying inflation

These findings convey two important remarks. First, when we enlarge the dataset, we find that the accuracy gains are of similar magnitude as before. Second, the inflation compass is robust to the product-level disaggregation, in the sense that using more detailed data does not enhance forecast accuracy. This is outlined by the entries nearly identical to unity in the bottom row of Table 4, which exhibit the ratio of RMSFE between the inflation compass computed from the 5-digit classes and that using the 4-digit classes. In fact, these marginal differences in forecast accuracy are confirmed by the lack of statistical significance of those entries. One should bear in mind that using 4-digit ECOICOP classes, as examined in Section 5, already entails considering a relatively large level of disaggregation with almost 100 HICP subitems.

We now turn our attention to the second dimension of disaggregation leveraging the country-level data. In particular, we enlarge the dataset to cover the 4-digit ECOICOP classes for 12 euro area countries as in the construction of PCCI, amounting to more than 1,000 series in total. Thereby, we explore an even larger dataset aimed to capture country-level inflationary pressures.

Figure 8 displays the inflation compasses for the two same episodes addressed above. We find that the readings of the inflation compasses during these two episodes are in line with those obtained before.



Figure 8: Inflation compasses using 4-digit country-level data.

Lastly, Table 5 reports the results of the forecasting exercise using the abovementioned level of disaggregation.

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	Forecast horizon				
Underlying inflation	h = 12	h = 18	h = 24	h = 30	h = 36
HICPX	0.954	0.935*	0.948	0.982	0.973*
HICPXX	0.960	0.939*	0.937	0.968*	0.965**
HICPXXX	0.985	0.983	0.985	0.985	0.976*
Trimmed mean (10%)	0.958	0.905**	0.910*	0.956*	0.965*
Trimmed mean (30%)	0.933**	0.917**	0.931*	0.965*	0.974**
Weighted median	0.930**	0.935**	0.953	0.985	0.974*
Supercore	0.921**	0.921*	0.945	0.971**	0.954**
PCCI	0.921	0.980	1.005	0.976*	0.963**
Inflation compass	0.991	1.005	1.006	1.001	1.008

Notes: ***, **, ** denote statistical significance at 1%, 5% and 10% significance levels, respectively. HICPX refers to the HICP excluding energy, HICPXX corresponds to the HICP excluding energy and food, and HICPXXX is the HICP excluding energy, food, travel-related items, clothing and footwear. The bottom row corresponds to the ratio between the RMSFE of the inflation compass computed from the 4-digit classes country-level data and the RMSFE using the 4-digit classes euro area data. The forecast errors are computed for the period from Jan-2020 until Dec-2022.

Table 5. Out-of-sample relative RMSFE using 4-digit country-level data.

We find similar gains when using the dataset with country-level data. Moreover, the inflation compass is robust to the country-level disaggregation, in the sense that bringing on board more data does not seem to enhance forecast accuracy, in general. Even though for h = 12 the inflation compass computed from the 4-digit classes country-level data outperforms that using the 4-digit classes data for the euro area, this difference is negligible, which is confirmed by the lack of statistical significance, as evidenced in the bottom row of Table 5.

7. Concluding remarks

A key feature of central bank mandates worldwide is their unwavering attention to monitoring inflation dynamics. The ECB is no exception. Monetary policy prescriptions in the euro area have typically relied on an assessment of the inflation outlook, considering incoming economic and financial data, the dynamics of inflation, and the effectiveness of monetary policy transmission.

In this regard, several techniques to filter out incoming data have been used, given the importance of gauging price pressures in a timely manner for the purposes of monetary policy responses. The idea of closely monitoring such tools is to abstract from transitory price movements and thereby produce a measure of underlying inflation.

We depart from the previous literature and propose a novel tool to gauge price pressures resorting to circular statistics, the so-called inflation compass. Given that

circular statistics have not been commonly used in economics, we laid out the basic intuition while streamlining the main theoretical concepts underneath the inflation compass. In particular, we illustrate the inflation compass reading and develop statistical inference based on bootstrap methods.

Unlike most alternative measures of underlying inflation, the inflation compass does not exclude any subitems of inflation, ensuring that all available information is used. This eliminates the need for ad-hoc selection of subitems and allows for a comprehensive analysis of all price data. Another feature of the inflation compass is its real-time reliability, in the sense that it is not revised backwards as new data arrives, thus providing policymakers with reliable real-time insights about price pressures. Furthermore, the transparency of the inflation compass sets it apart from other more intricate tools. In fact, the information conveyed by the inflation compass can be easily understood and interpreted, facilitating decision-making and communication.

Resorting to HICP disaggregated data for the euro area, covering almost one hundred series, we illustrate its usefulness for tracking underlying price pressures during key episodes of high and low inflation since the beginning of the euro area. We also take advantage of the properties of the inflation compass to shed light on the periods during which underlying inflation did not deviate from 2%, thus providing a characterisation of the full spectrum of price pressures in the euro area over the last decades.

In addition to its qualitative relevance in gauging price pressures, we provide evidence of the usefulness of the inflation compass for forecasting overall inflation up to 36 months ahead. Quantitatively, the inflation compass outperforms the measures regularly monitored in the euro area in a real-time forecasting exercise. We find that the forecast accuracy gains achieved with the suggested approach are, in general, statistically significant.

Finally, we conduct a robustness analysis where we investigate the performance of the inflation compass to monitoring price pressures amid challenging periods like the COVID-19 pandemic and the recent inflation surge. Our findings confirm its dominance even in such difficult times for policymaking. Moreover, as the suggested method can handle straightforwardly with large-dimensional data, we enlarged the dataset either by incorporating more detailed product-level data from the consumer price index or by taking on board country-level data rather than relying on aggregate euro area data. Either way, the main findings hold, which reinforces the robustness of the proposed procedure.

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