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Beyond Aggregates:

A Dual Lens on Eurozone Trend Inflation

Dilan Aydın Yakut

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Non-Technical Summary

Headline inflation rates reflect a combination of price changes that arise from various sources that can be temporary or persistent. On the other hand, underlying or trend inflation refers to persistent price changes but is not a directly observable variable. Therefore, from a policy perspective, it remains crucial to have measures tracking underlying price changes accurately. In addition to the existing signal-to-noise problem, the recent high inflation period posed additional challenges to understanding these dynamics.

This paper aims to investigate trend inflation in the euro area both for individual countries and in the aggregate. Conventional measures of trend inflation, such as core inflation that removes food and energy prices or simple time-series filters come with methodological caveats. For example, food and energy prices, although volatile, can also have persistent components. Moreover, aggregating inflation data across countries and/or sectors can mask significant differences. To address these challenges with conventional measures, we use a refined approach relying on unobserved component models to estimate trend inflation. To do so, we combine information from both the cross-sectional and time-series dimensions of the series. The analysis uses two lenses: (1) country-level perspective showing differences in trend inflation across the 19 euro area members and (2) sector-level perspective exploring how sectors (e.g., non-energy industrial goods, services) contribute differently to inflation dynamics. Using these econometric models, various measures of trend inflation are estimated. In addition, we empirically assess the performance of these novel measures and compare them with existing ones.

The empirical findings show that accounting for heterogeneity improves our understanding of the EA inflation. It matters not only to uncover differences underneath the aggregate series, but also in more general terms. First, trend inflation estimates vary significantly between both countries and sectors, particularly in the post-pandemic period. Goods initially drove trend inflation, followed by a rising contribution from services. Secondly, using multivariate models that incorporate sector-level or country-level data tend to outperform traditional univariate models in terms of precision and tracking of future headline inflation. Lastly, comparing various novel estimates and existing measures shows that no single measure perfectly captures underlying inflation, so policymakers should ideally use a combination of tools.

Beyond Aggregates:
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Dilan Aydın Yakut [*]

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Abstract

This study investigates the dynamics of trend inflation for both the euro area (EA) countries and the aggregate rates of the EA. To this aim, trend inflation rates are estimated using various forms of a flexible unobserved components model, allowing for outliers and stochastic volatility. Using granular sector-level data for country-level applications provides a finer comparison between the member countries. Both models exploiting the sector and country levels are considered for the euro area to understand the underlying dynamics more thoroughly. In addition, alternative estimates for the euro area are obtained by combining country-level results. The results show that the use of multivariate models improves precision and outperforms the univariate models at longer horizons. A horse race between these estimates and the other popular measures from the literature, such as PCCI, supercore, etc., shows that no single metric outperforms the others. Therefore, it remains crucial to have various measures in the toolbox of policymakers as they complement each other.

JEL Codes: E52, E33, C32, C11

Keywords: Trend inflation, persistence, unobserved components, the euro area

[*]Central Bank of Ireland, Monetary Policy Division. E-mail: dilan.aydinyakut@centralbank.ie. I thank Gabriel Arce-Alfaro, Emanuele Bacchiocchi, David Byrne, Daragh Clancy, Luca Fanelli, Luca Gambetti, Robert Goodhead, Reamonn Lydon, Fergal McCann, Laura Moretti and Alessia Paccagnini for their valuable comments on various drafts of the paper. Also, I greatly benefited from discussions of the seminar participants at the Italian Econometric Association Summer School in Bertinoro, IPECE-2021, University of Bologna, Central Bank of Ireland, IEA Annual Conference 2024. The views expressed are my own and do not necessarily reflect those of the Central Bank of Ireland.

1 Introduction

The recent high inflation environment necessitated a greater understanding of the extent of persistent components in headline inflation. Lagarde (2023) explicitly emphasised the importance of underlying inflation dynamics as part of the ECB's monetary policy reaction function in the recent high inflation and uncertain environment. However, disentangling the underlying inflation is challenging for several reasons.

First, some price changes are short-lived and might be related to an idiosyncratic shock or, more generally, temporarily responding to an economic cycle. On the other hand, some prices are affected more frequently by outliers or display greater volatility, making it challenging to pinpoint long-term persistent changes. In that respect, a signal-extraction problem must be solved. The second challenge arises directly from the nature of the data. The inflation rate is a macroeconomic variable obtained by aggregating individual sector-level price changes using their weights from a representative commodity basket consumed by households. However, as remarked by Altissimo et al. (2006), the cross-sectional aggregation of individual time-series might not be as innocent as it seems. That is to say, aggregation of series with different persistence and volatility characteristics can give rise to wash-out underlying dynamics in the series. They consider this potential mechanism to explain the puzzling behaviour that aggregate inflation rates have high persistence, whereas sectoral inflation rates display minimal persistence. Therefore, both the signal extraction problem and the nature of the aggregation process are essential to understanding the underlying inflation dynamics.

In Europe, the puzzling behaviour of inflation rates has attracted much attention since the Great Recession. "Twin puzzles" as explained in Friedrich (2016) refer to the surprisingly muted reaction of inflation rates to the business cycle during the recession and the subsequent recovery period. Although some papers (Coibion and Gorodnichenko, 2015; Mazumder, 2018) attempt to explain them relying on structural factors such as the role of well-anchored expectations, others (Bobeica and Jarocinski, 2017; Ciccarelli et al., 2017) claim that domestic and external factors related to the cycle played a crucial role. Although the evidence on the causes of the puzzles is far from conclusive, it is generally inferred that the underlying or trend inflation has shifted during this period.

As underlying inflation is not directly observed, different techniques have been applied to headline rates to obtain its permanent slow-changing component. The most conventional proxy for underlying inflation is core inflation, computed by excluding food and energy sectors from the Harmonised Index of Consumer Prices (HICP) in the EA. However, this measure heavily relies on the assumption that food and energy prices are very volatile and not persistent, so we can obtain a trend component by excluding them from the headline rates. An interesting empirical fact noted by Mazumder (2018) is that between

2012 and 2015, headline inflation in the euro area declined more than core inflation measured by the HICP, excluding food and energy. Peersman (2022) shows that changes in international food prices play an important role in explaining the inflation puzzles. Using US data, on the other hand, Giri (2022) finds evidence of a disconnect between conventional core inflation and headline inflation, while energy prices seem related to headline inflation at a broad range of frequencies. Thus, it might be essential to consider the potential changes in food and energy prices that the conventional core measure cannot capture.

Following the low inflation period, inflation rates have increased substantially in recent years. Initially, the shocks related to the pandemic, such as supply-chain disruptions and the reopening of the economies after a period of stringent measures, put pressure on prices. As noted in Bodnár et al. (2020) and Lane (2021), the impacts of the pandemic in different sectors have been remarkably heterogeneous. In the beginning, rising prices were mainly attributed to temporary factors and, therefore, can be related to the cyclical component of inflation rather than underlying inflation. However, another series of shocks pushed prices further up following the war in Ukraine since February 2022. These shocks led to an energy crisis accompanied by an increase in food and commodity prices. The unprecedented nature of these shocks and potential interactions made the existing signal extraction problem in inflation dynamics even more complicated. Although underlying inflation is recognised to have increased recently, the greater uncertainty surrounding the economy is also reflected in the wide range of underlying inflation measures monitored by the ECB, such as trimmed means, Supercore and PCCI, as mentioned in Lane (2023).[1]

This study investigates the underlying inflation in the euro area, considering two different sources of heterogeneity from both countries and sectors. To dissect trend inflation dynamics using a dual lens, various trend inflation measures are estimated based on an unobserved components model as proposed by Stock and Watson (2020) and its extensions. Then, I compare the performance of these measures based on several empirical criteria related to the precision of estimates and tracking future headline inflation. There are two groups of empirical applications. First, trend inflation rates are estimated using four different models separately for 19 European Monetary Union (EMU) countries. The models consist of univariate and multivariate-sector econometric models from Stock and Watson (2020) and extensions to obtain the trend estimates suggested by Almuzara and Sbordone (2022). The multivariate-sector model and extensions rely on granular data from 11 sectors to produce country-level trend inflation estimates. Comparing trend inflation estimates across countries shows that heterogeneity became more evident after the pandemic. The results suggest that the sectoral decomposition of the underlying inflation rates matters for understanding heterogeneity. Acknowledging the high uncertainty implied by the wider credible intervals in the post-pandemic, it is shown that the multivariate models outperform the univariate version in most countries. Secondly, I estimate trend inflation measures for the euro area aggregate. In addition

[1] Ehrmann et al. (2018) explains these measures in detail.

to the four models mentioned above, I propose another multivariate specification. This approach exploits the country's inflation rates rather than sectors, defined as a multivariate-country model. Lastly, alternative measures of trend inflation are computed by pooling the country-weighted average of the individual country results estimated in the first part.

The contributions of the paper are several-fold. First, I provide a novel application of Stock and Watson (2020) for 19 EMU countries individually. As noted in several papers, (e.g., Marcellino et al., 2003; Garnier et al., 2015; Vlekke et al., 2020), despite the presence of the monetary union, the inflation dynamics in the member countries were considerably diversified in the pre-pandemic period. In the recent period, although prices have increased globally, there have been significant variations in both the level of inflation rates and also the evolution of these rates as emphasised by Binici et al. (2022). In that respect, the empirical analysis allows me to compare the underlying inflation estimates at the country level in the area. To the best of my knowledge, this is the first attempt to systematically understand the heterogeneity across European countries and sectors, focusing primarily on the post-pandemic period. Considering the presence of unusual shocks affecting different sectors and their varying effects in the countries, it aims to uncover the dynamics beyond the aggregate data using a flexible statistical approach.[2] Secondly, I extend the application of the multivariate model to the country dimension rather than focusing on sectoral inflation rates. This approach addresses two different sources of heterogeneity in the euro area inflation rates. The first is emerging from the differences between the sectoral inflation rates, whereas the second is related to the disparity of the country-level inflation rates in the monetary union. I also produce trend estimates based on the extension suggested by Almuzara and Sbordone (2022). Moreover, alternative trend inflation measures are proposed for the euro area by applying the multivariate sector model to the individual countries and pooling the results. From a policymaker's perspective, it remains essential to know how useful these different underlying inflation measures are in assessing the inflation outlook's evolution and better informing policy decisions. As highlighted by Bańbura et al. (2023), Lane (2023), among others, there has been great uncertainty among the different underlying inflation measures of the euro area after the pandemic. Therefore, an empirical assessment based on several metrics, precision, root mean square errors, and lead-lag analysis, is conducted to understand the usefulness of different measures. In addition to comparing trends estimated in this paper, I also assess the performance of these trend inflation measures relative to others, such as conventional core inflation, other frequency exclusion measures, Supercore, and PCCI.[3] The results show that it is important to inform policy decisions using various models, especially in a high-uncertainty environment, as no single model outperforms at all horizons.

[2]This study relies on a reduced form model and does not aim to investigate structural relations on different shocks affecting the economy in the recent period. Banbura et al. (2023) provides a comprehensive analysis of the estimation of different shocks affecting core inflation in the euro area.

[3]The HICP excluding food and energy is referred to as core inflation in the euro area.

The plan of the paper is as follows. Section 2 provides a review of the literature. Section 3 discusses the data, and Section 4 describes the methodology. Section 5 presents the estimation results and provides an empirical assessment for different measures. Section 6 concludes the study.

2 Literature Review

In order to estimate the permanent, or trend, component of the inflation, various methods with different levels of statistical complexity are proposed in the literature. There are three strands of the literature. The first approach relies on cross-sectional exclusion measures. These sectors are excluded following the specification of the most volatile items in the aggregate inflation series. The trend measure is constructed as the weighted average of the remaining sectors. The implicit assumption in this technique is that the sectors displaying high volatility tend to have low intrinsic persistence. Therefore, a trend inflation measure that would reflect only persistent movements can be obtained by excluding volatile sectors. To illustrate, HICP, which excludes energy, food, alcohol, and tobacco produced by the ECB, core inflation based on PCE of the US Bureau of Labor Statistics, weighted median and the trimmed mean proposed by Bryan and Cecchetti (1994), CPI excluding eight items by Clark (2001), optimally trimmed mean by Dolmas (2005) rely on trend inflation measures obtained by the exclusion of specific components.

In these approaches, although there are advantages of the low computational cost and the simplicity of conveying information to the public (Nickel and O'Brien, 2018), they suffer from considerable limitations. To begin with, the excluded items, such as food and energy, to avoid volatile movements are highly likely to be important in the consumption decision. On the other hand, the tacit assumption that the highly volatile components tend to display lower persistence is questionable. In fact, Ehrmann et al. (2018) show that the volatility and persistence measures are not necessarily inversely correlated. To illustrate, some energy components such as gas, heat, and electricity exhibit high persistence and volatility levels. Removing the energy component from the trend would also leave out the persistent price movements, which is counter-intuitive. The exclusion measures may considerably lead to the contraction of the information set and mislead policy.

The second strand of the literature focuses on the time-series dimension to estimate trend inflation. Among univariate approaches[4], Nelson and Schwert (1977) suggest an integrated moving average model for the estimation of trend inflation. Atkeson and Ohanian (2001) propose a "naive" quarterly estimator based on inflation in the previous four quarters. Alternatively, Cogley (2002) suggests a novel core infla-

[4] On the multivariate approach, Coibion and Gorodnichenko (2015), Chan et al. (2018), and Mertens and Nason (2020) mainly focus on the estimation of trend inflation related to real macroeconomic variables such as unemployment or output gap and also the inflation expectations

tion measure relying on exponential smoothing methods. As trend inflation, by definition, represents the low-frequency, permanent movements of the inflation series, a low-pass filter allowing for these movements to be decomposed is utilised. A seminal paper, Stock and Watson (2007), uses an unobserved components model. Aggregate inflation comprises a trend and a cycle component in their setup. Then, trend inflation is modelled as a random walk process with stochastic volatility. Their main finding regarding the Great Moderation period is that the inflation rate becomes harder to forecast despite declining volatility. In that respect, modelling trend inflation, the long-term expectation of inflation series, beyond the univariate models, becomes a challenging task. As pointed out in many papers, such as Cogley et al. (2010), Clark and Davig (2011), in addition to Stock and Watson (2007), the inclusion of stochastic volatility in trend inflation models is crucial. This strand of the literature enriched the modelling dynamics by considering both the persistence of trend inflation and the changing volatility without imposing any assumption on the relation between these features. Unlike the exclusion measures, these approaches incorporate time-series properties of inflation rates. However, working directly with the aggregate inflation series causes the undermining of rich sector dynamics. As emphasised by Altissimo et al. (2006, 2009), aggregation can give rise to severe problems if the individual prices are heterogeneous and the extent of common movement is limited. From another aspect, Marcellino et al. (2003) study whether it is better to use the euro area aggregate prices or to model them at the country level and then pool them into aggregate series regarding forecast performance. Their results confirm considerable gains from modelling disaggregate prices rather than using the aggregate variable. Overall, both the exclusion measures and the time-series model focusing on the aggregate inflation rate suffer from different methodological drawbacks.

An alternative approach is to incorporate the cross-sectional and the time-series dynamics of prices in a unified frame. In that respect, the focus is to model sectoral inflation rates rather than aggregate inflation. Hubrich (2005) compares forecasting of aggregate series relative to aggregation of the sector-level forecasts using the monthly data throughout 1992:01 to 2001:12 in the euro area. They emphasise the possibility of having improved or deteriorated forecasts using the aggregated version of the sectoral forecasts. While considering that the dynamic properties of the series at the disaggregated level might improve the precision, it is also possible to have more misspecification problems in the disaggregated data. They especially underline this problem related to the sectors for which forecasting is difficult, such as food and energy. The empirical results, where five sectors, processed and unprocessed food, industrial goods, energy and services are included, confirm that using the disaggregated data does not necessarily improve the precision. Bilke and Stracca (2007) suggest a novel measure using 93 components of the monthly HICP for the euro area throughout 1995:01 and 2007:01. After modelling each price change as autoregressive processes, they determine the persistence of each measure by summing the autoregressive coefficients. Then, they re-weight each sector according to their persistence to construct the core inflation measure. Their empirical results confirm that the conventionally excluded sectors display a greater persistence coefficient than their original weights. Altissimo et al. (2009) estimate a dynamic factor model using 404 sectors in the euro area for 1985:Q1-2004:Q2. They allow each sector to have idiosyncratic and common components to uncover heterogeneity among the sectors. The results confirm that although the idiosyncratic shocks primarily drive the sectoral inflation rates, one common component also affects the sectors. Moreover, they point out that a greater degree of persistence in the original aggregate inflation series is affected not only by the cross-sectional aggregation procedure but also by the high persistence of services inflation. Stock and Watson (2016) suggest an unobserved components model with stochastic volatility and outliers to estimate trend inflation in the United States. They use prices from 17 sectors of the PCE for the period of 1959:Q1-2015:Q2. The empirical results suggest that the multivariate econometric model produces more precise estimates than the univariate model. Stock and Watson (2020) extend the former paper to a seasonal unobserved components model with stochastic volatility and outliers and conduct an application to the aggregate euro area inflation data for 2001:Q2-2018:Q1. Bańbura and Bobeica (2020) propose a novel trend inflation measure using a dynamic factor model for the euro area.[5] Following estimating a low-frequency common component using the sectoral inflation rates in 12 countries, they construct the PCCI using their relative weights in the consumption basket and the euro area, respectively. Extending the univariate model by Stock and Watson (2007), Eo et al. (2023) allows for a time-varying correlation of goods and services trend to investigate their relative contribution to the volatility of trend estimates in the US. They find that the goods sector mainly drives the lower volatility in trend inflation.

3 Data

The data series are monthly harmonised consumer price indexes for sectors and headlines, annual sector weights, and annual country weights. These series were retrieved from Eurostat. The data are not seasonally adjusted and cover the period from 2001:M04 to 2023:M09. 11 sectors are classified according to the product type by classification of individual consumption by purpose (COICOP). As shown in Table 1, there are six goods[6], and five sectors belong to services. The data set includes 19 countries as listed in Table B.3 and the euro area aggregate series.[7] The different frequencies of the series are converted following Stock and Watson (2020). That is to say, the monthly price indexes are converted into

[5] Different from Stock and Watson (2020), they impose the stationarity assumption to the inflation rates. Moreover, the trend inflation is constructed using only common factors, and the idiosyncratic sectoral dynamics are excluded. They estimate the model after removing outliers from the data and seasonally adjust the series using ARIMA-X12.

[6] NEIG stands for non-energy industrial goods.

[7] The euro area aggregate refers to the euro area with the changing composition of countries as defined in the official statistics.

quarterly data by taking the monthly averages. Then, the quarterly inflation rates are calculated as log differences of the indexes multiplied by 400.[8] The data on the alternative underlying inflation measures[9] were retrieved from the Statistical Data Warehouse of the ECB.

Table 1: Sectors by product type

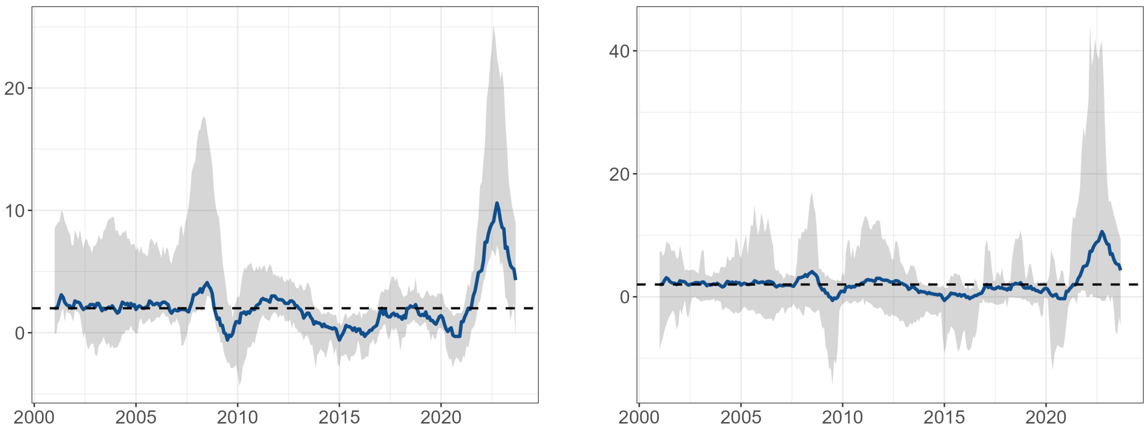
Goods		**Services**
Food	Industrial	Communication
Processed	NEIG Durable	Housing
Unprocessed	NEIG Semi-durable	Miscellaneous
	NEIG Non-durable	Recreation
	Energy	Transportation

The annual sector and the country weights are converted into quarter frequency using the Kalman smoother as in Stock and Watson (2020). The country (sector) weights represent the share of each country (sector) in the EA (the consumer basket of the country) and add up to 100. Table B.2 shows the average weights of sectors in each country and each country's average weights in the euro area aggregate. Food and energy sectors, which are conventionally excluded from the core inflation, comprise approximately 30 per cent of the basket for most countries. Unlike other countries, the weights are higher than 40 per cent in the central and eastern EA countries. The share of non-energy industrial goods forms approximately one-fourth of the basket, ranging between 23 per cent in Ireland and 30 per cent in Luxembourg. Therefore, the goods category is nearly 60 per cent of the consumption basket, whereas the services represent around 40 per cent. Among the services, recreation is generally the largest sector with a great level of dispersion that can be as high as a quarter of the basket in Ireland to 12 per cent in Germany. After recreation, the greater weights are related to housing, miscellaneous, and transportation services. Therefore, beyond the price changes, the decomposition of the consumption basket also contributes to the differences across countries. Concerning the weight of countries in the euro area aggregate, the four big countries, Germany, France, Italy, and Spain, account for nearly 78 per cent of the area.

Figure 1 shows the headline inflation rate in the euro area (blue-dotted lines) and the range of the rates in the countries and sector inflation rates, respectively. The euro area headline inflation rates are computed as weighted averages of these countries and sectors. The EA headline inflation rate had been relatively stable, around 2 per cent, before the Great Recession and displayed an inverse U shape before reaching -0.6 in July 2009. In the following years, it recovered to its pre-crisis level. However, after 2012, the inflation rate declined gradually despite the economic recovery from the twin crises. Except for a short period in 2018, the rates remained below two per cent. Following the start of the pandemic, the

[8]Following the analysis, the results are converted into monthly rates as the underlying inflation measures are usually reported at this frequency. Using monthly rates in the analysis is computationally costly due to the model's flexibility and tends to produce more erratic results.

[9]Table B.1 provide a summary of these measures.



(a) Country heterogeneity

(b) Sector heterogeneity

Figure 1: The euro area headline inflation rates

implementation of stringent lockdown measures in 2020: Q2 hampered demand strongly, and the inflation rates turned negative in the second half of 2020. However, the inflation rate increased substantially from 2021 due to a series of unusual shocks caused by global supply chain disruptions, the reopening of economies, and the war in Ukraine. Following the peak at 10.6 per cent in October, the inflation rates started to decline due to the receding shocks and ample monetary policy tightening by the ECB.[10]

As evident from the range of country headline inflation rates (left) and sector inflation rates (right), the aggregate series camouflages the intrinsic features of these granular series. To start with the country dimension, although the euro area inflation rate was very stable before the global financial crisis, the figure shows great disparities among the countries.[11] As shown in Figure A.1 in the appendix, inflation rates have been relatively volatile in the countries that joined the euro area later, as represented in the bottom panel. Similarly, the inflation rates changed abruptly around the crises in countries like Greece, Ireland, and Portugal, which were severely affected by the debt crisis. However, the figure suggests that the decline in rates from 2012 is evident in both the aggregate level and individual countries, as indicated by the shrinking range of the interval. Moreover, the narrowing interval also implies the higher convergence of the inflation rates in the euro area. Since the summer of 2021, on the other hand, the inflation rates have diverged, as shown by the widening range of inflation rates. Although the gap started to shrink after reaching the peak in August 2022, there is still considerable heterogeneity in the disinflation processes of these countries.

Concerning the sectors, the range of the figure on the right shows that the price changes of the sectors tend to be more volatile than the headline inflation rates. In the appendix, figure A.2 shows that heterogeneity is even greater if one considers the behaviour of price changes in different sectors. As

[10] The ECB started to increase interest rates in July 2022. From July 2022 to September 2023, the rates increased by 450 basis points.

[11] The range also includes the headline rates of the late joiners to the EA.

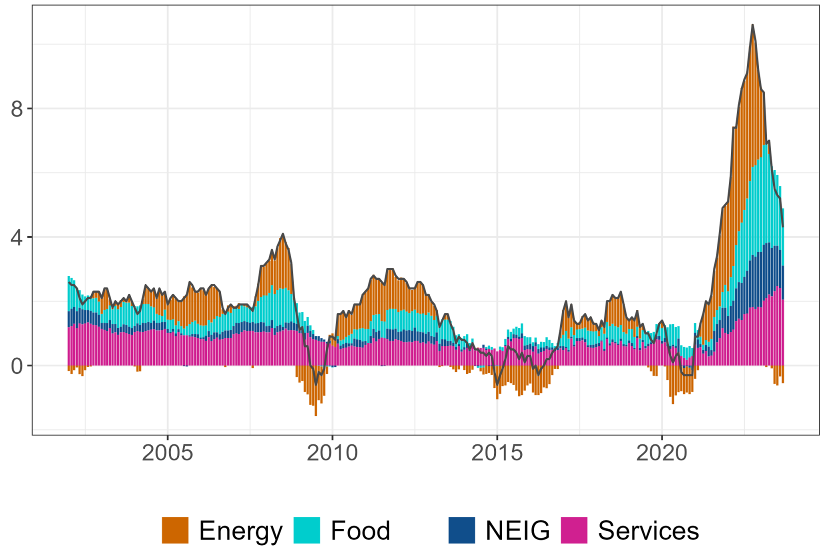


Figure 2: The contribution of sectors to headline inflation

conventionally known, food and energy prices display greater volatility, whereas prices of NEIG and services change relatively smoothly. On the other hand, these volatile sectors do not necessarily show lower persistence compared to the others. To illustrate, the price changes in energy seem persistently low after 2011. Moreover, the figure shows that even prices in the sectors known to vary slowly have surged substantially in the recent inflation period. Therefore, the figures suggest that the behaviour of sectoral price changes is not as simple as the assumption of persistence volatility trade-off.

To further inspect the sources of these price changes, Figure 2 shows the contribution of different sectors to the annual euro area inflation in percentage points from 2002:M1 to 2023:M09. During the Great Recession, the sectoral contribution to aggregate prices shrank for all sectors, and even the energy sector contributed negatively. The partial recovery from 2010 was reversed around late 2011, and the services and energy prices initially drove the decline. Then, non-energy industrial goods and food prices followed in the next years. Once again, the contribution of the energy prices was negative from 2013 until late 2016.

In the recent inflation surge period, the contribution of all sectors to the headline inflation increased considerably. However, the role of the energy sector was prominent. Following the reversal of declining energy prices in 2021:Q1, the energy sector's contribution increased substantially in the following period. The war in Ukraine exacerbated the existing pressures, and the contribution to headline inflation reached 4.45 percentage points in October 2022. Since then, the contribution of energy has declined and turned negative in the second half of 2023.

Similarly, higher contributions from food prices skyrocketed after the start of the war in Ukraine and climbed above three percentage points in early 2023. In another goods sector, the contribution of

NEIG to the headline followed an upward trend as early as 2021, resulting from supply chain disruptions and supply-demand mismatches after the reopening of economies. Contrary to the historically low contribution to headline inflation, the higher prices in the sector escalated the pressures further, and the contribution peaked at 1.74 percentage points only in February 2023. Therefore, the figure shows that the contribution of goods to headline inflation has been very substantial in the last years, and this pattern reversed since early 2023. On the other hand, higher prices in the services sector later affected headline inflation than goods. The contribution by services started to increase slightly after the reopening in the summer of 2021. However, the contribution increased gradually over the following two years, reaching 2.47 percentage points in July 2023. Despite the recent signs of easing pressures in the services sector, the relatively persistent nature of this sector can imply a slower decline compared to the goods sector.

4 Methodology

This paper uses an unobserved components model with stochastic volatility. The model used in the paper originated from the seminal paper by Stock and Watson (2007), which introduces an univariate unobserved components model with stochastic volatility describing the inflation process better than the Phillips curve type multivariate models. Extending upon the paper, Stock and Watson (2016) develops a multivariate unobserved components model with stochastic volatility and outliers. The model incorporates sector-level data in a dynamic factor model with time-varying factor loadings. More recently, Stock and Watson (2020) extended this approach to model a seasonal component in addition to trend and cycle.[12] In this paper, I use the model specified by Stock and Watson (2020), and the extensions are based on this model. More specifically, factor estimation relies on dynamic factor models.

4.1 Univariate Econometric Model

The univariate econometric model estimates trend inflation by decomposing the aggregate inflation rate into three sub-components: trend, cycle, and seasonal, as shown in the measurement Equation 1. Each component is obtained by relying on specifications reflecting their distinct characteristics. That is to say, the trend is described as in Equation 2 so that it captures the low-frequency, persistent movements in the original series. It follows a random walk process and represents the expected long-term inflation rate. On the other hand, the cyclical component, Equation 3, is a martingale difference sequence, but it includes a process represented by x_t to capture the outliers in the cycle. $x_t = 1$ with probability $1 - p$ when there is no outlier in the cycle, and $x_t \sim U(2, 10)$ with probability p when there is an outlier with a

[12] As shown in Stock and Watson (2016), there are no gains from having time-varying factor loadings, so the loadings are not time-varying in Stock and Watson (2020).

standard deviation two to ten times higher than the other observations detected in the cycle. The outlier x_t is independent of the innovations of the state and volatility equations (5). The seasonal component is defined in Equation 4. Following Harvey (1989), there are two assumptions imposed on the seasonal component. Firstly, the seasonal component must repeat itself in the same quarter of the year. That is to say, $s_{T'+k|T} = s_{T'+k+4|T}$ for all $T' > T$. Moreover, the seasonal components cancel each other out in a year. As we do not expect to see seasonality in annual frequency, the cumulative effect over one year is zero as expressed by $\sum_{k=1}^{4} s_{T'+k|T} = 0$.

$$\pi_t = \tau_t + \varepsilon_t + s_t \tag{1}$$

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t}\upsilon_{\Delta\tau,t} \tag{2}$$

$$\varepsilon_t = \sigma_{\varepsilon,t}x_t\upsilon_{\varepsilon,t} \tag{3}$$

$$s_t + s_{t-1} + s_{t-2} + s_{t-3} = \sigma_{s,t}\upsilon_{s,t} \tag{4}$$

In summary, the model is represented by the measurement (1) and the state equations (2-4) in levels. The volatility equation shown by Equation 5 indicates that the logarithm of volatility follows a random walk process where $k = \Delta\tau, \varepsilon, s$. Moreover, $(\upsilon_{\Delta\tau,t}, \upsilon_{\varepsilon,t}, \upsilon_{s,t}, \eta_{\Delta\tau,t}, \eta_{\varepsilon,t}, \eta_{s,t})$ are assumed to be distributed independently and identically normal with zero mean and unit variance.

$$\Delta ln(\sigma_{k,t}^2) = \gamma_k \eta_{k,t} \tag{5}$$

The univariate model requires initial conditions on trend τ_0, seasonal component $(s_{-3}, s_{-2}, s_{-1}, s_0)$, and the volatilities $ln(\sigma_{\Delta\tau,0}), ln(\sigma_{\varepsilon,0}), ln(\sigma_{s,0})$. Moreover, priors on the scale of variance innovations $(\gamma_{\Delta\tau}, \gamma_{\varepsilon}, \gamma_s)$ and the outlier probability p are needed. The initial conditions are assumed to have independent diffuse Gaussian priors. The priors on the scales of trend, seasonal, and cyclical innovation variances follow uniform distributions, and the prior probability of outliers follows a beta distribution.[13] The model is estimated using Markov Chain Monte Carlo Methods. Following the initialisation of draws by 10,000 iterations, 50,000 iterations are conducted, saving every ten draws to estimate the model. In order to deal with the non-Gaussian measurement error, a 10-component mixture of normal distributions is utilised as suggested by Omori et al. (2007).

Using the decomposition of headline inflation rate π, trend inflation is estimated by the univariate unobserved components model. This model is called U-HICP and is used for country and euro area applications. For the euro area, an additional measure is constructed by pooling the country estimates

[13] The online appendix of Stock and Watson (2016) explains the details of prior selection and initial conditions. I follow the parameters directly from Stock and Watson (2016) and Stock and Watson (2020) except for the prior parameters on the outlier probability. Considering the greater frequency of outliers in the recent pandemic period, the parameters are loosened such that there can be an outlier each year, contrary to the original paper, allowing for only one outlier in each of four years.

from the U-HICP model results. The new measure, U-HICP-P, is obtained as a weighted average of U-HICP trend estimates of the countries. The country weights are retrieved from the data in Table B.2.

4.2 Multivariate Econometric Models

Multivariate-sector model (MS-HICP)

The multivariate econometric model has a measurement equation similar to Equation 1. However, on the left-hand side, there are sector-level inflation rates rather than headline inflation, as in the univariate model. The inflation rate of the sector i at time t consists of three sub-components, as shown in the measurement equation 6.

$$\pi_t^i = \tau_t^i + \varepsilon_t^i + s_t^i \tag{6}$$

Each of the three components consists of common and sector-specific or idiosyncratic components, as represented by c and s, respectively. Thus, in open form, it can be written as:

$$\pi_t^i = \underbrace{\alpha_i^{\tau}\tau_{c,t} + \tau_{s,t}}_{\tau_t^i} + \underbrace{\alpha_i^{\varepsilon}\varepsilon_{c,t} + \varepsilon_{s,t}}_{\varepsilon_t^i} + \underbrace{\alpha_i^{s}s_{c,t} + s_{s,t}}_{s_t^i} \tag{7}$$

Instead of capturing the persistent component of headline inflation rates as in the univariate model, the multivariate-sector model focuses on modelling the persistent component of each sector's inflation rate. In this approach, the sectors are modelled together, and each sector's trend inflation consists of two different components, as shown in Equation 8.

$$\tau_t^i = \alpha_i^{\tau}\tau_{c,t} + \tau_{s,t} \tag{8}$$

$\tau_{c,t}$ shows the common trend shared across all sectors and loaded into the trend in sector i by α_i^{τ} coefficient. The common trend component captures the persistent changes influencing many sectors economy-wide. On the other hand, $\tau_{s,t}$ represents the idiosyncratic trend affected by sector-specific changes. Similar to the univariate model Equation 2, both the common and the sector-specific trend inflation follow random walk processes. Also, the state equations for the seasonal and cyclical components hold similarly. The volatility equations are also modelled as logarithmic random walk processes.

In the multivariate model, the initial conditions are required for both the common and sector-specific trend, seasonal component, and volatilities. In addition to that, similar to the univariate model, the priors on the scale of variance innovations and the outlier probability p and priors on factor loading must be specified. In order to identify the components and the factor loading separately, we are required to impose two normalisations. In addition to these normalisations, the initial conditions and the priors are the same as in the univariate model. The first normalisation is to characterise the common components and the sector-specific components individually. For this reason, it is assumed that the common components (trend, seasonal, and log volatilities) are zero initially. The second normalisation is to differentiate between the factor loading and the common factors, requiring the standard deviation of common factors to be one. After imposing the normalisation and setting the initials and priors, the model is estimated by 60,000 Markov Chain Monte Carlo (MCMC) iterations.

Following the estimation of sector trends, the aggregate trend inflation is constructed by weighting the trend of each sector by their shares in the consumption basket. The multivariate-sector trend (MS-HICP) is represented as:

$$\tau_t = \sum_{i=1}^{N} w_{it} (\alpha_{i,\tau} \tau_{c,t} + \tau_{s,t}) \tag{9}$$

where N shows the number of sectors and w_{it} is the share of each sector in the consumption basket.

Multivariate-country model (MC-HICP)

In addition to the MS-HICP model suggested by Stock and Watson (2016), one can also consider another dimension of disaggregation through countries for the euro area application. The area consists of many countries characterised by different features. Considering the heterogeneity underneath the inflation rates of these countries, there can be potential gains from modelling them together in the multivariate setting. Thus, the multivariate econometric model can be applied from a country-level aspect. This second version of the multivariate model uses headline inflation rates in each member country to produce the estimates for the euro area aggregate. In this model, the common and country-specific components are considered differently from the first version, which deals with common and idiosyncratic components among the sectors in a particular country or the euro area. This model can be applied only to the euro area aggregate, which differs from the multivariate-sector model. Assuming that each country is represented by j, trend inflation in the euro area can be shown as:

$$\tau_t = \sum_{j=1}^{K} \omega_{jt} (\alpha_{j,\tau} \tau_{c,t} + \tau_{j,t}) \tag{10}$$

where K shows the number of countries in the area and ω_{jt} is the share of each country in the euro area.[14]

Multivariate core trend (MCT-XFE and MCT-XE)

Alternatively, Almuzara and Sbordone (2022) proposes an underlying inflation measure based on Stock and Watson (2016). Following the estimation of the model using the measurement and state equa-

[14] I use $K = 12$ to include these countries that have been in the euro area since the beginning of the sample in 2001.

tions, they suggest obtaining trend inflation by excluding food and energy sectors in the aggregation procedure. In that respect, although the model includes the dynamics of these sectors in the estimation process, they are excluded ex-post from trend inflation estimates. Thus, different from Equation 9 in the multivariate-sector model, the multivariate core trend, MCT-XFE, is represented as:

$$\tau_t = \sum_{i=1}^{N'} w'_{it} (\alpha_{i,\tau} \tau_{c,t} + \tau_{i,t}) \tag{11}$$

where N' shows the number of sectors except for food and energy and $w'_{it}$is the share of each sector adjusted for food and energy in the consumption basket. Similarly, one can also consider excluding only the energy sector in the aggregation process; this model is called MCT-XE.

Finally, similar to the measure obtained by pooling the univariate country results, U-HICP-P, I also consider pooling the separate country results of the multivariate-sector model, MS-HICP-P, and multivariate core trends, MCT-XFE-P, and MCT-XE-P for the euro area aggregate trend inflation estimates. Overall, four different measures from the U-HICP, MS-HICP, MCT-XFE and MCT-XE are estimated for the country-level applications. In addition to these four measures, MC-HICP and the pooling measures, U-HICP-P, MS-HICP-P, MCT-XFE-P, and MCT-XE-P, are used for the euro-area aggregate.

5 Empirical Results

The unobserved component models estimate trend inflation by decomposing headline series into trend, cyclical, and seasonal components. In the estimation process, the dynamic features of each component are considered, as explained in Section 4. This section is divided into two main subsections.

The first part provides trend inflation estimates for the euro area countries from a comparative perspective. Based on MCT-XFE model estimates, I investigate country-level patterns. Trend estimates are decomposed in two ways to understand the evolution of these patterns after the pandemic. The first decomposition provides the extent to which goods and services drive trend inflation. Secondly, the estimates are decomposed into common and sector-specific components to examine each country's underlying inflation drivers. After discussing the estimates from different models, the potential precision gains from using different models are investigated at the country level. Lastly, the performance of these trend inflation estimates and the conventional core inflation measures are assessed in terms of predicting future headline inflation.

In the following subsection, the aggregate euro area results are discussed. Similar to the country results, the estimates from various models and the decomposition are presented. In addition to the models used in the individual country analyses, the euro area results also include the multivariate-country model estimates and pooled estimates obtained using the country-level results of the first part. Following the estimation results, I empirically assess these estimates and compare them to the other existing measures in the literature, including core inflation, trimmed means, and PCCI; table B.1 summarises the measures used in the comparison in addition to the novel measures. The assessments are based on several criteria, including bias and volatility properties, tracking long-term movements in the headline inflation, and leading properties as in Bańbura and Bobeica (2020).

5.1 Countries

5.1.1 Estimation Results

Figure 3 shows trend estimates using the multivariate-sector model but excludes food and energy sectors after the estimation suggested by Almuzara and Sbordone (2022).[15] The results allow us to understand the evolution of the overall inflation outlook in the sample period and compare the member countries. As evident in the figure, the trend inflation estimates suggest great heterogeneity across different countries. In the first decade, the trend was around two per cent and followed a smooth pattern, especially in the big countries. Among the four biggest countries, trend inflation in Germany is shown to be the smoothest and less responsive to economic changes. The estimate shows that trend inflation has been systematically below two per cent except for the recent period. Trend inflation estimates declined considerably in the other members, such as the Netherlands, Portugal, and Spain, potentially reflecting the convergence after the formation of the monetary union. On the other hand, the estimates suggest very volatile underlying inflation dynamics that are well above two per cent in the countries that later joined the union. The empirical results confirm that there were downward adjustments in the trend inflation estimates around the Great Recession period for most of these countries. The extent of the decline is more limited and smoother in the core countries like Germany and France. The break around the crisis was very abrupt, on the other hand, in the Baltic States and Ireland. Compared to the other countries, the trend estimates suggest a greater reduction of the Irish trend rate, which recovered only partially afterwards. The estimated trend of inflation rates shows that the decline occurred, especially after the sovereign debt crisis in countries like Greece, Spain, and Portugal. Moreover, the results also confirm the gradual decline in the level of trend inflation for the majority of the countries during the 2010s in line with the missing inflation as discussed by Ciccarelli et al. (2017), and Bobeica and Jarocinski (2017). Thus, the decline of the trend estimates after the crises shows that these events affected the structural dynamics of inflation rates beyond temporary movements related to the business cycle. Koester et al. (2021) emphasise that a mix of cyclical factors, structural trends such as globalisation, demographic changes and positive supply

[15] Figure A.3 shows full set of estimates for the countries. Also, Figure A.4 presents the estimated outliers in the cylical component of energy.

shocks played a role in low inflation in this period.

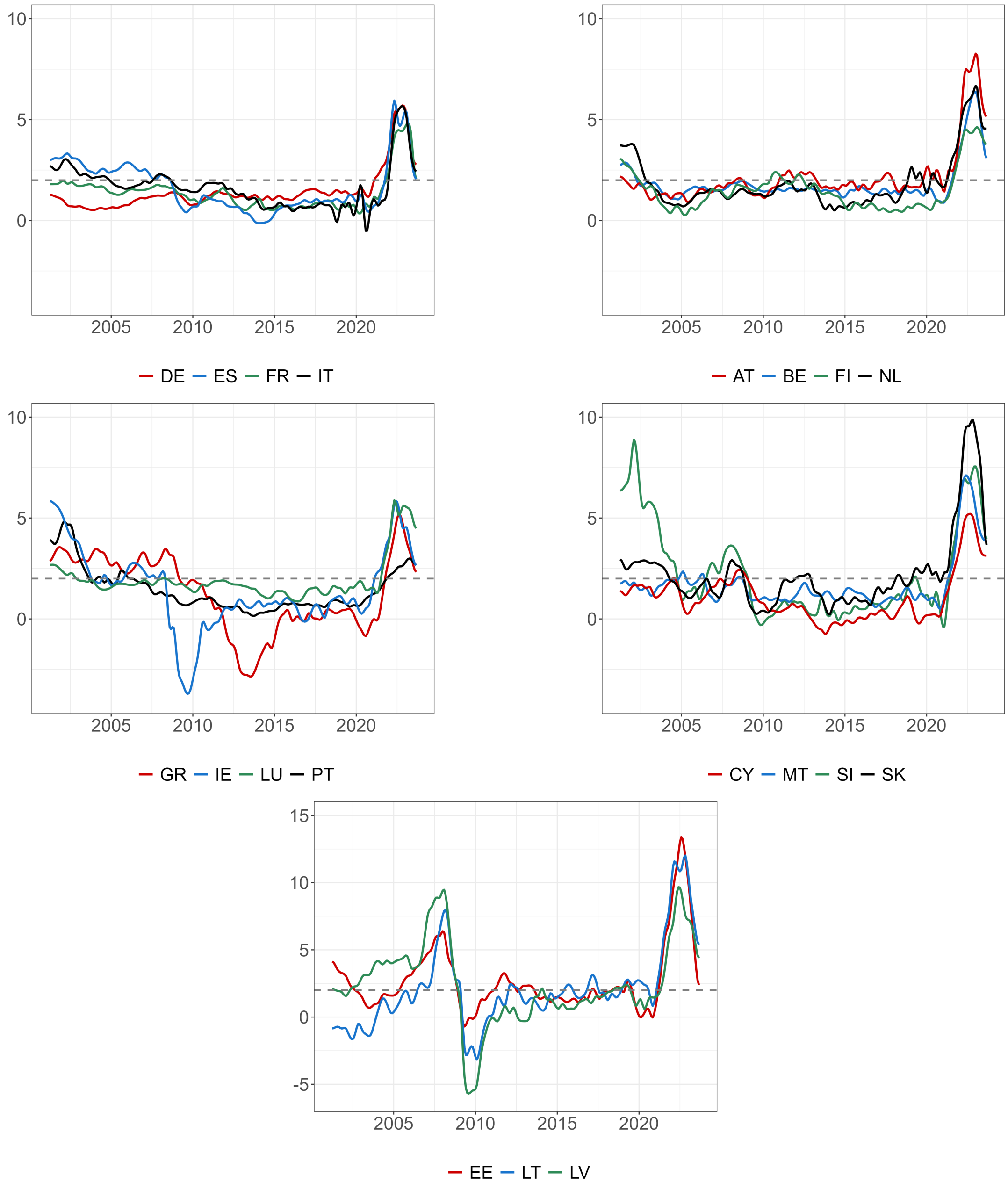


Figure 3: The euro area countries trend inflation estimates

Following a decade of muted inflation, in the aftermath of the pandemic, the trend estimates skyrocketed to historically high levels and showed massive volatility. The figure shows that the dispersion across the member countries also increased substantially. In most countries, the trend rates decreased immediately in the second quarter of 2020. The reaction of trend inflation in Germany was relatively subdued in the initial phase of the pandemic and started to increase in late 2020. Like Germany, the trend estimates in Austria and Ireland exceeded two per cent as early as the first quarter of 2021. Other countries followed the rise of trend estimates beyond the threshold over the year. The estimates show that Spain, France, and Italy reacted in the last quarter of the year or early 2022. These estimates show there is an increase in trend inflation for all countries. However, they also indicate there are substantial differences across countries. The initial drivers of the inflation rates were mainly related to international factors, such as supply chain issues followed by the upsurge in food and commodity prices after the invasion of Ukraine. Since most of these pressures arise from imported inflation, Baba et al. (2023) mentions that it can be unexpected to see such a great divergence across the countries. However, the market structure in these sectors and the ability of firms to pass through the increasing costs potentially played a role. In addition to the external factors, the rapid opening of the economies with the recovery pushed the services inflation closely linked to the domestic component of the inflation rates as discussed by BIS (2023). In that respect, the inflation of services could also have played a role in the diverse experiences of the member countries.

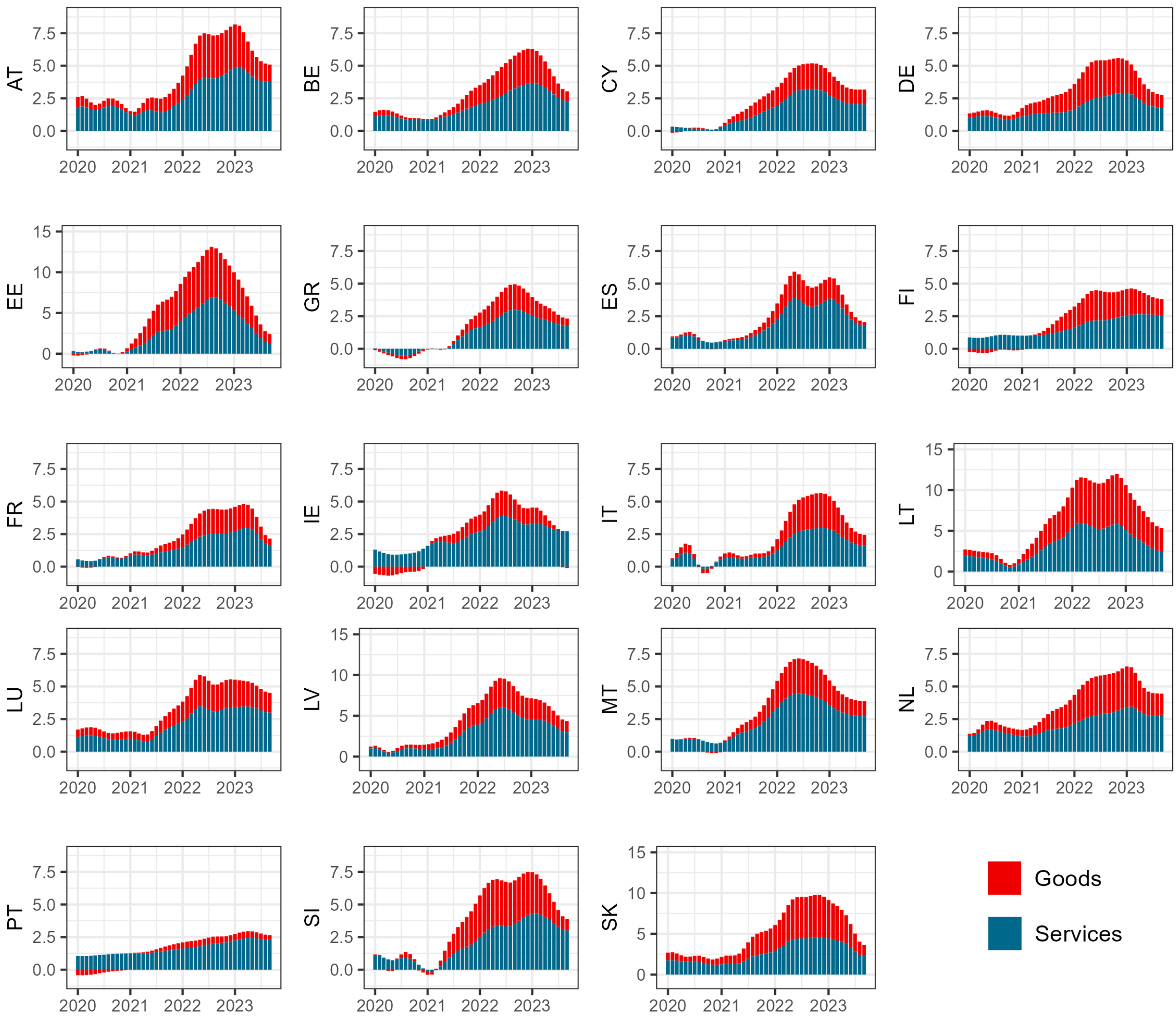


Figure 4: Decomposition of trend inflation by sectors (countries)
Note: The vertical scales are different for EE, LT, LV, and SK.

As the multivariate sector models estimate trend inflation for each sector, disentangling the sector dynamics beyond the aggregate trend inflation rates is possible. Figure 4 shows the contribution of goods and services sectors to trend estimates.[16] As expected, the initial phase of inflation in 2021 has been driven mainly by the goods sector affected by supply-chain disruptions. In that respect, the earlier responses in the group of countries greatly reflect the more substantial pass-through of international pressures on the goods sector. Unlike Germany, these impacts were limited until late 2021 in Italy, France and Spain. The decomposition shows that the underlying pressures in the services sector have also greatly contributed to the rising inflation in Spain compared to the others. In general, the contribution of services relative to goods has remained limited until mid-2022. Following the ease of supply issues affecting the goods sector and the intense pent-up demand, especially in the services, the contribution of this sector has also increased considerably from the second half of 2022. As explained by Di Giovanni et al. (2022), BIS (2023), the shift in consumption from services to goods in the earlier phase of the pandemic reversed later on and affected the relative price of these sectors. The empirical results also confirm the change in the sectoral dynamics for the trend inflation estimates in the euro area countries. This pattern seems even stronger in the countries that experienced more significant and earlier increases in goods trend as discussed.

As the figure suggests, trend inflation estimates for Central and Eastern European countries have increased more than those of other countries. The goods-services decomposition shows that although the relative contribution of the goods sector to trend inflation outpaced the services in these countries, both sectors pushed trend inflation further up compared to the countries. In that respect, Falagiarda (2024) shows that in addition to the greater impact of energy price changes on these countries due to their higher dependence on Russian energy and higher energy intensity in production, domestic factors such as tighter labour markets also played an important role on the severe rise of prices.

Figure 5 shows the decomposition of trend estimates into sector-specific and common components in the countries. Unlike the shocks affecting sectoral prices, the common component reflects widespread pressures in many sectors. The common component of trend inflation tends to be either negative or very small in most countries until mid-2021. However, after that, the estimates suggest that the underlying prices started to rise in all sectors and, therefore, became broad-based, as reflected by the extent of common components. On the other hand, following the peak of the contribution reflecting economy-wide price pressures around late 2022 to early 2023, the common trends have started to decline substantially. Therefore, the evidence suggests that the recent disinflation dynamics emerged from the alleviation of broad economic pressures rather than reflecting sector-level declines, such as the NEIG sector, after the dissipation of supply-chain disruptions.

[16] Figure B.4, in the appendix, shows the average relative contributions of four sectors: food, energy, NEIG and services to trend inflation estimate in more detail.

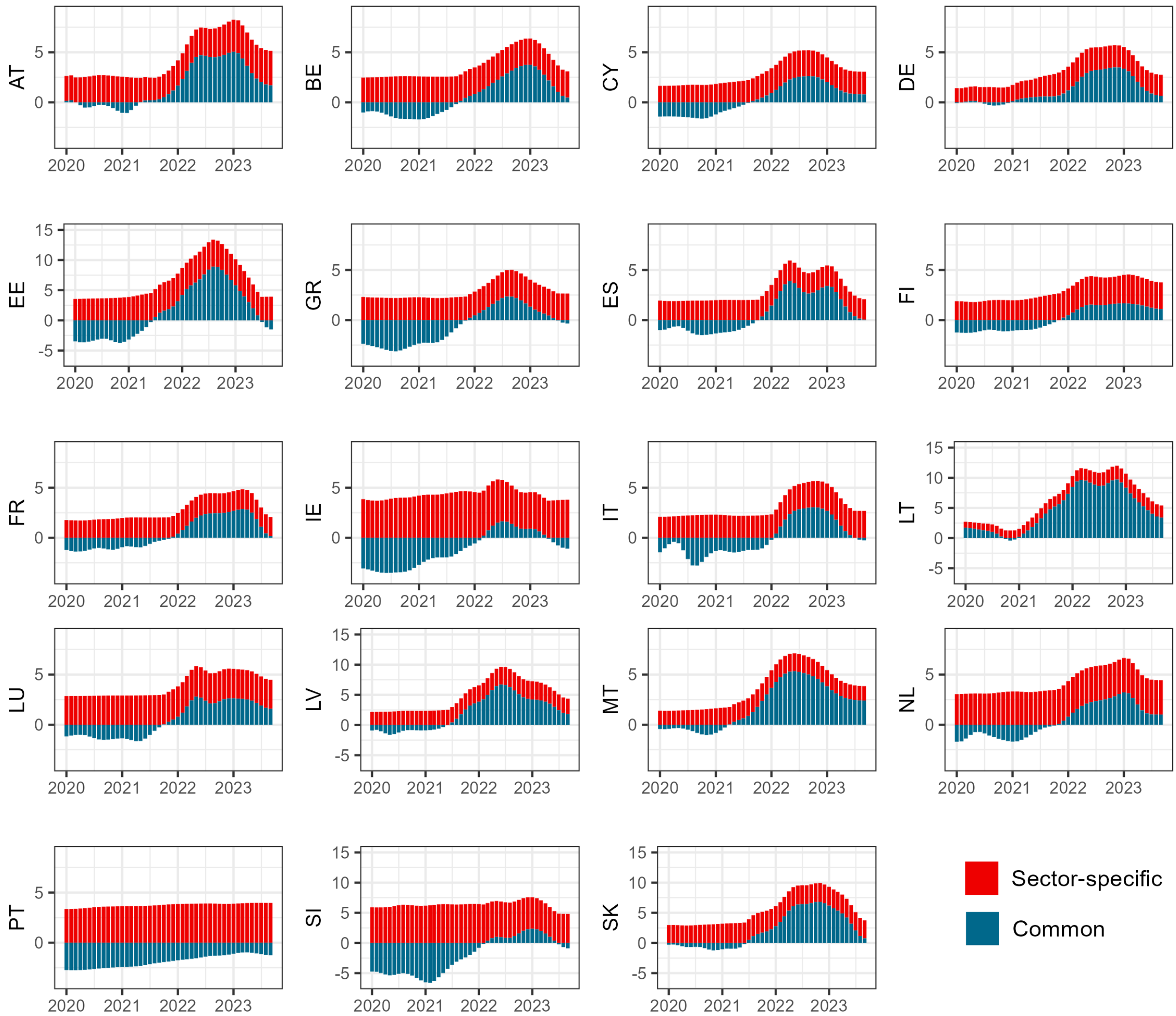


Figure 5: Decomposition of trend inflation by components (countries)
Note: The vertical scales are different for EE, LT, LV, and SK.

5.1.2 Empirical Assessment

This subsection provides an empirical assessment of these different measures to understand their relative performance based on the precision and tracking of future headline inflation.

First, the credible intervals produced by these different models enable us to understand how precisely each model estimates trend inflation. In that respect, Figures A.5 show the width of the 68 per cent credible intervals, averaged for two different sample periods.[17] As shown in the figure, except for Belgium and Latvia, the multivariate models provide more precise estimates, evident from the lower uncertainty around the estimates in both samples before and after the pandemic.[18] On average, the multivariate-sector model provides 25 per cent narrower estimates compared to the univariate model pre-pandemic. As ev-

[17] The first sample starts from 2003 to be consistent with the next section's results for the euro area. The Supercore measure used in the comparison is available only after 2003.

[18] In these countries, the univariate model provides more precise estimates. Modelling sectoral inflation rates deteriorates the precision of trend inflation estimates.

idenced by the greater difference between the width of credible intervals, the precision gains tend to be higher in the four biggest countries, Germany, France, Italy, and Spain. Unsurprisingly, the estimation uncertainty reduces further in the multivariate core trend models due to excluding food or food and energy sectors ex-post the estimation. On average, the model excluding energy shrinks the uncertainty by around 34 per cent versus excluding food and energy by 48 per cent compared to the multivariate-sector model. The precision of all models deteriorated to a great extent in the post-pandemic sample, which is in line with the unusual behaviour of inflation rates historically. Despite the rising uncertainty, the estimates by the multivariate-sector model also perform better than the univariate estimates. The exclusion of food and energy shrinks the intervals by almost 60 per cent compared to the multivariate-sector model. In that respect, the results show the greater role of spiking energy prices on the higher uncertainty. The comparison of the credible intervals shows that the multivariate models outperform the univariate model in terms of precision. Thus, the results obtained by modelling individual sectors and then aggregating them seem to capture the slowly-moving permanent component of inflation rates better than directly modelling the aggregate inflation rates. On the other hand, as demonstrated by the lower uncertainty surrounding the multivariate estimates excluding food and energy, these models provide considerable precision gains over the inclusion of all sectors.

Although the precision of trend inflation estimates provides an important metric to compare different models, it is also crucial to understand how these measures can track the changes in future headline inflation. Table B.5 shows root mean squared errors (RMSE) of these estimates in addition to two conventionally used underlying inflation measures, headline excluding food and excluding food and energy, against the future headline inflation at the horizons $h = 3, 6, 12, 24$. The results emphasise the importance of using a set of measures rather than a specific measure, as none of the models outperform each other across all countries. Although the performance of the estimates varies for the countries and horizons, several general conclusions can be drawn from the table. First, the traditional measures underperform considerably against the model-based estimates at all horizons.[19] Contrary to the poor precision performance discussed above, the univariate model performs relatively well in most countries to predict headline inflation three and six months ahead.

On the other hand, the performance of the multivariate model at shorter horizons is better in several countries, including Belgium, Italy, and the Baltic states. The multivariate sector model generally outperforms the others by moving the horizon to one year ahead. For predicting two-year-ahead inflation rates, either the multivariate sector model or the multivariate core trend measures are proven to be useful depending on the country. In addition to the four biggest countries, the multivariate core trend inflation outperforms the other measures in Greece, Austria, and the Netherlands. Therefore, the results suggest

[19] Three exceptions are for h=24, in Belgium, Latvia and Lithuania.

that these models are useful for predicting future headline inflation rates at various horizons. Whereas the univariate model tends to outperform at shorter horizons, the multivariate models work better at longer horizons. The traditionally used measures relying on excluding volatile sectors perform poorly compared to these estimates. Figures A.6 and A.7 show the time-varying root mean squared errors of these underlying inflation measures at forecasting one-year ahead and two-year ahead headline inflation using rolling windows.[20] As suggested by the lower RMSEs, the performance of the different underlying inflation measures has been improved relatively during the 2010s. However, they have increased quite substantially due to the greater uncertainty after the pandemic.

5.2 Euro area

5.2.1 Estimation Results

For the euro area, trend inflation rates are estimated using the same four models as discussed above (U-HICP, MS-HICP, MCT-XFE, MCT-XE). In addition to these, I propose an alternative model: the multivariate-country model, MC-HICP, using the weighted average of countries after modelling each of them in the multivariate unobserved components model. Lastly, I propose four additional measures based on the pooling of individual country estimates as presented in Section 5.1 to see if these measures relying on country information improve upon the other models.

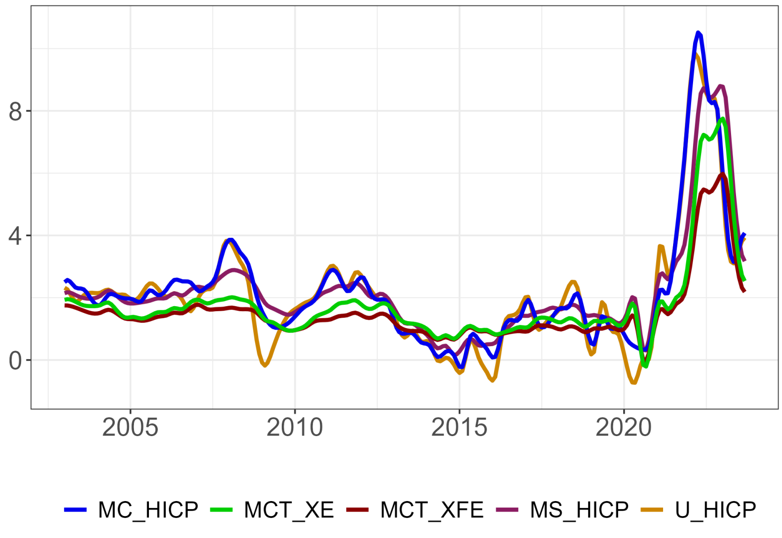


Figure 6: Trend inflation estimates for the EA

First, Figure 6 shows the estimation results for the previous four models and the multivariate-country model. Similar to the country-level estimates, trend inflation estimates using various models also capture a decline around the Great Recession followed by a partial recovery back to around 2 per cent. The

[20] The window size is selected as ten years to provide a relatively slow-moving measure.

magnitude of the adjustment is relatively great in the univariate model estimates, whereas the other models suggest a milder decrease. Moreover, all models agree on the gradual decline in the trend estimates from 2011. On the recent rise of inflation rates, all trend inflation estimates display a large increase from 2021 onwards. However, the extent of the increase is very extreme for the multivariate-country model estimates. Potentially, the persistent inflation readings above 10 per cent in many countries, including the ones with the greatest weight in the second half of 2022, pushed the estimates to that level. As the multivariate-country model takes the commonality across the country dimension different from others, this result can be explained through the persistence of headline rates in that period. On the other hand, it has also adjusted down relatively fast compared to the other estimates. Concerning the smoothness properties, the univariate and multivariate country models tend to behave similarly and are more volatile than the multivariate sector model. The post-estimation exclusion models, MCT-XE and MCT-XFE, produce the smoothest estimates among the others. Figure A.8, in the appendix, shows the estimation results obtained by pooling each corresponding individual country results from the previous section using their weights for the aggregation. As evidenced from the figure, modelling each country individually to generate the euro area trend estimates helps to smooth more than estimating the euro area aggregate independent of which model is used for the estimation.

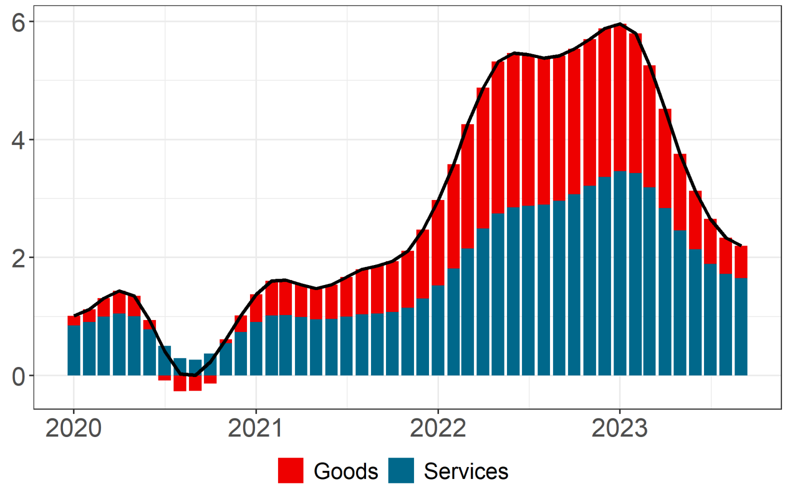


Figure 7: Decomposition of trend inflation by sectors (euro area)

The multivariate sector models enable us to decompose trend inflation estimates into goods and services, as shown in the previous section. Figure 7 presents the contribution of each sector to trend inflation estimates by the MCT-XFE model for the euro area.[21] The figure shows the goods sector has dominated the surge in trend inflation estimate. Compared to the month before the pandemic, the share of goods in trend inflation increased from 16 per cent to 49 per cent in early 2022. Although the contribution from the services has also increased due to the reopening effects from the summer of 2021, the contribution by

[21]The multivariate-sector model (MS-HICP) has the exact same decomposition; only the scales are different as all sectors are included.

goods to trend outweighed the services sector. The decomposition suggests the shift in the decomposition from services to goods started to ease in 2023 but is still above the pre-pandemic levels. Recently, the estimates suggest that both goods and services sectors contributed to the disinflation, as shown by the lower rates. However, it is also obvious that the decline in goods has been more dramatic as the contribution declined from 2.5 percentage points to 0.55 percentage points since the beginning of 2023.

The multivariate model estimates trend inflation as the sum of common and idiosyncratic components. To understand the drivers of the recent upsurge in the euro area inflation rates, Figure 8 shows the decomposition of the MCT-XFE model to these components after 2020. As the figure suggests, trend inflation has been mainly driven by the common component showing that sector-wide pressures in the economy have pushed the trend estimate down until late 2021. Beforehand, the increase in trend has been only marginally associated with the higher sector-specific component.

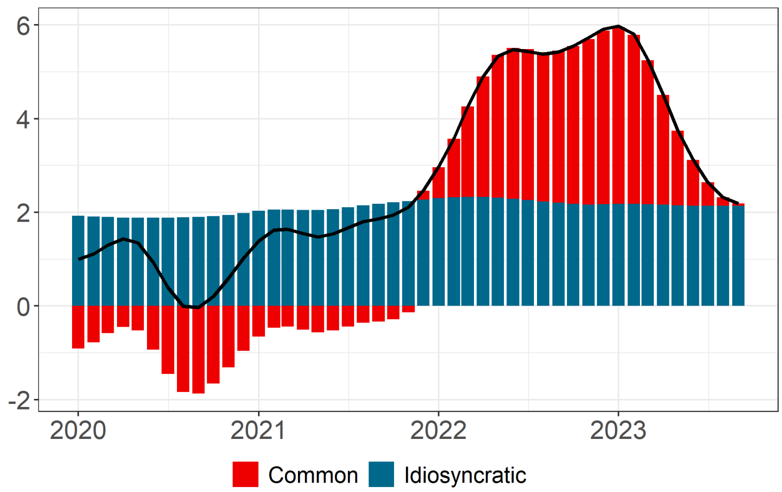


Figure 8: Decomposition of trend inflation by components (euro area)

5.2.2 Empirical assessment

This subsection compares these measures among each other in addition to the other measures frequently used by the ECB as summarised by Bańbura et al. (2023). For this reason, the empirical metrics, precision of the estimates, bias and volatility properties, tracking long-term movements, and leading properties for headline inflation rates are investigated.

<u>**Precision**</u>

Figure 9 reports the width of 68 per cent credible intervals averaged over two different sample periods to understand how precisely various models estimate the trend inflation rates. The results show that using disaggregated information from sectors or countries in the pre-pandemic period decreases the estimation uncertainty compared to the univariate model. In the multivariate-sector (-country) model, the credible intervals are 32 (21) per cent narrower compared to the univariate model. On the other hand, after the pandemic, the uncertainty increases considerably for all models. In that case, using disaggregated data from countries, as in the multivariate-country model, produces more uncertain estimates than univariate model estimates. As shown in the previous sub-section, the greater heterogeneity across countries could potentially make the uncertainty greater compared to the sectors. On the other hand, both models, using the exclusion of volatile sectors after estimation, improved upon other models in both samples as expected.

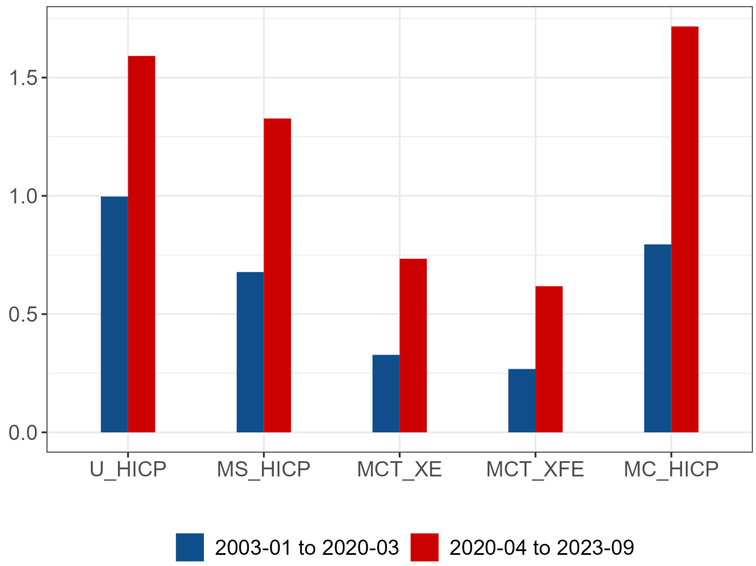


Figure 9: Precision: the width of the 68 per cent credible intervals

Bias and volatility

In terms of bias and volatility, an ideal underlying inflation measure should have a similar sample average with the headline inflation but also display lower volatility. Figure 10 shows the trade-off between bias and volatility of underlying inflation measures in two different samples. The bias is measured as the difference between average headline inflation and the average underlying inflation measure. The volatility on the vertical axis represents the coefficient of variation of these different measures. Table B.6, in the appendix, provides more detailed descriptive statistics of underlying inflation measures and the headline inflation rates. In the pre-pandemic sample, the average headline inflation rate is 1.63, and most of these underlying inflation measures have a slight negative bias. On the other hand, after the pandemic, as shown by the greater negative bias, most of these measures underestimate headline rates considerably. This pattern is especially valid for the measures excluding food and energy prices, as shown in the most extreme case by the PCCI-XFE. Despite the substantial deterioration in most of these measures, trend inflation estimates by the unobserved components model relying on the univariate model, multivariate-sector, and country models have rather small bias terms. However, the smaller bias comes with a cost of higher volatility. In terms of volatility, all underlying measures become worse off in the second sub-sample. Among those measures, PCCI-XFE and PCCI produce smoother estimates despite these estimates tending to underestimate headline inflation. As evidenced by the figure, the pooling estimates from the multivariate-sector model display slightly higher volatility than the PCCI, but the estimates have a smaller bias. Overall, pooling country results seem to reduce the volatility of the estimates compared to the original models using the euro area rates. Therefore, the results confirm that there is no free lunch in terms of bias volatility trade-off. It is important to know the properties of different underlying inflation measures.

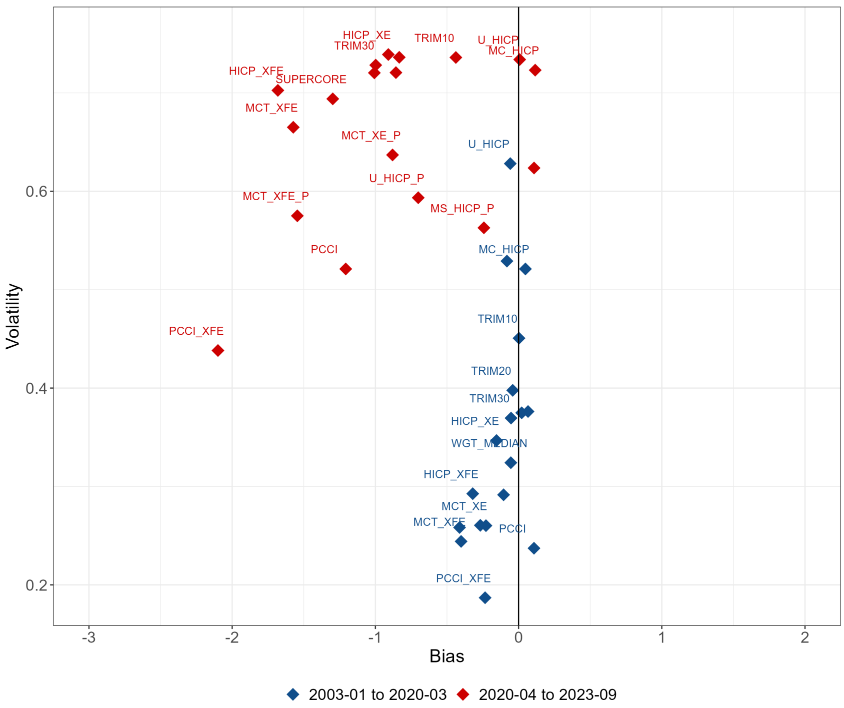


Figure 10: Bias and volatility

Tracking the long-term changes

Another criterion for underlying inflation measures is to track long-term movements in the headline inflation rates. To this aim, Table B.7 shows the root mean squared error of various underlying inflation measures against two-year and three-year moving averages of headline inflation rates. The table, similar to the previous results, confirms that it becomes more difficult to track the headline inflation in the second sample that covers the post-pandemic period. In the first sub-sample, multivariate-sector model estimates, pooling estimates from the multivariate-sector model, and trimmed means, weighted median measures perform similarly and outperform other measures to follow the long-term headline inflation rates. In the second sample, on the other hand, the performance of the multivariate-sector model deteriorates, whereas the pooling measure remains a top-performing measure similar to trimmed means.

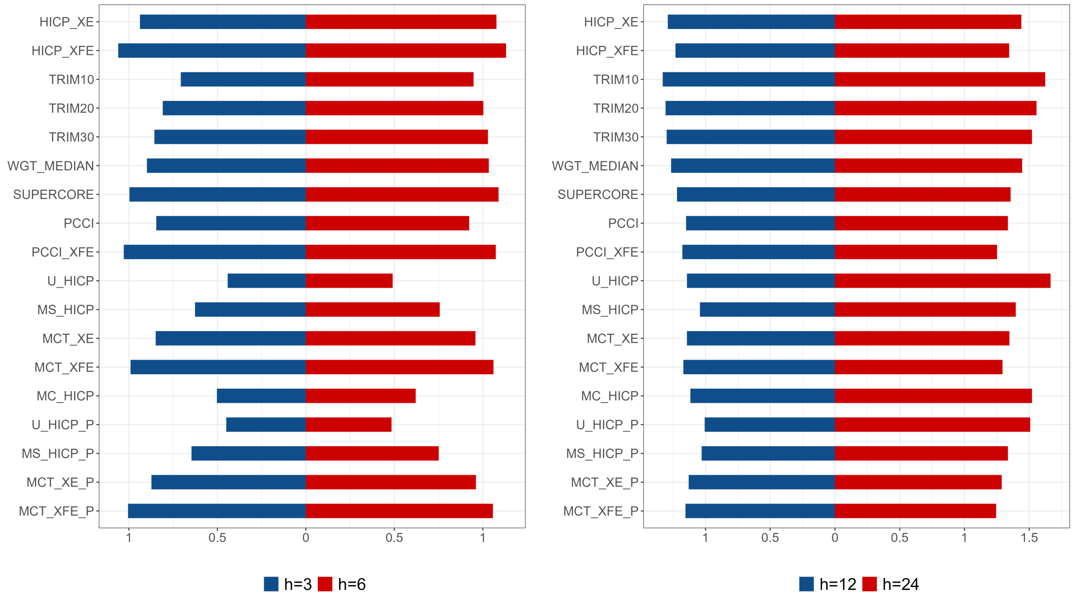


Figure 11: Average RMSE future inflation, h=3,6,12,24

Leading properties

As underlying inflation is a variable that is used to inform policy decisions, it should ideally provide a forward-looking view on the evolution of headline inflation. In that respect, it is expected to have leading properties for the headline inflation. Figure B.8 shows the RMSE of various underlying inflation metrics against the future headline inflation at h=3,6,9,12.[22] At shorter horizons up to one year (left), the figure shows that the univariate model and its pooled version, and the multivariate-country models outperform others. On the other hand, the measures excluding food and energy, HICP-XFE, PCCI-XFE, MCT-XFE, and MCT-XFE-P perform very poorly. Therefore, the results suggest that although these measures, such as univariate or multivariate-country models, have been shown to have greater volatility, they also provide a good alternative to understanding the near-term future developments up to a one-year horizon. On the other hand, the measures excluding certain sectors seem to fail to capture these dynamics of headline inflation. The figure (right) shows that the pooling estimates of univariate and multivariate-sector models perform the best among the other measures at a one-year horizon. At two years, PCCI-XFE and MCT-XFE-P perform relatively well, similar to each other, followed by the MCT-XFE model.

In addition to comparing the mean squared errors, Table B.9 shows the estimation results from the regression of the difference between the current inflation and 12 months ahead of inflation on underlying inflation measures. It compares the performance of these underlying inflation measures in two samples, including and excluding the pandemic period. The left panel, excluding the pandemic, shows that all these measures tend to display great persistence, as demonstrated by the underlying inflation coefficient. When the sample period includes the pandemic, then the coefficients belong to the conventional core

[22] Figure A.9, in the appendix shows the results for h=36.

measure, and other cross-sectional exclusion measures decline considerably. As shown by R^2, the explanatory power of the unobserved components models outperforms the other measures. The main result is not influenced by the inclusion of the pandemic period. Unlike very similar performances of the pooled univariate model and the multivariate-sector models, the inclusion of the recent period makes the pooled univariate model the best-performing measure. Table B.10 demonstrates the maximum correlation between the underlying inflation measures and the headline inflation in terms of lead-lag properties. As shown, the conventional cross-sectional exclusion measures and supercore tend to follow headline inflation rather than leading it. On the other hand, PCCI, the univariate model and its pooling version, the multivariate-sector model and its pooling version, and the multivariate-country model are shown to be leading indicators for headline inflation in a range of horizons between 1 to 4 months according to the magnitude of correlation.[23]

6 Conclusion

This paper investigates the evolution of trend inflation in the nineteen euro area countries and the euro area aggregate by using unobserved components models based on Stock and Watson (2020). The data cover the period from 2001:01 to 2023:09. Different from the exclusion-based methods focusing solely on the cross-sectional information from different sectors and the time-series methods giving attention to the aggregate inflation series, the method used in this study tackle the estimation of trend inflation with a unified approach by combining both dimensions. That is to say, both the cross-sectional information and also the richer time-series dynamics of sectoral inflation are addressed by virtue of the method. There is no consensus in the literature about estimating trend inflation since it is an unobserved variable. Moreover, the signal-extraction problem becomes further complicated if the data process includes a seasonal pattern and outliers. The unobserved components model used in the paper permits the address of these different technical challenges in an appropriate way. Concerning the analysed countries, despite the presence of a monetary union, the inflation dynamics of these countries exhibit considerable heterogeneity. For this reason, we aim to conduct the analysis at the country level to unveil the potential difference between the countries in addition to the aggregate euro area data.

Overall, the empirical results confirm that greater heterogeneity is present not only in the headline rates but also embedded in the underlying inflation dynamics, as shown by different levels and the evolution of trend inflation estimates for the countries. The higher heterogeneity observed in the post-pandemic period has been mainly affected by the sectoral decomposition of underlying inflation. That is to say; although the goods sector initially drove the differences, the services contributed afterwards.

[23] Table B.11 shows underlying inflation measures' ability to signal headline inflation's turning points for peak and trough dates.

Therefore, both sector and country-level heterogeneities are important to understanding the euro area inflation dynamics. With regard to the various underlying inflation measures, the results show that the multivariate-sector model generally tends to produce more precise estimates and performs better at two to three-year horizons compared to the univariate model. On the other hand, the univariate model can be useful in understanding shorter horizon dynamics. The results show that the performance of all measures deteriorated starkly in the post-pandemic period, as reflected by the wider credible intervals, greater volatility and bias, and lower ability to track future inflation. As shown, it remains crucial to have various measures at policymakers' disposal.

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Appendix

A Figures

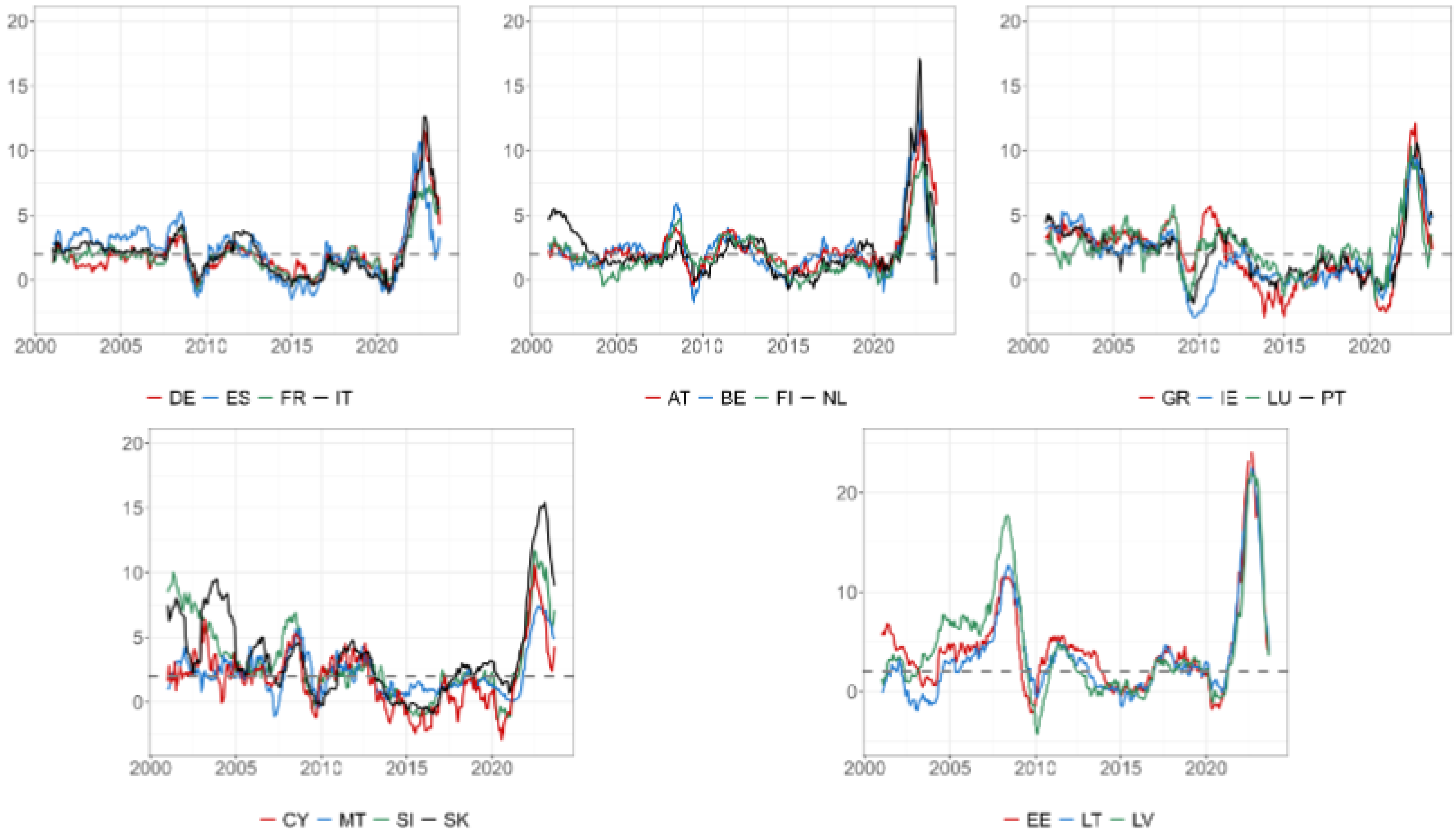
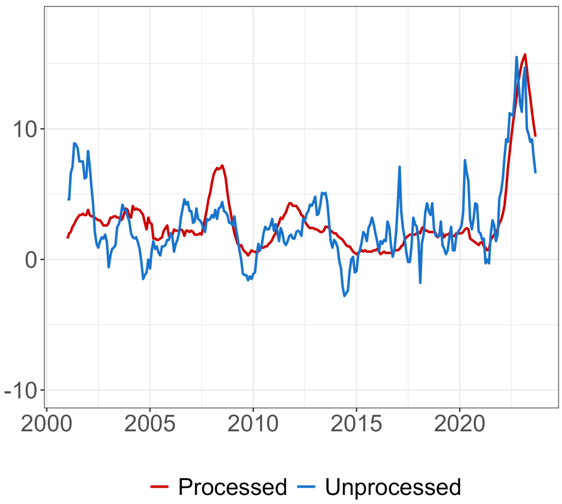
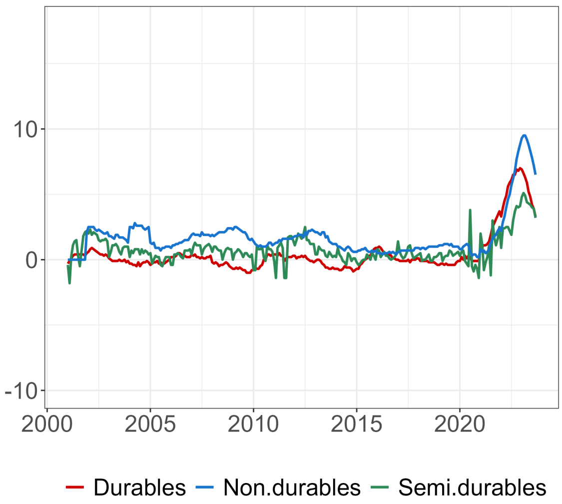


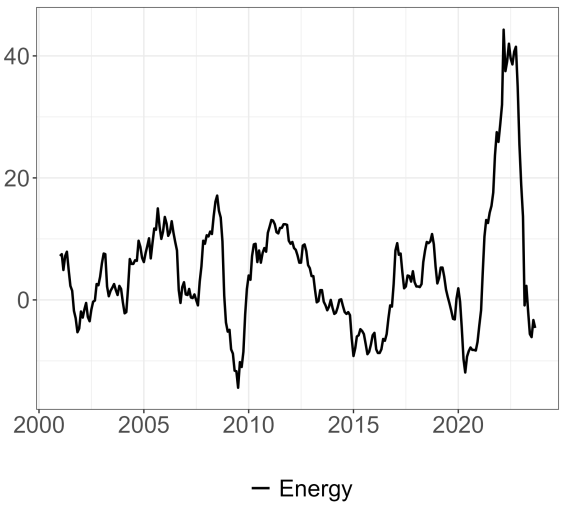
Figure A.1: Headline inflation rates of the EA countries



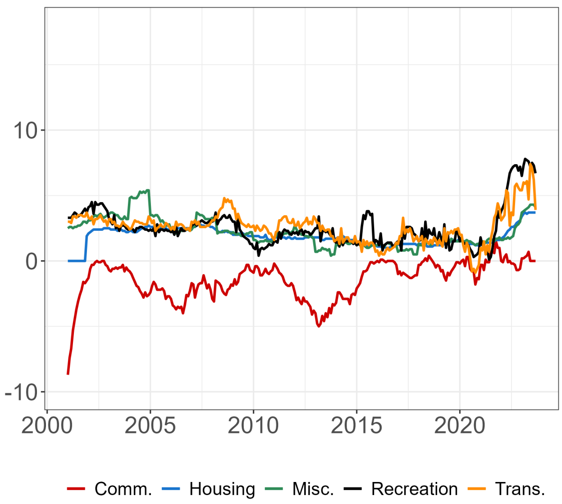
(a) Food



(b) Non-energy industrial goods



(c) Energy



(d) Services

Figure A.2: The euro area sector inflation rates

Note: The scale of vertical axes is different for (c) Energy.

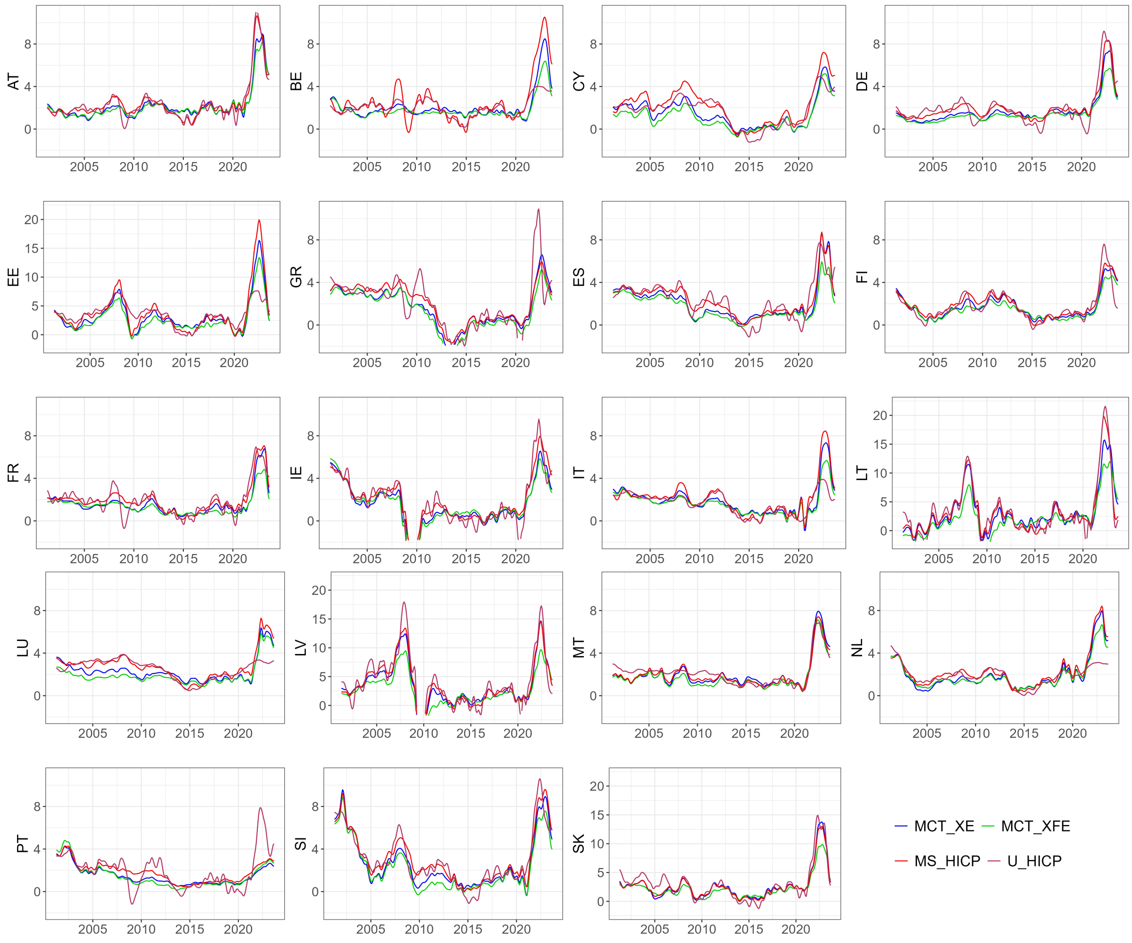


Figure A.3: Trend inflation estimates for the EMU countries
Note: The vertical scales are different for EE, LT, LV, and SK.

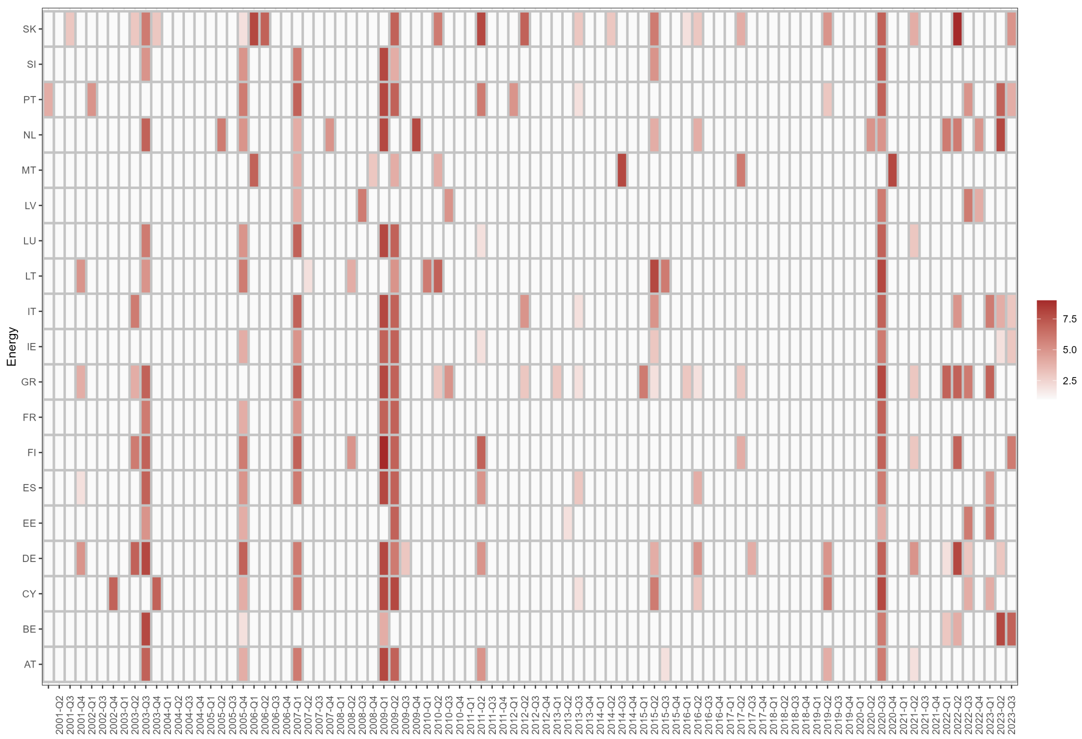


Figure A.4: Cycle outliers in energy

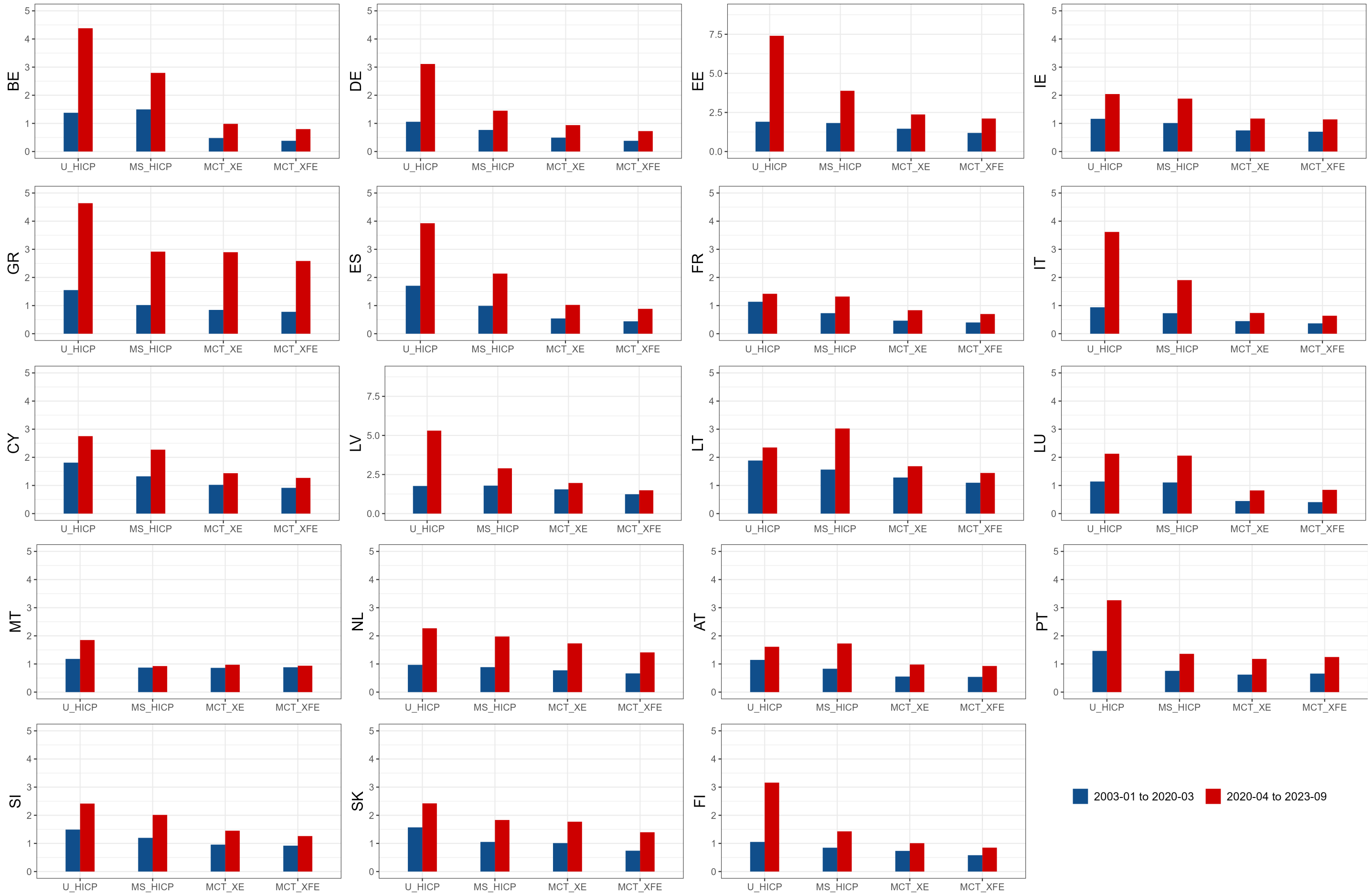


Figure A.5: The average width of 68 per cent credible intervals

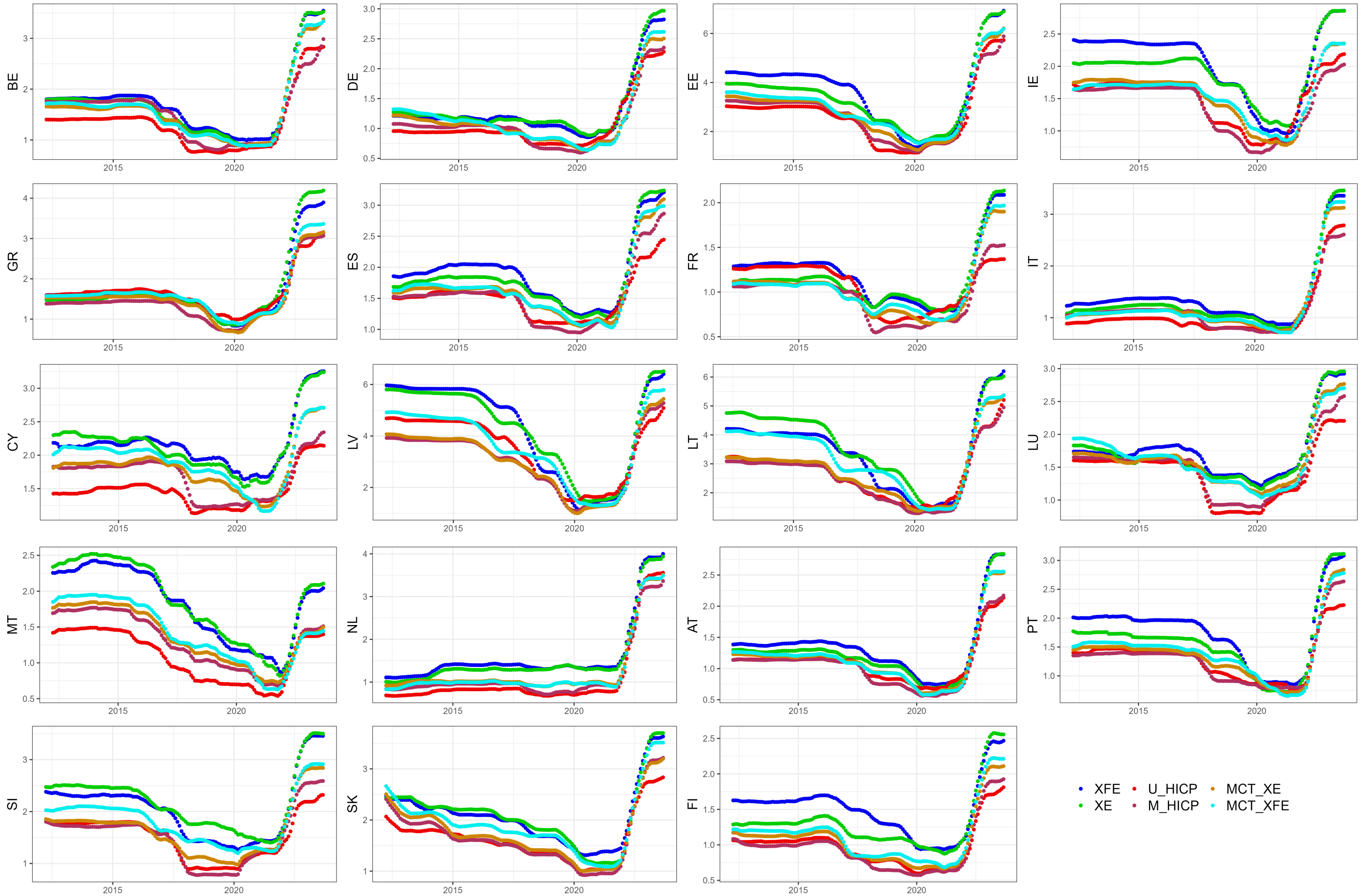


Figure A.6: RMSE: Rolling regression estimates, h=12

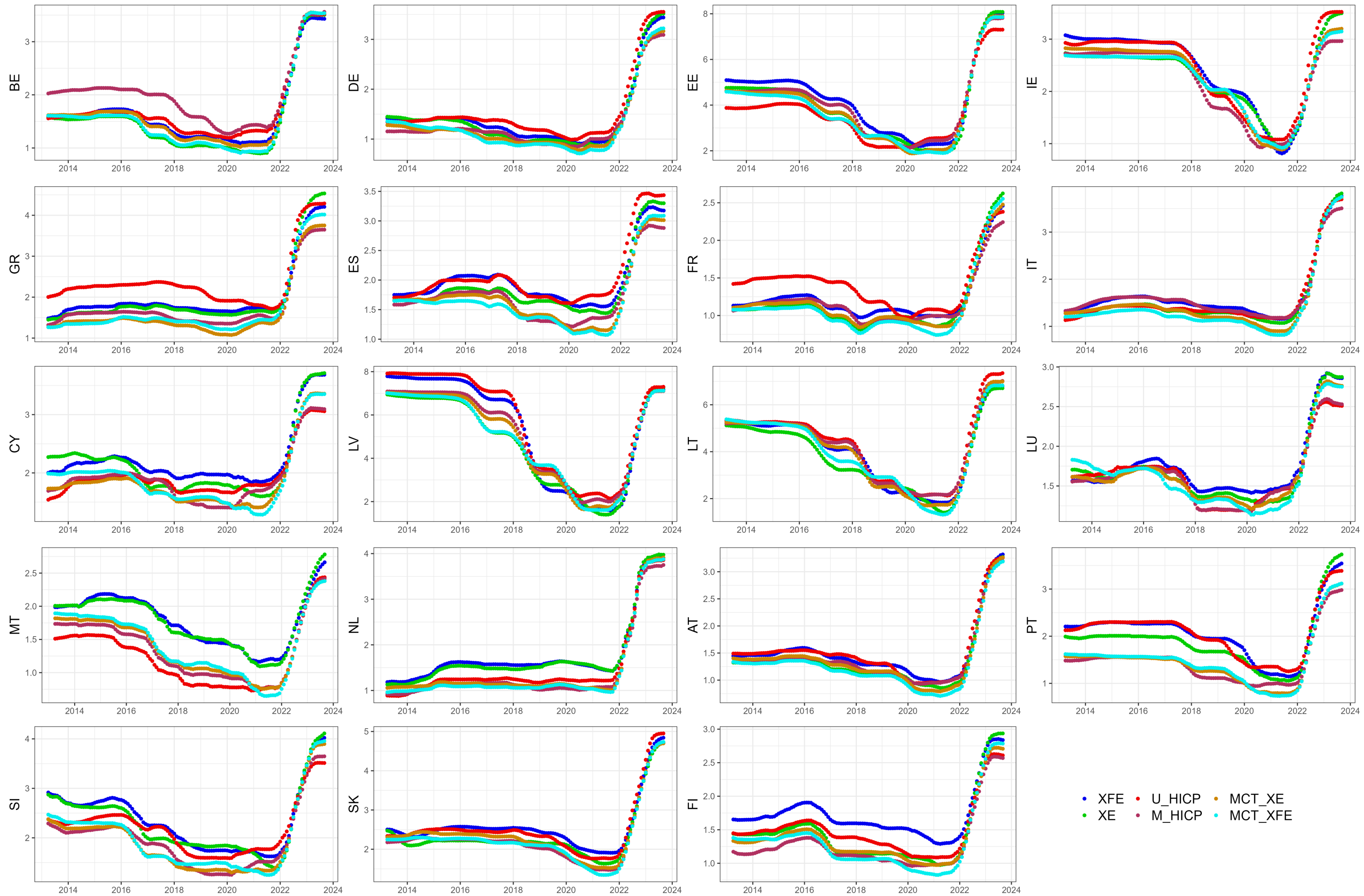


Figure A.7: RMSE: Rolling regression estimates, h=24

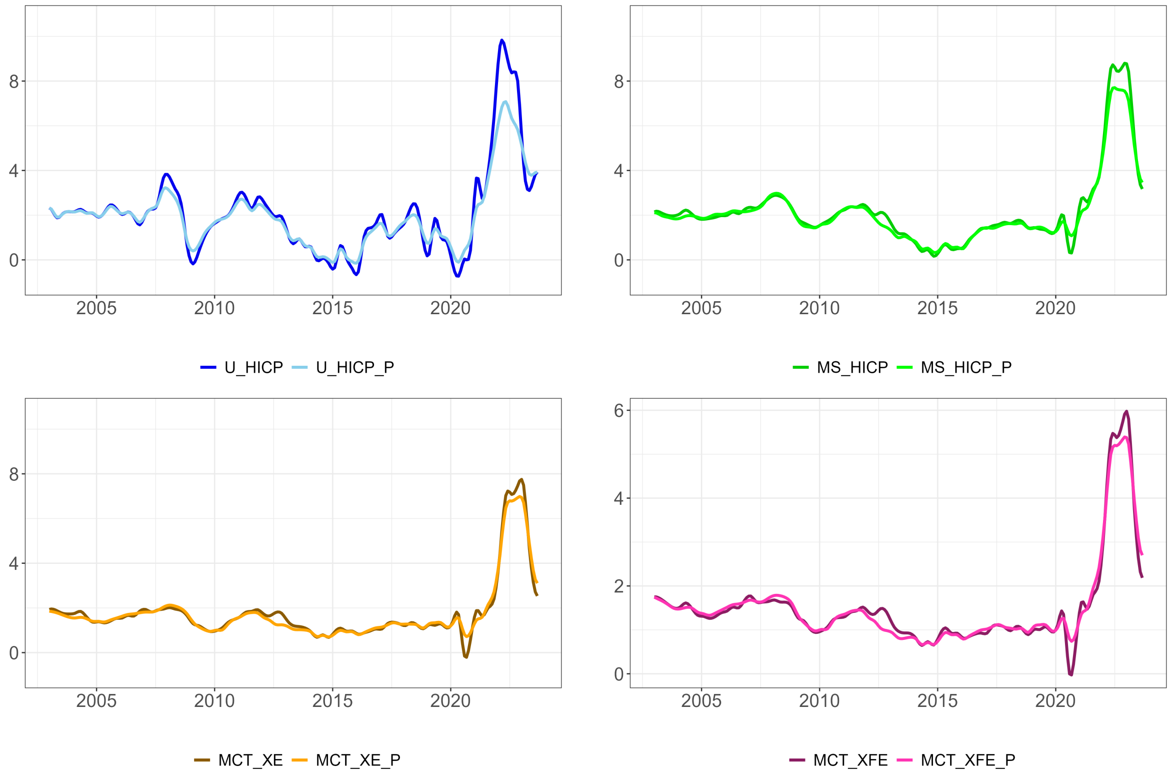


Figure A.8: Trend estimates of the pooling models

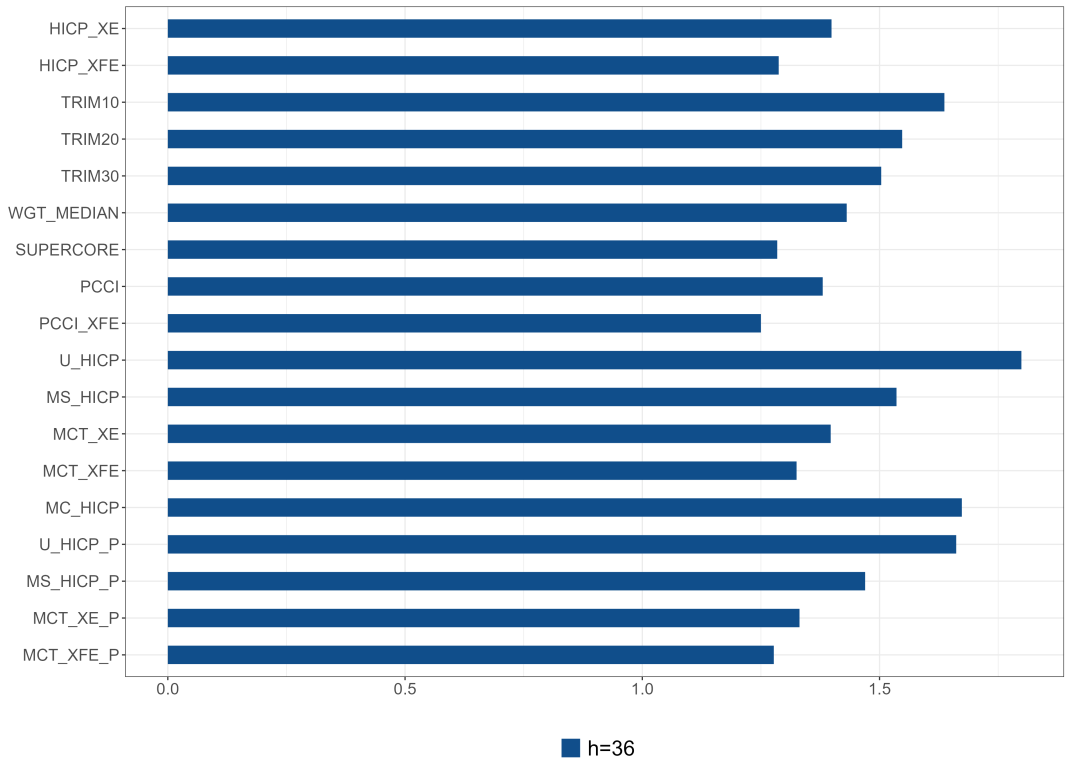


Figure A.9: Average RMSE future inflation, h=36

B Tables

Table B.1: Underlying inflation measures

	Method	CSE	FE	CF
HICPXE	Permanent exclusion of energy	Yes	No	No
HICPXFE	Permanent exclusion of food and energy (core)	Yes	No	No
TRMEANxx	Temporary exclusion of most volatile sectors (xx per cent from both tails)	Yes	No	No
WGT_MEDIAN	Temporary exclusion of most volatile sectors	Yes	No	No
SUPERCORE	Temporary exclusion of sectors with low correlation with output gap (ECB 2014, O'Brien (2018)	Yes	Yes	No
PCCI	Unobserved components model for sectors in 12 EA countries Bańbura and Bobeica (2020)	No	Yes	Yes†
PCCI_XFE	Permanent exclusion of food and energy from PCCI Bańbura and Bobeica (2020)	Yes	Yes	Yes†
U_HICP	Unobserved components model for the EA HICP Stock and Watson (2020)	No	Yes	No
MS_HICP	Multivariate unobserved components model for sectors in the EA Stock and Watson (2020)	No	Yes	Yes†
MCT_XFE	Permanent exclusion of food and energy after estimation of MUCSVO Almuzara and Sbordone (2022)	Yes	Yes	Yes†
MCT_XE	Permanent exclusion of energy after estimation of MUCSVO (extension)	Yes	Yes	Yes†
MC_HICP	Multivariate unobserved components model for the EA countries (extension)	No	Yes	Yes††
U_HICP_P	Pooling individual country-level estimates from U_HICP (extension)	Yes	Yes	No
MS_HICP_P	Pooling individual country-level estimates from MS_HICP (extension)	No	Yes	Yes††
MCT_XE_P	Pooling individual country-level estimates from MCT_XE (extension)	Yes	Yes	Yes†
MCT_XFE_P	Pooling individual country-level estimates from MCT_XFE (extension)	Yes	Yes	Yes†

Note: CSE, FE, and CF stand for Cross-sectional Exclusion, Frequency Exclusion, and Common Factor, respectively.
† Across sectors, †† Across countries

Table B.2: Sector and country weights

	Euro Area	Belgium	Germany	Estonia	Ireland	Greece	Spain	France	Italy	Cyprus
Processed Food	12.77	13.72	11.76	21.36	14.75	15.07	12.71	13.14	12.54	14.96
Unprocessed Food	6.83	7.17	4.61	8.15	5.49	8.62	10.18	7.33	7.97	7.42
D Industrial	9.69	9.96	9.90	7.40	8.23	6.98	8.57	9.57	9.97	8.74
SD Industrial	10.89	10.47	9.91	11.26	7.97	12.07	11.52	9.89	13.36	10.71
ND Industrial	7.84	9.12	8.12	9.26	6.44	6.33	7.38	8.21	7.01	7.71
Energy	9.65	10.33	11.00	12.85	9.08	7.84	10.58	8.85	8.24	9.13
Communication	2.98	2.94	2.85	4.14	2.96	3.87	3.33	2.93	2.74	3.50
Housing	10.41	9.13	14.56	4.12	6.95	5.82	7.44	11.03	7.46	4.97
Miscellaneous	7.26	7.38	7.62	4.42	8.51	9.45	4.89	7.76	6.84	8.03
Recreation	14.70	14.85	12.50	12.50	25.54	17.72	18.90	12.51	15.77	20.01
Transportation	6.99	4.93	7.18	4.53	4.07	6.23	4.49	8.78	8.12	4.82
Country Weight		3.51	28.07	0.10	1.38	2.75	11.66	20.51	18.18	0.17

	Latvia	Lithuania	Luxembourg	Malta	Netherlands	Austria	Portugal	Slovenia	Slovakia	Finland
Processed Food	22.01	23.11	19.04	14.37	12.71	11.06	12.96	16.31	18.18	15.91
Unprocessed Food	10.07	10.04	4.07	7.01	5.08	4.60	9.70	6.80	7.01	5.88
D Industrial	6.06	7.07	12.48	11.60	11.05	11.09	10.46	10.47	6.77	10.39
SD Industrial	9.48	11.26	10.27	9.91	11.10	11.01	9.44	10.44	8.61	10.44
ND Industrial	9.83	10.30	7.71	8.88	7.87	7.78	8.01	8.64	12.44	8.51
Energy	13.62	13.49	11.61	6.21	9.62	8.15	9.06	12.98	16.10	7.62
Communication	4.25	3.56	1.80	3.13	3.65	2.29	2.96	3.32	4.04	3.03
Housing	4.58	2.90	7.74	4.91	11.45	8.98	5.87	3.41	5.04	12.24
Miscellaneous	4.20	4.77	6.96	4.90	8.78	7.09	8.90	7.58	4.62	6.56
Recreation	10.52	9.66	13.74	23.47	13.10	21.40	17.00	14.44	13.19	13.82
Transportation	5.38	3.84	4.58	5.60	5.58	6.54	5.63	5.61	4.01	5.60
Country Weight	0.10	0.16	0.29	0.06	5.14	3.25	2.19	0.27	0.47	1.75

Note: The weights add up to 100. For the countries that joined the euro area after 2001, the country weights are calculated as the average of the years they are in the area. The averages are taken between 2001 to 2023.

Table B.3: Country acronyms

Code	Country	Code	Country
AT	Austria	IT	Italy
BE	Belgium	LT	Lithuania
CY	Cyprus	LU	Luxembourg
DE	Germany	LV	Latvia
EE	Estionia	MT	Malta
GR	Greece	NL	Netherlands
ES	Spain	PT	Portugal
FI	Finland	SI	Slovenia
FR	France	SK	Slovakia
IE	Ireland		

Table B.4: The contribution of sectors to trend inflation estimates

	AT	BE	CY	DE	EE	GR	ES	FI	FR	IE
Food	0.18	0.25	0.20	0.25	0.28	0.48	0.40	0.27	0.30	0.18
NEIG	0.23	0.14	0.17	0.24	0.19	0.16	0.12	0.20	0.16	0.11
Energy	0.20	0.36	0.37	0.22	0.33	0.08	0.18	0.19	0.26	0.31
Services	0.39	0.24	0.26	0.29	0.20	0.28	0.31	0.34	0.28	0.40
	IT	LT	LU	LV	MT	NL	PT	SI	SK	
Food	0.29	0.33	0.22	0.44	0.31	0.24	0.15	0.27	0.41	
NEIG	0.18	0.24	0.20	0.14	0.22	0.25	0.07	0.22	0.23	
Energy	0.29	0.19	0.27	0.17	0.00	0.19	0.26	0.25	0.12	
Services	0.24	0.25	0.32	0.25	0.47	0.32	0.51	0.27	0.24	

Note: The share of each sector averaged between 2020:04 to 2023:09.

Table B.5: RMSE future headline inflation (countries)

Horizon	BE						LT					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.61	1.48	0.99	**0.71**	1.32	1.44	2.68	1.73	1.26	**1.04**	1.60	2.50
h=6	1.65	1.59	1.02	**0.79**	1.42	1.50	3.06	2.36	1.15	**1.10**	1.69	2.61
h=12	1.67	1.74	**1.34**	1.52	1.57	1.59	3.64	3.36	2.65	**2.56**	2.76	3.22
h=24	**1.53**	1.65	1.73	2.01	1.64	1.56	**3.75**	4.00	4.27	4.17	4.00	3.92
	DE						LU					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.14	0.97	**0.43**	0.73	0.89	1.00	1.55	1.51	1.27	**1.23**	1.40	1.47
h=6	1.22	1.09	**0.52**	0.84	0.97	1.06	1.63	1.62	**1.28**	1.30	1.47	1.53
h=12	1.33	1.29	1.06	**1.05**	1.12	1.16	1.69	1.74	**1.40**	1.48	1.61	1.62
h=24	1.39	1.43	1.53	1.29	1.26	**1.25**	1.69	1.74	1.63	**1.62**	1.65	1.63
	EE						MT					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	2.37	1.86	1.85	**1.23**	1.76	2.27	1.19	1.03	**0.94**	0.94	1.03	1.16
h=6	2.71	2.54	1.96	**1.49**	2.00	2.41	1.47	1.37	**0.91**	1.02	1.09	1.20
h=12	3.41	3.64	**2.63**	2.74	2.92	3.06	1.86	1.81	**1.08**	1.31	1.37	1.42
h=24	3.93	4.24	**3.62**	4.03	3.86	3.78	1.76	1.78	**1.22**	1.34	1.39	1.42
	IE						NL					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.23	1.18	0.61	**0.60**	0.87	1.02	1.16	1.10	**0.87**	0.87	0.94	1.01
h=6	1.46	1.48	**0.63**	0.73	0.99	1.09	1.31	1.31	**0.86**	0.92	1.02	1.06
h=12	1.91	2.03	1.49	**1.38**	1.55	1.56	1.54	1.62	**1.08**	1.16	1.27	1.24
h=24	2.28	2.44	2.42	**2.18**	2.28	2.23	1.75	1.78	1.50	1.39	1.44	**1.39**
	GR						AT					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.51	1.36	**0.67**	1.26	1.47	1.64	1.02	0.92	**0.47**	0.56	0.78	0.87
h=6	1.56	1.49	**0.68**	1.29	1.48	1.63	1.14	1.11	**0.51**	0.67	0.90	0.97
h=12	1.73	1.71	1.65	**1.44**	1.53	1.64	1.25	1.34	1.09	**1.05**	1.16	1.16
h=24	1.96	1.99	2.38	1.76	**1.62**	1.70	1.36	1.50	1.51	1.40	1.37	**1.29**
	ES						PT					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.49	1.39	**0.72**	1.13	1.34	1.48	1.21	1.10	**0.61**	1.24	1.34	1.41
h=6	1.63	1.60	**0.77**	1.25	1.45	1.54	1.30	1.32	**0.63**	1.23	1.34	1.40
h=12	1.80	1.89	**1.49**	1.51	1.63	1.64	1.58	1.76	1.30	**1.28**	1.37	1.42
h=24	1.87	1.99	2.06	1.71	1.69	**1.64**	1.88	2.06	2.06	**1.46**	1.47	1.49
	FR						SI					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	0.97	0.83	**0.42**	0.60	0.75	0.89	1.77	1.38	**0.72**	1.03	1.22	1.51
h=6	1.03	0.97	**0.41**	0.67	0.82	0.93	1.92	1.59	**0.82**	1.15	1.34	1.60
h=12	1.13	1.19	1.06	**0.94**	1.02	1.04	2.19	2.04	**1.51**	1.51	1.63	1.82
h=24	1.16	1.23	1.41	1.17	1.15	**1.11**	2.28	2.35	2.18	1.95	**1.93**	1.98
	IT						SK					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.05	0.96	0.70	**0.61**	0.93	1.05	1.38	1.05	**0.81**	1.08	1.12	1.47
h=6	1.11	1.11	0.71	**0.70**	1.01	1.10	1.64	1.42	**0.83**	1.19	1.24	1.58
h=12	1.32	1.40	**1.06**	1.13	1.22	1.23	2.07	2.06	**1.63**	1.66	1.74	1.92
h=24	1.53	1.64	1.56	1.63	1.48	**1.40**	2.32	2.56	2.51	**2.26**	2.35	2.26
	CY						FI					
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE
h=3	1.74	1.73	**1.12**	1.41	1.61	1.77	1.12	0.93	**0.46**	0.63	0.73	0.96
h=6	1.93	1.91	**1.11**	1.47	1.69	1.84	1.19	1.15	**0.49**	0.68	0.80	0.99
h=12	2.15	2.16	**1.46**	1.67	1.81	1.91	1.31	1.49	0.97	**0.94**	1.06	1.12
h=24	2.14	2.22	1.95	1.90	**1.86**	1.90	1.43	1.72	1.49	**1.28**	1.38	1.31
	LV											
	XFE	XE	U_HICP	MS_HICP	MCT_XE	MCT_XFE						
h=3	2.88	1.84	**1.40**	1.61	1.95	2.94						
h=6	3.34	2.72	**1.37**	1.48	1.84	2.87						
h=12	4.28	4.26	3.44	**3.02**	3.06	3.58						
h=24	**4.74**	5.28	5.63	5.08	4.92	4.86						

Table B.6: The descriptives for headline and underlying inflation rates

	Bias			Volatility					
	Average			SD			MAC		
Measure	Total	S1	S2	Total	S1	S2	Total	S1	S2
HICP_AROC	2.11	1.63	4.49	2.00	0.96	3.53	0.24	0.20	0.46
HICP_XE	1.83	1.47	3.58	1.41	0.51	2.65	0.15	0.11	0.32
HICP_XFE	1.56	1.31	2.81	1.04	0.38	1.97	0.15	0.12	0.27
TRIM10	2.04	1.63	4.05	1.66	0.74	2.98	0.16	0.13	0.33
TRIM20	1.94	1.59	3.66	1.46	0.63	2.69	0.13	0.10	0.30
TRIM30	1.90	1.58	3.49	1.37	0.58	2.54	0.12	0.08	0.30
WGT_MEDIAN	1.90	1.57	3.48	1.33	0.51	2.51	0.14	0.10	0.34
SUPERCORE	1.81	1.52	3.19	1.17	0.44	2.22	0.10	0.08	0.21
PCCI	2.00	1.74	3.28	0.98	0.41	1.71	0.11	0.08	0.26
PCCI_XFE	1.56	1.40	2.39	0.61	0.26	1.05	0.06	0.04	0.14
U_HICP	2.06	1.57	4.50	1.95	0.99	3.30	0.21	0.15	0.48
MS_HICP	2.18	1.69	4.60	1.70	0.64	2.87	0.11	0.05	0.41
MCT_XE	1.78	1.40	3.63	1.39	0.36	2.62	0.10	0.04	0.39
MCT_XFE	1.51	1.23	2.92	1.05	0.30	1.94	0.07	0.03	0.28
MC_HICP_12	2.17	1.68	4.61	1.92	0.87	3.33	0.17	0.11	0.45
U_HICP_P	1.93	1.55	3.79	1.45	0.82	2.25	0.13	0.10	0.26
MS_HICP_P	2.09	1.65	4.25	1.49	0.62	2.39	0.09	0.05	0.28
MCT_XE_P	1.74	1.36	3.61	1.30	0.35	2.30	0.07	0.03	0.26
MCT_XFE_P	1.51	1.22	2.95	0.99	0.31	1.69	0.05	0.02	0.19

Note: SD and MAC stand for Standard Deviation and Mean Absolute Change, respectively. S1 (S2) refers to the period between 2003:01 to 2020:03 (2020:04-2023:09).

Table B.7: RMSE against the centred moving average of headline inflation

	Two-year			Three-year		
Measure	S1	S2	Total	S1	S2	Total
HICP_XE	0.46	1.31	0.69	0.46	1.39	0.70
HICP_XFE	0.60	1.91	0.97	0.53	1.66	0.82
TRIM10	0.29	0.99	0.50	0.42	1.49	0.71
TRIM20	0.29	1.14	0.55	0.36	1.37	0.64
TRIM30	0.31	1.28	0.61	0.34	1.37	0.63
WGT_MEDIAN	0.35	1.34	0.64	0.32	1.39	0.63
SUPERCORE	0.46	1.52	0.76	0.38	1.40	0.66
PCCI	0.47	2.11	0.99	0.44	1.75	0.84
PCCI_XFE	0.59	2.75	1.27	0.53	2.27	1.06
U_HICP	0.59	2.37	1.13	0.66	2.52	1.20
MS_HICP	0.28	1.58	0.71	0.30	1.80	0.80
MCT_XE	0.48	1.70	0.84	0.44	1.76	0.83
MCT_XFE	0.64	2.11	1.05	0.58	1.87	0.92
MC_HICP_12	0.45	2.32	1.06	0.54	2.52	1.15
U_HICP_P	0.43	1.67	0.80	0.48	1.53	0.75
MS_HICP_P	0.31	1.35	0.63	0.33	1.37	0.65
MCT_XE_P	0.52	1.53	0.80	0.48	1.48	0.75
MCT_XFE_P	0.65	2.05	1.04	0.59	1.73	0.89

Table B.8: RMSE future headline inflation (euro area)

	RMSE future inflation					**RMSE future inflation (relative to headline RMSE)**				
Measure	h=3	h=6	h=12	h=24	h=36	h=3	h=6	h=12	h=24	h=36
HICP_XE	0.94	1.08	1.29	1.44	1.40	1.58	1.08	0.91	0.80	0.75
HICP_XFE	1.06	1.13	1.23	1.35	1.29	1.79	1.13	0.86	0.73	0.68
TRIM10	0.71	0.95	1.33	1.62	1.64	1.20	0.95	0.94	0.91	0.89
TRIM20	0.81	1.00	1.31	1.56	1.55	1.36	1.00	0.92	0.87	0.84
TRIM30	0.86	1.03	1.30	1.52	1.50	1.44	1.03	0.92	0.85	0.81
WGT_MEDIAN	0.90	1.03	1.27	1.45	1.43	1.51	1.03	0.89	0.80	0.77
SUPERCORE	1.00	1.09	1.22	1.36	1.28	1.69	1.09	0.86	0.74	0.68
PCCI	0.85	0.92	1.15	1.34	1.38	1.45	0.92	0.82	0.74	0.74
PCCI_XFE	1.03	1.07	1.18	1.25	1.25	1.73	1.07	0.83	0.68	0.66
U_HICP	0.44	0.49	1.14	1.67	1.80	0.77	0.49	0.82	0.93	0.98
MS_HICP	0.63	0.76	1.04	1.40	1.54	1.06	0.76	0.73	0.77	0.83
MCT_XE	0.85	0.96	1.14	1.35	1.40	1.45	0.96	0.80	0.74	0.75
MCT_XFE	0.99	1.06	1.17	1.29	1.33	1.68	1.06	0.82	0.70	0.70
MC_HICP	0.50	0.62	1.12	1.52	1.67	0.87	0.62	0.78	0.84	0.91
U_HICP_P	0.45	0.48	1.01	1.51	1.66	0.76	0.48	0.71	0.83	0.90
MS_HICP_P	0.65	0.75	1.03	1.34	1.47	1.10	0.75	0.71	0.74	0.79
MCT_XE_P	0.87	0.96	1.13	1.29	1.33	1.49	0.96	0.79	0.70	0.71
MCT_XFE_P	1.00	1.06	1.15	1.24	1.28	1.71	1.06	0.81	0.67	0.67

Table B.9: OLS regression results

	2003:01-2020:03			**2003:01-2023:09**		
Measure	Intercept	Coefficient	R^2	Intercept	Coefficient	R^2
HICP_XE	0.11	0.99***	0.28	0.40***	0.47***	0.05
HICP_XFE	0.28***	0.99***	0.42	0.53***	0.57***	0.10
TRIM10	-0.05	1.48***	0.20	0.30**	0.73***	0.03
TRIM20	0.01	1.21***	0.25	0.34***	0.50***	0.03
TRIM30	0.02	1.13***	0.28	0.35***	0.49***	0.04
WGT_MEDIAN	0.02	1.10***	0.33	0.35***	0.50***	0.05
SUPERCORE	0.07	1.04***	0.42	0.40***	0.56***	0.08
PCCI	-0.16**	1.18***	0.44	0.21*	1.00***	0.20
PCCI_XFE	0.20***	0.99***	0.42	0.49***	0.61***	0.14
U_HICP	-0.01	1.19***	0.34	0.16	1.40***	0.35
MS_HICP	-0.16***	1.74***	0.62	0.04	1.87***	0.36
MCT_XE	0.24***	1.19***	0.47	0.51***	0.94***	0.15
MCT_XFE	0.40***	1.08***	0.48	0.67***	0.84***	0.17
MC_HICP	-0.15**	1.54***	0.41	-0.01	1.53***	0.31
U_HICP_P	0.07	1.72***	0.63	0.39***	2.15***	0.58
MS_HICP_P	-0.07	1.68***	0.60	0.18*	1.81***	0.37
MCT_XE_P	0.29***	1.18***	0.48	0.57***	1.03***	0.19
MCT_XFE_P	0.42***	1.10***	0.49	0.69***	0.89***	0.20

Note: *, **, and *** denote 0.1, 0.05, and 0.01 significance levels.

Table B.10: Lead and lag analysis

Measure	Correlation	
	Max.	Lead
HICP_XE	-5	0.950
HICP_XFE	-4	0.923
TRIM10	-1	0.983
TRIM20	-2	0.975
TRIM30	-3	0.973
WGT_MEDIAN	-3	0.964
SUPERCORE	-4	0.943
PCCI	2	0.950
PCCI_XFE	0	0.937
U_HICP	4	0.965
MS_HICP	1	0.951
MCT_XE	0	0.935
MCT_XFE	0	0.933
MC_HICP	4	0.956
U_HICP_P	4	0.975
MS_HICP_P	1	0.958
MCT_XE_P	0	0.944
MCT_XFE_P	0	0.939

Table B.11: Turning points analysis

	Peak Dates						
HICP_AROC	2004M05	2005M09	2008M07	2011M11	2017M02	2018M10	2022M10
PCCI	x	2006M04	2007M12	2011M04	x	2018M11	2022M06
U_HICP	x	2005M08	2007M12	2011M03	x	2018M06	2022M03
MS_HICP	2004M05	x	2008M03	2011M11	x	x	2022M12
MCT_XE	x	x	2008M02	2011M11	2015M05	2017M07	2023M01
MCT_XFE	x	x	2007M02	2011M11	2015M05	2017M07	2023M01
MC_HICP	x	2006M06	2008M02	2011M03	x	2018M08	2022M04
U_HICP_P	x	2005M08	2007M12	2011M03		2018M06	2022M05
MS_HICP_P	x	x	2008M03	2011M05	x	x	2022M07
MCT_XE_P	x	x	2008M02	2011M09	2015M05	2017M08	2022M12
MCT_XFE_P	x	x	2008M03	2011M09	2015M05	2017M08	2022M12
	Trough Dates						
HICP_AROC	2005M01	2006M10	2009M07	2015M01	2018M02	2020M12	
PCCI	2005M01	2006M11	2009M11	2015M01	x	2020M09	
U_HICP	2005M02	2006M11	2009M02	2016M01	x	2020M05	
MS_HICP	2005M01	x	2009M11	x	x	2020M09	
MCT_XE	2005M05	x	2009M11	2014M11	2016M02	2018M11	
MCT_XFE	2005M05	x	2009M11	2014M05	2016M03	2018M11	
MC_HICP	2004M01	2007M02	2009M06	2015M02	x	2020M08	
U_HICP_P	2005M02	2006M11	2009M02	2016M01	x	2020M05	
MS_HICP_P	x	x	2009M10	x	x	2020M09	
MCT_XE_P	2005M05	x	2009M11	2014M11	2016M02	2018M11	
MCT_XFE_P	2005M05	x	2009M11	2014M05	2016M02	2018M11	

T: +353 (0)1 224 6000
www.centralbank.ie
publications@centralbank.ie

Bosca PO 559, Baile Átha Cliath 1, Éire
PO Box 559, Dublin 1, Ireland