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Security through stability.

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For well-informed monetary policy decisions, central banks gather a wide range of data on the state of the economy, including several inflation measures. When pursuing a forward-looking monetary policy, policymakers ideally rely on measures that indicate where inflation is heading in the medium term, e.g. when shocks to the economy will have disappeared. To complement the set of inflation measures commonly used in the decision-making process, we construct maximally forward-looking core inflation, as proposed by Goulet Coulombe et al. (2024), for the euro area and its seven largest economies. Since the euro area aggregate summarizes diverse economic conditions and responses to shocks within the region, constructing maximally forward-looking core inflation for individual member states provides additional insights into the heterogeneity and commonalities across countries. Overall, our results confirm our measure's strong performance in predicting medium-term inflation developments, which holds for all economies in the set. We identify key economic sectors that provide useful signals for future headline inflation and find a broad consistency across the seven largest euro area economies.

JEL classification: C53, E31, E37, E52
Keywords: underlying inflation, inflation forecasting, inflation subcomponents, euro area

Major central banks routinely monitor various measures of inflation to understand prevailing price movements. Typically, they are more concerned about the persistent sources of inflationary pressures rather than about temporary fluctuations. For example, the inflation surge that started in 2021 sparked a crucial debate on whether the observed pressures were a transitory phenomenon or whether they would translate into a persistent increase in prices. Since inflation data are exposed to multiple sources of noise, aggregate inflation (or "headline" inflation) is usually not the primary choice when it comes to answering such fundamental questions. Instead, policymakers typically rely on underlying (or core) inflation measures, whose purpose is to signal medium-term inflationary trends.

Especially when pursuing a forward-looking monetary policy, separating informative signals from highly volatile data helps indicate where headline inflation will settle in the medium term. This task, however, becomes particularly complex in the euro area, where the aggregate inflation rate is influenced by multiple sources of noise arising from both different sectors and individual countries. Given that each euro area economy exhibits unique inflation dynamics because of its individual structural and historical characteristics and responses to economic shocks vary across countries, the aggregate constitutes a melting pot of heterogeneous inflationary pressures. Consequently, it can be informative to consider individual euro area economies and identify the most important subcomponents of their cross-sectional price data when considering the medium-term developments of their headline inflation rates.

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In this paper, we construct predictive core inflation measures for the seven largest euro area economies[2] based on Goulet Coulombe et al. (2024). The methodology they propose uses inflation subcomponents to forecast the headline rate and reweights these subcomponents to be maximally forward-looking. As such, their methodology directly targets the predictability of a core inflation measure for the headline rate, which is highly desirable when pursuing a forward-looking monetary policy. Moreover, by taking a cross-sectional perspective, it allows for evaluating the role of inflation subcomponents across countries.

Our results show that using inflation components helps improve the predictive accuracy for headline inflation across euro area countries in the medium term. This holds for pre- and post-COVID-19 pandemic periods. Our analysis yields valuable insights into which sectors provide forward-looking signals, which are less informative, and into whether these characteristics vary across the seven largest economies in the euro area. We find that, for all countries under observation, maximally forward-looking core inflation gives low weight to highly volatile subcomponents such as energy and food, while assigning high weight to goods and services like housing, recreation and other services. This suggests a broad alignment with commonly used core inflation measures. Moreover, our weighting schemes for the different economies are broadly consistent and do not show signs of significant heterogeneity.

This paper is structured as follows: In section 1, we discuss the relevance of core inflation for policy decisions in central banking and review the literature on existing measures and the role of inflation subcomponents. Section 2 presents the methodology used to construct the maximally forward-looking core inflation measure for the seven largest euro area economies. Section 3 summarizes our forecasting results and identifies sectors indicative of medium-term developments in each country. Section 4 concludes.

1 Core inflation and its relevance for monetary policy

Core inflation measures serve as key input for monetary policy assessment in major central banks since they are built on the goal of signaling the direction in which inflation is heading in the medium term. Ehrmann et al. (2018) describe the role of measures of underlying inflation as follows, “The central bank faces the problem of distinguishing in real time the ‘signal’ on medium-term inflationary pressure contained in the HICP inflation data from the ‘noise’ stemming from temporary or idiosyncratic factors. To this end, measures of underlying inflation are routinely monitored. Generally, their purpose is to obtain an estimate of where headline inflation will settle in the medium term after temporary factors have vanished.”

That being said, creating a measure of underlying inflation requires isolating persistent developments from highly volatile behavior. The resulting inflation series should be free of effects from idiosyncratic factors and transitory shocks that dissipate in the near term. That means a well-behaved core inflation measure has the following properties (see, e.g., Clark, 2001): (1) a small bias with respect to headline inflation and (2) low variance. Moreover, with regard to pursuing a forward-looking monetary policy, it should have (3) strong predictive power with respect to headline inflation. Such a measure serves to indicate in which direction inflation will be heading in the medium term.

[2] Germany, France, Italy, Spain, Netherlands, Belgium and Austria.

1.1 Existing core inflation measures

Inflation measures central banks commonly monitor are either based on simple exclusion rules or rely on modeling techniques that extract underlying developments in the data. The most prominent inflation measure, which is usually reported as "core inflation," permanently excludes food and energy components. Since commodity prices are highly volatile and their fluctuations are often induced by supply shocks, it is difficult for monetary policymakers to frame a proper response to these specific inflationary pressures (Gordon, 1975; Eckstein, 1981; Motley et al., 1997). Based on these arguments, the concept of permanent exclusion is often extended to additional subcomponents such as those related to housing or tourism, or subcomponents are excluded from the measure on the basis of other criteria. These include overall price volatility (see Clark, 2001; Acosta, 2018), cyclical volatility (see Dolmas, 2009) and persistence (see Bilke and Stracca, 2007). Other studies take more structural approaches into account and focus on subcomponents that are sensitive to the economic business cycle. These approaches include Supercore for the euro area (see Ehrmann et al., 2018) and the Federal Reserve Bank (FRB) San Francisco Cyclical Core Personal Consumption Expenditures (PCE) Inflation (see Mahedy et al., 2017; Stock and Watson, 2020).

Permanently excluding specific subcomponents from the aggregate has a number of drawbacks. Excluded subcomponents may provide useful signals for future inflation despite being highly volatile, e.g. by potentially inducing second-round effects on inflation expectations and wages, of which policymakers should be aware (Cecchetti and Moessner, 2008). Included subcomponents, on the other hand, may carry substantial amounts of noise and/or be subject to transitory shocks that blur the overall trend (Verbrugge, 2022). As an alternative, the literature suggests reducing volatility and extracting the medium-term trend via temporary exclusion. Trimmed mean inflation and median inflation (Bryan and Pike, 1991; Bryan and Cecchetti, 1993; Bryan et al., 1997) address the aforementioned issues by ensuring cross-sectional smoothing over time. Given that the distribution of monthly price changes is hardly ever symmetric but features substantial skeweness, a symmetrically trimmed core inflation measure may deviate from the underlying trend over short time horizons. This motivates an asymmetric trimming approach as in, e.g., Bryan et al. (1997) and Dolmas (2005), who exclude a higher share of the upper tail of the monthly price change distribution from their trimmed mean inflation measure.

Moving along the spectrum of econometric complexity, we find model-based inflation measures built to detect the underlying trend in numerous inflation components. A well-established concept is to extract the common component of all subindices with a dynamic factor model that identifies shared factors influencing the data. For example, the European Central Bank (ECB) monitors the persistent and common component of inflation (PCCI; Banbura and Bobeica, 2020), whereas the Federal Reserve Bank of New York constructs the multivariate core trend (MCT; Stock and Watson, 2016).

1.2 Using inflation subcomponents for a predictive core inflation measure

Many studies have shown that using inflation subcomponents is beneficial for predicting the aggregate inflation rate (see i.a. Marcellino et al., 2003; Espasa and Albacete, 2007; Giannone et al., 2014; Fulton and Hubrich, 2021; Boaretto and Medeiros, 2023). Using inflation subcomponents allows for capturing heterogeneous factors to which the aggregate is exposed. Moreover, using various price series provides additional information, e.g. on trends, short-term fluctuations or structural breaks that can potentially be extracted by a forecasting model (Espasa et al., 2002; Bermingham and D'Agostino, 2014). Other studies find small or muted improvements when applying disaggregated approaches (Benalal et al., 2004; Hubrich, 2005; Hendry and Hubrich, 2011, Chalmovianský et al., 2020). Difficulties may arise due to the accumulation of misspecifications, estimation uncertainty, instabilities and innovation errors, all of which influence the forecasting accuracy of the aggregate.

Leaving plain forecasting performance aside, building on inflation subcomponents comes with several benefits. First, it allows for a breakdown of the aggregate into inflationary versus noninflationary (or even deflationary) components. As such, it offers policymakers more detailed information on the origins of prevailing price pressures. Since inflation subcomponents vary in their reactions to monetary policy in terms of extent and speed, a disaggregated perspective is essential for informed monetary policy decision-making. As Aruoba and Drechsel (2024) show, the aggregate response of headline inflation to a monetary policy shock differs substantially from individual responses across the range of inflation subcomponents. While some components respond quickly and in the expected direction, others exhibit long lags or may even react in the opposite direction. Hence, examining cross-sectional inflation data provides valuable insights into the transmission of monetary policy shocks, while relying on aggregate indices only may blur the picture.

Core inflation measures that are based on inflation subcomponents and that directly target the predictive performance with regard to headline inflation are rather rare. Suggestions in the literature include Ravazzolo and Vahey (2009), who propose a forecast-based core inflation measure based on each individual subcomponents' performance in density predictions, and Gamber and Smith (2019), who combine disaggregated inflation subindices in a standard linear regression model to formulate a core inflation measure. In a recent study, Goulet Coulombe et al. (2024) propose using a regularization-based approach which aggregates inflation subcomponents based on their explanatory power with respect to future headline inflation. It allows for incorporating high levels of disaggregation and ensures interpretability through constraints on the coefficients. In the following, we apply the concept of maximally forward-looking core inflation proposed by Goulet Coulombe et al. (2024) to the euro area aggregate and the seven largest euro area economies and provide useful insights into the predictive power of the different subcomponents.

2 Methodology: maximally forward-looking core inflation

We base our analysis on Albacore (adaptive learning-based core inflation), a method proposed by Goulet Coulombe et al. (2024). It linearly aggregates inflation subcomponents so that the resulting series is maximally predictive of future headline inflation. By focusing on the forward-looking criterion, Albacore combines the benefits of using inflation subcomponents for predicting aggregate inflation and at the same time provides a trackable measure for underlying inflation. That is, the goal is not to perform a plain forecasting exercise which yields the best possible forecast for headline inflation but to determine the weights of subcomponents so that the resulting aggregate is a good medium-term predictor, and to thus provide a measure of underlying inflation.

This goal is achieved by using a simple machine-learning algorithm called "assemblage regression," which is a generalization of the popular ridge regression model.[3]

The authors propose two versions of maximally forward-looking core inflation: Albacore (components) in components space, which means that the algorithm uses the disaggregated inflation subcomponents and assembles them according to their predictability, and Albacore (ranks) in ranks space, which means that we rank inflation subcomponents from the lowest to the highest values at each point in time, like in a trimmed mean inflation, and the algorithm is allowed to decide what weight to assign to each of the ordered time series ("ranks").

The first case is a supervised weighting approach, in which the algorithm assembles disaggregated inflation subcomponents and directly targets future headline inflation. Following Goulet Coulombe et al. (2024), we let $\pi_{t+1:t+h}$ denote the h-step headline inflation rate averaged over $t+1$ to $t+h$ and $\mathbf{\Pi}_t$ the K-dimensional vector of inflation subcomponents, both in quarter-on-quarter changes at time t (for $t = 1, \dots, T$). To obtain the optimized weights for Albacore (components), $\widehat{w}_c$, for the basket of components we minimize the following loss function:

$$\widehat{w}_c = \arg\min \textstyle\sum_{t=1}^{T-h} (\pi_{t+1:t+h} - w'\mathbf{\Pi}_t)^2 + \lambda \|w - w_{headline}\|_2 \quad (1)$$
$$st\ w \geq 0, w_l' = 1.$$

Note that instead of shrinking coefficients toward 0, the penalty term ($\lambda\|w - w_{headline}\|_2$), with the quadratic Euclidian norm between both weight vectors, pushes the solution toward the official Eurostat headline inflation weights ($w_{headline}$). Also, the two constraints introduced in the assemblage regression make sure that coefficients sum to 1 and are nonnegative. As such, the methodology ensures that the resulting weights are (1) interpretable as weights, (2) optimized to be forward-looking while they (3) remain aligned with the official headline weights in the limit (i.e., when $\lambda \to \infty$).

The second version is a supervised trimming approach. Here, the monthly growth rate of inflation subcomponents is ordered from the lowest to the highest values at each point in time before they enter the minimization problem as regressors. To achieve this, $\boldsymbol{O}_t$ defines the K-dimensional vector of ordered inflation subcomponents and we obtain the optimized weights for Albacore (ranks), $\widehat{w}_r$, as follows:

$$\widehat{w}_r = \arg\min \textstyle\sum_{t=1}^{T-h} (\pi_{t+1:t+h} - w'\mathbf{O}_t)^2 + \lambda \|Dw\|_2 \quad (2)$$
$$st\ w \geq 0,\ \ \bar{\pi}_{t+1:t+h} = \bar{\pi}^*_{ranks,t}.$$

The penalty term ($\|Dw\|_2$) opts for a smooth distribution of the weights, with D being the difference operator (i.e., $\sum_{r=1}^{K}(w_r - w_{r-1})^2$). For Albacore (ranks), weights are constrained to be nonnegative and the resulting inflation series needs to have the same long-run mean as headline inflation. Again, these restrictions are designed to optimize the regression problem with respect to predictability and at the same time ensure interpretability as an underlying inflation measure.

[3] Ridge regressions belong to the class of regularization-based techniques. They are used to improve predictive accuracy by adding a penalty term which prevents the model from fitting too closely to the data. This is particularly important when using a large number of regressors in an estimation.

Being inspired by trimmed mean inflation, this approach focuses on the cross-sectional distribution of inflation subcomponents. For further details, please refer to Goulet Coulombe et al. (2024).

3 Albacore for euro area countries

We use monthly HICP data from Eurostat, disaggregated at the four-digit Classification of Individual Consumption by Purpose (COICOP) level. We construct the series for the euro area and for its seven largest economies: Germany, France, Italy, Spain, Netherlands, Belgium and Austria. To address substantial irregularities in some subindices, we either remove them from our set or replace them with their three-digit or two-digit aggregates. This leaves us with 92 subindices for the euro area, 66 for Germany and France, 67 for Austria, 62 for Belgium, the Netherlands and Italy, and 55 for Spain. All data series are seasonally adjusted and run from April 2002 until March 2024.[4]

For our analysis, we focus on the 12-months-ahead horizon, which allows us to take a medium-term perspective and use quarter-on-quarter changes of the series. Following Goulet Coulombe et al. (2024), our evaluation is based on two out-of-sample test sets, one covering the pre-pandemic period (January 2010 to December 2019) and the other the post-pandemic period (January 2020 to March 2024). Given that euro area HICP data are typically not subject to significant revisions, our analysis is based on a pseudo-out of sample evaluation. For countries with revised price data, it may be of interest to conduct a real-time exercise. To determine whether the resulting inflation series is indeed a reliable indicator of future headline inflation developments, we evaluate the point forecasting performance of Albacore with root mean squared errors (RMSEs) against a set of benchmarks. These include the headline inflation rate, the core inflation rate (excluding energy and food) as well as the 30% trimmed mean inflation rate for each country in our sample. Benchmarks are combined in a nonnegative ridge regression including and excluding the intercept. This strategy resembles a forecasting combination scheme, which is often found to beat simple univariate benchmarks (Diebold and Shin, 2019; Hauzenberger et al., 2023).

3.1 Forecasting performance

Overall, both Albacore series yield a good point forecasting performance with regard to the euro area aggregate as well as the individual euro area economies (see table 1). We find substantial gains for both the pre- and post-pandemic periods, with improvements for the pre-pandemic period being higher for most countries (except for the Netherlands). Additionally, we observe that including an intercept in the benchmark specification is beneficial, if at all, only for the pre-pandemic sample. Compared to the euro area aggregate, we find similar (or even stronger) performance with regard to the individual countries, suggesting that Albacore can effectively manage potentially more volatile subcomponents than those reflected in the weighted average across countries. These results suggest a potential for constructing the euro area aggregate by optimizing weights across both countries and components. As shown by Goulet Coulombe et al. (2024), a geographical assembling of inflation series can indeed improve the model's performance; such a step, however, is outside the scope of the present study.

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[4] For seasonal adjustment, we use the Census X-13ARIMA-SEATS Seasonal Adjustment Program from the seasonal package in R (Sax and Eddelbuettel, 2018). For series with heavy irregularities, we either remove severe outliers after the seasonal adjustment step or replace them with their two- or three-digit aggregates. Note that, depending on data quality, this data-wrangling step may affect the estimate and alter results.

Table 1

Forecasting performance of Albacore

	Euro area	Austria	Belgium	Germany	Spain	France	Italy	Netherlands
Pre-pandemic sample								
Albacore (components)	0.9	0.9	0.8	0.7	0.9	0.8	0.8	0.7
Albacore (ranks)	1.0	0.8	0.9	0.8	0.9	0.8	1.0	0.8
Predictive combinations with intercept	1.0	0.8	0.9	0.7	1.1	0.9	1.1	0.8
Post-pandemic sample								
Albacore (components)	0.9	0.9	0.9	0.9	0.9	1.2	1.0	0.7
Albacore (ranks)	1.0	0.9	0.9	1.0	0.9	1.0	1.0	0.7
Predictive combinations with intercept	1.0	1.1	0.8	1.2	0.9	1.1	1.0	0.9

Source: Authors' calculations.

Note: The table gives root mean-squared errors (RMSEs) relative to the predictive combinations without intercept. The benchmarks combine HICP headline inflation, HICP core inflation and the 30% trimmed mean in a nonnegative ridge regression. Values below one show forecasting improvements over the benchmark, while values above one indicate inferior performance. The pre-pandemic sample covers the period from January 2010 to December 2019. The post-pandemic sample covers January 2020 to March 2024.

When evaluating the model's performance with regard to each country before the outbreak of the COVID-19 pandemic, we find a remarkable performance of Albacore (components) for Germany and the Netherlands and of Albacore (ranks) for Austria against our main benchmark without intercept. Note, however, that including the intercept for this set of countries makes the benchmark hard to beat. This is due to the low and stable inflation rates these countries experienced before the pandemic, which caused the constant in the model to become more important. This effect is amplified because we chose a relatively long forecasting horizon.

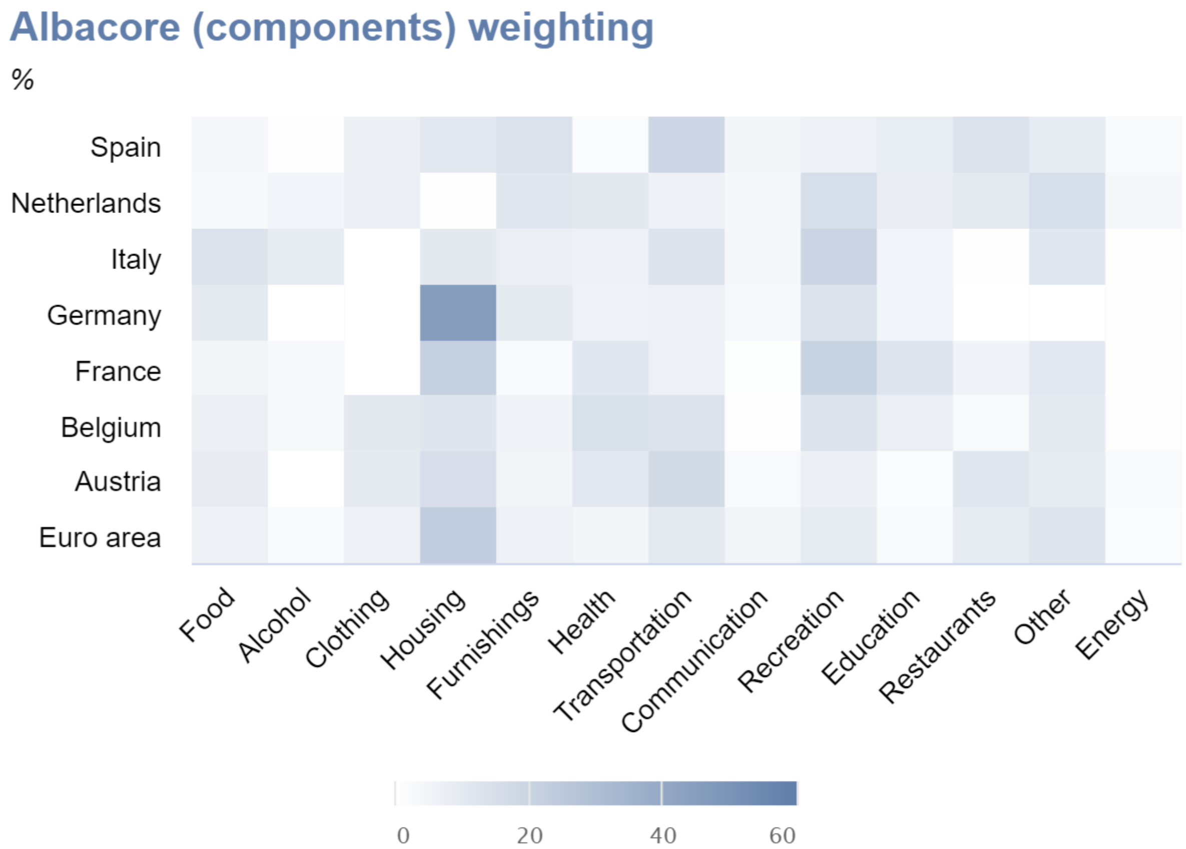
For the post-pandemic sample, the strongest improvements against both benchmarks can be achieved for the Netherlands. Given that the Netherlands saw a strong surge in their headline inflation rate, peaking at 17.1% in September 2022, simple benchmarks have difficulties to predict these strong dynamics. Conversely, we find that simple benchmarks perform well for economies like France, which saw a less severe increase in its headline inflation rate during 2022/2023. Belgium is the only country for which the benchmark outperformed both Albacore measures by considerable margins for the post-pandemic period. We find that Albacore mainly loses ground during the rebound of headline inflation observed in late 2023.

The resulting inflation series can be found in chart A2 in the annex. We summarize key findings for the post-pandemic period. First, for all countries in our sample, both Albacore measures reduce volatility compared to headline inflation, especially for 2020 and 2021. For the surge of inflation, we find early signs of upward pressures from both Albacore measures for Austria, Belgium and Italy. For all other countries as well as the euro area aggregate, Albacore (ranks) is the first to point toward upward tendencies. For the turning point, we find harmony across all core inflation measures. Finally, our results for recent months reveal some heterogeneity between countries. While for all countries in our set, the newly built underlying inflation measure is still above pre-pandemic levels, it remains particularly elevated for France, Austria and Belgium. This can be traced to exceptionally low levels of inflation recorded before the pandemic in France and to strong underlying pressures that are fading out more slowly in Austria and Belgium. Yet, our Albacore measures point toward an ongoing disinflationary process for all countries observed.

3.2 The role of inflation subcomponents across euro area countries

In this subsection, we explore the role of inflation subcomponents for the predictive performance of Albacore across the different euro area countries. We identify key economic sectors that are important for predicting inflation trends in the medium term and highlight those that receive less weight due to the low signal they produce. To do this, we summarize the final weights Albacore (components) assigns to the various disaggregated inflation series presented in chart 1 as well as the differences to the official weights given in chart 2. A more detailed illustration can be found in chart A3 in the annex. For the purpose of illustration, we aggregate the weights of the subcomponents back to level 2.

Chart 1



Source: Authors' calculations.
Note: We aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

As we would expect from a core inflation measure that reduces noise and signals medium-term developments, the energy component is assigned low to zero weight. Moreover, we find low weight for the subcomponents "food including nonalcoholic beverages" and "alcohol including tobacco and narcotics," subcomponents that are excluded from official core inflation.[5] Another

[5] While energy and food prices can certainly have predictive power during specific periods, their high volatility limits the usefulness of their signals for longer-term forecasting. As demonstrated by Goulet Coulombe et al. (2024), both components

group of subcomponents that is deemed unimportant by Albacore (components) is communication. While energy and food are characterized by high volatility, communication services and equipment are components with constant or even deflationary paths. As such, the former is too volatile and the latter too persistent (or downward bound) to signal medium-term trends.

In general, higher importance is assigned to services and goods related to housing, recreation and other services (which include, i.a., insurance and financial services). For Germany and France, housing clearly receives the highest weight, while recreation is most important in the Netherlands and Italy. In Austria and Spain, we find transportation to be the top-weighted component. Note that these observations are broadly reflected in the official Eurostat weighting scheme (see chart A1 in the annex). Even more interesting are, thus, the differences between our results and the official weights, as these suggest which components deserve greater attention than usual when monetary policy aims to be forward-looking.

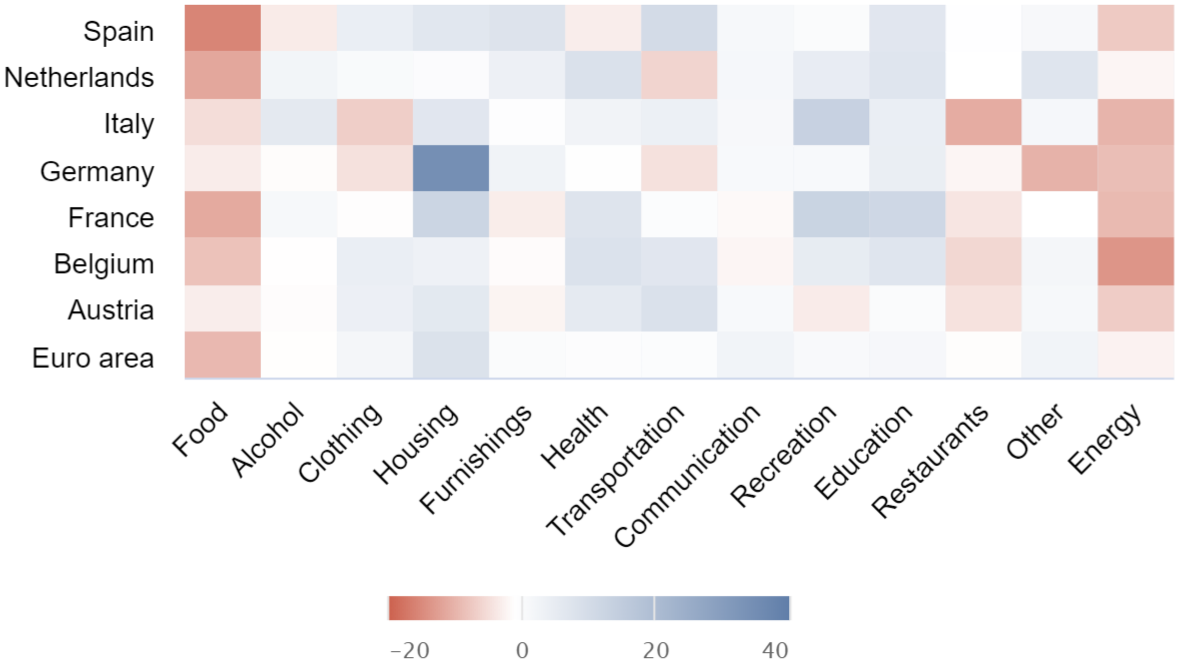
A comparison of our outcomes to the official weights reveals that assigning a low weight on energy and food constitutes a substantial downweighting of the corresponding subcomponents (see chart 2). Services and goods related to communication, on the other hand, already have a low weight in the official headline inflation aggregate, so our outcome would not suggest a major change. Even though subcomponents in the restaurants category receive substantial weights for several countries (Austria, Spain, the Netherlands) in our measure, their high weight in the official aggregate reduces their importance for the aggregate across all countries. Our calculation assigns higher importance to housing, recreation, education and health in all countries. This supports an intuitive finding, which is also shown in Goulet Coulombe et al. (2024): Albacore (components) reduces the focus on highly volatile subcomponents and on overly persistent ones, while, at the same time, it increases the importance of core goods and services that indicate the overall growth trend of various price series. Notably, this holds for all seven economies under review, which suggests that they show little heterogeneity with respect to the forward-looking features of their inflation subcomponents.

receive positive weights in the very short run, but these weights diminish rapidly as the forecasting horizon extends. Furthermore, their predictive power is highly dependent on the nature of the prevailing shock, which reduces their general adequacy.

Chart 2

Differences between Albacore (components) and official weighting

Percentage points



Source: Authors' calculations.
Note: This chart shows the difference between Albacore (components) weights and official Eurostat weights for each country and the euro area in percentage points. For Albacore (components), we aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

3.3 A cross-sectional trimming perspective

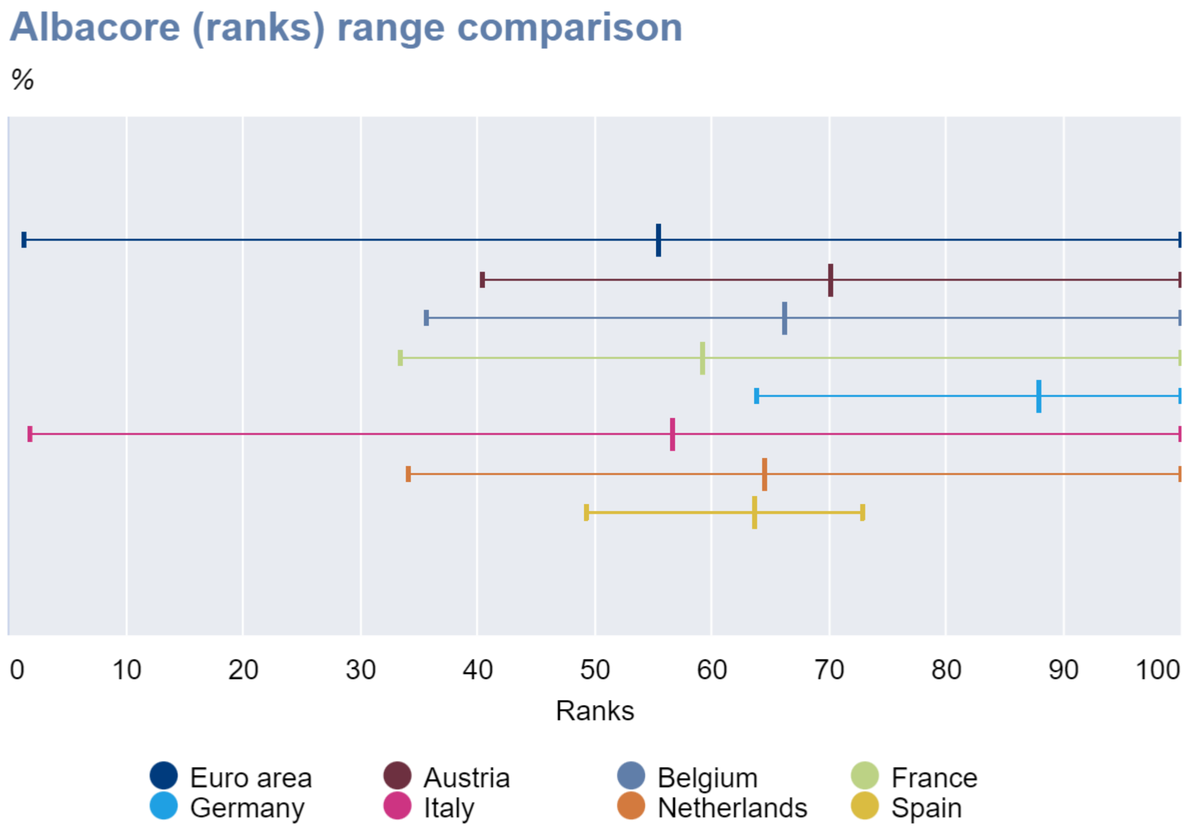
Inspecting the weights of the second measure, Albacore (ranks), allows us to shed light on similarities and differences between the various maximally forward-looking trimming schemes in place across the largest euro area economies. As an insightful add-on, Goulet Coulombe et al. (2024) demonstrate that it is possible to translate the trimming-based weights back into components space. This is particularly useful for our purpose, as it provides insights into the importance of subcomponents for the different countries, but from a time-varying perspective. In the trimming approach, the weight of each subcomponent depends on its location in the distribution at each point in time, implying that different subcomponents are assigned different weights over time (or are even excluded at some periods). Thus, we can identify subcomponents that are predominantly found in the tails or at the center of the distribution over time and see how this varies across our set of countries.[6]

First, we focus on the distributions resulting from the supervised weighting approach. For all countries, we see that the trimming is asymmetric and that it is left-skewed, upweighting the upper part of the distribution (see chart 3 and chart A4 in the annex for more details). While two

[6] In charts 3 and 4, we focus on the median of the components' weights over time.

countries, Germany and Spain, suggest a relatively sparse solution, weights for Italy are densely distributed. Apart from these countries, the norm seems to be a smooth, but highly asymmetric trim assigning weights to the upper two-thirds of the distribution.

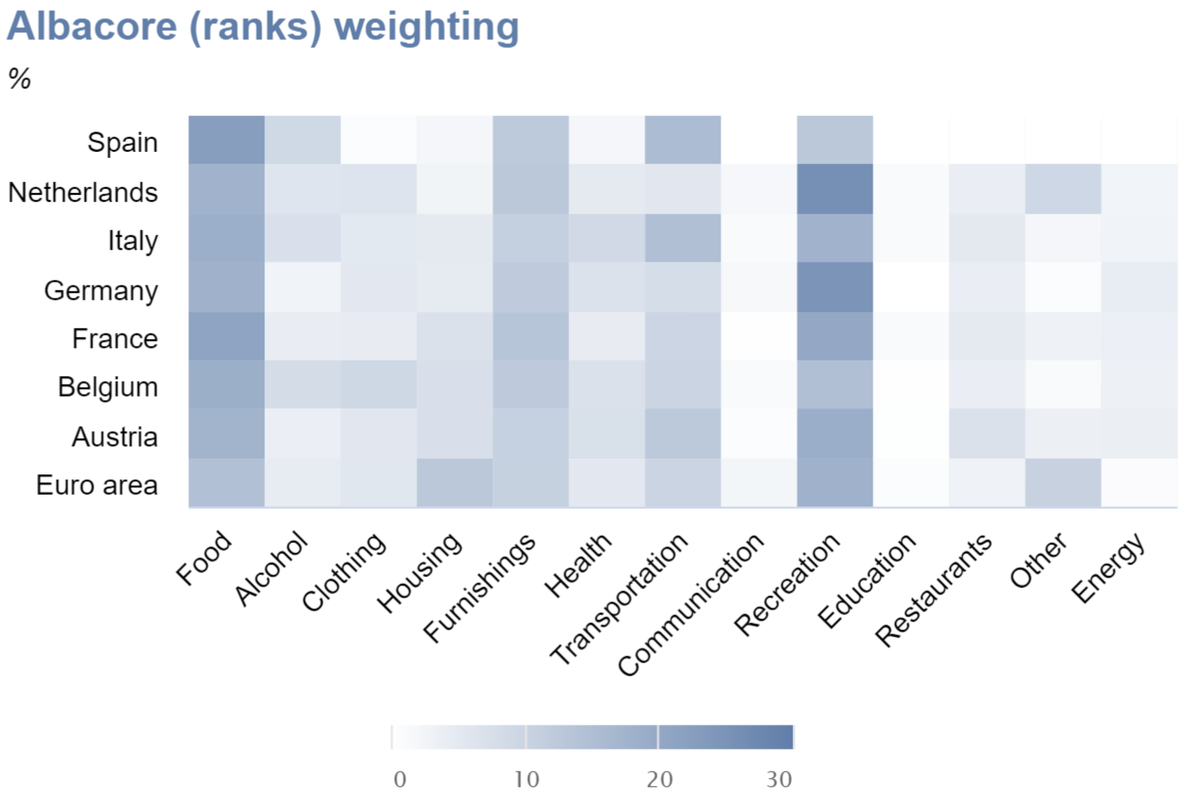
Chart 3



Source: Authors' calculations.
Note: This chart shows the distribution of Albacore (ranks) for each country and the euro area in percent. It indicates the range between the highest and lowest rank receiving a non-zero weight as well as the rank with the highest weight. Results are based on estimates for the period from April 2002 to December 2019.

Converting weights back to components reveals that components with the highest weights averaged over time belong to the food and recreation category (see chart 4). Moreover, furnishings and transportation frequently show up in those parts of the distribution that receive high weights. Low importance is assigned to services and goods in the communication and education category, which can be explained by their low to negative growth rates. This fact places them in the lower parts of the distribution, which receives little to no weight.

Chart 4



Source: Authors' calculations.
Note: This chart shows the median weights of Albacore (ranks) for each country and the euro area over time, transformed back to components space, in percent. For more details on the transformation process, see Goulet Coulombe et al. (2024). We aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

When evaluating our results relative to the official weights (see chart 5), some of our previous findings are confirmed while others are set aside. First, energy decreases in importance, which is something we find for all countries under review and both Albacore measures. Second, subcomponents related to communication are found not to be informative for forward-looking measures, while those related to recreation are. Food, however, tells a different story for Albacore (ranks). Being frequently located in the middle to upper parts of the distribution of monthly price growth, the corresponding subcomponents enter the aggregate with even higher weights than in the headline inflation rate. Similarly, housing flips its sign and is less important in Albacore (ranks) while it was upweighted in Albacore (components) for most economies in our set.

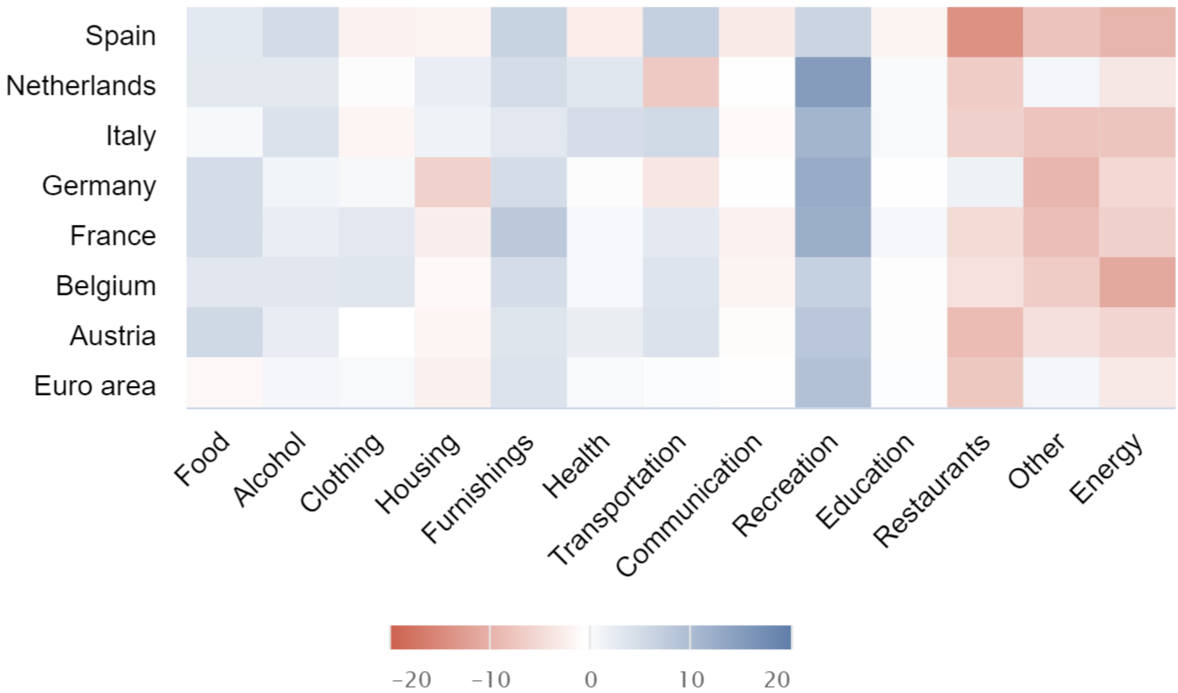
As in Albacore (components), we do not observe significant heterogeneity across countries, although some results are country specific. Examples include a higher weight on the restaurants category for Germany and a lower weight on the transportation category for the Netherlands and Germany. These observations, however, are not due to large differences between the results produced by Albacore (ranks) but can be explained by the fact that the corresponding official weights differ significantly from the other countries. Chart A1 in the annex reveals that Germany features a considerably lower weight on restaurants than all the other economies in our sample.

Conversely, transportation subcomponents in Germany and the Netherlands have relatively high weights. Albacore (ranks), in general, does not show any striking differences across countries.

Chart 5

Differences between Albacore (ranks) and official weighting

Percentage points



Source: Authors' calculations.
Note: This chart shows the difference between median Albacore (ranks) weights over time, transformed back to components space, and official Eurostat weights for each country and the euro area, in percentage points. For Albacore (ranks) in components space, we aggregate components back to level 2. Results are based on estimates for the period from April 2002 to December 2019.

4 Conclusion

Basing inflation forecasts on inflation subcomponents can be beneficial in terms of forecasting performance, and building a thorough analysis on inflation subcomponents can be highly informative with respect to different developments in individual sectors and countries. In this study, we constructed a maximally forward-looking core inflation measure for the seven largest euro area economies, which is found to perform well in terms of signaling inflation trends in the medium term. Components identified as important inflation drivers in the medium term are goods and services related to housing, recreation and other services. Energy subcomponents are found not to be informative due to their high volatility. Results for food subcomponents are somewhat ambiguous in the sense that they receive a low weight for the measure based on inflation subcomponents while, when we use the monthly price growth distribution for a supervised trimming approach, the corresponding results show up frequently in highly weighted parts of the distribution. Regarding country heterogeneity in the euro area, we do not find significant differences when it comes to forward-looking properties of inflation subcomponents.

From a central bank perspective, the homogenous nature of our findings supports the common narrative, i.e. discounting temporary supply shocks and concentrating on more persistent underlying pressures. Given their good forecasting performance, monitoring inflation measures based on maximally predictive inflation subcomponents offers valuable insights into sector-specific and country-specific inflation trends. By identifying commonalities across countries, this approach supports more targeted and effective policy interventions.

References

Aruoba, S. and T. Drechsel. 2024. The long and variable lags of monetary policy: Evidence from disaggregated price indices. NBER Working Paper 32623.

Banbura, M. and E. Bobeica. 2020. PCCI – a data-rich measure of underlying inflation in the euro area. ECB Statistics Paper 38.

Benalal, N., J. L. Diaz Del Hoyo, B. Landau, M. Roma and F. Skudelny. 2004. To aggregate or not to aggregate? Euro area inflation forecasting. ECB Working Paper 374.

Bermingham, C. and A. D'Agostino. 2014. Understanding and forecasting aggregate and disaggregate price dynamics. Empirical Economics 46(2). 765–788.

Bilke, L. and L. Stracca. 2007. A persistence-weighted measure of core inflation in the euro area. Economic Modelling 24(6). 1032–1047.

Boaretto, G. and M. C. Medeiros. 2023. Forecasting inflation using disaggregates and machine learning. arXiv preprint arXiv:2308.11173.

Bryan, M. F. and S. G. Cecchetti. 1993. Measuring Core Inflation. NBER Working Paper 4303.

Bryan, M. F., S. G. Cecchetti and R. L. Wiggins. 1997. Efficient Inflation Estimation. NBER Working Paper 6183.

Bryan, M. F. and C. Pike. 1991. Median Price Changes: An Alternative Approach to Measuring Current Monetary Inflation. Economic Commentary. January 12.

Cecchetti, S. G. and R. Moessner. 2008. Commodity prices and inflation dynamics. BIS Quarterly Review. 55–66.

Chalmovianský, J., M. Porqueddu and A. Sokol. 2020. Weigh(t)ing the basket: aggregate and component-based inflation forecasts for the euro area. ECB Working Paper 2501.

Clark, T. E. 2001. Comparing Measures of Core Inflation. Federal Reserve Bank of Kansas City Economic Review 86(2).

Diebold, F.X. and M. Shin. 2019. Machine Learning for Regularized Survey Forecast Combination: Partially-Egalitarian Lasso and its Derivatives. International Journal of Forecasting 35(4). 1679–1691.

Dolmas, J. 2005. Trimmed Mean PCE Inflation. Federal Reserve Bank of Dallas Working Paper 506.

Dolmas, J. 2009. Excluding Items from Personal Consumption Expenditures Inflation. Staff Papers 7. Federal Reserve Bank of Dallas. June.

Eckstein, O. 1981. Core Inflation. Prentice-Hall. Englewood Cliffs, N. J.

Ehrmann, M., G. Ferrucci, M. Lenza and D. O'Brien. 2018. Measures of underlying inflation for the euro area. Economic Bulletin Articles 4.

Espasa, A. and Albacete, R. 2007. Econometric Modelling for Short-Term Inflation Forecasting in the Euro Area. Journal of Forecasting 26(5). 303–316.

Espasa, A., E. Senra and R. Albacete. 2002. Forecasting inflation in the European Monetary Union: A disaggregated approach by countries and by sectors. The European Journal of Finance 8(4). 402–42.

Fulton, C. and K. Hubrich. 2021. Forecasting US Inflation in Real Time. Econometrics 9(36). 1–20.

Gamber, E. N. and J. K. Smith. 2019. Constructing and evaluating core inflation measures from component-level inflation data. Journal of Forecasting 38(8). 833–852.

Giannone, D., M. Lenza, D. Momferatou and L. Onorante. 2014. Short-term inflation projections: A Bayesian vector autoregressive approach. International Journal of Forecasting 30(3). 635–644.

Gordon, R. J. 1975. Alternative responses of policy to external supply shocks. Brookings Papers on Economic Activity 1975(1). 183–206.

Goulet Coulombe, P., K. Klieber, C. Barrette and M. Göbel. 2024. Maximally Forward-Looking Core Inflation. arXiv preprint arXiv:2404.05209.

Hauzenberger, N., F. Huber and K. Klieber. 2023. Real-time inflation forecasting using non-linear dimension reduction techniques. International Journal of Forecasting 39(2). 901–921.

Hendry, D. F. and K. Hubrich. 2011. Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate. Journal of Business & Economic Statistics 29(2). 216–227.

Hubrich, K. 2005. Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy? International Journal of Forecasting 21(1). 119–136.

Mahedy, T., and A. Shapiro. 2017. What's Down with Inflation? FRBSF Economic Letter 35. Federal Reserve Bank of San Francisco.

Marcellino, M., J. H. Stock and M. W. Watson. 2003. Macroeconomic forecasting in the euro area: Country specific versus area-wide information. European Economic Review 47(1). 1–18.

Motley, B. 1997. Bias in the CPI: "Roughly Right Or Precisely Wrong". FRSBF Economic Letter 16. Federal Reserve Bank of San Francisco.

Ravazzolo, F. and S. P. Vahey. 2009. Measuring Core Inflation in Australia with Disaggregate Ensembles. Proceedings of RBA 2009 Conference. 178–195.

Sax, C. and D. Eddelbuettel. 2018. Seasonal Adjustment by X-13ARIMA-SEATS in R. Journal of Statistical Software 87(11). 1–17.

Stock, J. H., and M. W. Watson. 2016. Core Inflation and Trend Inflation. Review of Economics and Statistics 98(4). 770–784.

Stock, J. H., and M. W. Watson. 2020. Slack and Cyclically Sensitive Inflation. Journal of Money, Credit and Banking 52(S2). 393–428.

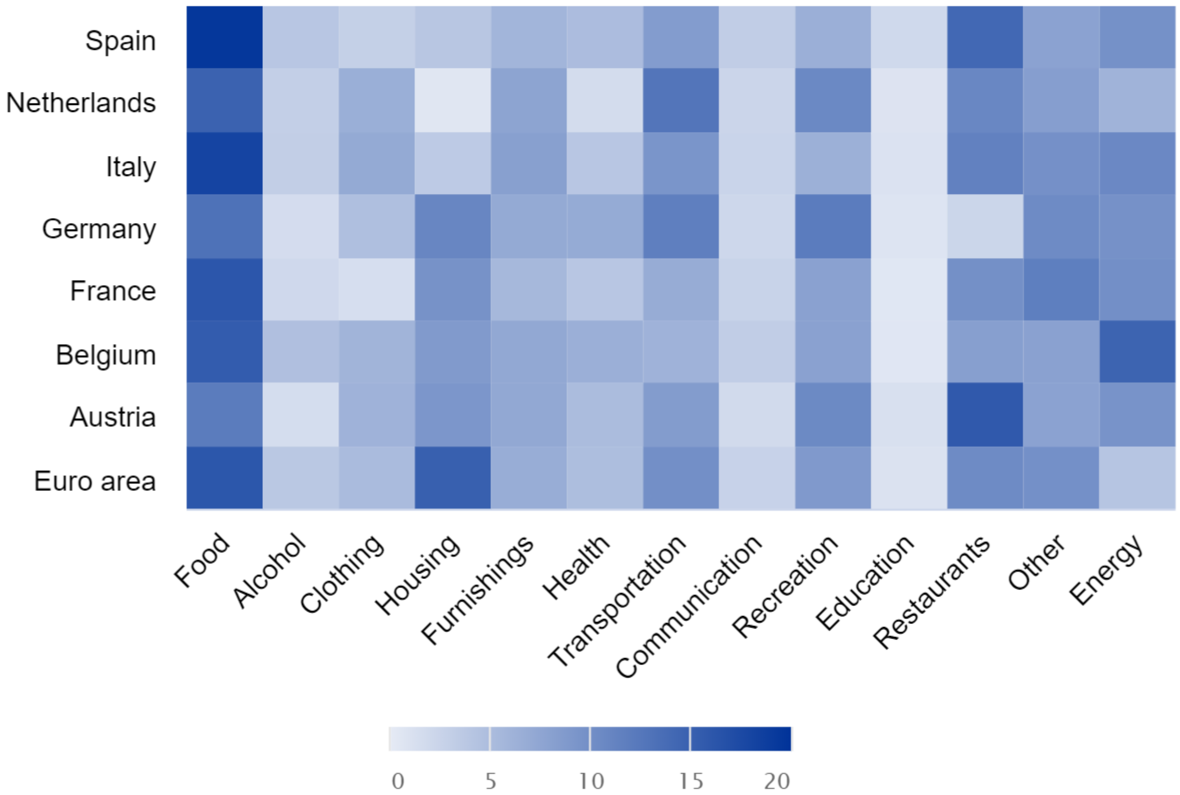
Verbrugge, R. 2022. Is it Time to Reassess the Focal Role of Core PCE Inflation in Assessing the Trend in PCE Inflation? Economia 45(89). 73–101.

Annex

Chart A1

Official weighting (2023)

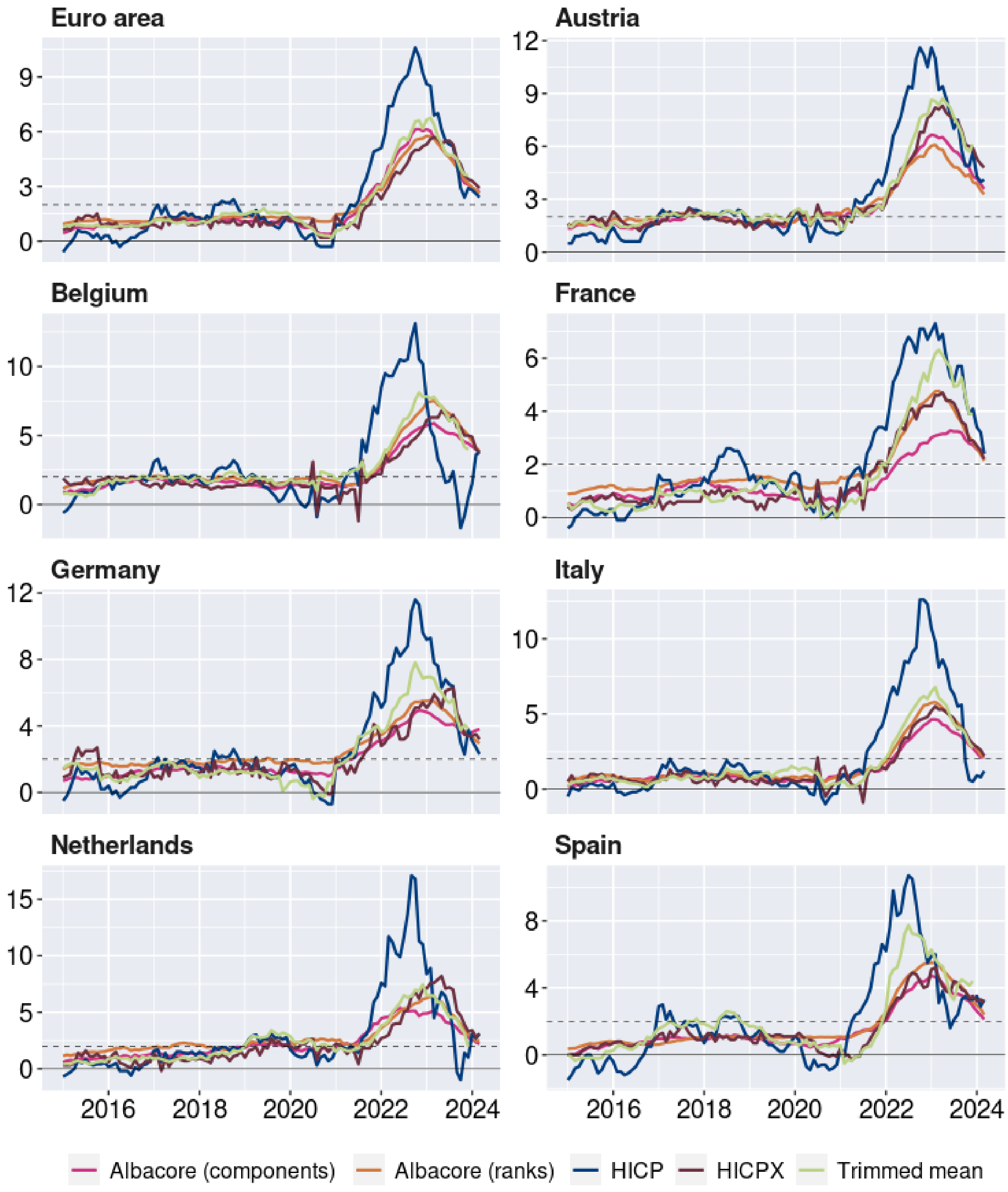
%



Source: Eurostat.

Core inflation measures over time

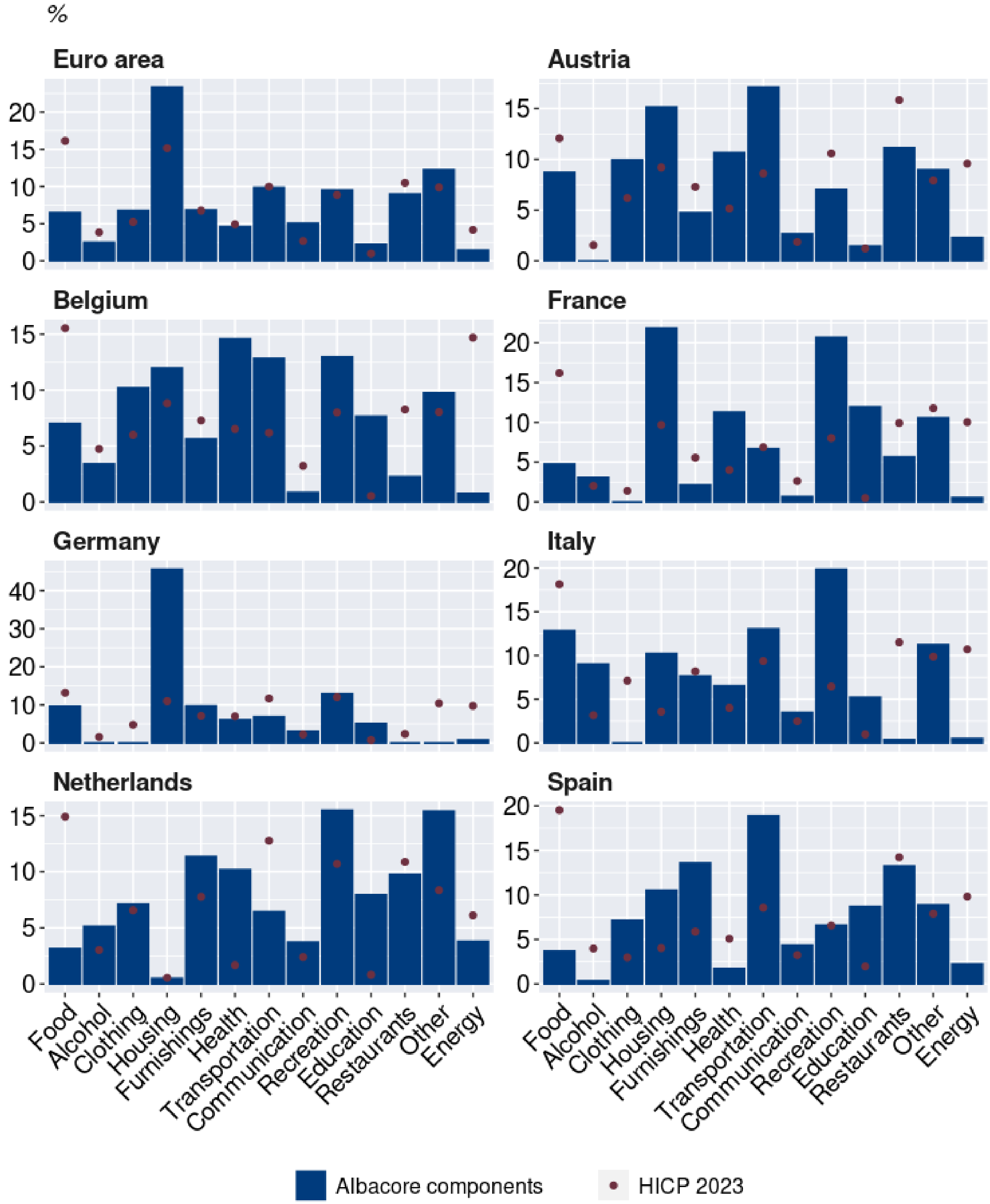
%



Source: Eurostat, authors' calculations.
Note: HICPX refers to HICP inflation excluding energy and food.

Chart A3

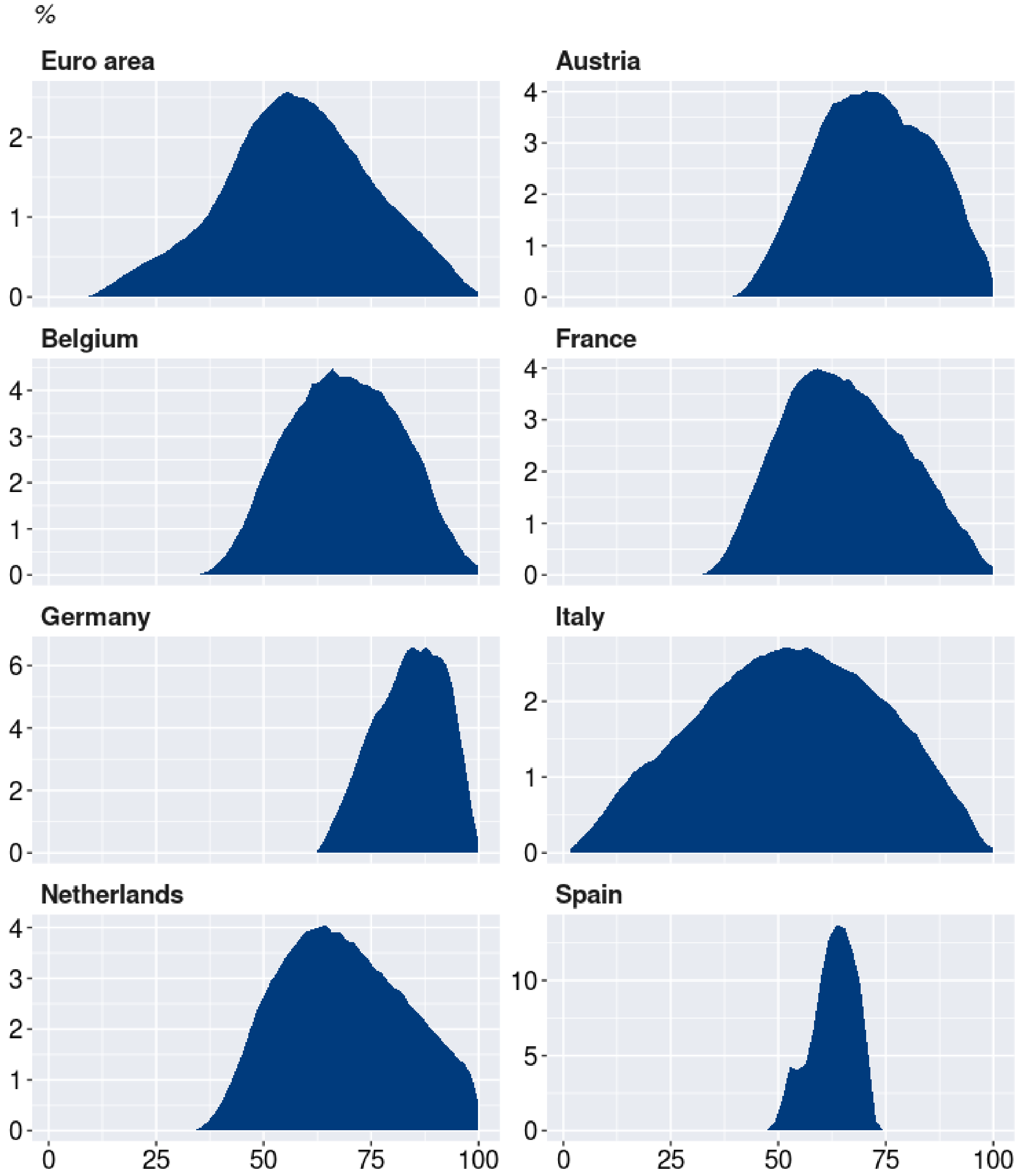
Albacore (components) weighting per country



Source: Eurostat, authors' calculations.

Chart A4

Albacore (ranks) weighting per country



Source: Authors' calculations.

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