Banc Ceannais na hÉireann
Central Bank of Ireland
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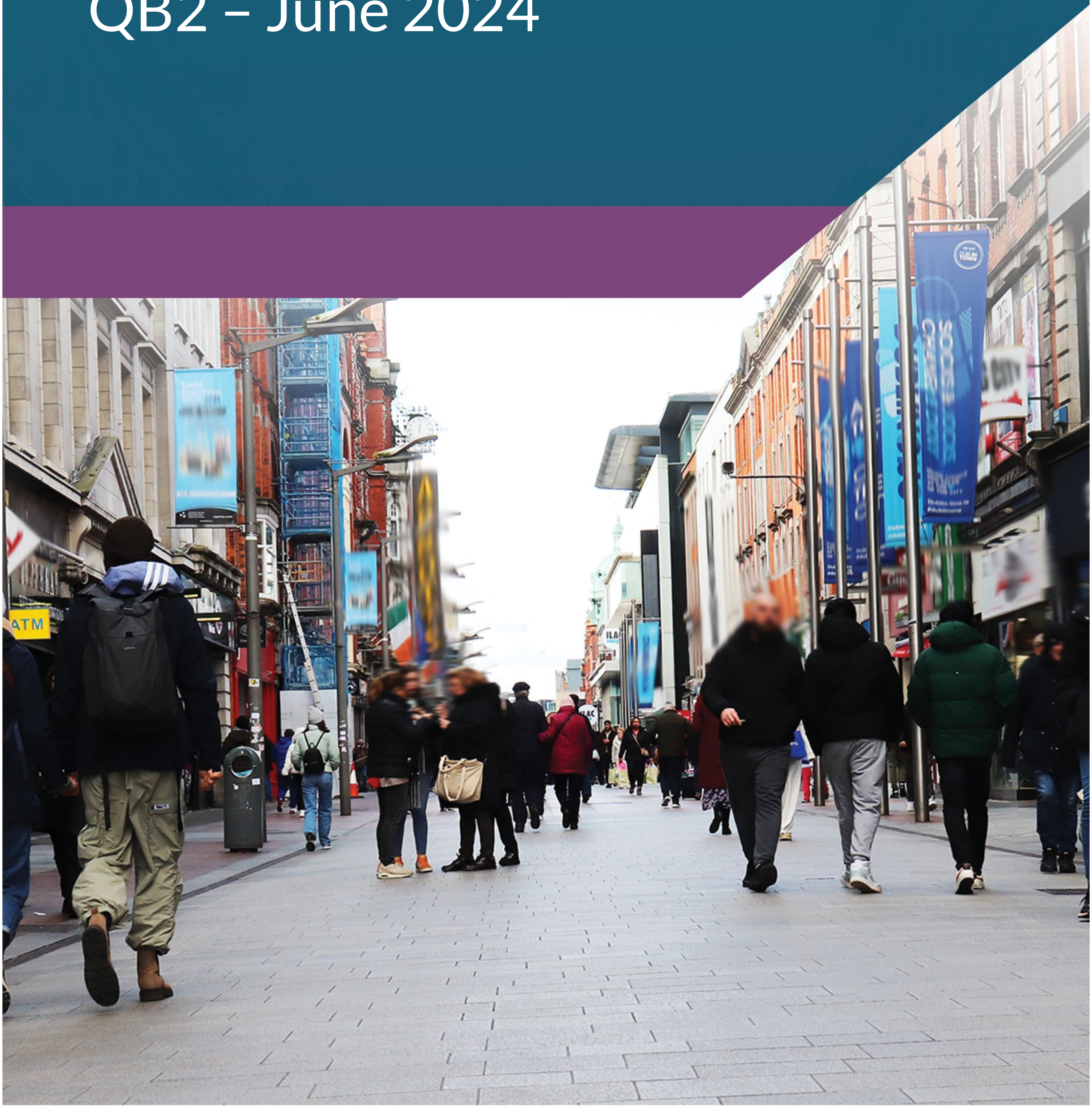

Contents

Inflation Forecasting at the Central Bank of Ireland

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Abstract

Analysing changes in inflation and forecasting its future path are important exercises in assessing overall economic conditions and as an input to domestic and monetary policy decision making. Lately, large and unexpected shocks, such as the Covid-19 pandemic and the Russia-Ukraine war, have complicated this task and have prompted many forecasters to review their approaches. This *Article* provides an overview of the recent experience in analysing and forecasting inflation in Ireland, outlines the tools and methods used by Central Bank staff to conduct these analyses, and how those practices have been changing in light of recent experience and methodological advances.

1. Introduction

As a Central Bank in a monetary union, our forecasts of inflation serve two important purposes. Firstly, setting monetary policy for the euro area requires analysis of inflation dynamics across member countries that may be at different stages of the business cycle. Accurate and credible forecasts of inflation are a crucial input in the setting of monetary policy, since interest rate decisions taken today will have their full effect on the economy and prices in one to two years' time (Lane, 2022). Secondly, understanding the interaction of inflation dynamics and broader domestic macroeconomic developments is crucial for the Bank to fulfil its economic advice mandate and in the formulation of domestic economic policy.

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[1] Irish Economic Analysis Division. Thanks to Thomas Conefrey, David Cronin, Vahagn Galstyan, Robert Kelly, Vasileios Madouros, Martin O'Brien, and Cian Ruane for comments on an earlier draft. All remaining errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the Central Bank of Ireland or the European

In this context, the Central Bank produces inflation forecasts for the current and the next two calendar years. The key variable of interest is the year-over-year change in the Harmonised Consumer Price Index (HICP). In addition, forecasts for its main components of energy, food, non-energy industrial consumer goods (NEIG) and services are also published. These forecasts are published in the *Quarterly Bulletin* together with a detailed analysis of recent economic and price developments in Ireland. In addition, the Central Bank contributes its forecasts for Ireland to the Eurosystem Staff Macroeconomic Projections for the euro area twice per year, in June and December.

The task of inflation forecasting is very complex. This complexity stems from changing relationships between economic variables and uncertainty stemming from exogenous shocks. Many studies have shown that is difficult to find a forecasting model that improves upon a simple benchmark model, such as a random walk or an autoregressive process (Faust and Wright, 2013). Using the random walk model, a forecaster naively predicts that the future inflation rate will be the same as the current rate of inflation. The autoregressive model also relies on the inflation rate in the previous period, i.e., AR(1), to predict inflation but does not assume a strict one-to-one relationship. The standard Phillips curve model of inflation, where inflation is assumed to be related to economic activity or labour market conditions, has been often criticised, with evidence that it does not improve upon these simple univariate models (Atkeson and Ohanian, 2001; Stock and Watson, 2007). Nevertheless, some research has shown that information on variables other than inflation itself can help to improve forecast accuracy (Faubert, 2021; Fulton and Hubrich, 2021; Medeiros et al., 2021).

Earlier literature on forecasting Irish inflation found evidence of inflation being predominantly determined by external factors. This partly reflects the fixed exchange rate regime with sterling until 1979. For instance, Irish inflation in the 1962-1974 period can be explained to a large extent by inflation in the UK, driven by the prevalence of goods imported from the UK (Geary, 1976; Browne (1984). The exchange rate dynamics in the late 1990s was the key driver of a spike and a subsequent decline in Irish inflation in the early 2000s (Honohan et al., 2003; Honohan and Lane, 2004). It has also been shown that oil price information is a very important determinant of Irish inflation (Bermingham, 2008). In the period after Ireland joined the Exchange Rate Mechanism, domestic factors received more attention in the literature.[2] More recent studies find support for the role of domestic factors in determining Irish

[2] For a brief overview, see Gerlach et al. (2016).

inflation, such as the overall or short-term unemployment rate, measures of unemployment and output gaps, employment growth, etc.[3] For instance, Bermingham et al. (2012) find that a relationship between inflation and domestic slack exists[4], albeit it is dependent on the cyclical position of the economy. Gerlach et al. (2016) demonstrate that labour market conditions influenced Irish inflation not only in more recent decades, i.e., 1980-2012, but also over the longer period 1926-1979.

Both external and domestic factors matter for forecasting Irish inflation. The relative importance of external and domestic factors over the period 2007-2017 are evaluated in Byrne and Zakipour-Saber (2020). Since the global financial crisis, external factors (e.g. the exchange rate and oil prices) have resurfaced as important determinants of inflation. However, domestic factors such as labour market slack have been increasingly important in more recent years of their sample. Faubert (2021) finds that domestic economic conditions are relevant for headline, core and, particularly, services inflation in Ireland over the period 1999-2019, while exchange rate and international commodity prices (e.g. oil price) matter for modelling headline and core inflation but not services. This is in line with other recent studies taking a dual approach to Irish inflation, with an important role for exchange rate and commodity price dynamics, as well as domestic conditions (Reddan and Rice, 2017; Byrne, McLaughlin and O'Brien, 2022).

The global inflationary surge, beginning in 2021 until recently, has necessitated that central banks and policy institutions reassess their framework for forecasting inflation.[5] In particular, forecasts dependant solely on models estimated on historical time series tend to revert to the long-run average inflation rate towards the end of the typical projection horizon of about three years (Schnabel, 2024). This reflects assumptions that supply side shocks are transitory. It is possible that large and persistent supply shocks, such as those seen in recent years, could become a feature of the global economy (Lagarde, 2023). It is thus important that data analysis and modelling tools used for forecasting inflation are reviewed and improved over time.

In this paper, we describe the current framework for analysing and forecasting inflation used in the Central Bank of Ireland, following the regular update of modelling tools conducted early in 2024. Section 2 outlines how inflation

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[3] The unemployment gap indicates whether unemployment is below or above its level consistent with non-accelerating inflation. The output gap show the output level relative to its potential level.
[4] This is true not only for headline but also for core and services inflation.
[5] See Ben Bernanke's review of forecasting at the Bank of England here.

forecasts for Ireland and the euro area have compared to observed outturns in recent past. Section 3 describes the suite of analytical tools used by the CBI to decipher underlying inflation trends in Ireland, which tend to provide useful signals about medium-term inflationary pressures. Section 4 provides details of the overall forecasting framework, selection and evaluation of the forecasting models used to inform the projections for individual components of inflation. Section 5 concludes.

2. Historical forecasting accuracy and post-pandemic surge

The Covid-19 pandemic and the Russian invasion of Ukraine have made forecasting inflation even more difficult worldwide in recent years (Koch and Noureldin, 2023). Firstly, the pandemic led to significant disruptions in economic activities, causing fluctuations in consumer demand patterns as well as large-scale supply disruptions globally. Secondly, the pandemic introduced unprecedented levels of uncertainty and volatility in the global economy, making it difficult for traditional forecasting models to account for such extreme conditions (Bobeica and Hartwig, 2023). Additionally, the Russian invasion of Ukraine led to heightened volatility in commodity markets and exchange rates – in particular in the market for natural gas (Caldara et al., 2022). Furthermore, the conflict has disrupted supply chains and trade relationships, resulting in large swings in the wholesale price of many intermediate inputs. Political repercussions of the invasion, such as sanctions and shifts in energy policies, have also added complexity to forecasting inflation by introducing additional variables that can influence inflation rates (Arce, Koester and Nickel, 2023).

To illustrate how these disruptions made it difficult to forecast inflation, the Central Bank's one-year-ahead inflation forecasts are compared with actual inflation outturns since 2016 (Figure 1). Similar to the finding of Byrne and Zakipour-Saber (2020), which looked at the period 2006 to 2016, inflation forecasts between 2016 and 2019 performed well. However, the Central Bank's forecasts for inflation in 2022 and 2023 (conducted in 2021 and 2022, respectively) turned out to be quite inaccurate. To a great extent, these large forecast errors can be explained by the fact that it was impossible to foresee the severe pandemic shock, which led to a collapse in prices and economic activity back in 2020, and a subsequent fast recovery. Similarly, the Russian invasion of Ukraine in 2022 and the subsequent war was not part of any central expectation at the time of the forecast exercises in 2021. By the third *Quarterly Bulletin* of 2022, a greater understanding of the underlying dynamics governing the post-pandemic inflationary surge had developed and there were reduced forecast errors for 2023 in those *Bulletins*.

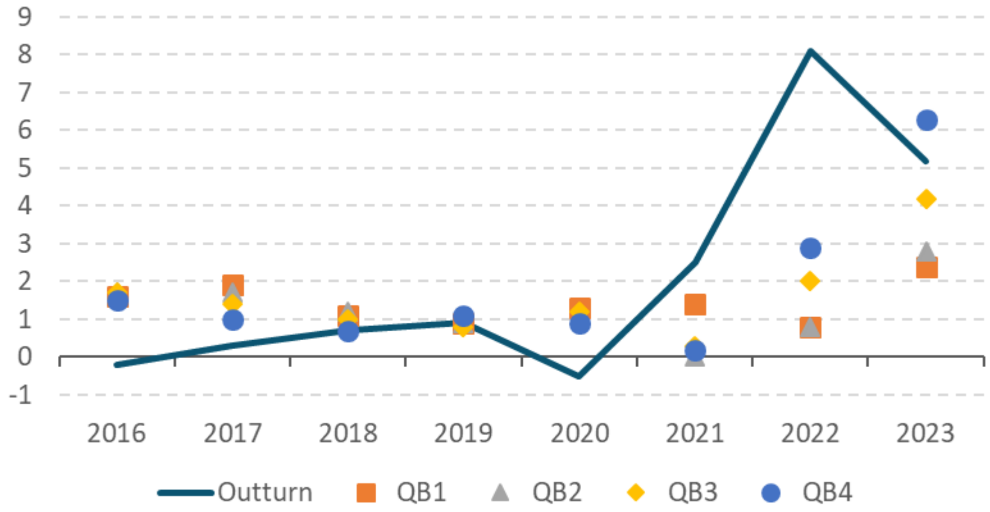
The decomposition of the inflation forecast errors for 2022-23 shows that the majority of the error is explained by forecast errors in energy and food prices (Figure 2). Forecasts of energy and food prices are primarily determined by market-based expectations of future commodity prices – see Section 4 (e.g. those of crude oil, natural gas and agricultural commodities). If actual commodity prices turn out to be substantially different from these market-based expectations, large forecast errors materialise. This was precisely the case in the period 2021-2023 (Figures 3 and 4). In early 2021, markets expected oil prices to average $60 per barrel and food commodity prices to remain broadly flat during 2022. For various reasons, primarily the supply shock induced by the Russian invasion of Ukraine, oil prices at times exceeded $100 per barrel and food commodity prices increased by around 40% during 2022 (Figures 3 and 4).

During 2020, the forecast was that inflation would recover in 2021, which it did, but it under-predicted the magnitude of the inflation resurgence as the economy reopened in 2021. Forecasts for 2022, conducted in 2021, were obviously unable to incorporate the effects of the Russian invasion of Ukraine, and the associated increases in energy costs as well as second-round effects on other goods and services occurring via higher production input costs. These second round effects led to forecast errors spreading into broader non-energy industrial goods (NEIG) and services, particularly in 2022 (Figure 2). Forecasts for these components also contained a direct energy measure resulting in an underestimation of inflation for the same reasons as for the energy and food components. Unprecedented increases in global shipping costs also contributed to the underestimation in goods prices. The historical downward bias inherent in Irish NEIG prices, related to the approach to quality adjustment adopted by the Central Statistics Office (CSO) in compiling NEIG prices, also resulted in lower model estimates for the goods forecasts. The services forecasts may also have underestimated the strength in the demand and the recovery in prices after the lockdowns ended. Strong disposable income, supported by government measures, as well as profit recovery by some firms led to stronger than expected prices in 2022. The services forecast for 2023 was also affected by a change in the measurement methodology by the CSO, which resulted in some underestimation in prices.[6]

Similarly, inflation forecast errors of the European Central Bank staff and the Eurosystem also increased in 2021 before declining in 2023 (Chahad et al., 2024). Energy prices accounted for most of their errors up until early 2022, especially in countries most exposed to the war in Ukraine. Then, an unexpected surge in food prices also started to be more important in driving errors. Later on, other factors were also starting to play a more prominent role, e.g., indirect effects of previous energy price spikes on other goods and services. In 2023, energy prices falling faster than expected led to forecast errors in the opposite direction. The ECB's Survey of Professional Forecasters (SPF) for the euro area also suffered from large prediction errors around the time of the pandemic and energy shocks. The Bank of England's review of its forecasting framework, which was led by Ben Bernanke, also pointed out that large forecast errors were observed at the Bank of England as well as other large central banks. Between 2016 and 2022, average forecast errors from the Central Bank of Ireland were in line with those from other Eurosystem central banks (Figure 5).

Forecasts of one-year ahead inflation failed to capture the surge in inflation in 2022

Figure 1
Per cent



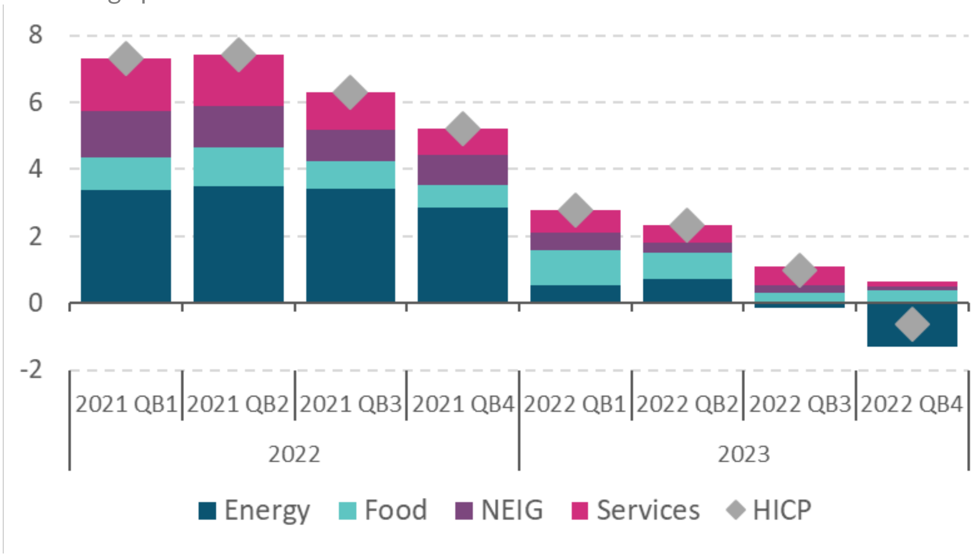
Source: CSO and Central Bank of Ireland.

Notes: The solid line refers to the average annual increase in the level of the harmonised index of consumer prices. Each marker refers to the forecast of that inflation rate in each Bulletin in the previous year. For example, the value of QB1 in 2016 refers to the forecast of the annual HICP inflation rate as published in the 1st Quarterly Bulletin of 2015 (published in March).

[6] CSO, 2023. Change in Methodology for International Package Holidays.

Forecasting errors were largely driven by errors in forecasting Energy and Food Inflation

Figure 2
Percentage points

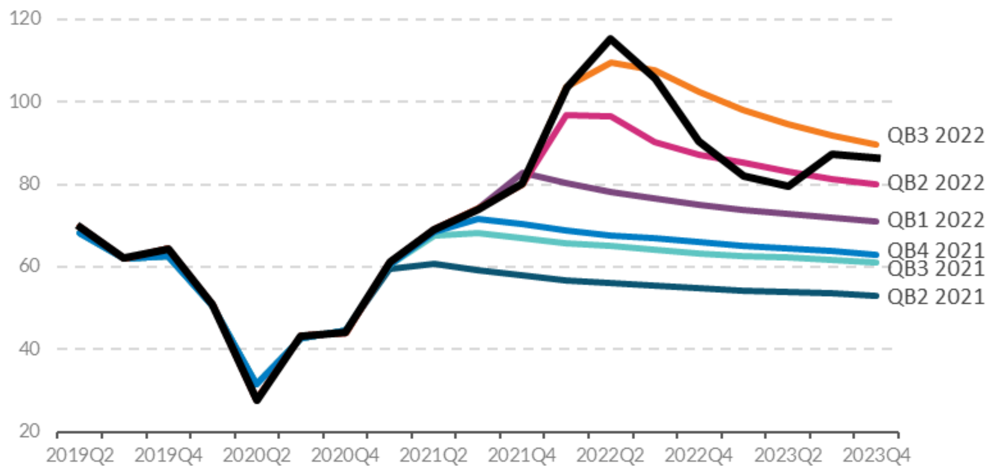


Source: CSO and Central Bank of Ireland.

Notes: HICP forecasting errors decomposed into the forecasting errors in their constituent parts. Errors refer to the forecast error of that inflation rate in each Bulletin in the previous year. For example, 2021 Q1 is the HICP inflation forecast error for 2022 decomposed into the contribution of the forecast error of Energy, Food, NEIG, and Services inflation.

Underlying energy assumptions failed to anticipate the rise in energy prices

Figure 3
Oil Price USD (base 2015 = 100)

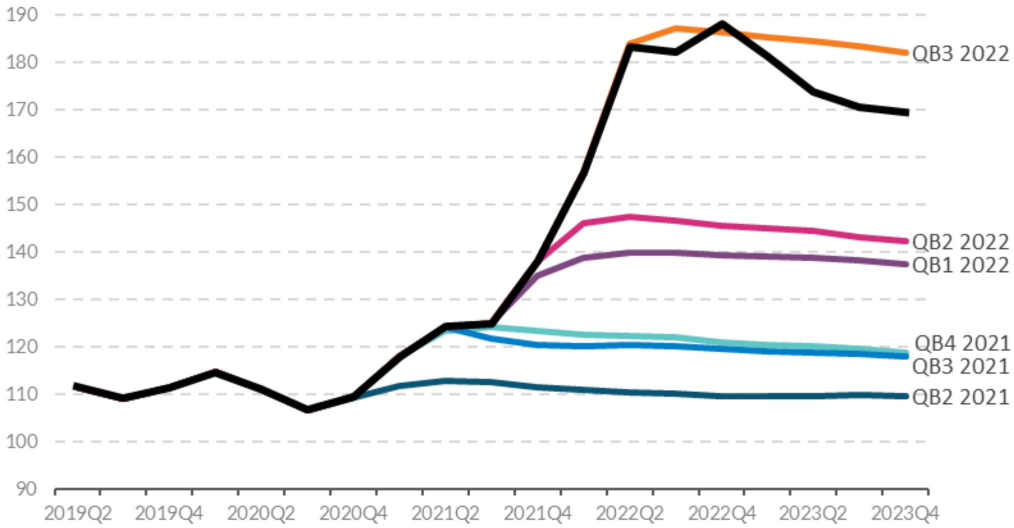


Source: ECB technical assumptions

Notes: Oil price assumptions used to forecast energy inflation for the Quarterly Bulletin each quarter from Q1 2021 to Q2 2022. The black line signifies real data.

Food price assumptions failed to anticipate the rise in food prices

Figure 4
Farm-gate and wholesale market prices (base 2015 = 100)

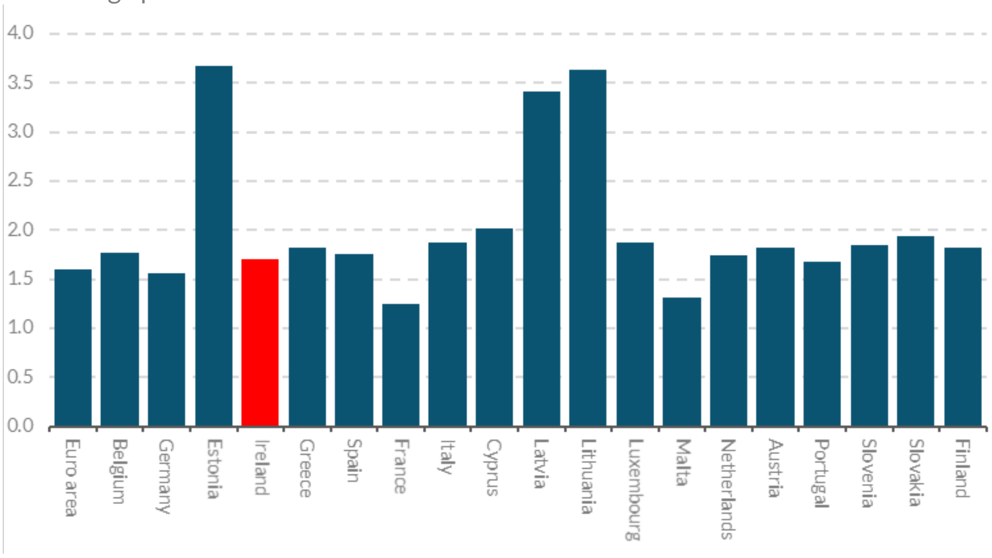


Source: ECB technical assumptions

Notes: HICP forecasting errors decomposed into the forecasting errors in their constituent parts. Errors refer to the forecast error of that inflation rate in each Bulletin in the previous year. For example, 2021 Q1 is the HICP inflation forecast error for 2022 decomposed into the contribution of the forecast error of Energy, Food, NEIG, and Services inflation.

On average, forecast errors in the Central Bank of Ireland are in line with other national central bank forecasts in 2016-2022 period

Figure 5
Percentage points



Source: ECB, Central Bank of Ireland calculations

Notes: Average forecast errors of one-year ahead inflation for forecasts submitted to the ECB by Eurosystem Staff between 2016 and 2022. Forecasts are submitted in June and September of each year.

3. Measures of underlying inflation

It is important to monitor recent changes in actual inflation, also utilising more granular consumer price index data, before estimating forecast models. Current inflation data and price trends in the recent past may be helpful in informing about future developments in inflation. For instance, the weighted distribution of price changes across the consumer basket covered by the HICP informs about how wide-spread are large price increases among HICP items and how this share has been changing over time (e.g., Figure 30 in QB4 2023). Instantaneous inflation measures provide an insight into most recent prices changes and can inform about the trajectory of annual inflation over the next few months (see Figure 23 in QB4 2023). Over the past year, the Central Bank developed a range of so-called underlying inflation measures for Ireland, which may be informative of where inflation is heading in the medium term. This section presents these measures, which are used in conjunction with our formal forecasting models, and assesses their predictive ability.

The ECB, together with euro area national central banks, sets monetary policy with the aim of achieving annual headline inflation of 2 per cent in the euro area *over the medium term*. There are several reasons to focus on medium term inflationary pressures as opposed to current headline inflation. Temporary idiosyncratic shocks unrelated to underlying economic conditions lead to shifts in prices that are often quickly reversed. Furthermore, monetary policy decisions about the policy interest rate take time to affect consumer prices. Thus, it is important to know where inflation is headed in the future to make a decision today.

As part of the Bank's toolkit for understanding current inflation and forecasting future dynamics, a range of underlying inflation measures are monitored.[7] Underlying inflation relates to the notion of an unobserved slow-moving (persistent) component of inflation. Measures of underlying inflation aim to provide a signal as to where headline inflation is likely to stand after temporary shocks fade. Headline HICP inflation can be volatile due to sudden, unanticipated events of uncertain duration, e.g., oil price shocks or extreme weather events. Monitoring underlying inflation helps to remove such short-term noise. [8] These measures can be either exclusion-based, where specific

[7] This toolkit contains wide-ranging data on economic activity, prices, as well as consumer and firms' expectations about inflation and economic situation, among other things.

[8] In addition to all underlying inflation measures, bank's economists also regularly monitor what are key drivers of past inflation dynamics. Using a model-based approach one can decompose inflation dynamics into those driven by supply and demand forces (McLaughlin and Conefrey, 2023).

items of the HICP basket are removed, or model-based, where an econometric model is estimated to filter out the transitory inflation component, while retaining the persistent component. The next sub-section explains in detail the underlying inflation measures used at the Central Bank (Figure 6).

3.1 Exclusion-based measures

Prices of certain consumer items are known a priori to be volatile, providing a noisy signal about inflationary pressures. Thus, such items can simply be excluded from the overall price index to remove the noise on a permanent basis. The *permanent exclusion* underlying inflation measures exclude the same items every month, assuming that the persistence and volatility of inflation in those items do not change over time. The key permanent exclusion measure is the *HICP excluding food and energy*, i.e., core HICP.[9] It represents around 70 per cent of the total HICP basket, since energy and food has a weight of around 30 per cent.[10] Additionally, the *HICP excluding energy and unprocessed food*, representing approximately 85 per cent of the basket, is also monitored.

In contrast, temporary exclusion measures exclude items that may differ from one month to another (e.g., trimmed mean). They allow for potentially changing volatility in the price changes of individual items or for temporary spikes in typically non-volatile items. In other words, outliers in price changes are removed each month. For instance, trimmed mean inflation measures remove from the HICP a pre-specified share of items with the largest price increases or decreases in a given month. The share defines how much is removed from the top and bottom of the (weighted) price change distribution across the items. In this regard, the Central Bank uses the *trimmed mean inflation at 10 and 30 per cent*. Trimmed mean inflation at 10 per cent (30 per cent) removes the top and bottom 5 (15) per cent of the weighted distribution of price changes in a given month.[11] Trimmed means are complemented with the *weighted median*, which is simply the inflation rate of the basket item in the middle of the weighted distribution.[12]

The main advantage of permanent exclusion measures is that they are simple to calculate and interpret due to a fixed composition. Temporary exclusion measures are somewhat less transparent as it is difficult to track what is

[9] Alcoholic beverages and tobacco are also excluded as part of the food component.
[10] This reflect the average share over the period 1999-2024. The weights of HICP sub-components are updated each year but typically do not differ substantially from one year to the next.
[11] All temporary exclusion measures are based on year-on-year inflation rates of over 80 HICP items.
[12] This is equivalent to 100 per cent trimming.

excluded each month. Nevertheless, they account better for temporary large price changes in typically non-volatile components of inflation that would be included in permanent exclusion measures. A common disadvantage is that all exclusion-based measures are not fully representative of overall consumer prices and they tend to exclude items that are very salient for consumers, such as food and petrol and energy bills

3.2 Model-based measures

Persistent price changes increase the chance of second-round effects occurring.[13] Even volatile price changes could prove to be persistent such that both volatility and persistence of the price index components should be considered (da Silva Filho and Figueiredo, 2015). For instance, food prices could increase sharply due to draughts, floods, too hot or too cold weather conditions, etc. Such increases would be expected to reverse soon; however, this may not be the case if a sequence of extreme weather events prolongs the period of rising food prices. Higher food prices may lead to higher prices in services sectors where food is part of the cost (e.g., restaurants). In such cases, food inflation should not be excluded from underlying inflation measures. Following da Silva Filho and Figueiredo's (2015) method, the Central Bank constructed the *Persistence and Volatility Adjusted Rate* of inflation (PVAR) for Ireland. This measure is based on over 80 HICP items, where each item is re-weighted according to how volatile and persistent its inflation rate for that item was in the last three years. A higher weight is given to the items with more persistent price changes[14] (i.e., today's price change is heavily influenced by past price changes) and to the items with lower relative volatility[15] (i.e., how stable over the past three years is the gap between the item's inflation rate and overall inflation rate).

Another model-based measure of underlying inflation in the toolkit – *Common Inflation* – is based on a dynamic factor model that extracts the common trend in price changes across individual components of the basket.[16] The common component of inflation excludes the temporary idiosyncratic component from each HICP item considered. The aim is to uncover the part of inflation driven

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[13] Second-round effects occur when agents pass on the inflationary impact of price increase to wage and price setting, potentially leading to a wage-price spiral.

[14] The persistence of the inflation rate of an item is measured as the sum of the autoregressive coefficients from an estimated AR(p) model over the rolling 36-month window. Lag number p is selected according to the Schwarz criterion, allowing for the maximum of 3 lags.

[15] To measure volatility for each item, the standard deviation of the gap between its inflation rate and overall inflation rate, using 36 months rolling window, is calculated.

[16] Based on over 80 HICP items. For methodological details, see Box E, QB1 2022.

by general increases in consumer prices, i.e., where all prices are affected by the same underlying economic shock(s).

The final model-based measure used at the Central Bank is the *Core Trend Inflation*, constructed using an unobserved components model with stochastic volatility and outliers. The Core Trend inflation captures the persistent component in core inflation (excluding food and energy), while removing seasonal and irregular components (Aydin-Yakut, 2023).[17]

It is important to note that model-based measures are not flawless despite being more sophisticated than simple exclusion measures. They are more difficult to construct and misspecification of assumptions or parameters can lead to misleading results. Moreover, they tend to be revised over time due to model estimates being updated as new data are published. Finally, model-based measures can be more challenging to communicate as the models can obscure the underlying factors underpinning the changes in inflationary dynamics.

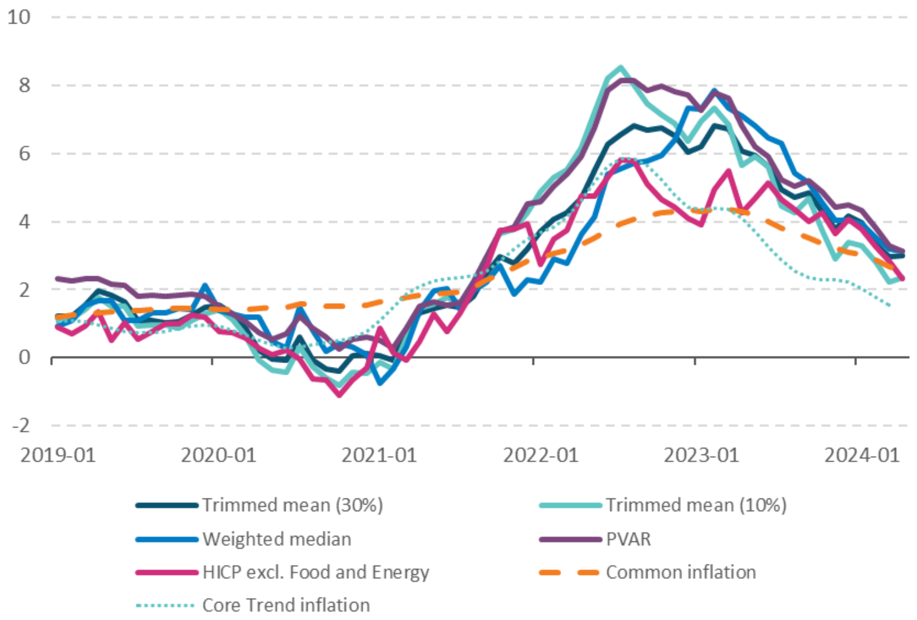
3.3 Assessment of underlying inflation measures

Different underlying inflation measures may provide conflicting signals about medium term inflation at times and the (relative) performance of any one measure may also change over time (Figure 6). This sub-section evaluates the relative success of the underlying inflation measures in tracking and predicting medium-term inflationary pressures using a number of empirical criteria: volatility, unbiasedness, overall precision and forecasting accuracy.

[17] Note that the estimation procedure however uses the information on food and energy items but they are excluded at the last stage when trend inflation across components is aggregated up.

Central Bank monitors a range of underlying inflation measures as they may provide conflicting signals at times

Figure 6
Annual percent change (%)



Source: Eurostat, CBI calculations.

Notes: Measures of underlying inflation in year-on-year percent changes. Last observation is March 2024 for Core Trend inflation measure and April 2024 for all the rest.

The time period of the analysis spans between November 2004 and August 2022. As a proxy for the persistent component of inflation, it is standard to use a 24-month centred moving average of monthly headline inflation when evaluating how well underlying inflation measures track medium-term inflation. For out-of-sample forecasting of trend inflation, the average monthly HICP inflation over the subsequent two years is used. The Technical Annex provides details of how the benchmark series are calculated and the detailed results of the in-sample assessment that follows here.

With respect to volatility, underlying inflation measures are less volatile compared to headline inflation. The evidence of unbiasedness is mixed, with many underlying inflation measures deviating by 40 basis points on average from the benchmark over the full period. At the same time, headline inflation is a relatively unbiased indicator.[18] To evaluate the *precision in tracking* the persistent component of inflation, each measure is compared with the

[18] To measure the bias, we calculate the *average difference* between the benchmark series for medium-term inflation trend (24-month centred moving average of monthly headline inflation) and each underlying inflation measure.

benchmark series at each point in time.[19] Current values of Core Trend inflation tend to provide a better signal about the underlying inflation trend than simply using the headline rate. However, the remaining measures perform worse than the headline.

The out-of-sample *forecasting accuracy* of underlying inflation measures is assessed by comparing contemporaneous values of underlying inflation measures with the benchmark for future medium-term inflation, i.e., average monthly HICP inflation over the next 24 months. This exercise is based on the observed data only. Common inflation and Core Trend inflation have the lowest RMSEs and also outperform headline inflation (see the Technical Appendix for the calculation of out-of-sample RMSE). Thus, their current values are more informative about the persistent inflation component over the next two years. Other measures also appear to be slightly better or at least no worse than headline inflation. Across the two sub-samples, the common and core trend inflation measures remain the best performers; however, the relative performance of other measures varies over time (Figure 7). While only four measures beat the headline rate in the first sub-sample, this figure rises to six in the second half.[20]

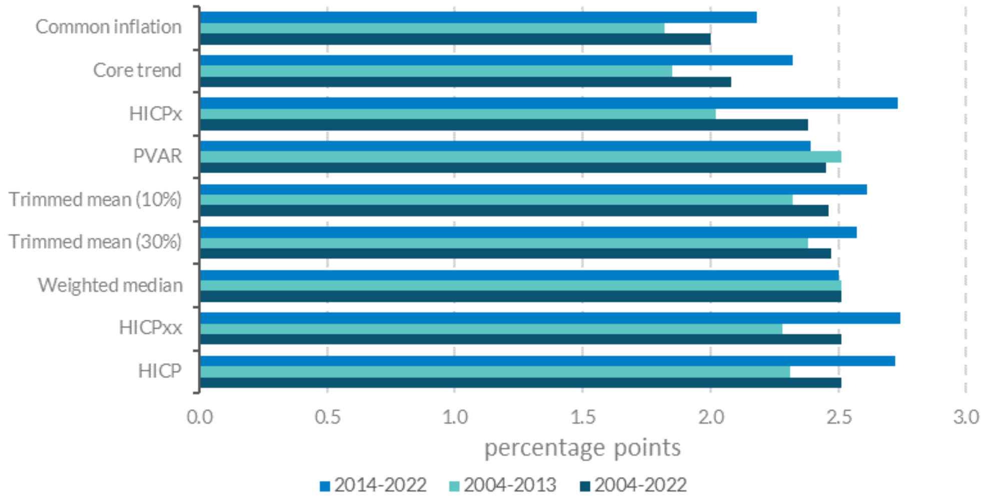
Overall, there does not seem to be a single best underlying inflation measure that meets all optimal criteria, in line with similar analysis for the euro area (Bańbura et al., 2023). Nevertheless, these measures can be useful in providing a signal about the medium-term inflationary pressures, in addition to headline inflation, and thereby inform any judgement that is applied to the output from forecasting models when arriving at a final forecast. Time-varying predictive ability underpins the rationale for the current approach of maintaining and monitoring many different measures.

[19] The root mean squared error (RMSE) is calculated to compare the measures numerically (see Technical Annex for details).

[20] There is some bias present, measured as average difference between underlying inflation measure and inflation trend, although in the full sample it is not significantly different from zero. However, it greatly increases in magnitude in the second sub-sample, as all measure implied a lower average inflation trend that it turned out to be. This likely reflects difficulties in predicting pandemic-related spike in inflation.

Out-of-sample forecast accuracy varies across time and measures of underlying inflation

Figure 7



Source: Eurostat, CBI calculations.

Notes: The figure shows Root Mean Squared Errors for each underlying inflation measure with respect to two year ahead trend inflation over the three sample periods. The measures are sorted by the full-sample RMSE in ascending order.

4. Forecasting framework at the Central Bank

4.1 Bottom-up strategy

The analysis of recent developments in Irish inflation and inflation forecasts for the current and the next two calendar years are produced each quarter and are published in the *Quarterly Bulletin*. In general, the forecasting process consists of multiple steps: 1) production of a forecast using a baseline forecasting model; 2) assessment of risks to the baseline forecast; 3) assessment of any ad-hoc factors known to affect inflation over the projection horizon but omitted from the baseline model; 4) application of an expert judgment, if deemed necessary.

In order to produce a baseline forecast for headline inflation, a bottom-up approach is followed to account for the fact that inflation dynamics are different across inflation components (Table 1). This reflects different driving forces as discussed in the introduction. Energy inflation is the most volatile and has been on average the highest average inflation. In contrast, services inflation is the least volatile but higher than food or non-energy industrial goods (NEIG) inflation, on average. Lowest inflation has been recorded for

NEIG component, which on average has been negative, partly reflecting difficulties in quality adjustment (Keating and Murtagh, 2018).

The bottom-up approach involves forecasting selected individual inflation components first, and then aggregating their forecasts in the next step (Figure 8). In other words, the headline inflation forecast is a weighted average of forecasts of its components.[21] Among the four main components of headline inflation, only services inflation is forecasted directly. Meanwhile, forecasts for energy, food and non-energy industrial goods (NEIG) (blue boxes, Figure 8) are the aggregates of forecasts of their sub-components (green boxes, Figure 8). For each component that is forecasted directly, a baseline forecasting model has been selected, which is then regularly evaluated and updated or changed when required.

Table 1: Statistical properties of headline inflation and its components in 2000-2024

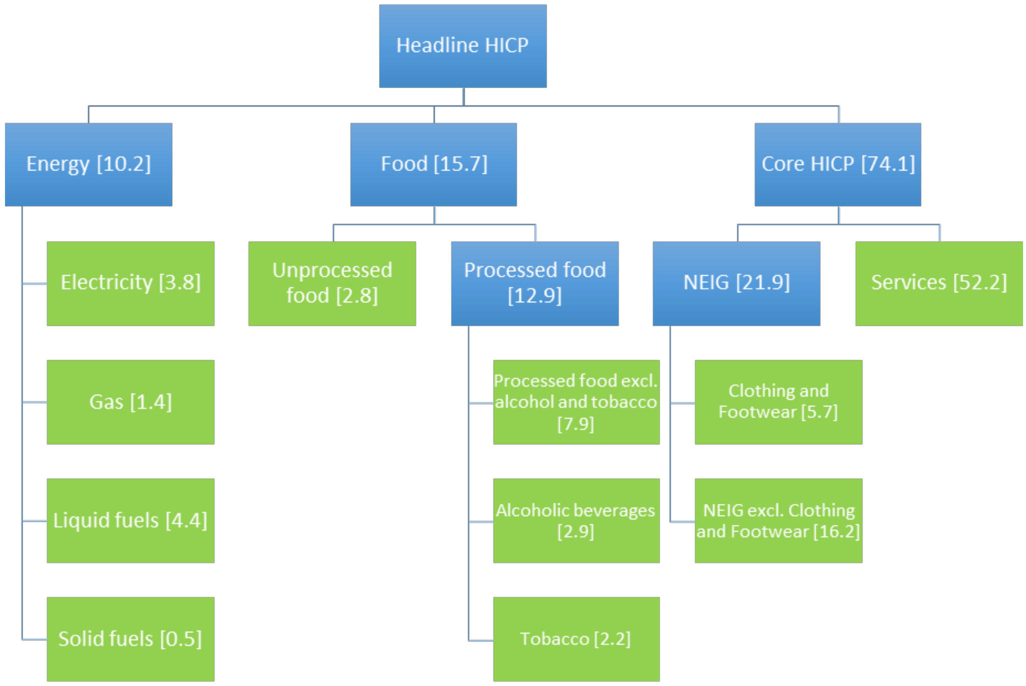
	HICP	Food	NEIG	Energy	Services
Mean	1.9	1.7	-1.6	5.3	3.1
Min	-2.9	-5.6	-8.6	-13.4	-1.1
Max	9.6	11.5	5.7	54.1	8.7
Standard deviation	2.4	3.1	2.6	11.1	2

Notes: all statistics provided in terms of year-on-year percentage changes. Source: Eurostat, CBI calculations

[21] The weights are fixed to consumption patterns of the previous year.

Overview of the bottom-up forecasting approach: headline inflation forecast is an aggregate of forecasts of its components

Figure 8



Notes: Bottom-up approach to forecasting inflation. The figures in square brackets denote the component's weight in the overall HICP. Blue boxes show components where forecasts are a weighted average of sub-components. Green boxes denote components that are forecast directly.

4.2 Baseline forecasting models: selection and evaluation

This section provides a brief discussion of how the baseline model for each inflation component is selected to be used in the Bank's forecasting framework. The performance of forecasting models often varies over time, reflecting changes in the relative roles of various inflation predictors, and/or changing model parameters. Therefore, the forecasting models in the Central Bank's toolkit are regularly reviewed and updated, if needed. The process of evaluation is the same as that for the initial selection of the baseline model.

A set of models is considered in order to identify the best forecasting model for each inflation component, i.e., the baseline model, drawing on the existing literature with respect to selecting predictors and the choice of econometric models. This set always includes a naïve model that acts as a benchmark, often a simple autoregressive model where a time series is forecast based on a constant and its own lag only, i.e., the AR(1) model. The remaining models in the set may differ in terms of 1) the number and type of predictors included; 2) the number of lags at which those predictors are included; or 3) the type of model used (e.g., ARMA vs. ARDL). The baseline model is selected from the set based on the analysis of the in-sample properties and out-of-sample forecasting accuracy.

To evaluate the in-sample properties, i.e., how well each model performs at matching the observed outturn, the fit of the models over the estimation sample period is analysed. Metrics such as the standard error of the regression, adjusted R-squared statistic, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) are used for this purpose.

As the best fitting model does not always provide the most accurate forecasts, it is also assessed how well the models predict inflation out of sample. The steps are as follows. First, the models are estimated over the initial (shorter) sample period.[22] Second, the forecasts for year-on-year inflation rate are produced for the next three years and compared to the actual data to calculate the forecast errors in each month of the forecast period. Third, the Root Mean Squared Error (SME) is calculated (see Technical Annex for details). The RMSE is the standard deviation of a model's forecast error and shows how far the predictions are from outturns. The larger the standard deviation is, the less accurate the model forecast is. Then, an extra month of data is added to the estimation sample and a new forecast over the next three years is produced with a new RMSE generated. This procedure is repeated numerous times until all available data at that time are used up.[23] Finally, the average RMSE over all recursive steps for each model is calculated. The baseline forecast model for each inflation component is then selected taking into account the fit of the model and the relative forecasting accuracy compared to other models in the set of models for that inflation component. Typically, more weight is given to out-of-sample forecasting accuracy.

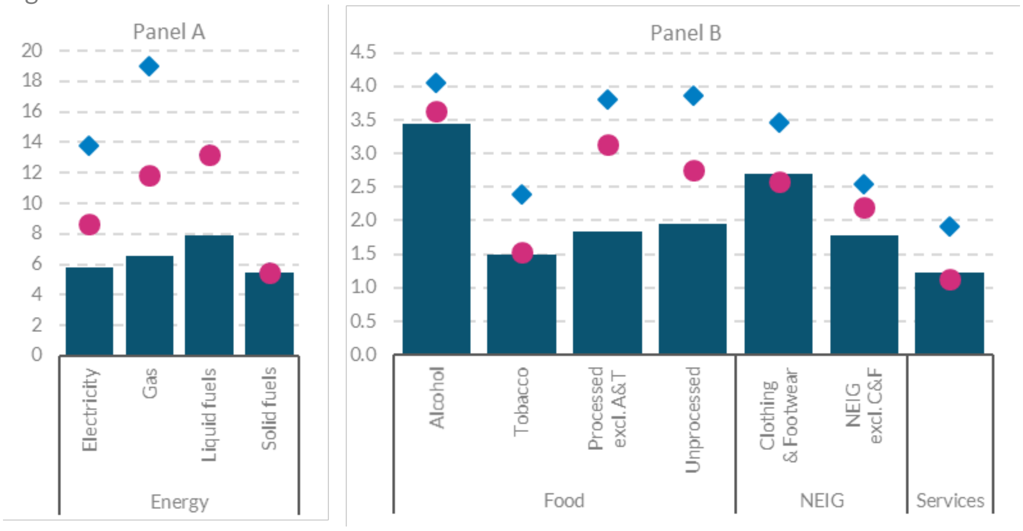
Generally, the baseline model on average produces more accurate or at least as-accurate forecasts as the simple benchmark model as well as performing much better than the worst performing model in the set (Figure 9). Energy inflation is the most difficult to forecast, as indicated by a much larger average RMSE of each energy component (Panel A, Figure 9), than any other inflation component (Panel A, Figure 9). In contrast, the baseline model for services has the lowest average RMSE (1.2). Assuming normally distributed forecast errors,

[22] In the latest model selection and evaluation exercise the initial period ended in January 2012.
[23] In the latest assessment, the models were estimated up to the end of 2020, to be able to construct forecasts and errors to the end of 2023, the last data point available at that time.

this implies that 95 per cent of forecast errors should fall within the range between -2.4p.p. and 2.4p.p.

Baseline models on average produce more accurate or at least as accurate forecasts as the simple benchmark model

Figure 9



Notes: Each bar in the figure shows average RMSE of a baseline model for energy inflation components (Panel A) and non-energy components (Panel B). Average RMSEs of the benchmark (pink dot) and worst performing model (blue diamond) are also shown. Forecast evaluation period spans 2012-2023, with the final three-year ahead forecast referring to the period 2021-2023.

It is important to distinguish that the "point" forecasts discussed thus far are the forecasters' estimate of the most likely evolution of the relevant variable. However, the discussion of the forecast will also communicate both risks and uncertainty surrounding the forecasts. In this context, risks have a narrow range of outcomes with probabilities that can be estimated. For example, inflation forecasts are heavily influenced by oil price assumptions, but one can derive marked based estimates of the probability that oil prices would be, for example, $10 higher than assumed in the baseline forecast (see, for example, Byrne and Lawton, 2022). Uncertainty on the other hand involves unknown and unpredictable outcomes. An example of this is the forecast error discussed in section 2, which derived from the Russian invasion of Ukraine in March 2022. There is also "model-based uncertainty", which refers to random fluctuations in the data which cannot be explained by the model.

With this in mind, there is a need for regular sensitivity analyses as well as alternative scenarios that could inform forecasters about the risks to the baseline forecast. Forecasters can then also communicate that the forecast is also subject to uncertainty. . This has been especially the case in the past few years. The distribution of risks to the forecast increased substantially in light of recent large and unprecedented shocks. Consequently, Central Bank staff have developed and used tools to produce alternative forecast scenarios at the height of the pandemic (see for instance Box B in QB1 2021).

The next four sub-sections will briefly describe the baseline forecasting models of the main inflation components used in the Central Bank. Table 2 provides an overview of these models (see the Technical Annex for more details on model specifications).

Table 2: Forecasting models

Item	Modelling approach	Predictors
Electricity	Regression model of monthly growth rates	European wholesale electricity prices (in euro)
Gas	Regression model of monthly growth rates	European wholesale gas prices (in euro)
Liquid fuels	Regression model of monthly growth rates	EUR/USD exchange rate, international Brent crude oil price (in US dollars)
Solid fuels	Random walk model	Own lags
Unprocessed food	ARDL model	Own lags, current values and lags of EUR/USD exchange rate, farm-gate and wholesale food commodity prices, oil and gas commodity prices
Processed food excl. alcohol and tobacco	ARDL model	Own lags, current values and lags of EUR/USD exchange rate, farm-gate and wholesale food commodity prices, oil and gas commodity prices
Alcoholic beverages	AR model	Own lags
Tobacco	AR, MA and ARMA models	Own lags
NEIG: Clothing and Footwear	ARDL	Own lags, current values and lags of EUR/GBP exchange rate, non-energy non-food commodity prices, oil and gas commodity prices
NEIG excl. Clothing and Footwear	ARDL	Own lags, current values and lags of EUR/GBP exchange rate, non-energy commodity prices, oil and gas commodity prices
Services	ARDL	Own lags, current and past values of consumption growth, wage growth and energy inflation

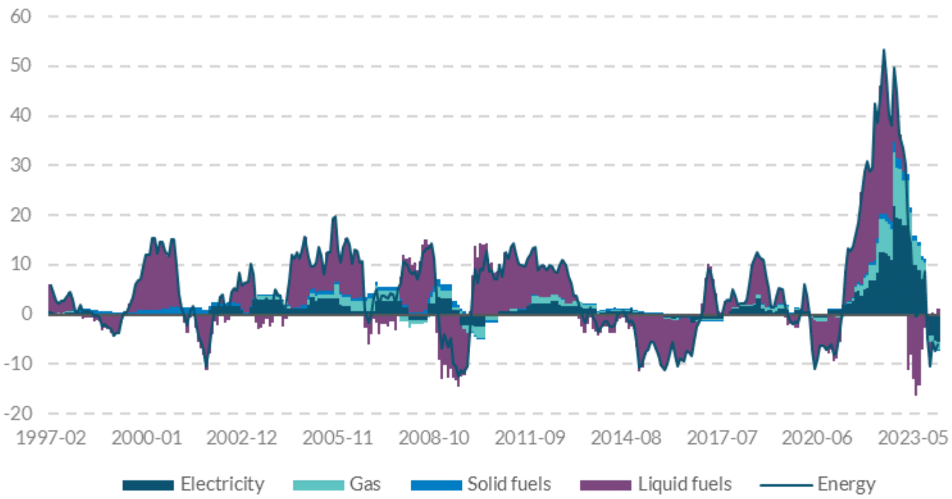
Notes: over the forecast horizon, predictors follow the assumed path based on either financial markets or recent averages of these variables. More details provided in the sub-sections for each inflation component. Information on model specifications is provided in the Technical Annex.

4.2.1 Energy inflation

Historically, HICP energy inflation largely reflected dynamics in liquid fuels, e.g. home heating oil, car fuels (Figure 10), which account for 43.3 per cent of the total energy price index. Electricity component accounts for another 37.5 per cent and has become a significant driver of energy inflation in recent years. Fluctuations in gas prices are also significant drivers of energy inflation recently, both directly and indirectly (via electricity generation).

Energy inflation is mostly driven by its liquid fuels component but the relative role of electricity and gas inflation increased in recent years

Figure 10
year-on-year percent change and percentage point contributions



Sources: Eurostat, CBI calculations.

Notes: The figure shows contributions to year-on-year energy inflation from its four components.

Domestic energy inflation is largely determined by external factors since Ireland is a small open economy and is a price taker in the global commodity markets. Historically, the price of oil has been the main driver of consumer energy inflation in Ireland and Irish consumer energy prices were highly correlated with the international oil price (Bermingham, 2008; O'Brien and Weymes, 2010). As the energy market's structure changed, this relationship weakened somewhat in the most recent decade. Irish gas and electricity markets were gradually deregulated, starting in 2012 and electricity and gas prices became fully market-based. The latest energy price shocks in 2021-2022 highlighted the fact that wholesale electricity and natural gas prices have become relatively more important for consumer energy prices (Byrne and Lawton, 2022). This has led to several changes in the forecasting approach.

Energy commodity prices and the euro exchange rate against the US dollar form the basis for domestic energy pricing and are the key inputs to energy inflation forecasts.[24] Until recently, the oil price in euro was used to forecast HICP liquid fuels, electricity and gas inflation, assuming a two-month pass-through of changes in wholesale oil prices to consumer prices. In response to recent energy price shocks, wholesale electricity and gas prices are now also taken as forecast inputs. The assumed pass-through of wholesale prices to consumer prices has lengthened for electricity and gas components, reflecting the use of forward contracts and hedging strategies by domestic energy suppliers (CRU, 2023). This hedging practice helps to insulate consumer prices from short-term volatile movements in wholesale energy prices.

More specifically, the baseline forecast for electricity (gas) inflation is derived from a simple econometric model where a monthly percentage change in consumer electricity (gas) prices is regressed on a fifteen-month moving average of monthly per cent changes in wholesale electricity (natural gas) prices in euro (see also the Technical Annex). For liquid fuels, a two-month moving average of monthly per cent changes in the Brent crude oil price (in euro) is used instead in the baseline forecasting model.[25] Finally, the HICP index for solid fuels is forecasted with a random walk model, i.e., it is kept constant at its latest value over the forecast period.

Over the forecast horizon, assumed future values for energy commodity prices are based on financial market expectations as implied by the respective futures contracts.[26] The US dollar oil price is converted to euro using the EUR/USD exchange rate. The exchange rate is fixed over the projection horizon at its average value over the ten business days preceding the cut-off date.

Ireland's exposure to various global shocks, uncertainty surrounding the degree of the pass-through of wholesale energy prices to consumer energy prices, and price changes by energy suppliers in discrete periods help explain why energy prices are generally the most volatile component of the HICP. This adds to the difficulty of forecasting this component of inflation. Forecast errors for energy can have a large bearing on the overall inflation forecast accuracy,

[24] International energy commodity prices are typically priced in the US dollars.
[25] A relatively quick pass-through of wholesale price movements continues to be assumed as before.
[26] An alternative to financial market expectations is to use a satellite model to predict wholesale energy prices based on their past values. Past internal assessments showed that information from futures contracts for energy products helps to improve the forecasting accuracy.

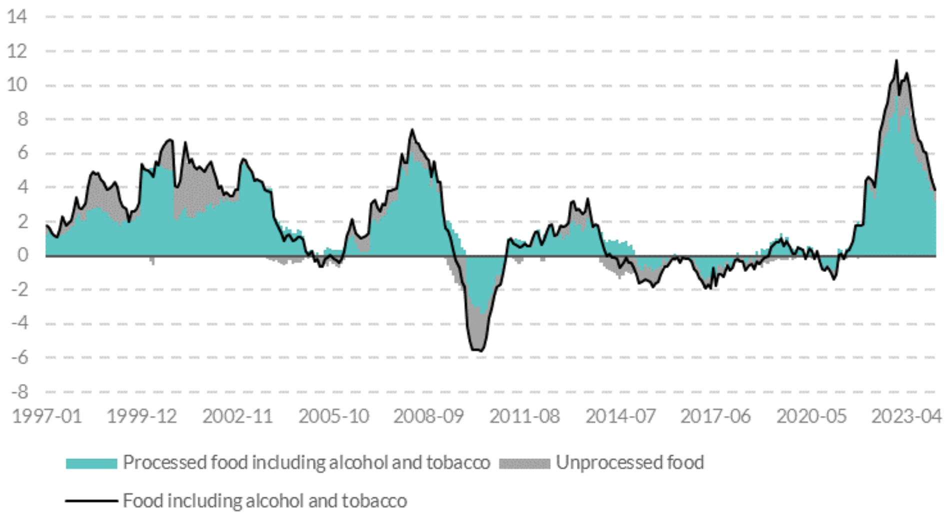
even if its weight in the total HICP is relatively small at 10.2 per cent (Byrne, McLaughlin and Scally, 2023).

4.2.2 Food inflation

Food inflation, to a large extent, reflects processed food price dynamics, given its much larger weight in the food price index (approximately 80 per cent) compared to unprocessed food (Figure 11). The unprocessed food sub-component is forecast directly, while the processed food forecast is the aggregation of forecasts for alcoholic beverages, tobacco and the rest (Figure 8).

Food Inflation is driven by its processed food component

Figure 11
year-on-year percent change and percentage point contributions



Sources: Eurostat, CBI calculations.

Notes: The figure shows contributions to year-on-year food inflation from its two components.

As in the case of energy inflation, since a large share of Irish food is imported, food price inflation in Ireland is greatly influenced by global factors via food commodity markets, exchange rate dynamics as well as trade costs. Recent energy price shocks also highlighted the role of energy as an input in growing raw food materials and producing food products, e.g. the price of fertilizers jumped up substantially on the back of a positive gas price shock.[27] Extreme weather events also have a bearing on food inflation; however, they are extremely difficult to model and forecast. In recent years, disruptions to grain

[27] This blog post discusses the factors behind fertilizer prices.

supply and transportation due to the war in Ukraine also had an impact on food prices.[28]

The baseline forecasting model for both unprocessed food and processed food excluding alcohol and tobacco is an *Autoregressive Distributed Lag* (ARDL) model, commonly used to forecast inflation (Bermingham, 2008; Bessonovs and Krasnopjorovs, 2021; Anderl and Caporale, 2023). In general, a month-on-month percentage change in a price index is regressed on its own lags and current and lagged values of other determinants. In addition to past values of the price index itself, the following variables are used as inputs in forecasting inflation of both unprocessed food and processed food excluding alcohol and tobacco: the EUR/USD exchange rate, euro area farm-gate and wholesale food commodity prices in euro, and energy commodity price index for Ireland in US dollars, calculated as a weighted average of oil and gas prices.[29] Seasonal dummy variables are included to account for the seasonality in food prices. As in the case of energy forecasts, future values of energy commodity prices are based on futures contracts, while the exchange rate is fixed over the projection horizon. Assumptions about farm-gate and wholesale agricultural prices are provided by the European Central Bank.

To produce baseline forecasts for alcoholic beverages and tobacco, versions of an *Autoregressive Moving-Average* (ARMA) model are used (Meyler, Kenny and Quinn, 1998). In these models, the time series in question is modelled and forecasted in terms of its own lags (autoregressive part, AR) and the current and past values of an error term (moving-average part, MA). Seasonal ARMA models also include seasonal AR and MA terms.[30] Hence, a forecaster relies on the past behaviour of prices to predict future prices for these two food index components, also accounting for seasonal patterns.

More specifically, alcoholic beverages inflation is forecast using autoregressive terms only, with seasonal dummies included as for other food inflation components. For tobacco, the average forecast from three models is used: 1) AR terms with seasonal dummies; 2) MA terms and seasonal MA terms; 2) both AR and MA terms, including respective seasonal terms.

4.2.3 NEIG inflation

The NEIG component is split into two sub-components for forecasting purposes (Figure 8). The Clothing and Footwear item is a much smaller

[28] See here for more details how the Russian invasion of Ukraine contributed to an increase in global food prices.
[29] This synthetic energy variable is calculated and provided by the ECB.
[30] In some models, seasonal dummy variables are used instead.

component and is modelled separately to the remainder of NEIG. The latter includes a large variety of household items, such as electrical items, furniture, DIY items, stationary and toiletries. The weight of non-energy industrial goods in the total HICP is larger than that of both the energy and food components. In the years prior to the pandemic, this component was critical to explaining the low inflation rates arising in Ireland due to global disinflationary forces as well as measurement issues in the NEIG price index in Ireland (Byrne and Scally, 2018).

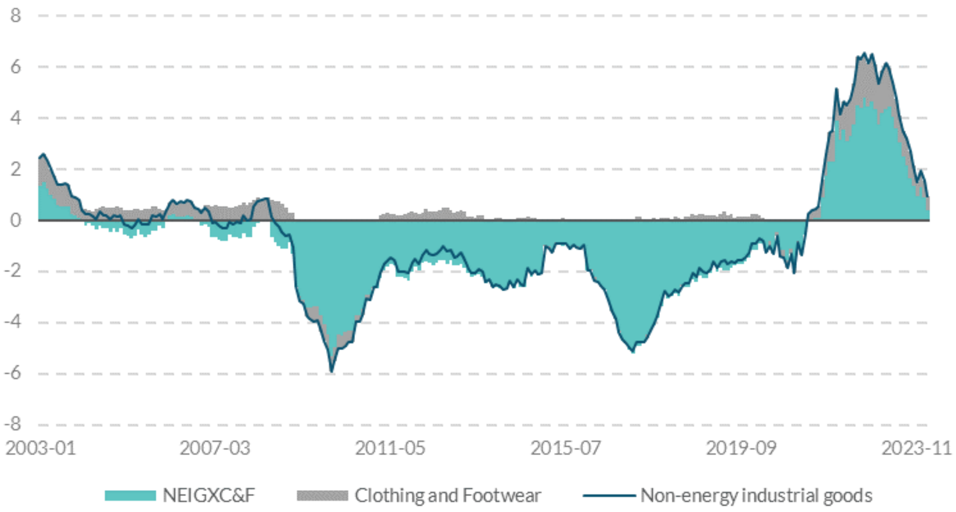
The difficulty in adjusting the price index for quality changes partly explains a prominent downward trend in Irish NEIG prices in the CSO index (QB1 (2024)[31], which also reflects the dynamics of commodity prices and exchange rates. As a result of the downward trend, i.e., falling prices, NEIG inflation has been predominantly negative (Figure 12). The downward trend appears to have halted and reversed during the pandemic and NEIG inflation has now turned positive. This mostly relates to the global supply chain pressures and increased costs of trade and transport, increased demand for goods during the lockdowns as well as higher energy costs boosting productions costs in the manufacturing sector (see Prices and Cost section in QB3 2022). The most recent data signal a halt in the positive trend. The CSO has partially addressed the measurement issue by introducing changes in the methodology to adjust for quality changes in some NEIG items, which may have reduced the tendency for measured NEIG index to decline.[32]

[31] For more details on NEIG measurement issues see Keating and Murtagh (2018) and Byrne and Scally (2018).

[32] Related changes in the methodology are summarised here: CSO (2019), CSO (2021).

NEIG inflation has been often negative but it increased sharply during the pandemic

Figure 12
year-on-year percent change and percentage point contributions



Sources: Eurostat, CBI calculations.

Notes: The figure shows contributions to year-on-year NEIG inflation from its two components.

A significant proportion of NEIG inflation is imported and as such, exchange rates and commodity prices play an important role for goods inflation in Ireland (Reddan and Rice, 2017). Both NEIG components are forecasted using an ARDL model. The set of the predictors, other than the series itself, is the same for both: the EUR/GBP exchange rate, non-energy non-food commodity prices and energy commodity prices (a weighted average of gas and oil prices). However, the number of lags of these predictors differ across the two NEIG components.

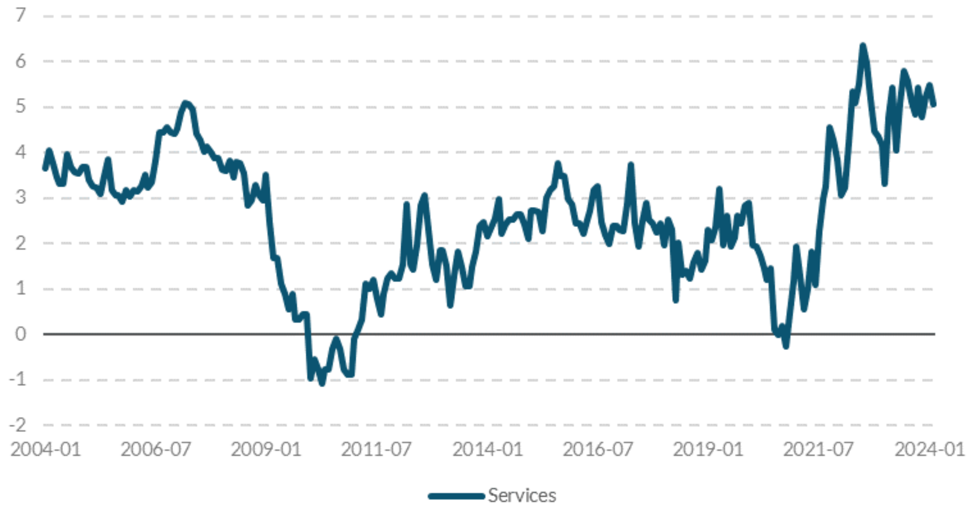
With respect to the futures values of the determinants over the projection horizon, futures markets are relied upon as with other inflation components. The assumption for the exchange rate is based on its 10-day average as with other inflation components.

4.2.4 Services inflation

Services inflation is the largest and "stickiest" component of headline inflation in comparison to food, energy and NEIG inflation (Figure 13). With over 50 per cent weight in the basket, it is a significant contributor to overall inflation. Generally, services inflation does not exhibit large fluctuations and it has the lowest standard deviation and the smallest range between the smallest and largest observations across all components (Table 1).

Services inflation is the stickiest component of headline inflation

Figure 13
year-on-year percent change (%)



Sources: Eurostat. Notes: Year-on-year services inflation in per cent.

Services are typically much less traded than goods and so global factors are less important for it than for other inflation components. However, the ripple effects of recent energy price shocks on prices of all other goods and services via higher energy input costs demonstrated that some global commodity prices may have had a greater impact on services inflation over recent years.[33] Labour costs, such as wages, make up a larger share of input costs in the services sector compared to the manufacturing. Thus, services inflation reflects domestic demand pressures to a greater extent than other inflation components. Many recent studies find that domestic economic activity (domestic demand) is relevant in determining Irish inflation and its services component. For instance, Gerlach et al. (2016) and Byrne, McLaughlin and O'Brien (2022) find the role of the unemployment gap, i.e., the difference between the unemployment rate and its trend level, consistent with non-accelerating inflation, in explaining inflation. A number of other economic activity measures were shown to be relevant for inflation: output's deviation from its trend (also as measured by modified domestic demand), changes in the unemployment rate and the non-employment index, and potential labour force growth (Faubert, 2021).

As in the case of some other inflation components, a version of an ARDL model is estimated to forecast services inflation. The baseline forecast model contains

[33] Our internal assessment showed that forecast performance of the model improved during the pandemic period when energy price inflation was also included.

the following forecast inputs: growth in real consumption, growth in nominal compensation per employee and wholesale energy price inflation in US dollars, based on a weighted average of oil and gas prices.[34] Over the forecast horizon, future values of commodity prices are based on financial market expectations as implied by futures contracts, while future values for consumption and compensation per employee (wages) are provided by internal forecasts, which are produced as part of the quarterly forecast exercise.

During the pandemic period, macroeconomic variables were distorted by pandemic-specific developments. Therefore, the model of services inflation also includes a dummy variable that takes value of 1 in the second quarters of the years 2020 and 2021 and zero otherwise. This helps to account for sharp changes during that time.

4.3 Risk assessment and expert judgement

As discussed in previous sections, focusing solely on point forecasts from the baseline models would ignore uncertainty surrounding model parameters and specification as well as forecast inputs, i.e., the economic outlook, including financial and global commodity developments.

In order to assess the balance of risks to the baseline forecast, satellite forecasting models may be used to produce alternative forecasts. Such risks may be related to model misspecification, i.e., some relevant predictors may be missing, a time-varying forecasting performance may arise, etc.[35] These satellite models typically come from the evaluation set, with good past forecasting performance. They could be versions of the baseline models or entirely different models. For instance, services inflation could be also forecasted using growth in modified domestic demand rather than using consumption growth as in the baseline model. Similarly, a Vector Autoregression (VAR) model could be applied to the same predictors as in the baseline ARDL model. By comparing the baseline with alternative forecasts, it can be noted whether the baseline is within, below or above alternative forecasts. This allows a forecaster to form a view whether the baseline forecast is subject to either downside (alternative models point to lower forecasts) or

[34] The energy variable is calculated and provided by the ECB. Quarterly macroeconomic data is interpolated into monthly where each monthly value in the given quarter is the same.
[35] It may also be useful to compare the bottom-up forecast for headline inflation with the top-down forecast where a single model is used to predict headline inflation directly. Currently, such a model is not being used given that past assessments did not yield favourable results for using such a model. Nevertheless, this could be reviewed again in future.

upside risks. Consequently, an informed expert judgment may be applied to the baseline forecast.

The expert judgement is informed not only by additional models but also based on close monitoring of relevant data, including the underling measures of inflation as well as announcements of fiscal policy or tax changes by the government, price changes by energy suppliers, etc. Expert judgment allows one to account for other relevant factors that are difficult to model due to either lack of good data, difficulties in making assumptions about future developments in those factors, or simply due to the very temporary nature of those factors. For instance, tax changes on consumer goods or services (e.g., VAT tax reductions during the pandemic and their subsequent reversals, excise taxes on alcohol and tobacco) lead to one-off changes in prices from one month to the next. If a tax change is known in advance, its effect may be estimated and included as an add-on to the baseline forecast for the relevant price index. Climate change effects on food price inflation are difficult to measure and predict in order to be able to account for their full impact over the forecast horizon. However, some judgement may be required to factor in the effects on food supply due to recent extreme weather events, for instance. Informed expert judgment help avoid or reduce forecast errors due to ad-hoc temporary factors.

Recent experience also highlighted the fact that new predictors may become useful over time while current predictors may become relatively less important. For instance, disruption of supply chains globally has been an important driver of an increase and a subsequent decrease in inflation, especially goods inflation. It is also clear that some processes and relationships between economic variable are or could become non-linear. Machine learning techniques could provide forecasts that account for non-linear relationships. Box A presents a short discussion of recent developments in that area.

In light of changes to economic environment, Central Bank staff continue to develop and regularly review a set of satellite and baseline forecast models as well as other econometric tools, which are useful to inform about inflation outlook. This is an ongoing process to ensure an adequate forecasting infrastructure.

Box A: Artificial intelligence, machine learning and inflation forecasting

Over the years, and as outlined in this article, researchers and practitioners have explored various methodologies to enhance the accuracy and efficiency of inflation forecasting models. With the advent of Artificial Intelligence (AI) and machine learning (ML) techniques, there has been growing interest in leveraging these methods to improve inflation forecasting. Indeed, central banks including the FED (Faria-e-Castro and Leibovici, 2024) and the ECB (Lenza et al, 2023) have begun publishing inflation forecasts using these techniques. This box examines the literature and current state of research regarding the use of ML techniques in inflation forecasting, highlighting some key methodologies, empirical findings, and challenges.

ML techniques encompass a broad spectrum of differing methods, including multilayer neural networks, random forests and natural language processing. These techniques offer the potential to capture nonlinear relationships, handle large and diverse datasets, and adapt to changing economic environments, making them potentially attractive for inflation forecasting. Machine learning techniques offer the advantage of capturing complex patterns and relationships in data without relying on strict economic assumptions or assumptions about the statistical properties of the underlying data. In terms of data usage, some studies and techniques use traditional macroeconomic and financial data while other techniques use more diverse data, such as micro, textual, satellite imagery, social media and web traffic data.

The use of ML techniques in inflation forecasting represents a promising avenue for improving predictive accuracy and understanding inflation dynamics. The performance of these models varies but some produce improvements in out-of-sample Root Mean Squared Error (RMSE) tests over standard techniques. The FED model, which uses a Large Language Model (LLM), generated a lower RMSE over most years and most time horizons. The ECB's model, which use a ML technique called Quantile Regression Forest, found that for core inflation the ML model was marginally more accurate than their standard BVAR. For headline inflation, the ML model was better able to capture the prolonged period of low inflation before and during the coronavirus (COVID-19) pandemic – but was outperformed by the standard BVAR during the Great Recession and its aftermath. In addition to the FED, Bybee (2023) conducts a similar study using a LLM's expectations of inflation based on a sample of news articles from the Wall Street Journal. Araujo and Gaglianone (2020) also find that ML random forests outperformed a range of traditional forecasting methods in terms of RMSE when applied to a large database of macro and financial variables in determining Brazilian inflation.

Other ML models have gained traction in inflation forecasting due to their ability to extract patterns from historical data and make predictions based on learned relationships. Studies by Croushore and Stark (2001) use Support Vector Machines to forecast inflation by mapping historical data into higher-dimensional space to find a hyperplane that best separates different classes of inflationary periods. Giannone, Reichlin, and Small (2008) demonstrate the effectiveness of random forests and gradient boosting in capturing nonlinearities and improving forecast accuracy by combining the predictions of multiple models.

Deep Neural Networks, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have shown promise in capturing complex temporal dependencies and nonlinearities inherent in inflation data. Research by Paranhos (2021) applied LSTM networks to inflation forecasting and achieved improved predictive accuracy in out-of-sample tests compared to benchmark models. Binner et al. (2024) use a Multi Recurrent Neural Network approach to forecast inflation one year ahead for the UK. This method combines several type of weighted feedback links from each neuron to other neurons with in the same or preceding layers.

Hybrid models that combine ML techniques with traditional econometric approaches have been proposed to leverage the strengths of both methodologies. For instance, Theoharidis et al. (2020) used a hybrid deep learning model that merges Variational Autoencoders and Convolutional LSTM Networks to forecast inflation, demonstrating enhanced forecasting performance over standalone traditional models.

Despite the potential benefits of ML techniques in inflation forecasting, several challenges exist. These include data quality issues where ML techniques use large and diverse datasets, which may be subject to missing values and other quality issues and be difficult to monitor. Moreover, model interpretability can be an issue, particularly for deep learning architectures like neural networks, and are often considered 'black boxes'. Understanding how these models arrive at their predictions can be challenging, raising concerns among policy makers and stakeholders that require transparent and explainable forecasting methods. When ML techniques deal with complex datasets, they can be prone to overfitting – performing well with training data but not with new data sets. Ensuring that the trained models generalise well to new data is important for robust inflation forecasting. Some interesting 'tinfoil hat' questions about the use of ML models arise if you consider that the some ML models potentially have access to the all the information available on the internet and could be cheating in out-of-sample tests by looking up actual inflation rates.

In conclusion, while numerous studies have demonstrated the efficacy of ML models in this domain, further research is needed to address methodological challenges and enhance the interpretability of ML-driven forecasts for practical applications in policymaking. ML models have demonstrated improvements in prediction over standard techniques but may not be as useful for causal inference as traditional econometric techniques. For now, these ML techniques are likely to provide another tool in the toolbox for researchers and analysts in addition to the standard techniques already used.

5. Conclusion

The Covid-19 pandemic and the Russian invasion of Ukraine have made forecasting inflation extremely difficult in recent years. Large, unexpected shocks to energy and food prices resulted in large forecast errors in forecasts published by the Central Bank of Ireland, as was the case in other central banks and policy institutions globally. In response, the Central Bank developed new analytical tools and continues to regularly review and update its main forecasting models and data inputs used in those models. As the extraordinary shocks faded, forecast errors in the most recent year declined compared to the errors made when these shocks were most prominent.

This paper presented and described the current framework for analysing and forecasting inflation used in the Central Bank of Ireland. A wide variety of measures of underlying inflation are monitored to determine the extent of medium-term inflationary pressures. It was shown that some of those measures may provide a more precise signal about medium-term inflationary pressures compared to information on the current headline inflation. Since different underlying inflation measures provide conflicting signals at times, it is very important to monitor a range of such measures and regularly assess their predictive ability.

The Central Bank applies a bottom-up approach to forecast headline inflation for the current year and two years ahead. The headline inflation forecast is the aggregation of model and judgement-based forecasts of the main components of inflation. Given that Ireland is a small-open economy, external inflationary pressures have a large influence on Irish inflation. For instance, global energy and non-energy commodity prices play an important role in forecasting energy and food inflation, as well as non-energy industrial goods inflation. This is less of a feature for services, which has a stronger domestic component. Thus, domestic wage pressures, labour market strength and domestic economic activity are relatively more important when forecasting services inflation. As global economy is changing, models for forecasting inflation at the Central Bank are also regularly reviewed to ensure their suitability for the current environment. As new tools and models become increasingly available (e.g. AI and Machine Learning), these may be incorporated into the inflation forecasting process as appropriate.

Technical Annex

Section 3.3

The proxy for medium-term inflation trend (benchmark) used to evaluate the in-sample bias and RMSE is calculated as follows:

$$1200 * \frac{(p_{t+h} - p_{t-h})}{(2 * h)}, where\ p_t\ is\ the\ \log level\ of\ the\ price\ index\ and\ h = 12$$

The proxy for medium-term inflation trend over the next two years used to evaluate the out-of-sample bias and RMSE is calculated as follows:

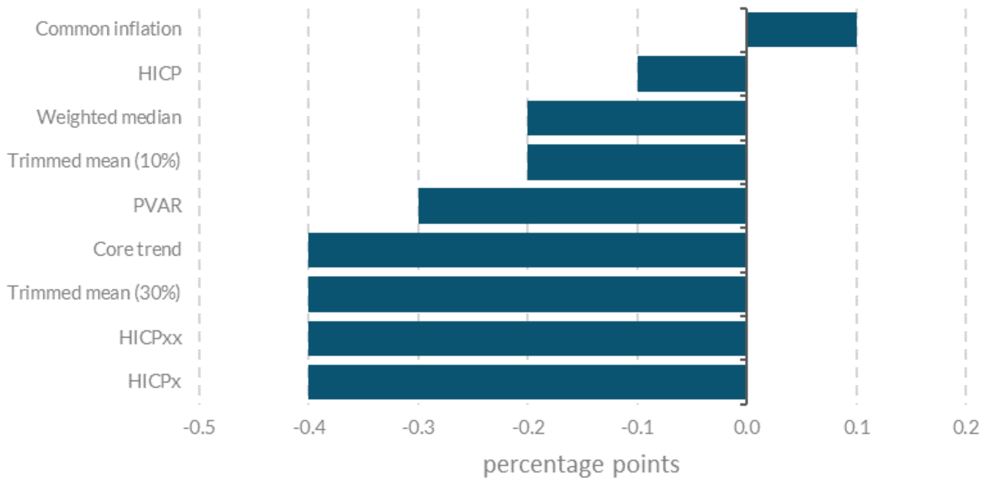
$$1200 * \frac{(p_{t+H} - p_t)}{H}, where\ H = 24$$

For each underlying inflation measure (UI), the RMSE against the benchmark is calculated using the below formula:

$$\sqrt{\sum_{t=1}^{n} \frac{(UI_t - Benchmark_t)^2}{n}}, where\ n\ is\ the\ number\ of\ observations\ in\ the\ sample$$

In-sample bias in the period 2004-2022

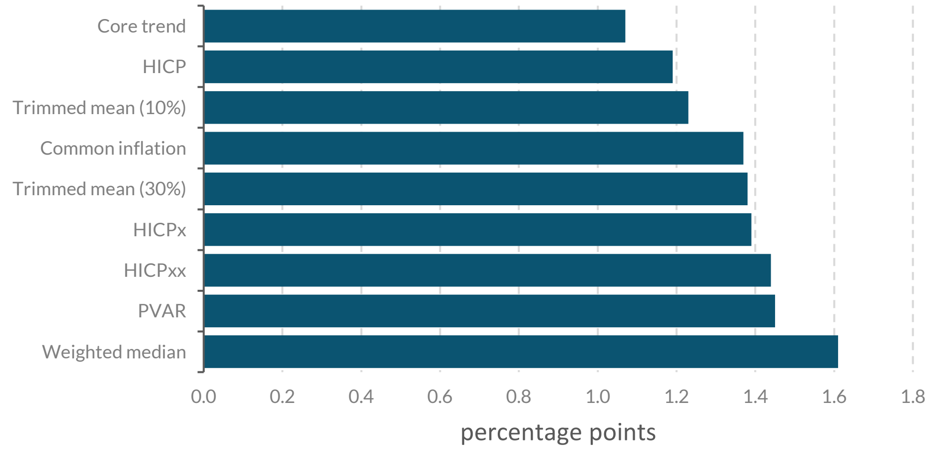
Figure A1



Notes: The bias is calculated as an average difference between the underlying inflation measure and the trend benchmark.

In-sample RMSEs in the period 2004-2022

Figure A2

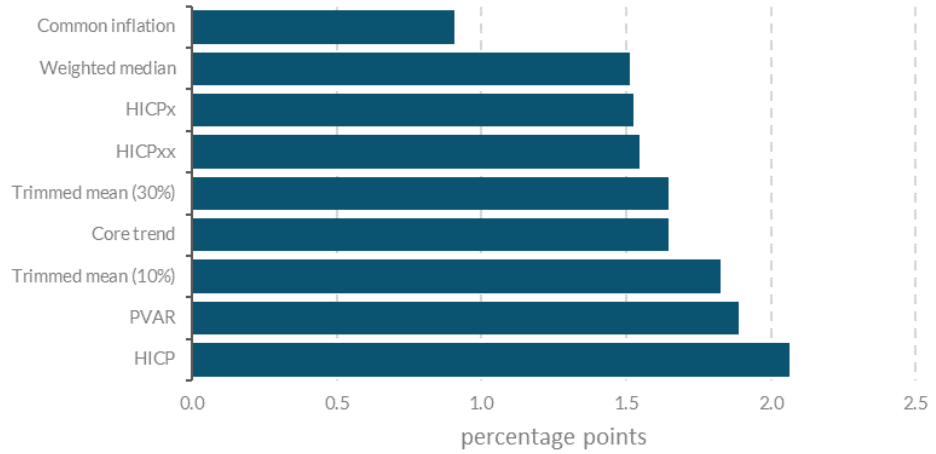


Source: CBI calculations, Eurostat

Notes: The figure shows Root Mean Squared Errors for each underlying inflation measure with respect to two year centred moving average inflation over the period 2004M11 to 2022M08.

Standard deviation of inflation measures

Figure A3



Source: CBI calculations, Eurostat

Notes: The figure shows standard devotion of each inflation measure over the period 2004M11 to 2022M08.

Section 4.1

The specification of a forecasting model for electricity (gas):

$$\pi_t^{electricity\ (gas)} = c + \beta 15mav\_\pi_t^{we\ (wg)} + \varepsilon_t$$

Where $\pi_t^{electricity\ (gas)}$ is a month-on-month inflation in consumer electricity (gas) prices and $\beta 15mav\_\pi_t^{we\ (wg)}$ is a 15-month moving average of month-on-month inflation in wholesale electricity (gas) prices.

The specification of a forecasting model for liquid fuels:

$$\pi_t^{liquid} = c + \beta 2mav\_\pi_t^{oileur} + \varepsilon_t$$

Where $\pi_t^{electricity\ (gas)}$ is a month-on-month inflation in consumer electricity (gas) prices and $\beta 15mav\_\pi_t^{we\ (wg)}$ is a 2-month moving average of month-on-month inflation in oil prices in euro.

A general specification of a forecasting ARDL model:

$$\pi_t^i = \alpha + \sum\nolimits_{p=1}^{n} \beta^p \pi_{t-p}^i + \sum\nolimits_{p=0}^{n} \boldsymbol{\gamma}^p \boldsymbol{x}_{t-p} + \sum_{m=1}^{11} \delta_m D_m + \varepsilon_t$$

where π_t^i denotes a month-on-month inflation rate and

$$i \in \left\{ \begin{matrix} unprocessed\ food, \\ processed\ excl.\ alcohol\ and\ tobacco, \\ clothing\ and\ footwear\ goods, \\ NEIG\ excl.\ clothing\ and\ footwear \end{matrix} \right\}$$

$\boldsymbol{x}_t$ is a vector of other determinants. The optimal lag length *p* is determined for each predictor based on the AIC. In addition, D_m represents *m* month dummy variable set to 1 for the month *m* and zero otherwise, where *m* includes months from February to December, with January as the base month.

A general form of an ARMA model (used for alcoholic beverages and tobacco inflation components):

$$\pi_t^i = \alpha + \sum_{p=1}^{n} \beta^p \pi^i{}_{t-p} + \sum_{p=1}^{m} \gamma^p \varepsilon_{t-p} + \varepsilon_t$$

where π_t^i denotes a month-on-month inflation rate in either alcoholic beverages or tobacco.

Services inflation model:

$$\pi_t^{services} = \alpha + \sum_{p=1}^{n} \beta^p \pi_{t-p}^{services} + \sum_{p=0}^{n} \boldsymbol{\gamma}^p \boldsymbol{x}_{t-p} + \varepsilon_t$$

where $\pi_t^{services}$ denotes a year-on-year inflation rate in services.

Section 4.2

Average RMSE to evaluate a model's forecasting accuracy is calculated as follows:

$\overline{RMSE}_i = \frac{\sum_{s=1}^{n} RMSE_s}{n}$, where $RMSE_s = \sqrt{\frac{\sum_{t=1}^{36}(forecast_t - actual_t)^2}{36}}$ and s denotes n^{th} recursive step ($s = 1, 2, \dots, n$), t is a month in the three-year forecast horizon ($t = 1, 2, \dots, 36$).

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