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A NEW PROPOSAL FOR FORECASTING INFLATION IN THE EUROZONE. A GLOBAL MODEL

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ABSTRACT

This paper evaluates the forecasting performance of the relatively new machine learning Global Unrefined (GlobalUN, hereafter) model with respect to inflation in the Eurozone. In this global pooled neural network framework, we use a quarterly panel dataset covering 20 euro-area countries (2001Q1–2025Q1) together with the EA-20 aggregate, which includes key variables such as HICP, energy prices, food, and others. Thus, the network remains simple yet flexible enough to absorb heterogeneity across countries. Our contribution of our work is crucial since monetary policy in the Eurozone hinges on accurate inflation forecasts (i.e., as ECB decisions target expected rather than current inflation). Our findings are crystal clear. The GlobalUN model outperforms all other benchmark models and the advanced machine learning XGBoost model in almost all Eurozone countries and horizons (i.e., the NAÏVE model seems to outperform in a few cases). These results are useful for policymakers, central banks, and fiscal institutions, as they should take the GlobalUN model into account as part of their arsenal.

Keywords: GlobalUN model, forecasting evaluation, inflation, Eurozone, Banking
JEL Classification: E31, E52, E58, C53

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1. Introduction

The conduct of monetary policy in the Eurozone rests on the centrality of inflation. The European Central Bank (ECB) defines price stability as a symmetric two percent inflation target over the medium term, clarified in its 2021 strategy review (European Central Bank, 2021). Inflation forecasts serve as the anchor of this framework because interest rate decisions respond to expected, not current, inflation. Recent episodes—including the pandemic, the energy price shock, and supply bottlenecks—have again demonstrated that accurate and timely forecasts are crucial for both monetary policy decisions and the credibility of the ECB (Banerjee, Hall, Kouretas, & Tavlas, 2023; Giannellis, Hall, Kouretas, & Tavlas, 2024).

The role of inflation is crucial for the monetary policy and credibility. Thus, the literature on inflation forecasting is extensive, employing a range of econometric and machine learning techniques. For example, Allayioti et al. (2024) shows that approximately one-third of Eurozone core inflation items are measurably sensitive to monetary policy shocks, underscoring the importance of reliable projections for gauging the impact of interest rate adjustments. The ECB's symmetric target strengthens expectation anchoring, especially when the effective lower bound constrains conventional easing (European Central Bank, 2025a). Delle Monache and Pacella (2024) highlight that cross-country heterogeneity—in fiscal policy, energy dependence, and labor markets—modifies how policy affects national inflation dynamics. These findings show the necessity of a stable and reliable forecasting framework that integrates both area-wide and country-level data.

The failures of 2021–2022 (i.e., due to Covid-19 pandemic crisis), when most forecasters underestimated the magnitude and persistence of the inflation surge, illustrate the costs of weak predictive frameworks (Banerjee et al., 2023). Forecast errors were state-dependent, larger when inflation was already elevated, and shaped by global energy and supply shocks (Delle Monache & Pacella, 2024). In response, the ECB has enhanced transparency on projections and their past performance, enabling external evaluation and methodological improvement (European Central Bank, 2025c). The case for model diversification and forecast combinations has thus strengthened, particularly in turbulent regimes (Hubrich & Skudelny, 2017; Hall, Tavlas, & Wang, 2023; Hall, Tavlas, Wang, & Gefang, 2024).

From a methodological perspective, three strands dominate the Eurozone inflation forecasting literature. First, factor models extract area-wide common components and have been applied to assess whether national data improve aggregate forecasts. Cristadoro, Venditti, and Saporito (2008) find that once area-wide data are accounted for, national variables add little for forecasting aggregate HICP, though they may help track ECB policy moves. Second, forecast combinations improve robustness during crises, with constrained weighting schemes yielding gains in periods of structural change (Hubrich & Skudelny, 2017; Candelon & Roccazzella, 2025). Third, short-term inflation projection (STIP) frameworks focused on specific components—such as energy and food—enhance real-time accuracy, as shown in national central bank models (Bessonovs & Krasnopjorovs, 2020; Albani et al., 2007) and recent ECB modules (Giammaria et al., 2025). These approaches converge on the need to incorporate global and component-level drivers into Eurozone forecasting.

Eurozone monetary integration adds further complexity into the forecasting procedure. A single monetary authority operates across heterogeneous economies. Flavin et al., (2009) show that in an enlarged Eurozone, pooling country-specific forecasts can outperform aggregate modeling. The degree of integration and convergence determines whether aggregate or disaggregated approaches perform better. During common global shocks, aggregate factors dominate during asymmetric disturbances, national information adds value. Earlier research on financial integration also shows that differences in banking structures and fiscal stances can shape the transmission of monetary policy and, by extension, the inflation process (see Kapopoulos & Lazaretou; 2007 for more details). Furthermore, Pereira et al., (2025) extends this literature by documenting evolving patterns of convergence and divergence in Eurozone inflation, demonstrating that integration is an ongoing process rather than a completed outcome.

The period 2020–2023 reinforced the importance of global drivers. International commodity prices, supply chain disruptions, and synchronized reopening effects accounted for most of the unexpected surge and the subsequent decline in Eurozone inflation (Delle Monache & Pacella, 2024). ECB studies confirm that global factors dominated, while national fiscal measures initially dampened and later amplified price pressures (European Central Bank, 2025b). This evidence suggests that forecasting models must integrate international linkages and allow for state-dependent transmission. Rolling windows, adaptive weights, and regime-switching approaches have been proposed to address these challenges (Hall et al., 2024; Banerjee et al., 2023).

However, important gaps remain, such as the limited comparative analysis across countries, insufficient integration of macroeconomic theory with data-driven methods, or the lack of attention to non-linear and complex dependencies of inflation. Specifically, many forecasting models either emphasize aggregate factors or focus narrowly on specific components, leaving limited capacity to integrate global, area-wide, and national information in a unified framework. Combination weights are often estimated ex post, limiting their usefulness in real time (Candelon & Roccazzella, 2025). Evaluation pipelines for subcomponents remain uneven despite evidence that energy and food shocks dominate recent forecast errors (Giammaria et al., 2025). The ECB's strategy review stresses the need for transparent links between forecasts, global drivers, and policy decisions (European Central Bank, 2021, 2025a). Addressing these gaps requires hybrid models that combine global information, area-wide dynamics, and targeted national modules, supported by adaptive forecast combinations.

Our study addresses these gaps by analyzing all the eurozone countries and developing a global model. The forecasting framework of global model (also referred to as cross-learning forecasting), uses one single (global) model that learns from a set of relevant time series in order to produce future predictions. In our work we apply a novel dataset using explanatory variables based on macroeconomic theory, detecting the channels of inflation, and conducting a cross-country comparative analysis. Investigating these issues is essential for monetary policy formulation and effective targeting inflation. Moreover, examining the degree of economic integration within the Eurozone and identifying differences and common patterns among member countries provide deeper insights into the transmission of monetary policy and the dynamics of price stability across the monetary union.

As the authors are aware, this is the first study to adopt the relatively new Global Unrefined (GlobalUN, hereafter) model developed by Hyndman et al. (2023) for inflation forecasting. The framework integrates global commodity and financial drivers, Eurozone-wide factor structures, and selected national modules where heterogeneity is significant. The proposed Global model aims to enhance short- and medium-term forecast accuracy, improve the interpretability of forecast revisions, and strengthen policy communication under the ECB's symmetric 2% objective. Furthermore, we employ a large sample of Eurozone countries (along with the EA-20 aggregate) over an extensive time series (2001Q1–2025Q1).

Our findings are straightforward. The GlobalUN model outperforms all benchmark models, including the advanced machine learning XGBoost model, across nearly all Eurozone countries and forecast horizons, with the NAÏVE model performing better only in a few isolated cases. These findings provide valuable insights for policymakers, central banks, and fiscal institutions, highlighting the importance of incorporating the GlobalUN model into their forecasting toolkit.

The remainder of the paper is structured as follows. Section 2 reviews the literature on inflation forecasting models. Section 3 outlines the methodological framework employed in this study, while Section 4 describes the dataset and provides a preliminary analysis. Section 5 presents the empirical results, and Section 6 concludes.

2. Literature review of main inflation forecasting models

2.1. Econometric and Time-Series Models

Univariate and multivariate time-series models remain standard benchmarks in inflation forecasting, with ARIMA widely used for its flexibility and ease of application. Studies in different contexts confirm its value. For example, research on Irish inflation and on Nigeria's monthly inflation rates found that well-specified ARIMA models can capture price dynamics effectively, producing forecasts with low errors and stable residuals when selected with a focus on out-of-sample accuracy (Meyler et al., 1998; Adubisi et al., 2018).

Adjusting for structural breaks can further improve forecasts. In Finland, incorporating such breaks into ARIMA models often led to better performance than rolling regressions or survey-based expectations, and in some cases even outperformed national research institute projections (Junttila, 2001). Comparisons with other approaches show that ARIMA remains competitive but not always dominant. Work on Austrian HICP inflation found that factor models could outperform ARIMA for certain subindices, with the best results achieved when factor and VAR forecasts were combined. Forecasts based on aggregated subindices also tended to be more accurate than those targeting headline inflation alone (Moser et al., 2007). Similarly, research comparing linear and neural network models for euro-area inflation showed that while neural networks can perform well, linear benchmarks like ARIMA still hold their ground as reliable reference tools (Binner et al., 2005). Performance also varies by institutional setting. In the EU, where inflation targeting is well established, ARIMA produced the most accurate 12-month forecasts. In the Western Balkans, where targeting frameworks are less rigid, nonlinear neural network models performed better, with Holt–Winters ranking second in both regions (Karadžić & Pejović, 2021).

VAR and VEC models are common tools for forecasting inflation. They capture how inflation moves with other macroeconomic variables over time. Panel VAR can improve accuracy by using richer data. In the euro area, sector-level panel VAR forecasts outperformed aggregate VARs, especially at short horizons (Dées & Güntner, 2017). In Nigeria, VAR worked best for short-term forecasts, while VEC models suited longer-term projections. Exchange rates, foreign prices, and government spending were important drivers (Uko & Nkoro, 2012). Time-varying parameter models can add further gains. A TVP-VAR for the euro area outperformed standard and Bayesian VARs in predicting CPI during crisis periods (Bekiros, 2014). Mixed-frequency models that combine monthly inflation with daily financial data also reduced forecast errors compared with standard VARs (Monteforte & Moretti, 2013). Institutional forecasts remain a strong benchmark. ECB projections were the most informative for euro area inflation from 2009 to 2021. Their relative importance fell after 2021, reflecting shifts in the economic environment (Candelon & Roccazzella, 2025).

2.2. Phillips Curve–Based Models

Phillips curve models link inflation dynamics to measures of economic slack. Their forecasting performance, however, remains contested. Stock and Watson (2007) argued that U.S. inflation is better captured by models with stochastic volatility and time-varying parameters. Such features account for the reduced forecasting power of traditional Phillips curve specifications. In inflation-targeting economies, results are more supportive. Gabrielyan (2019) found that Phillips curve models improved one-year-ahead forecasts for Sweden, Canada, and New Zealand once explicit targeting regimes were established. Forecast gains were weaker in earlier periods and varied across model specifications. Other evidence is more skeptical. Atkeson and Ohanian (2001) showed that NAIRU-based Phillips curve forecasts were no more accurate than a random walk benchmark. Their results indicate that the models perform poorly in predicting turning points in inflation.

2.3. Dynamic Stochastic General Equilibrium (DSGE) Models

DSGE models are derived from economic theory rather than purely statistical fitting. They combine microeconomic foundations, stochastic shocks, and dynamic adjustment mechanisms. This structure makes them suitable for structural analysis and policy evaluation.

In the euro area, an open economy DSGE estimated with Bayesian methods achieved forecasting accuracy comparable to VAR and VECM models. In several cases, it outperformed benchmark models such as the random walk (Adolfson et al., 2007). A Bayesian sticky-price DSGE also matched the performance of a-theoretical VAR models. In addition, it produced full predictive distributions, conditional forecasts, and measures of policy-relevant risks (Smets & Wouters, 2004).

However, forecasting superiority is not universal. A review of the literature concluded that DSGE models perform similarly to time-series models and official forecasts. None of these approaches predicted the 2007 recession, and all continued to forecast poorly during the downturn. The structural design of DSGE models may explain this pattern: backward-looking dynamics resemble those in time-series models, while forward-looking dynamics rely on expectations about future exogenous variables, which are inherently difficult to predict (Wickens, 2014).

2.4. Factor Models

Used to capture information from large datasets without overfitting. Factor models are designed to capture information from large datasets without overfitting. Dynamic factor models (DFM) in particular extract common components that summarize macroeconomic dynamics and can be used to forecast inflation. Meta-analyses show that factor models often outperform smaller models but not always pooled forecasts. They tend to work better for U.S. output and euro area inflation than for other regions or variables. Forecast accuracy improves when larger datasets are used, while variable pre-selection offers little benefit (Eickmeier & Ziegler, 2008). Applications to small open economies confirm the value of DFMs. A two-step DFM estimated with market and survey data produced more accurate forecasts for Jamaica than univariate and DSGE benchmarks.

Market-based data improved both in-sample and out-of-sample performance, showing that DFMs can be effective outside advanced economies (Aysun & Wright, 2024). In Poland, forecasts based on 92 monthly time series showed that DFMs outperformed autoregressive, VAR, and survey-based indicator models. Gains were clearer for short-term horizons, especially one-month ahead (Kotłowski, 2008). Extensions of factor modelling also enhance performance in advanced economies. For the U.S., euro area, and U.K., moving window techniques offered limited gains, but combining factor forecasts with time-varying weights improved accuracy substantially (Hall et al., 2023).

2.5. Machine Learning and Artificial Intelligence Approaches

Machine learning offers flexible, data-driven methods for forecasting inflation. These models capture nonlinearities, handle high-dimensional datasets, and often surpass linear benchmarks. In emerging economies, results are consistent. Random Forest and Gradient Boosting delivered the strongest forecasts for Nigeria, especially when foreign exchange reserves were included (Mirza et al., 2024). In Russia, tree-based models performed at least as well as autoregression and random walk benchmarks, confirming their early potential (Baybuza, 2018). In advanced economies, machine learning also shows clear benefits. For the United States, Random Forest models improved accuracy by exploiting nonlinear relations across predictors (Medeiros et al., 2021). In Turkey, tree-based ensembles combined with Shapley value explanations produced accurate and transparent forecasts under volatile conditions (Aras & Lisboa, 2022). China provides further evidence from large-scale applications. Penalized regressions and gradient boosting trees consistently outperformed traditional time-series and factor models. Key predictive signals came from food prices, producer costs, and credit conditions (Huang et al., 2025; Xu et al., 2025). Comparisons with traditional econometrics are mixed. In Romania, sentiment-augmented ARDL models outperformed several machine learning techniques in short-term horizons (Simionescu, 2025). Similar studies show that while Random Forests are not always dominant, they remain competitive under flexible loss functions (Behrens et al., 2018).

2.6. Mixed-Frequency and Real-Time Data Models

Mixed-frequency models use data collected at different intervals. They are useful when inflation is driven by fast-moving shocks. In the euro area, a Bayesian VAR with Student-t errors and stochastic volatility gave strong results. By turning quarterly GDP into monthly data, it produced more accurate forecasts than standard models, especially during energy shocks (Ertl et al., 2025). A nonparametric MIDAS model takes a different path. It smooths lag structures with penalized least squares and adapts better than parametric versions. Using daily indicators, it showed that commodity prices predict inflation up to a month ahead (Breitung & Roling, 2015).

3. Methodology framework

The following part depicts the models that were used for our study and the necessary preprocessing prior to their fitting.

<u>Naïve method</u>

The naïve method referred to as the simplest forecasting approach and is often used as a baseline. The naïve method forecast treats the latest data point as the best prediction for future values. It assumes that the most recent observation contains all the relevant information for predicting future values. Consequently, the forecast for T + h is set equal to the last known value y_T (Tashman, 2000):

$$\hat{y}_{T+h|T} = y_T$$

where h is the forecasting horizon, and $\hat{y}_{T+h|T}$ is the estimate of $\hat{y}_{T+h|}$ based on the data $y_1, y_2, \dots, y_T$. The naïve method is theoretically optimal when the underlying data follows an non-stationary process.

ARIMA

Autoregressive Integrated Moving Average (ARIMA) models exploit dependence on lagged values and past shocks after differencing stationarity to produce forecasts. Predictions are produced as linear combinations of previous observations and past errors. According to (Pankratz, 2009) the non-seasonal ARIMA(*p, d, q*) model can be written as

$$\phi(\Gamma)\nabla^d y_t = \mu + \theta(\Gamma)\varepsilon_t$$

where Γ is the backshift operator, ε_t is the error term at time t, $\phi(\Gamma)$ denotes the p-order autoregressive operator, $\theta(\Gamma)$ the q-order moving average operator, d denotes the *d*-order differencing operator, and μ the constant term.

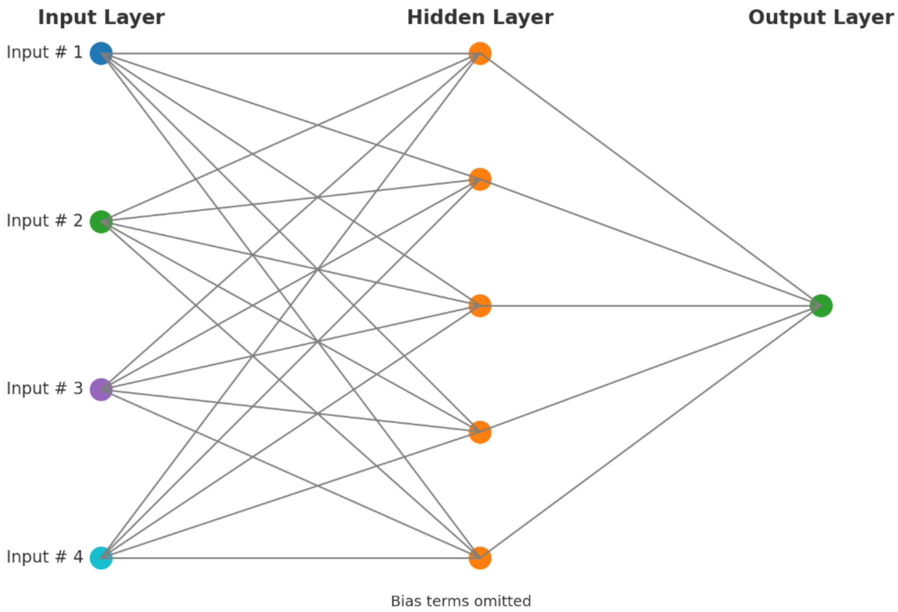
We select the autoregressive (p) and moving-average (q) parts using the Hyndman–Khandakar (2008) approach.[1] Following model estimation, we analyzed the residual mean for signs of bias and used the Ljung–Box test (Ljung & Box, 1978) with the Q statistic to evaluate residual independence.

Neural Networks

An artificial neural network (NN) is a stack of simple processing units arranged in layers that trains a nonlinear mapping $f(X)$ from an input vector of p variables $X = (X_1, X_2, \ldots, X_p)$ to a response Y. In a basic feed-forward network, the input layer provides the features to one or more hidden layers. Each hidden unit blends its inputs using learned weights, adds a small offset (a bias), and then applies a nonlinear function like ReLU. Stacking these layers lets the model capture patterns that a straight line can't. The example in Figure 1 has four inputs, one hidden layer with five units, and a single output; for simplicity, the figure leaves out the bias terms (Goodfellow, Bengio, & Courville, 2016).

[1] This approach runs unit-root checks, then searches over (p, d, q) options and picks the model with the lowest AIC information criterion.

Figure 1. Neural network with four inputs, a single hidden layer of five units, and one output



Considering regression and a neural network with a single hidden layer and a one-neuron output layer, the math proceeds as:

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j$$

where w_{ij} denote the weights, x_i the input variables, and b_j the bias. The pre-activation z_j is then passed through a nonlinear function g to produce the unit's output α_j:

$$\alpha_j = g(z_j)$$

In regression settings, the output layer typically contains a single neuron, and the network applies a final transformation to approximate the target variable. (e.g., Goodfellow, Bengio & Courville, 2016)

$$\hat{y} = \sum_{j=1}^{m} w_j' \alpha_j + b'$$

In our simulation the network's weights and bias terms are learned from the data during training via repeated forward propagation, loss evaluation, backpropagation, and parameter updates. To forecast the All-items HICP for each country, we develop an autoregressive feed-forward neural network trained on a 6-lag window (the previous six quarters) to produce one-step-ahead predictions within the training sample. The input window is set to six lags to keep sufficient training observations and limit overfitting risk. Multi-step-ahead forecasts for the out-of-sample period at Q1, Q2, and Q4 quarter horizons are produced recursively. Each one-step prediction is fed back as input to construct the subsequent steps. The network architecture comprises two hidden layers with 128 units each using Rectified Linear Unit (ReLU) activations, followed by a single linear output unit.

Global Unrefined (GlobalUN)

We implement a global pooled neural forecaster on a quarterly panel of 20 euro-area countries (2001Q1–2025Q1) plus the EA-20 aggregate, so that information can transfer across countries according to Hyndman et al. (2023). The predictor is a feed-forward ReLU Multilayer Perceptron (MLP) sized to the pooled dataset, so the network remains simple yet flexible enough to absorb heterogeneity across countries.

For each country and quarter we use a 6-lag window consisting of: (i) six lags of the target All-items HICP (autoregressive block), (ii) up to six lags of inflation-related indicators (HICP components: processed/unprocessed food, non-energy industrial goods, services, energy, a nominal unit-labour-cost measure based on hours worked and a world-demand indicator), and (iii) two rolling statistics of the target the 6-quarter rolling mean and rolling standard deviation both computed with a one-quarter shift so they only use data up to t−1. This construction prevents look-ahead bias.

Before training, we standardized each time series with a Z-score using only the training data, because the variables are on different scales:

$$z_t = \frac{y_t - \bar{y}}{s}$$

where z_t depicts the transformed series, $\bar{y}$ is the mean and, s is the standard deviation of the series.

We train the model globally (pooled across all countries) without grouping or filtering. Out-of-sample forecasts at Q1, Q2, and Q4 horizons are produced recursively: the one-step-ahead prediction is fed back to form the next step's lag window. In sum, our global pooled neural forecaster offers a transparent and reproducible way to harness cross-country information for quarterly inflation prediction. By combining a simple ReLU MLP with a six-lag autoregressive window and strictly past-only rolling statistics, the approach avoids look-ahead bias while remaining flexible enough to capture heterogeneous dynamics across the euro area. Out-of-sample forecasts are produced for Q1, Q2, and Q4 horizons using training-only standardization at each rolling origin.

XGBoost

We use a quarterly dataset covering 20 euro-area countries plus the Eurozone-20 aggregate to train a single XGBoost model to transfer information sharing across countries. Inputs include six quarterly lags of the following features: Processed food including alcohol and tobacco, Unprocessed food, non-energy industrial goods, Energy, Services (overall index excluding goods), Nominal unit labor cost (hours worked), and a World demand indicator. We also include strictly causal rolling statistics of the target with mean and standard deviation over a six-quarter window computed using data only up to $t-1$.

Forecasts are produced 1, 2, and 4 quarters ahead and synchronized with each country's calendar quarter. Evaluation follows a rolling-forecast-origin design with standard error metrics and MASE under quarterly seasonality, and hyperparameters are tuned per horizon to balance bias and variance.

Evaluation

We assessed the model performance through a rolling-origin forecast validation approach. This procedure overcomes the limitation of a simple train–test split, which would provide results for only one forecast horizon. Using the initial training set, we determined the best ARIMA order through model selection before applying the model in the rolling-origin forecasting process.

Under this validation framework, all forecasting models ARIMA, Naïve, Neural Network, XGBoost, and GlobalUN were re-evaluated on a training set that expanded by one step at each iteration. Forecasts were then generated recursively for horizons of 3, 6, and 12 months ahead. Bias was quantified using the Mean Error (ME), which exposes systematic over- or under-forecasting, while forecast accuracy was estimated via Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Scaled Error (MASE).

4. Data and Preliminary Analysis

The data are sourced from the databases of Eurostat and the European Central Bank (ECB).[2] Our dataset covers the period from 2001-03-01 to 2025-03-01 with quarterly frequency and includes all Eurozone countries as well as the average for the Eurozone-20 countries.[3] Table 1 presents a summary explanation of the endogenous variable (HCIP) and the exogenous variables used as explanatory variables in the machine learning models. We set the All-items HICP as the main variable that we predict and the exogenous variables are the sub-components, Processed food including alcohol and tobacco, Unprocessed food, Non-energy industrial goods, Energy and Services (overall index excluding goods) and economic variables the unit labor cost and economic demand indicator.

The selection of explanatory variables is based on the previous literature. For example, unit labour cost is considered one of the major factors determining inflation. King and Watson (2012), using a New Keynesian DSGE framework, showed that higher real labour costs drive increases in inflation. From a more empirical perspective, Bragoudakis (2014), using an error correction model, also finds a positive effect of unit labour costs on inflation. Thus, labour costs act as a fundamental driver of inflation in our model.

The choice of HICP subcomponents as explanatory variables is also motivated by a large body of research on the relative merits of forecasting using aggregated versus disaggregated data. For example, Hubrich (2005) analysed whether the accuracy of euro area inflation forecasts can be improved by aggregating or disaggregating forecasts of HICP subindices. Similarly, Porqueddu and Sokol (2020) compared direct forecasts of HICP (and HICP excluding energy and food) in the euro area and five member countries with aggregated forecasts of their main components, using large Bayesian VAR model

We therefore use the components as explanatory variables to ensure that the model captures consistent patterns across subindices. This approach exploits the

[2] Before any preprocessing step, the dataset was split into train data and test data. The test data covers the last 25 quarterly frequency and includes all Eurozone countries as well as the average for the Eurozone-20 countries.
[3] The list of countries presented in Table A1 in Appendix.

advantage of global models, which follow common trends, while using different components allows us to incorporate all available information and reduce the risk of forecast failures.

Finally, the world demand indicator is one of the most important explanatory variables. World demand influences HICP mainly by raising global commodity prices, which increases energy and food inflation, and by boosting exports and wages, which generate more persistent inflation in services and industrial goods. Exchange rate dynamics can further amplify these effects. Empirical studies have also used such variables: for example, Oulatta (2016) and Bruneau et al. (2007) employ global demand indicators or similar external factors to explain inflation dynamics. We also present the description and source of selected variables in Table 1.

Table 1: Description of Variables

Variable	Description	Source
All-items HICP	Harmonised Index of Consumer Prices (overall index, 2015=100)	Eurostat https://ec.europa.eu/eurostat
Processed food including alcohol and tobacco	Sub-index of HICP covering processed food, alcoholic beverages, and tobacco	Eurostat https://ec.europa.eu/eurostat
Unprocessed food	Sub-index of HICP covering food items	Eurostat https://ec.europa.eu/eurostat
Non-energy industrial goods	Sub-index of HICP covering durable and non-durable industrial goods excluding energy	Eurostat https://ec.europa.eu/eurostat
Energy	Sub-index of HICP covering energy-related goods and services.	Eurostat https://ec.europa.eu/eurostat
Services (overall index excluding goods)	Sub-index of HICP covering market and non-market services	Eurostat https://ec.europa.eu/eurostat

Nominal unit labour cost based on hours worked	Nominal unit labour cost (NULC) measures labour cost relative to labour productivity. Labour cost = compensation per hour worked; Productivity = GDP per hour worked. The index is shown as % change and 2015=100.	Eurostat https://ec.europa.eu/eurostat
World Demand Indicator (Export demand index)	This index reflects foreign demand for a country's exports, calculated as a weighted geometric average of trading partners' import volumes	European Central Bank

5. Empirical Results

We conduct a comparative evaluation of GlobalUN, ARIMA, Naïve, XGBoost, and a neural network baseline in a global, multi country setting that pools information across series. Models are assessed at 1, 2, and 4 quarter horizons using MAE, RMSE, MASE, and ME.

Across countries and horizons, GlobalUN attains the lowest MAE and RMSE on average, indicating superior point forecast accuracy and robust performance in the cross section. Relative to the seasonal naïve benchmark, MASE values for GlobalUN are generally above one, especially at longer horizons, which highlights both the difficulty of the task and the strength of the benchmark in this panel. Mean errors are typically positive and become more pronounced as the horizon lengthens, pointing to a mild tendency to over forecast in aggregate while the gains in MAE and RMSE remain clear.

ARIMA is competitive in a subset of countries at short horizons, but its errors expand as the horizon increases. The naïve benchmark provides a stable reference and can perform adequately in some short horizon cases, yet it remains weaker than GlobalUN on average. XGBoost and the neural network perform strongly in certain cases, most often at the shortest horizon, but their performance is less uniform across countries and their bias is more variable at longer horizons.

Overall, the evidence identifies GlobalUN as the most reliable approach in this setting. It consistently leads on MAE and RMSE from the short to the long horizon. GLOBALUN not only lowers average error but does so consistently, with stable performance under both scale-free (MASE) and squared-loss (RMSE) criteria and no systematic bias (ME). While XGBoost and the neural network retain localized strengths, their gains are episodic and do not alter the overall ranking.[4]

In this section, we present the forecasting performance of our models for horizons 1, 2, and 4. The evaluation metrics include Mean Error (ME); Mean Absolute Error (MAE); Root Mean Squared Error (RMSE and Mean Absolute Scaled Error (MASE), Tables 3-5 present the results for bias and accuracy of the out-of-sample forecasts for the three horizons under consideration.

[4] Full country by country results for all methods and horizons are reported in the Appendix (see Figures A1 to A5)

Table 3: Bias and Accuracy measures for 1 horizon

	GLOBALUN				Xgboost				ARIMA				NAIVE				NN			
Country	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**
Austria	**0,711**	**1,058**	**1,242**	**1,982**	1,615	2,077	2,356	3,891	2,157	2,253	2,841	4,22	1,243	1,372	1,723	2,569	2,506	3,203	4,73	6,001
Belgium	**0,676**	**1,27**	**1,666**	**2,23**	1,487	1,975	2,509	3,467	1,298	2,082	2,878	3,654	1,097	1,463	1,864	2,568	2,326	2,731	3,909	4,793
Croatia	**0,672**	**1,265**	**1,88**	**1,832**	1,806	2,327	2,928	3,368	1,445	2,041	2,908	2,954	1,292	1,499	2,064	2,17	3,458	4,38	6,231	6,341
Cyprus	**0,232**	**1,221**	**1,659**	**0,908**	0,238	2,164	2,73	1,609	0,938	2,311	2,878	1,719	0,636	1,739	2,12	1,293	2,308	3,235	4,213	2,406
Estonia	**1,399**	2,341	**3,023**	2,679	6,844	6,844	7,895	7,831	2,56	3,584	5,21	4,101	2,009	**2,329**	3,464	**2,665**	4,131	6,412	8,796	7,337
Euro area	**0,051**	**0,801**	**0,99**	**1,464**	1,094	1,309	1,785	2,391	1,033	1,394	1,957	2,547	0,923	1,082	1,443	1,976	2,068	2,784	3,876	5,086
Finland	**0,098**	**0,818**	**1,058**	**1,9**	0,443	0,947	1,301	2,199	0,833	1,266	1,74	2,94	0,738	0,824	1,159	1,914	1,856	2,523	3,51	5,86
France	**0,168**	**0,804**	**1,038**	**1,808**	0,663	0,918	1,349	2,062	0,922	1,114	1,485	2,504	0,778	0,861	1,137	1,935	1,713	2,046	2,942	4,599
Germany	**-0,032**	**0,792**	**1,108**	**1,613**	1,359	1,879	2,274	3,825	1,259	1,843	2,351	3,752	1,032	1,28	1,589	2,606	2,003	2,989	4,026	6,085
Greece	0,368	**0,959**	**1,193**	**0,822**	**0,229**	1,665	2,326	1,426	0,817	1,904	2,613	1,631	0,713	1,321	1,83	1,131	2,269	3,248	4,135	2,782
Ireland	**0,572**	**0,866**	**1,195**	**1,483**	1,02	1,558	2,218	2,666	0,923	1,448	1,808	2,479	0,769	1,004	1,352	1,717	2,528	3,193	4,315	5,464
Italy	**0,464**	**1,069**	**1,706**	**1,025**	0,903	1,649	2,168	1,58	0,608	2,296	2,905	2,2	0,785	1,575	2,01	1,509	2,011	3,253	4,598	3,117
Latvia	**0,656**	**1,83**	**2,517**	**1,839**	2,627	3	4,07	3,014	1,747	2,97	4,428	2,984	1,676	1,977	3,069	1,986	5,033	7,101	10,23	7,135
Lithuania	**-0,743**	2,536	3,443	3,213	6,281	6,281	7,39	7,958	2,352	2,75	4,049	3,484	1,88	**1,984**	**3,018**	**2,514**	3,337	5,842	8,425	7,401
Luxembourg	0,401	1,095	**1,369**	1,678	**0,356**	1,488	1,993	2,28	1,033	1,795	2,329	2,751	0,833	**1,058**	1,444	**1,621**	2,059	2,512	3,629	3,85
Malta	**-0,121**	**1,093**	**1,38**	**0,546**	0,27	3,707	3,898	1,851	1,069	3,649	4,225	1,823	0,696	3,297	3,836	1,647	1,919	4,563	5,63	2,279
Netherlands	**0,638**	**1,404**	**1,702**	**2,331**	1,853	2,349	2,81	3,9	2,709	3,362	4,736	5,582	1,195	1,632	2,064	2,71	3,149	3,937	5,202	6,537
Portugal	**0,033**	**1,052**	**1,446**	**1,457**	0,329	1,462	1,948	2,024	1,03	1,743	2,562	2,413	0,741	1,34	1,886	1,854	2,127	3,215	4,449	4,451
Slovakia	**0,37**	**1,288**	**1,689**	**2,038**	2,021	2,221	2,65	3,514	2,123	2,464	3,249	3,9	1,751	1,751	2,38	2,771	3,861	5,175	6,981	8,189
Slovenia	**-0,469**	1,283	**1,576**	1,61	0,91	1,731	2,283	2,172	1,223	1,849	2,453	2,32	0,997	**1,25**	1,723	**1,568**	2,934	4,076	5,385	5,114
Spain	**0,532**	**1,031**	**1,278**	**1,007**	0,827	1,555	2,265	1,519	1,074	1,863	2,43	1,82	0,82	1,306	1,656	1,276	2,054	2,556	3,719	2,497

Table 4: Bias and Accuracy measures for 2 horizons

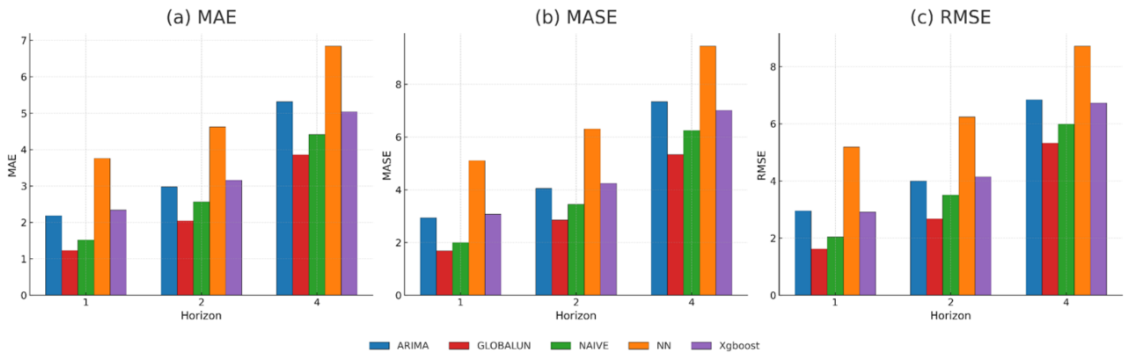
	GLOBALUN				Xgboost				ARIMA				NAIVE				NN			
Country	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**
Austria	**1,646**	**1,844**	**2,328**	**3,454**	2,548	2,801	3,174	5,247	3,302	3,361	4,245	6,296	2,44	2,44	3,151	4,571	2,996	4,272	5,845	8,004
Belgium	1,952	**2,431**	**3,125**	**4,267**	2,445	3,285	4,131	5,766	**1,53**	3,068	4,087	5,386	2,16	2,449	3,278	4,299	2,697	3,405	5,048	5,976
Croatia	**1,226**	**2,233**	**3,233**	**3,233**	2,618	3,167	4,225	4,585	1,524	2,643	3,953	3,827	2,536	2,839	3,773	4,11	4,017	5,569	7,468	8,063
Cyprus	0,967	**1,857**	**2,361**	**1,381**	**0,299**	3,025	3,802	2,25	1,092	2,729	3,493	2,03	1,278	2,663	3,348	1,981	2,842	3,844	4,722	2,859
Estonia	**2,877**	4,63	**5,857**	5,297	8,823	8,823	10,61	10,096	3,222	5,442	7,324	6,227	3,906	**4,215**	6,33	**4,823**	4,689	7,986	10,81	9,138
Euro area	**0,843**	**1,229**	**1,588**	**2,246**	1,557	1,851	2,525	3,383	1,101	2,04	2,78	3,728	1,836	1,949	2,601	3,561	2,32	3,497	4,706	6,389
Finland	0,597	**1,417**	**1,784**	**3,291**	**0,348**	1,503	2,115	3,492	0,845	1,859	2,535	4,317	1,457	1,521	2,167	3,532	2,047	3,008	4,134	6,986
France	0,808	1,404	**1,626**	3,155	**0,749**	**1,39**	1,994	**3,123**	1,107	1,478	1,991	3,321	1,554	1,616	2,143	3,632	1,913	2,541	3,487	5,711
Germany	**0,578**	**1,56**	**2,011**	**3,176**	1,905	2,265	2,895	4,61	1,496	2,623	3,34	5,339	2,019	2,28	2,908	4,64	2,179	3,629	4,883	7,387
Greece	0,491	**1,802**	**2,453**	**1,544**	**0,013**	2,284	3,263	1,957	0,861	2,609	3,513	2,235	1,459	1,978	2,791	1,694	2,937	3,997	5,057	3,424
Ireland	1,549	1,865	**2,385**	3,191	1,318	2,029	3,163	3,472	**1,109**	**1,801**	2,507	**3,081**	1,492	1,817	2,432	3,109	3,097	4,11	5,352	7,033
Italy	0,711	**1,538**	**2,009**	**1,474**	1,194	1,921	2,696	1,84	**0,672**	2,818	3,704	2,7	1,623	1,758	2,724	1,684	2,294	4,239	5,711	4,062
Latvia	1,782	**3,585**	**5,069**	**3,602**	4,266	4,535	6,696	4,557	**1,612**	4,965	6,665	4,989	3,284	3,644	5,684	3,662	5,785	8,625	12,14	8,667
Lithuania	**0,385**	4,55	**5,708**	5,765	8,28	8,28	10,22	10,491	2,952	4,547	6,219	5,761	3,66	**3,692**	5,76	**4,677**	3,51	7,281	10,65	9,224
Luxembourg	1,259	1,955	2,501	2,997	**0,211**	2,522	3,256	3,866	1,113	2,371	3,211	3,634	1,642	**1,816**	**2,479**	**2,783**	2,378	3,06	4,333	4,689
Malta	0,364	**1,32**	**1,7**	**0,659**	**0,277**	3,313	3,92	1,655	1,158	3,731	4,434	1,864	1,3	5,052	5,677	2,523	1,521	4,923	5,869	2,459
Netherlands	**1,722**	**2,474**	**3,013**	**4,109**	2,507	2,948	3,958	4,896	3,065	3,779	5,518	6,275	2,366	2,549	3,619	4,232	3,624	4,437	6,034	7,367
Portugal	0,542	**1,679**	**2,21**	**2,324**	**0,371**	1,939	2,804	2,684	1,323	2,472	3,368	3,422	1,488	2,148	2,835	2,973	2,357	3,7	5,181	5,122
Slovakia	**1,693**	**2,512**	**3,279**	**3,974**	3,519	3,604	4,572	5,703	2,667	3,52	4,641	5,57	3,396	3,396	4,5	5,374	4,159	6,572	8,612	10,4
Slovenia	**0,364**	**2,218**	**2,569**	**2,782**	1,047	2,712	3,793	3,402	1,346	2,358	3,373	2,958	2,004	2,248	3,084	2,82	3,264	5,224	6,582	6,554
Spain	1,425	1,992	**2,448**	1,946	**1,148**	2,136	3,243	2,087	1,277	2,338	3,135	2,284	1,641	**1,834**	2,512	**1,791**	2,414	3,152	4,411	3,079

Table 5: Bias and Accuracy measures for 4 horizons

	GLOBALUN				Xgboost				ARIMA				NAIVE				NN			
Country	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**	**ME**	**MAE**	**RMSE**	**MASE**
Austria	**3,831**	**3,853**	**5,059**	**7,219**	5,516	5,516	6,513	10,33	6,21	6,21	7,519	11,634	4,784	4,784	6,005	8,962	4,058	6,765	8,49	12,673
Belgium	3,122	**3,744**	**5,125**	**6,571**	4,95	5,302	6,923	9,307	**2,081**	5,611	6,938	9,849	4,226	4,292	5,767	7,534	3,237	4,969	6,805	8,721
Croatia	2,871	**3,902**	**5,566**	**5,649**	4,818	5,294	6,83	7,664	**2,146**	5,024	6,692	7,274	5,01	5,098	6,725	7,381	5,168	8,278	10,356	11,985
Cyprus	2,973	3,465	4,546	2,577	**1,261**	3,332	4,683	2,478	1,72	4,02	5,132	2,989	2,808	**3,25**	**4,234**	**2,417**	3,694	4,807	6,122	3,575
Estonia	6,943	8,644	11,58	9,89	13,143	13,143	16,099	15,04	4,623	10,108	13,479	11,566	7,796	**8,154**	**11,373**	**9,33**	**6,236**	11,956	15,432	13,68
Euro area	2,702	**2,908**	**4,188**	**5,312**	2,918	3,179	4,495	5,809	**1,375**	3,899	4,82	7,124	3,72	3,746	4,919	6,845	2,999	5,337	6,696	9,751
Finland	2,118	**2,509**	**3,711**	**5,827**	1,178	2,961	4,083	6,876	**0,915**	3,593	4,481	8,346	2,866	2,878	4,005	6,683	2,73	4,429	5,774	10,286
France	1,757	**2,092**	**2,765**	**4,703**	1,897	2,626	3,605	5,901	**1,65**	2,526	3,439	5,678	3,209	3,209	4,025	7,213	2,455	4,145	5,281	9,316
Germany	2,388	**2,99**	**4,223**	**6,086**	3,596	3,884	5,182	7,906	**2,023**	4,415	5,485	8,987	4,124	4,188	5,357	8,525	2,83	5,535	7,029	11,267
Greece	1,567	**3,165**	**4,243**	**2,711**	**0,844**	3,466	4,756	2,969	1,197	4,341	5,972	3,718	2,924	3,6	4,734	3,084	4,393	5,888	7,06	5,043
Ireland	2,594	3,335	**4,322**	5,706	**2,502**	3,471	5,042	5,94	1,757	3,528	4,48	6,038	3,056	**3,283**	4,455	**5,618**	4,013	6,091	7,421	10,424
Italy	2,318	**3,219**	**4,536**	**3,084**	2,53	3,281	5,048	3,144	**0,596**	4,8	6,472	4,599	3,247	3,314	5,028	3,175	3,087	6,258	7,956	5,996
Latvia	5,454	**6,608**	**9,943**	**6,64**	8,174	8,174	11,989	8,214	**1,778**	10,321	12,806	10,371	6,546	6,694	10,253	6,726	7,666	12,797	16,55	12,858
Lithuania	**3,113**	**6,278**	**8,961**	**7,954**	12,591	12,591	15,843	15,95	4,852	9,898	12,806	12,54	7,201	7,201	10,852	9,124	4,804	12,143	16,299	15,385
Luxembourg	2,92	3,487	**4,35**	5,343	2,034	**3,37**	4,822	**5,165**	**1,576**	3,914	5,069	5,998	3,385	3,515	4,476	5,386	2,977	4,513	5,75	6,916
Malta	1,54	**2,522**	**3,344**	**1,26**	**0,72**	2,864	3,69	1,43	1,844	4,634	5,541	2,314	3,132	3,132	4,026	1,564	2,41	5,957	7,242	2,975
Netherlands	**3,161**	**3,878**	**5,479**	**6,439**	4,937	5,156	6,751	8,562	4,028	6,206	8,388	10,304	4,794	4,794	6,296	7,961	4,432	5,851	7,863	9,715
Portugal	2,158	**2,986**	**4,39**	**4,134**	**1,41**	3,301	4,703	4,57	2,06	4,161	5,397	5,76	3,113	3,228	4,604	4,468	3,279	5,677	6,956	7,859
Slovakia	3,876	**4,62**	**6,365**	**7,311**	7,118	7,118	9,156	11,26	**3,581**	6,087	8,151	9,631	6,59	6,59	8,423	10,43	5,386	10,361	13,001	16,395
Slovenia	2,051	**3,518**	**4,606**	**4,413**	2,914	4,093	5,961	5,136	**1,847**	4,613	5,887	5,787	4,028	4,309	5,67	5,406	3,844	7,416	9,133	9,304
Spain	2,939	**3,336**	4,55	**3,259**	2,635	3,689	5,139	3,604	**2,156**	3,799	4,887	3,711	3,309	3,478	**4,519**	3,397	3,169	4,555	5,971	4,45

Figure 2 presents the results for the five forecasting models across three forecast horizons (3, 6, and 12 months), evaluated using three performance metrics: (a) MAE, (b) MASE, and (c) RMSE. The plotted values depict the average performance obtained from all rolling-origin forecast iterations for each model and horizon.

Figure 2. The average performance obtained from all rolling-origin forecast iterations for each model and horizon



In panel (a), which reports MAE, the GlobalUN model consistently achieves the lowest values across all horizons, indicating higher point-forecast accuracy. ARIMA and the naïve benchmark are relatively competitive at the short horizon, but their errors rise notably as the horizon lengthens. NN and XGBoost exhibit substantially higher MAE, especially at the twelve-month horizon.

Panel (b) presents MASE. GlobalUN attains the lowest MASE among methods at each horizon, although levels remain above one and increase with horizon—underscoring both the difficulty of the task and the strength of the naïve comparator. ARIMA approaches or exceeds two at longer horizons, while NN and XGBoost often exceed two, particularly at twelve months.

Panel (c) shows RMSE, which places greater weight on larger forecast errors. GlobalUN yields the lowest RMSE across horizons, reflecting stability and robustness. ARIMA is reasonable in the short run but weakens at medium and long horizons. In most cases, NN and XGBoost have the highest RMSE, so their forecasts are less dependable.

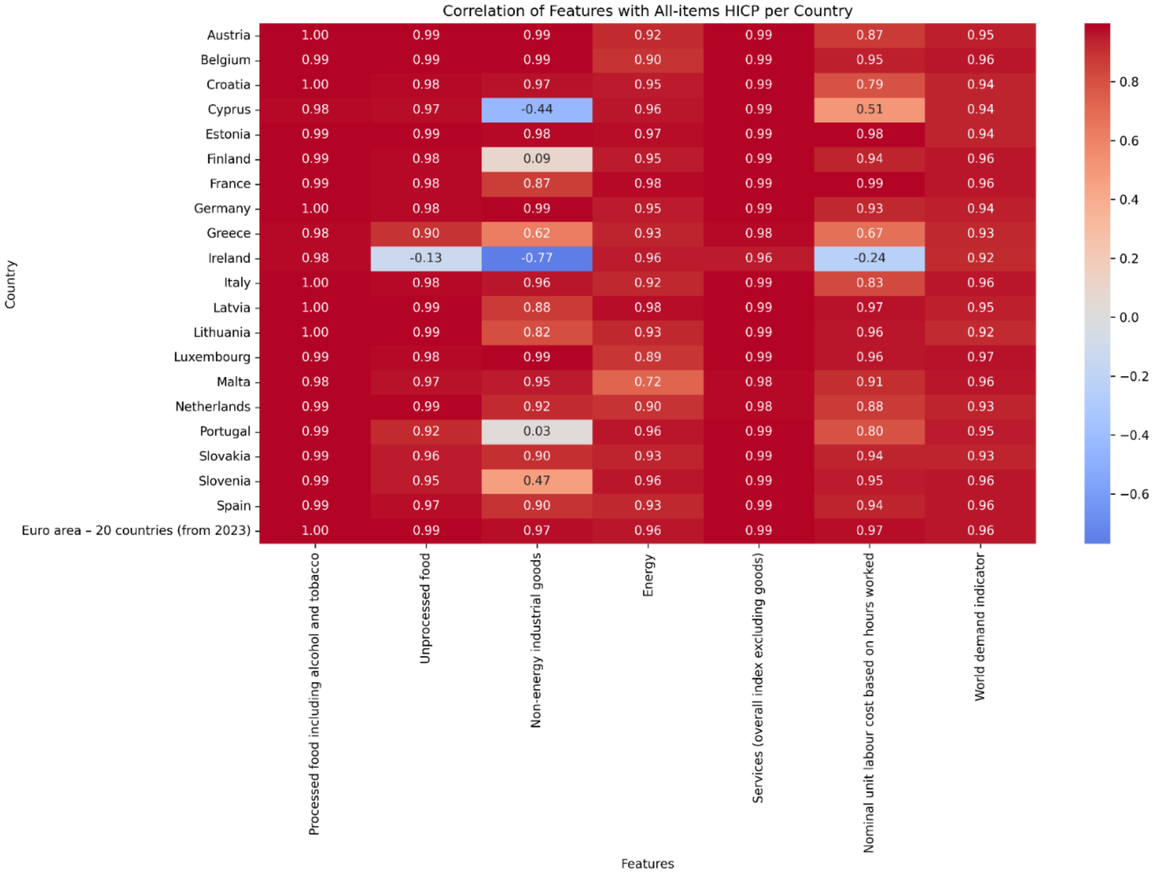
Overall, the figure shows GlobalUN is the most accurate and steady across errors and horizons. Its MASE is still above one, but the other models fall off much faster at longer horizons.[5]

The next figure (Figure 3) displays the correlation between each explanatory feature and the target variable (All-items HICP) for each country. The heatmap shows that most features show strong positive correlations with the target, indicating that increases in these variables are generally associated with increases in the overall HICP. Particularly high correlations are observed for Processed food including alcohol and tobacco, non-energy industrial goods, and Services (overall index excluding goods) across almost all countries.

By contrast, some features like Unprocessed food and Energy line up less with inflation in some countries and can even move the other way. That means what drives inflation isn't the same everywhere. When we build forecasts, we should watch both how strong the link is and which direction it goes, because each feature can matter very differently in stronger vs. weaker economies.

[5] An explicit visualization of the forecasting and actual price trajectories for all countries and horizons is provided in the Appendix (see Figures A1–A5 on Appendix).

Figure 3. Heat map of the correlation between each explanatory feature and the target variable (All-items HICP) for each country



6. Conclusions

In this study, we empirically evaluate five forecasting approaches (namely, GlobalUN, ARIMA, a seasonal naïve benchmark, XGBoost, and a simple neural network baseline), using a quarterly panel spanning twenty euro-area countries along with the EA-20 aggregate. We used a rolling-origin evaluation at one-, two-, and four-quarter horizons and aligned every forecast to each country's calendar. All inputs were constructed in a strictly causal way, with lags and rolling statistics computed only from information available up to $t{-}1$. Within that framework, a clear pattern emerged: the global, pooled learner (GlobalUN) consistently delivered the lowest MAE and RMSE across most countries and horizons, without becoming erratic as the horizon lengthened.

The message is straightforward but important. Sharing information across series helps, especially in a region like the euro area where common shocks ripple through countries with different amplitudes and lags. Pooled learning allows the model to borrow strength from neighbours when a single country's history is short, noisy, or buffeted by idiosyncratic events. In practice, that meant more stable errors at the one-quarter horizon and a slower deterioration as we moved to two and four quarters. While MASE values for GlobalUN are not below one—an honest signal of the task's difficulty and of the naïve benchmark's strength they are systematically lower than those of the competing models. Bias is low and directionally consistent, yielding forecasts that respond in a sensible way as conditions change.

The contrast with the alternatives helps to interpret the gains. ARIMA and the seasonal naïve rule have appeal in the short run because they are transparent and react quickly to the most recent data, yet their errors grow more quickly at longer horizons. XGBoost and a generic neural network showed pockets of competitiveness but lacked uniformity across countries and horizons; they were more sensitive to volatility and produced larger errors when the signal-to-noise ratio fell. None of this suggests that these tools are "bad"—rather, it underlines that in a multi-country inflation setting with quarterly frequency and heterogeneous dynamics, a disciplined form of pooling provides a steadier base.

There are also accessible ways to build on these results without turning the framework into a black box. A simple next step is structured pooling: keep the benefits of sharing information across countries but still let each country speak for itself—for example with global–local hybrids or a light hierarchical reconciliation. We can also feed the models richer, faster signals, energy prices, commodity futures, or a basic financial-conditions index—so they react sooner, especially at longer horizons when shocks matter more. And a few post-forecast tweaks small bias corrections or compact ensembles that anchor GlobalUN to a simple rule can help close the remaining MASE gap to the seasonal naïve benchmark without giving up the MAE/RMSE gains. None of these steps requires heavy machinery. They are incremental, testable, and easy to communicate.

Finally, the evaluation design itself is a strength worth keeping. By respecting calendar timing, relying on strictly causal features, and using a rolling-origin scheme, the exercise remains close to how forecasts are produced in practice. That makes the conclusions useful beyond the sample at hand. For policy teams and practitioners who need regular, country-by-country updates, GlobalUN offers a robust, workhorse baseline: accurate at short horizons, resilient as horizons lengthen, and straightforward to maintain. The approach also travels well it can be extended to probabilistic forecasts and uncertainty summaries, it can accommodate new countries or revised data with minimal friction, and it leaves room for transparent improvements as better signals become available.

In short, informed pooling is not a silver bullet, but in this setting, it is a reliable starting point that balances accuracy, stability, and usability. These results, which highlight the superiority of the GlobalUN model, are particularly valuable for policymakers, central banks, and fiscal institutions. By incorporating this framework into their analytical arsenal, decision-makers can enhance the accuracy of inflation forecasts, strengthen the design of monetary and fiscal policies, and finally improve economic stability across the Eurozone.

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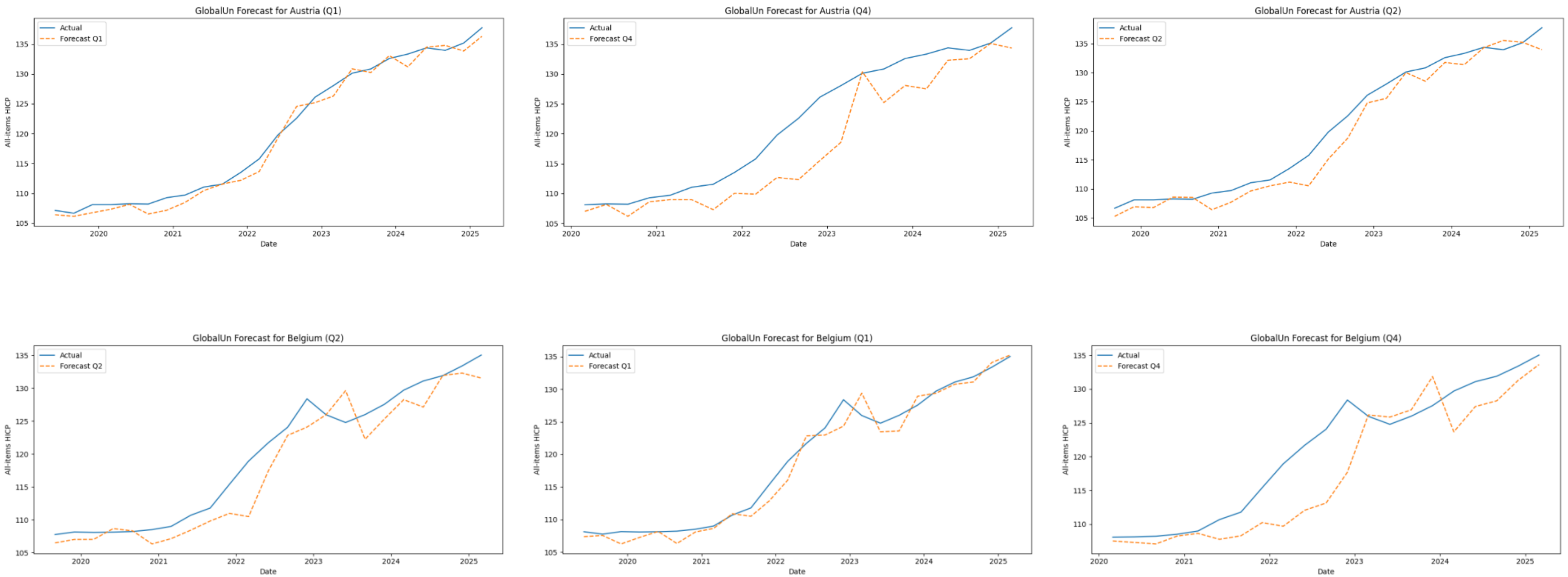
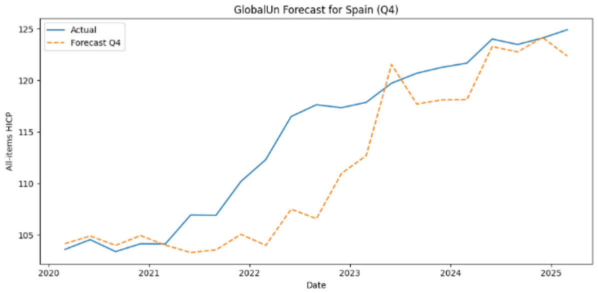
Appendix

Table A1: List of Countries

Country
Austria
Belgium
Croatia
Cyprus
Estonia
Euro area 20 countries (from 2023)
Finland
France
Germany
Greece
Ireland
Italy
Latvia
Lithuania
Luxembourg
Malta
Netherlands
Portugal
Slovakia
Slovenia
Spain

Figure A1. GlobalUN model: Actual vs Forecasts (Eurozone counties plus EA-20)

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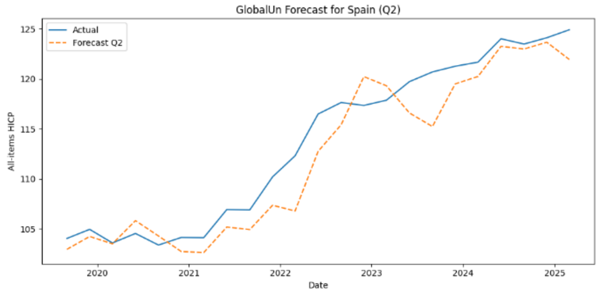
Actual
Forecast Q4
All-items HICP
Date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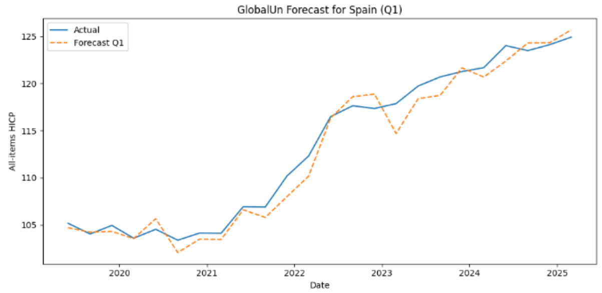
Actual
Forecast Q2
All-items HICP
Date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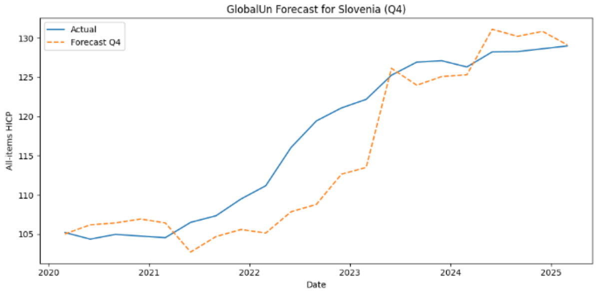
Actual
Forecast Q1
All-items HICP
Date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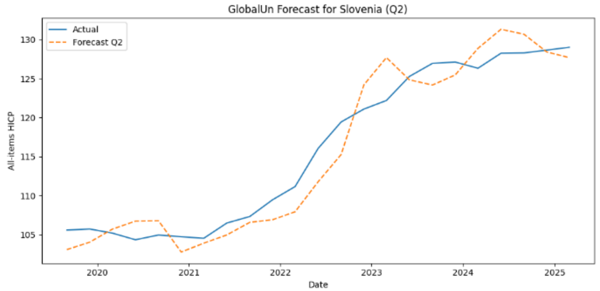
Actual
Forecast Q4
All-items HICP
Date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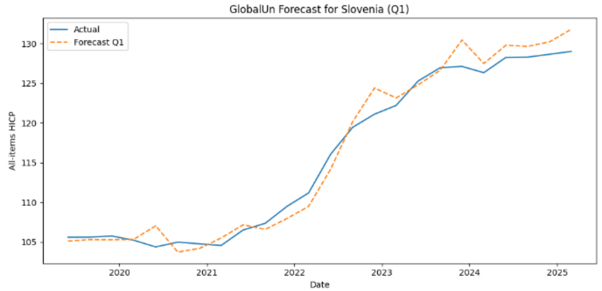
Actual
Forecast Q2
All-items HICP
Date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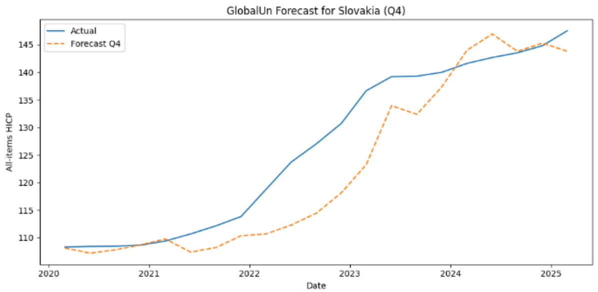
Actual
Forecast Q1
All-items HICP
Date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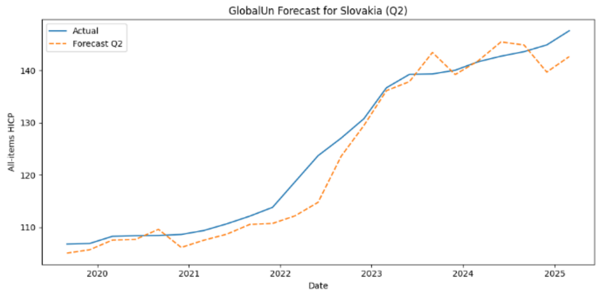
Actual
Forecast Q4
All-items HICP
Date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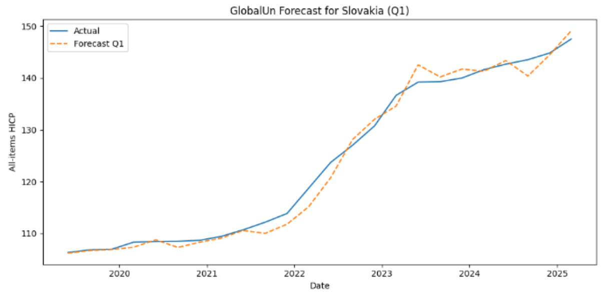
Actual
Forecast Q2
All-items HICP
Date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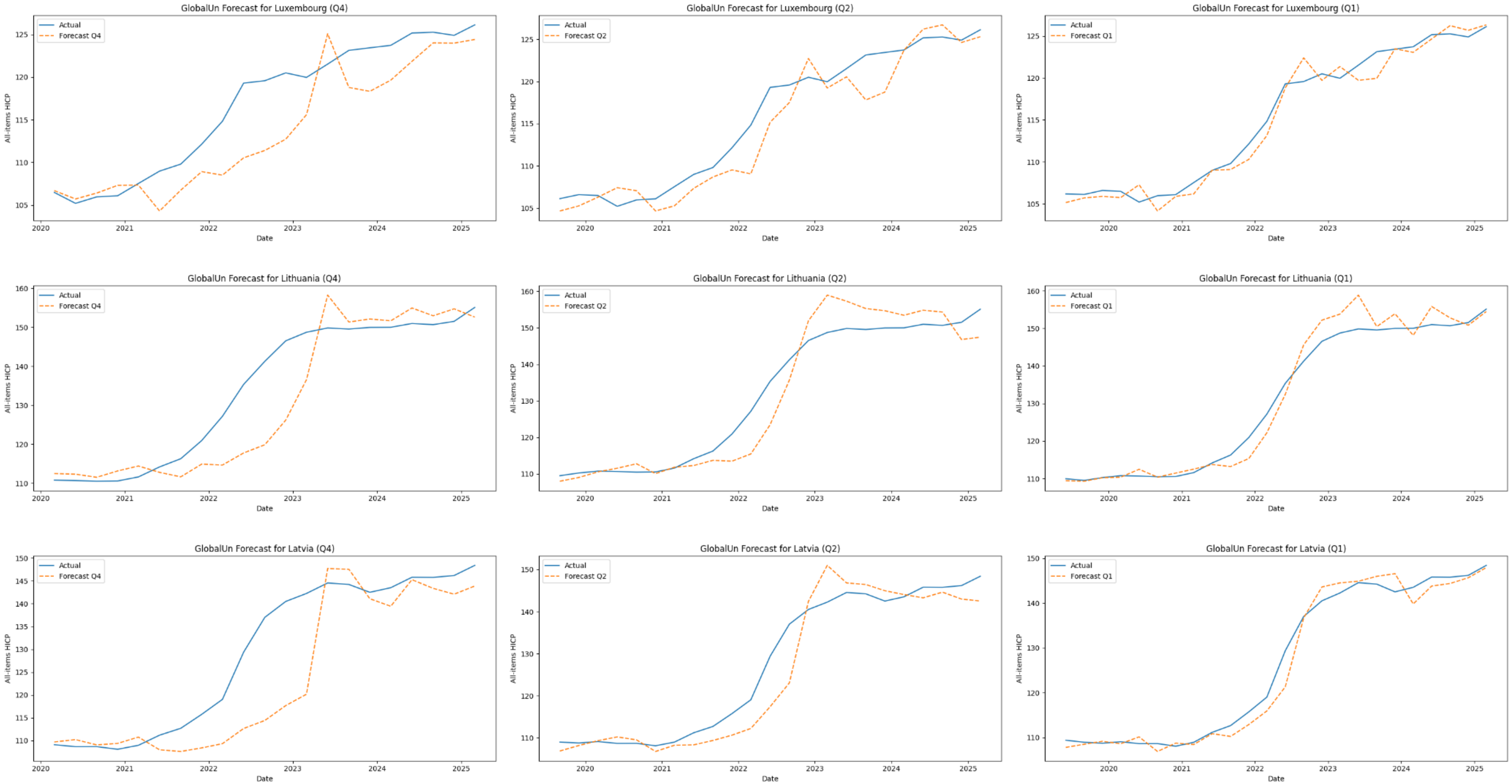
Actual
Forecast Q1
All-items HICP
Date


GlobalUn Forecast for Portugal (Q4)
GlobalUn Forecast for Portugal (Q2)
GlobalUn Forecast for Portugal (Q1)
GlobalUn Forecast for Netherlands (Q4)
GlobalUn Forecast for Netherlands (Q2)
GlobalUn Forecast for Netherlands (Q1)
GlobalUn Forecast for Malta (Q4)
GlobalUn Forecast for Malta (Q2)
GlobalUn Forecast for Malta (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date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GlobalUn Forecast for Luxembourg (Q2)
GlobalUn Forecast for Luxembourg (Q1)
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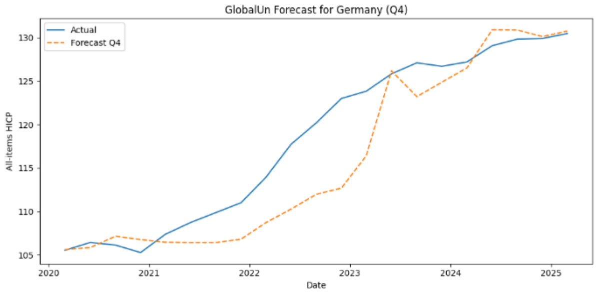
GlobalUn Forecast for Lithuania (Q2)
GlobalUn Forecast for Lithuania (Q1)
GlobalUn Forecast for Latvia (Q4)
GlobalUn Forecast for Latvia (Q2)
GlobalUn Forecast for Latvia (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date


GlobalUn Forecast for Italy (Q4)
GlobalUn Forecast for Italy (Q2)
GlobalUn Forecast for Italy (Q1)
GlobalUn Forecast for Ireland (Q4)
GlobalUn Forecast for Ireland (Q2)
GlobalUn Forecast for Ireland (Q1)
GlobalUn Forecast for Greece (Q4)
GlobalUn Forecast for Greece (Q2)
GlobalUn Forecast for Greece (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date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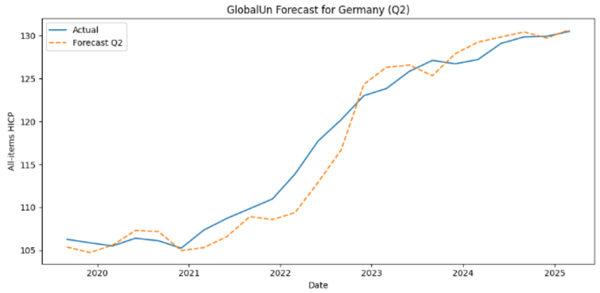
Actual
Forecast Q4
All-items HICP
Date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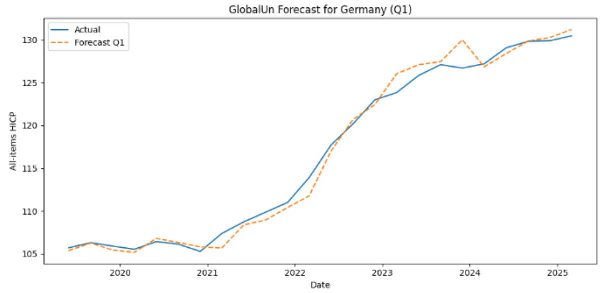
Actual
Forecast Q2
All-items HICP
Date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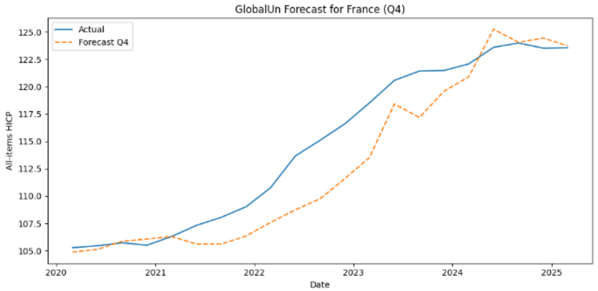
Actual
Forecast Q1
All-items HICP
Date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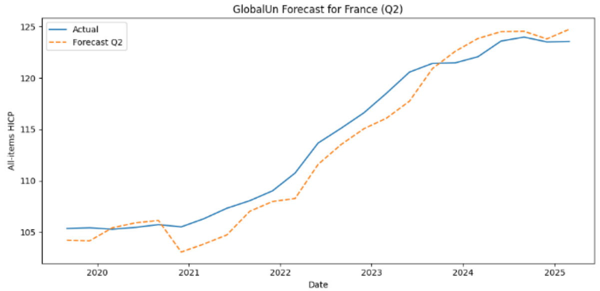
Actual
Forecast Q4
All-items HICP
Date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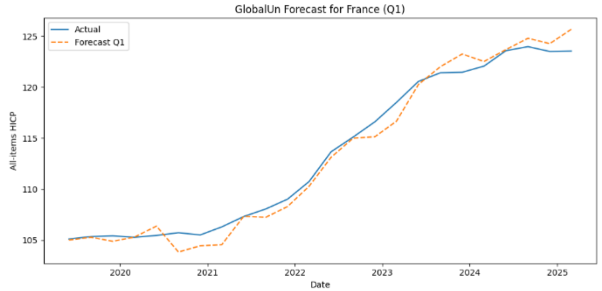
Forecast Q2
All-items HICP
Date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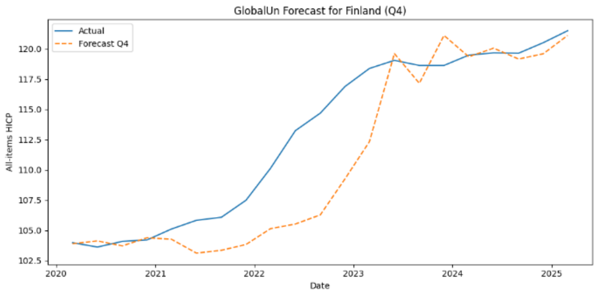
Forecast Q1
All-items HICP
Date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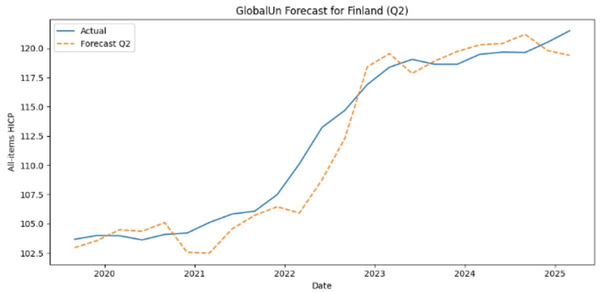
Forecast Q4
All-items HICP
Date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Forecast Q2
All-items HICP
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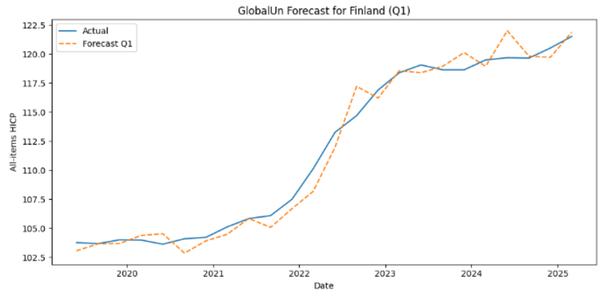
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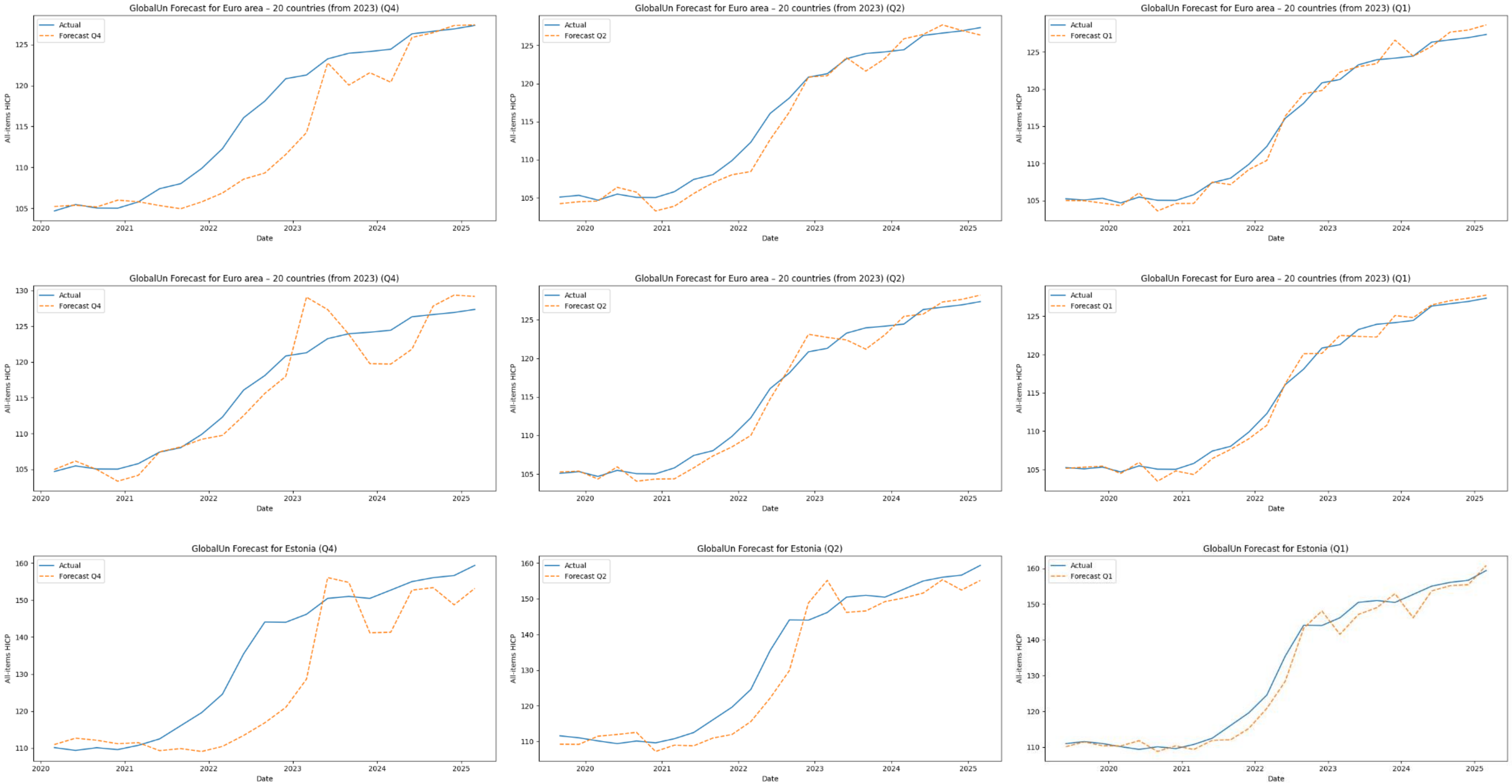
Forecast Q1
All-items HICP
Date


GlobalUn Forecast for Euro area – 20 countries (from 2023) (Q4)
Actual
Forecast Q4
GlobalUn Forecast for Euro area – 20 countries (from 2023) (Q2)
Actual
Forecast Q2
GlobalUn Forecast for Euro area – 20 countries (from 2023) (Q1)
Actual
Forecast Q1
GlobalUn Forecast for Euro area – 20 countries (from 2023) (Q4)
Actual
Forecast Q4
GlobalUn Forecast for Euro area – 20 countries (from 2023) (Q2)
Actual
Forecast Q2
GlobalUn Forecast for Euro area – 20 countries (from 2023) (Q1)
Actual
Forecast Q1
GlobalUn Forecast for Estonia (Q4)
Actual
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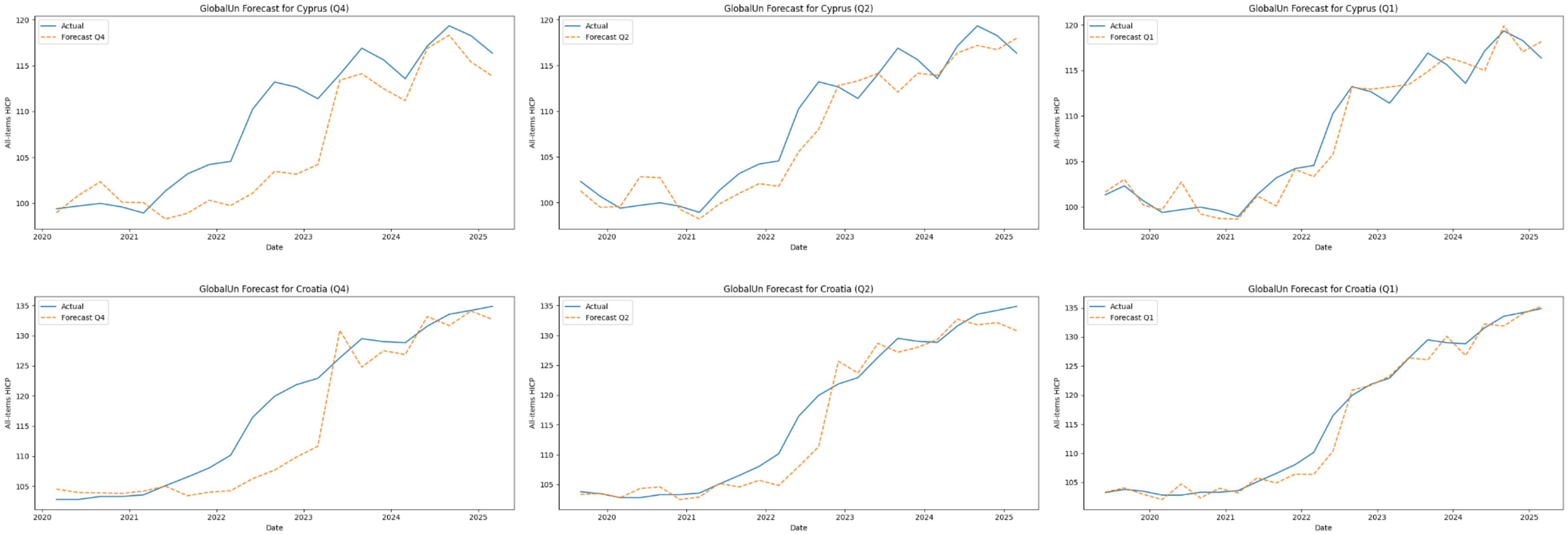
Forecast Q1
All-items HICP
Date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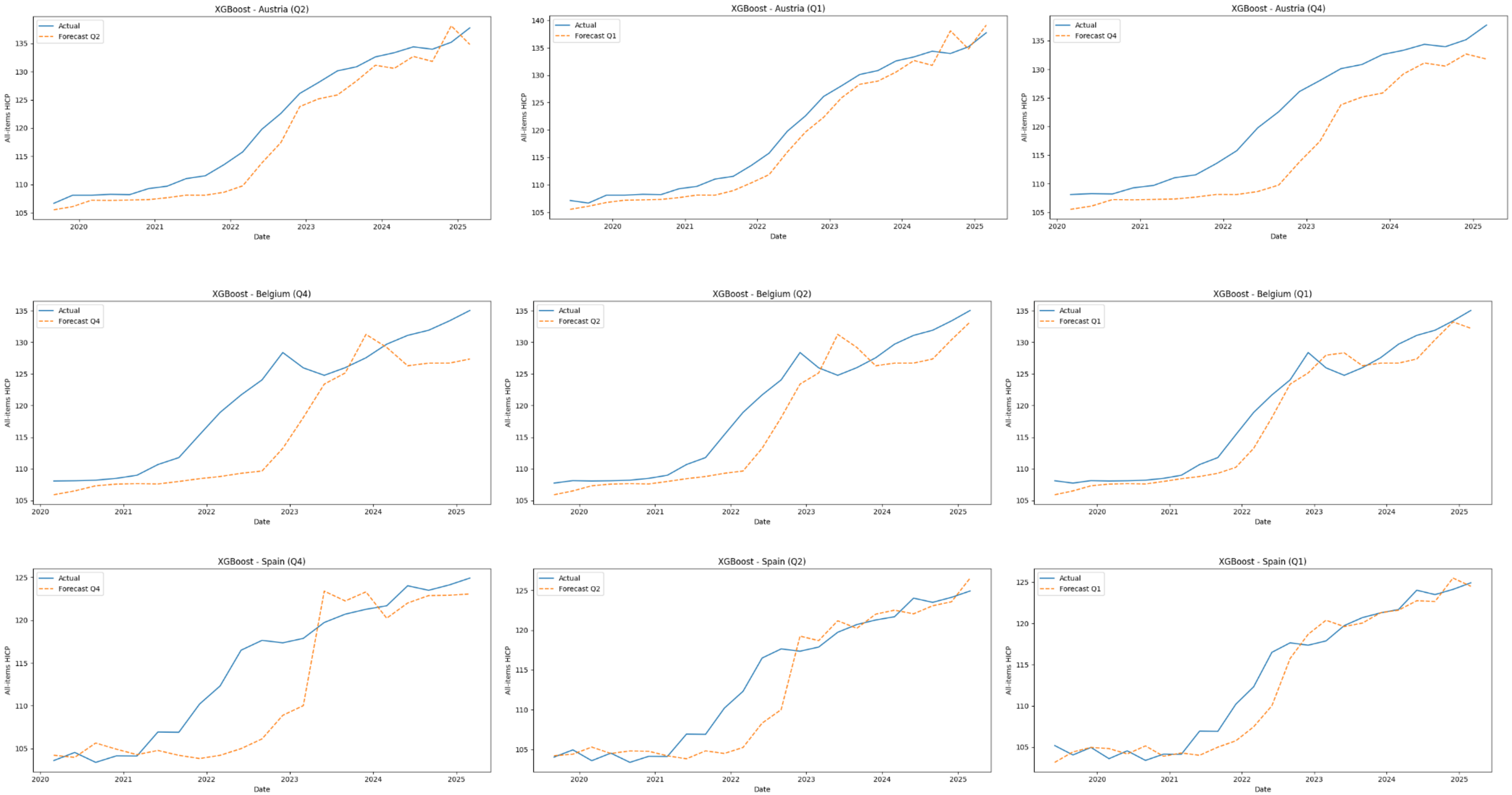
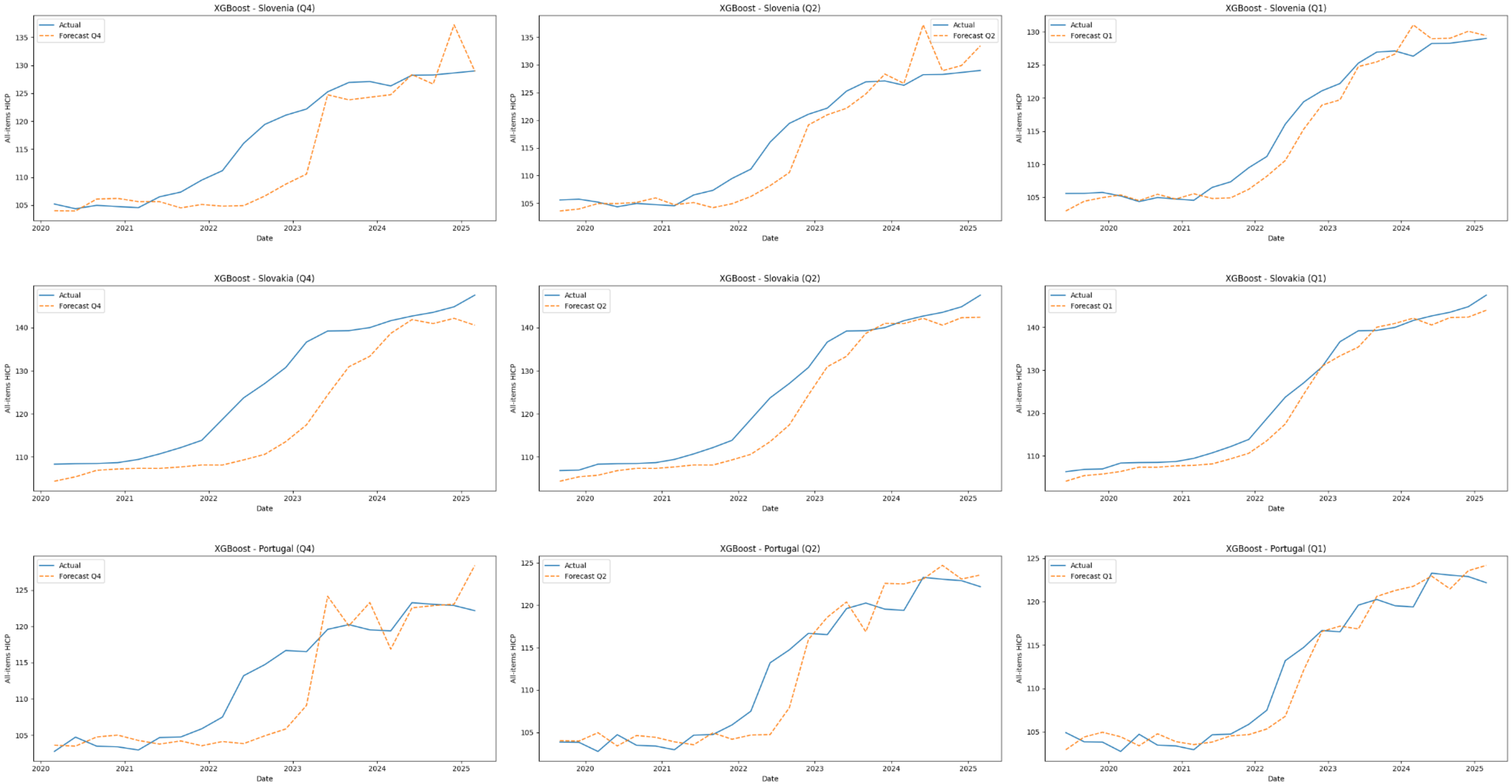
GlobalUn Forecast for Cyprus (Q2)
GlobalUn Forecast for Cyprus (Q1)
GlobalUn Forecast for Croatia (Q4)
GlobalUn Forecast for Croatia (Q2)
GlobalUn Forecast for Croatia (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date

Figure A2. XGBoost model: Actual vs Forecasts (Eurozone counties plus EA-20)




XGBoost - Slovenia (Q4)
XGBoost - Slovenia (Q2)
XGBoost - Slovenia (Q1)
XGBoost - Slovakia (Q4)
XGBoost - Slovakia (Q2)
XGBoost - Slovakia (Q1)
XGBoost - Portugal (Q4)
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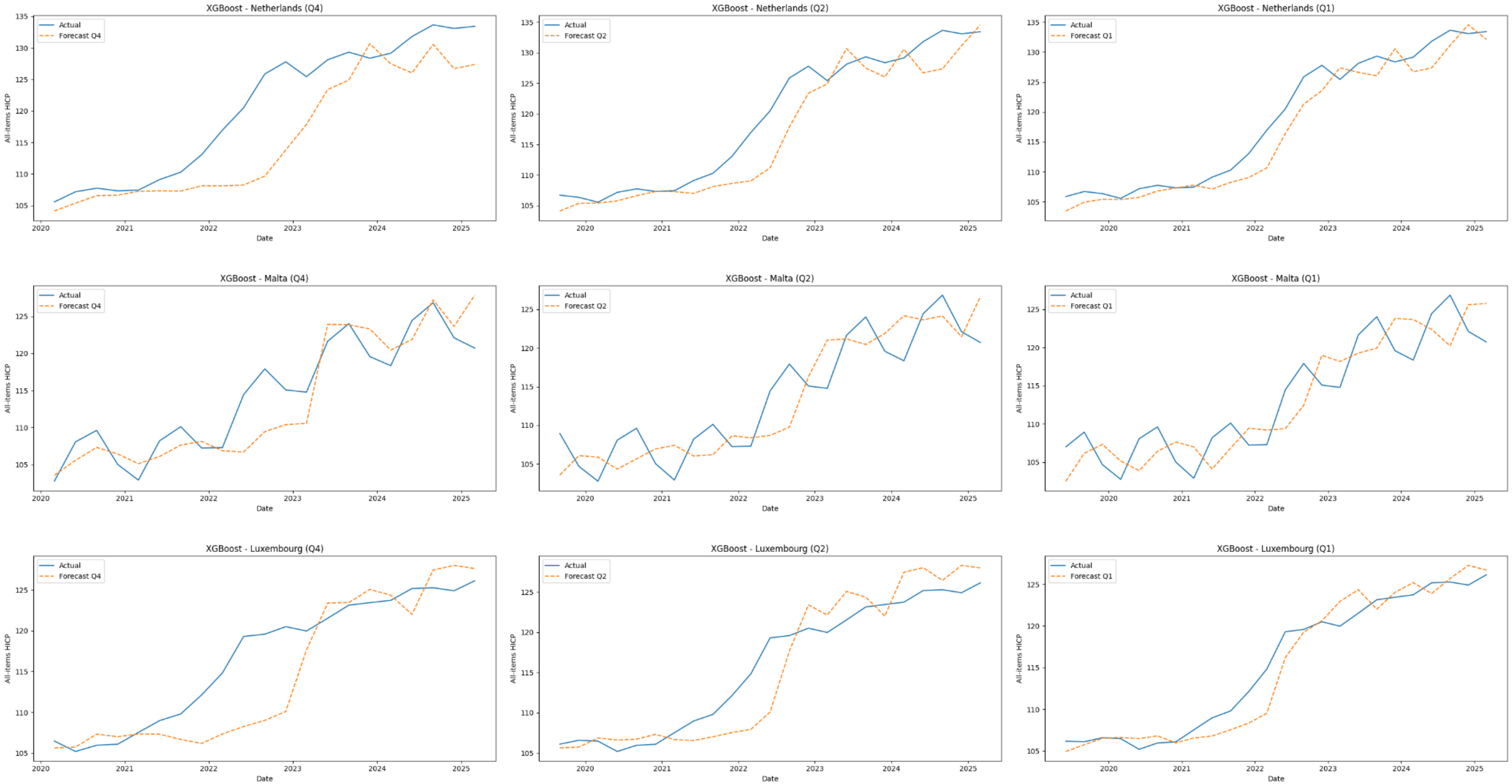
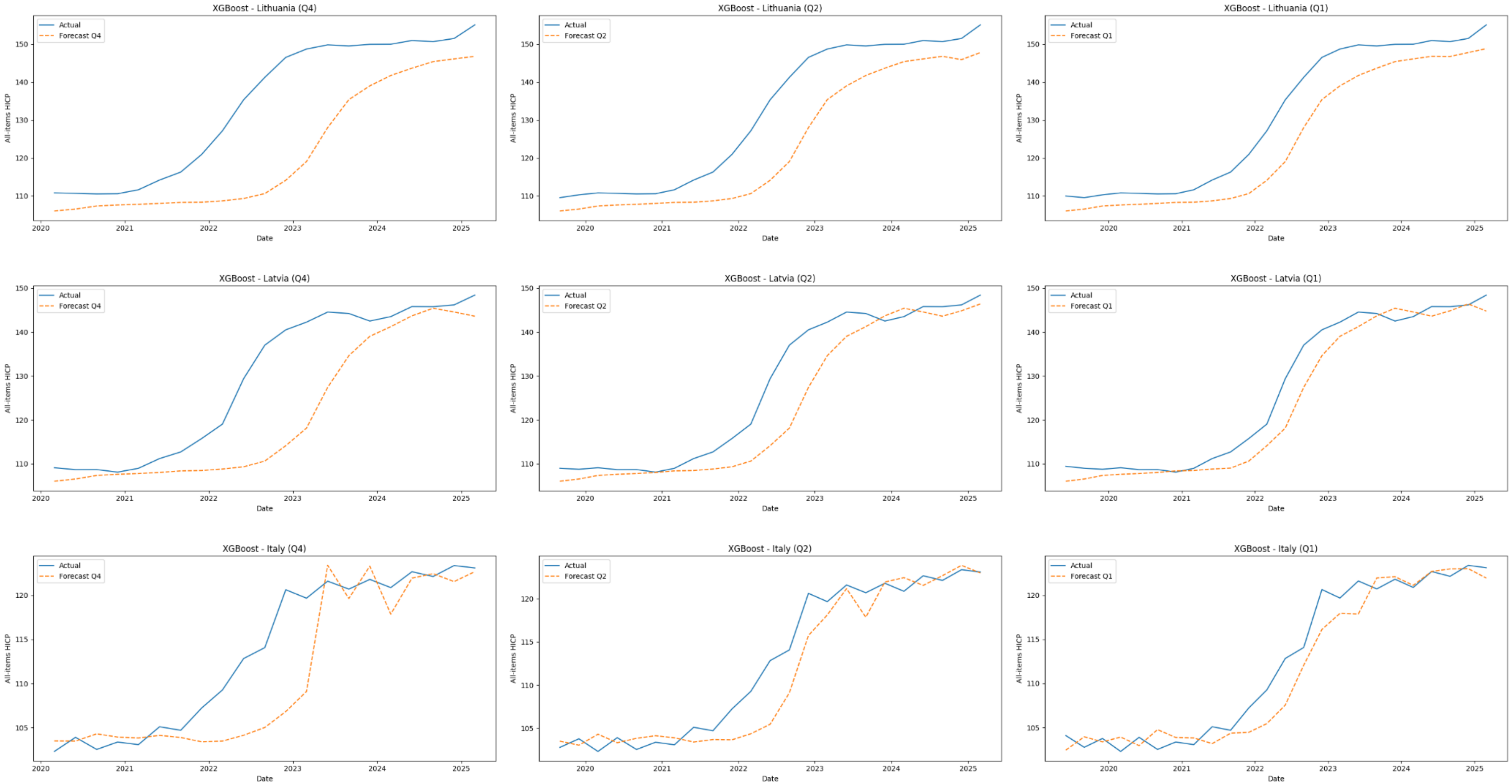
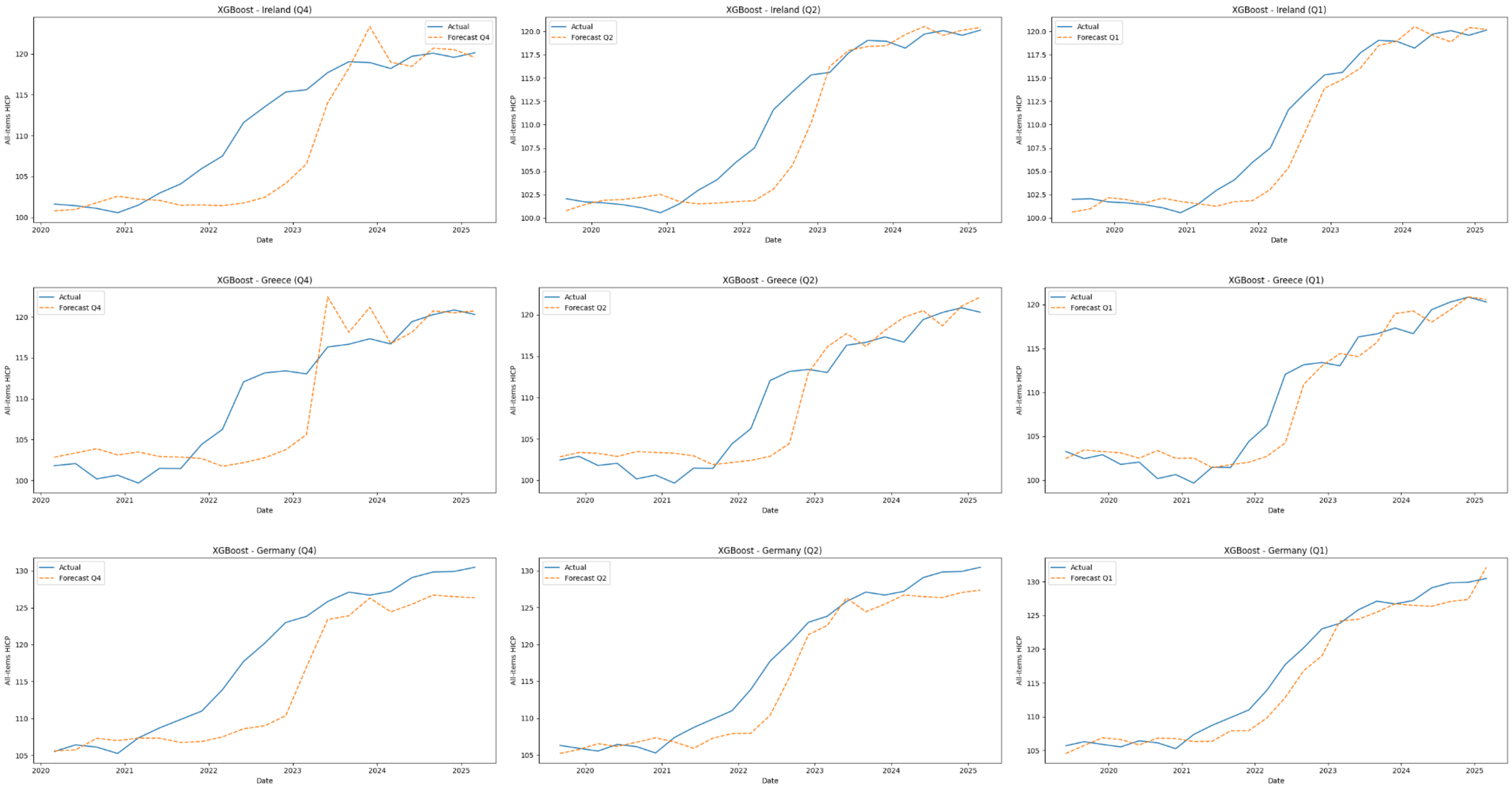
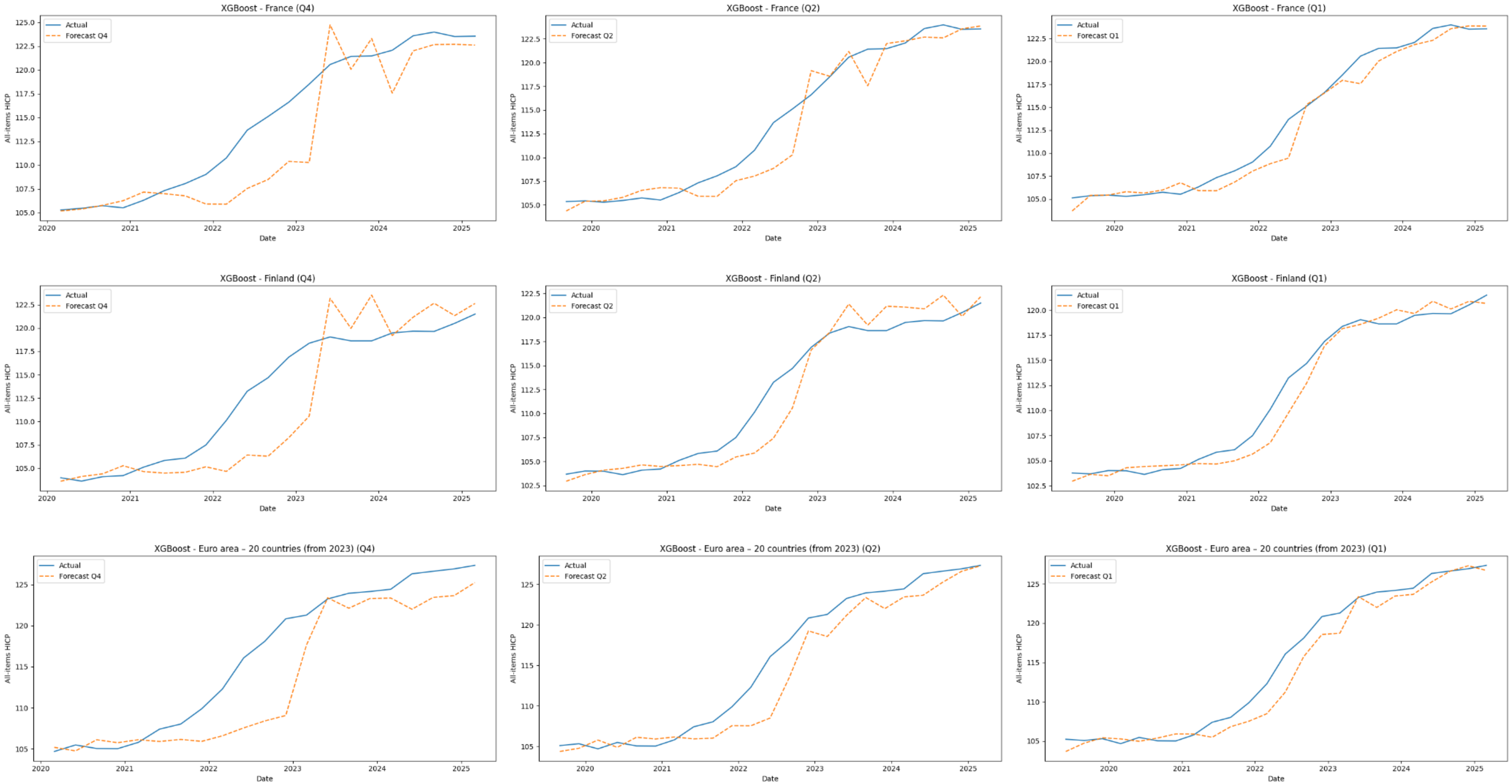
XGBoost - Portugal (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date


XGBoost - Netherlands (Q4)
XGBoost - Netherlands (Q2)
XGBoost - Netherlands (Q1)
XGBoost - Malta (Q4)
XGBoost - Malta (Q2)
XGBoost - Malta (Q1)
XGBoost - Luxembourg (Q4)
XGBoost - Luxembourg (Q2)
XGBoost - Luxembourg (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date


XGBoost - Lithuania (Q4)
XGBoost - Lithuania (Q2)
XGBoost - Lithuania (Q1)
XGBoost - Latvia (Q4)
XGBoost - Latvia (Q2)
XGBoost - Latvia (Q1)
XGBoost - Italy (Q4)
XGBoost - Italy (Q2)
XGBoost - Italy (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date


XGBoost - Ireland (Q4)
XGBoost - Ireland (Q2)
XGBoost - Ireland (Q1)
XGBoost - Greece (Q4)
XGBoost - Greece (Q2)
XGBoost - Greece (Q1)
XGBoost - Germany (Q4)
XGBoost - Germany (Q2)
XGBoost - Germany (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date


XGBoost - France (Q4)
XGBoost - France (Q2)
XGBoost - France (Q1)
XGBoost - Finland (Q4)
XGBoost - Finland (Q2)
XGBoost - Finland (Q1)
XGBoost - Euro area – 20 countries (from 2023) (Q4)
XGBoost - Euro area – 20 countries (from 2023) (Q2)
XGBoost - Euro area – 20 countries (from 2023) (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date

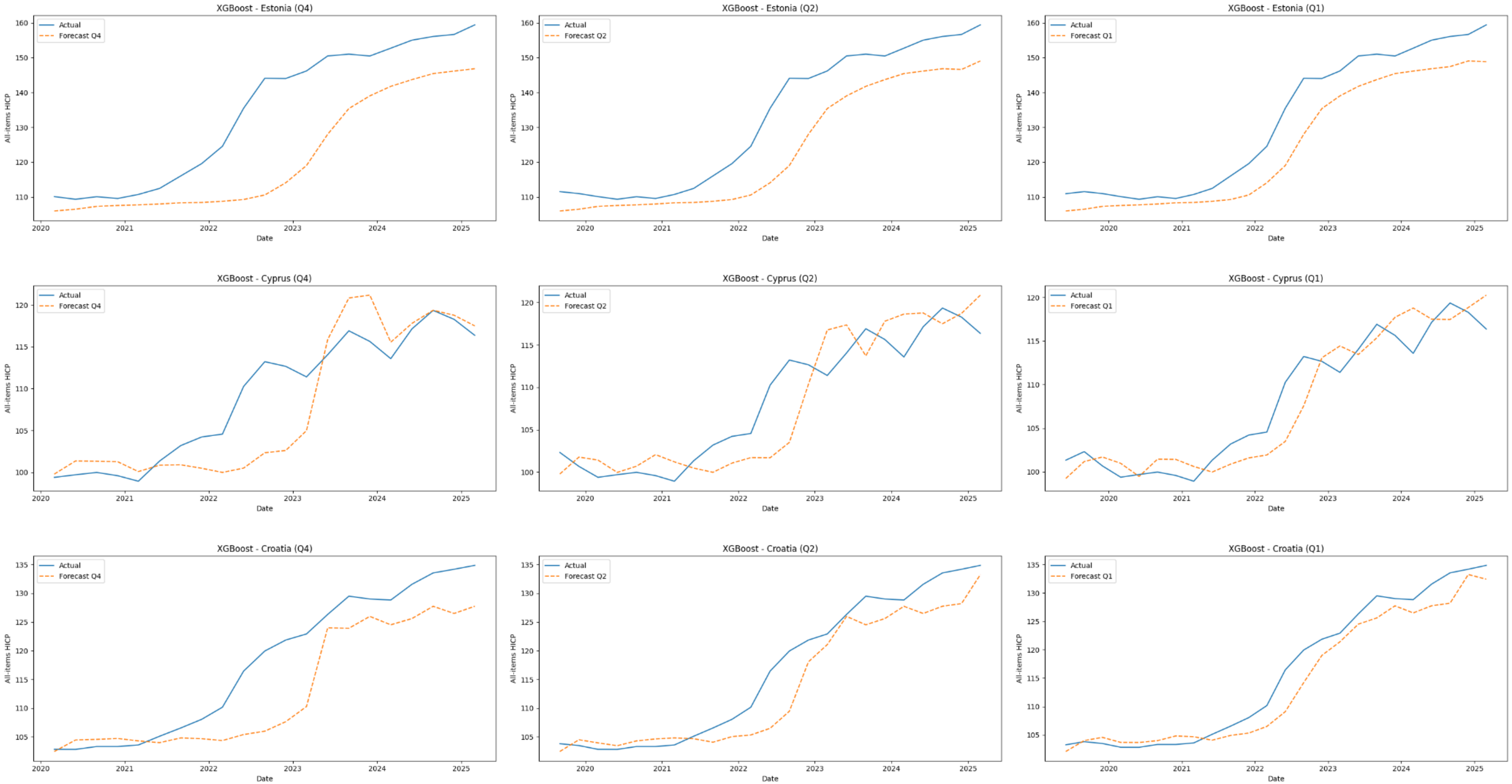
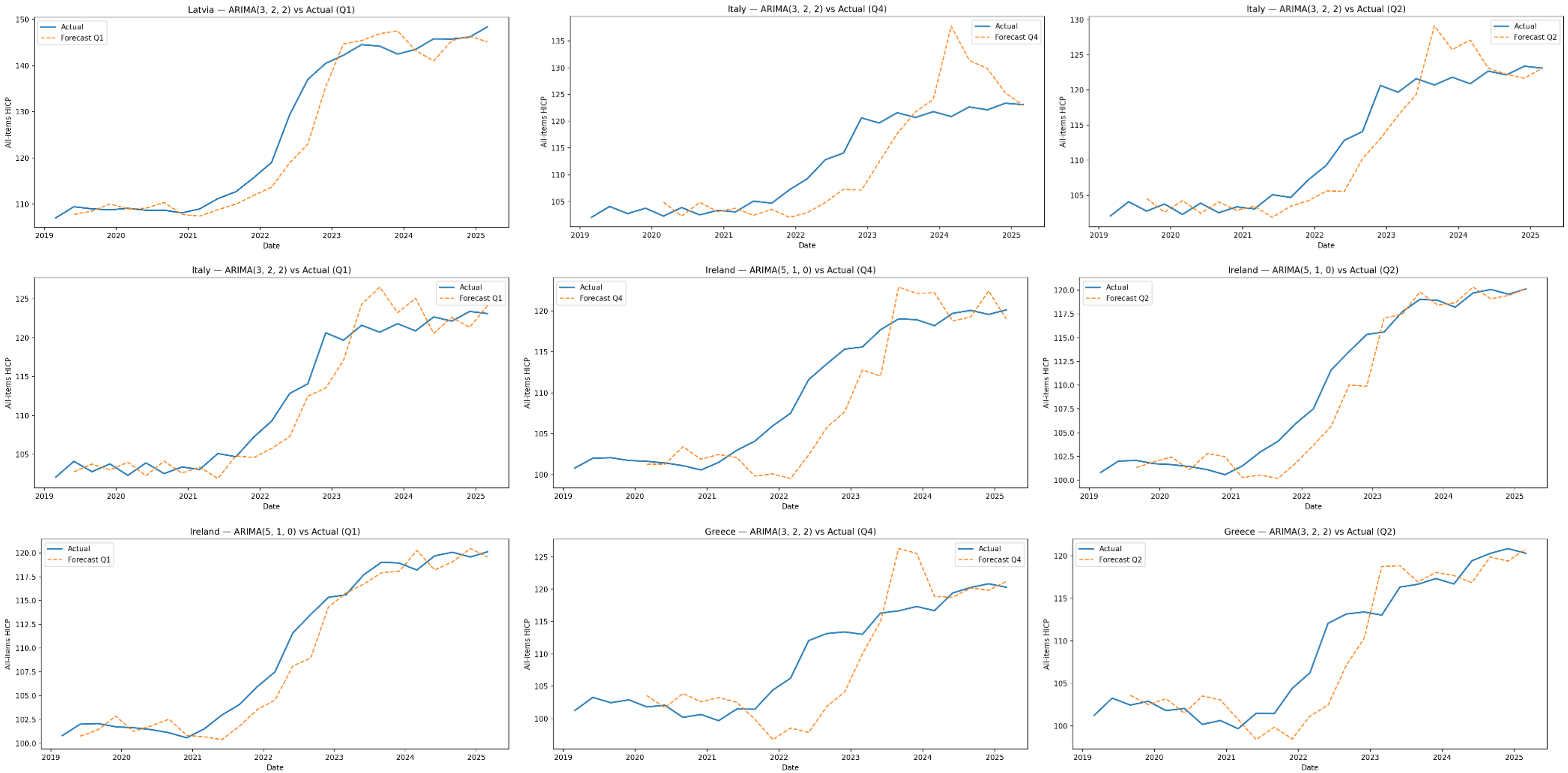
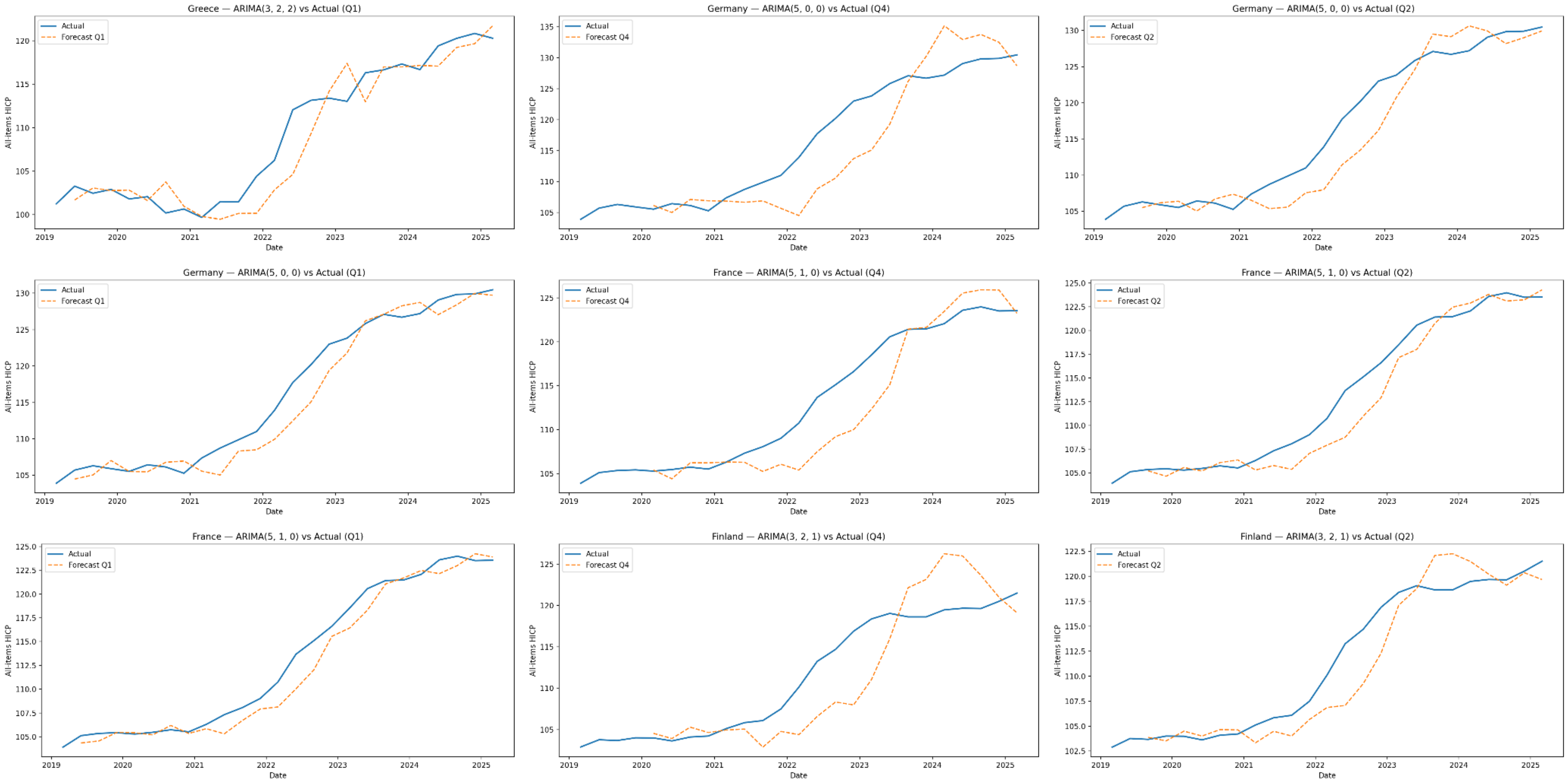
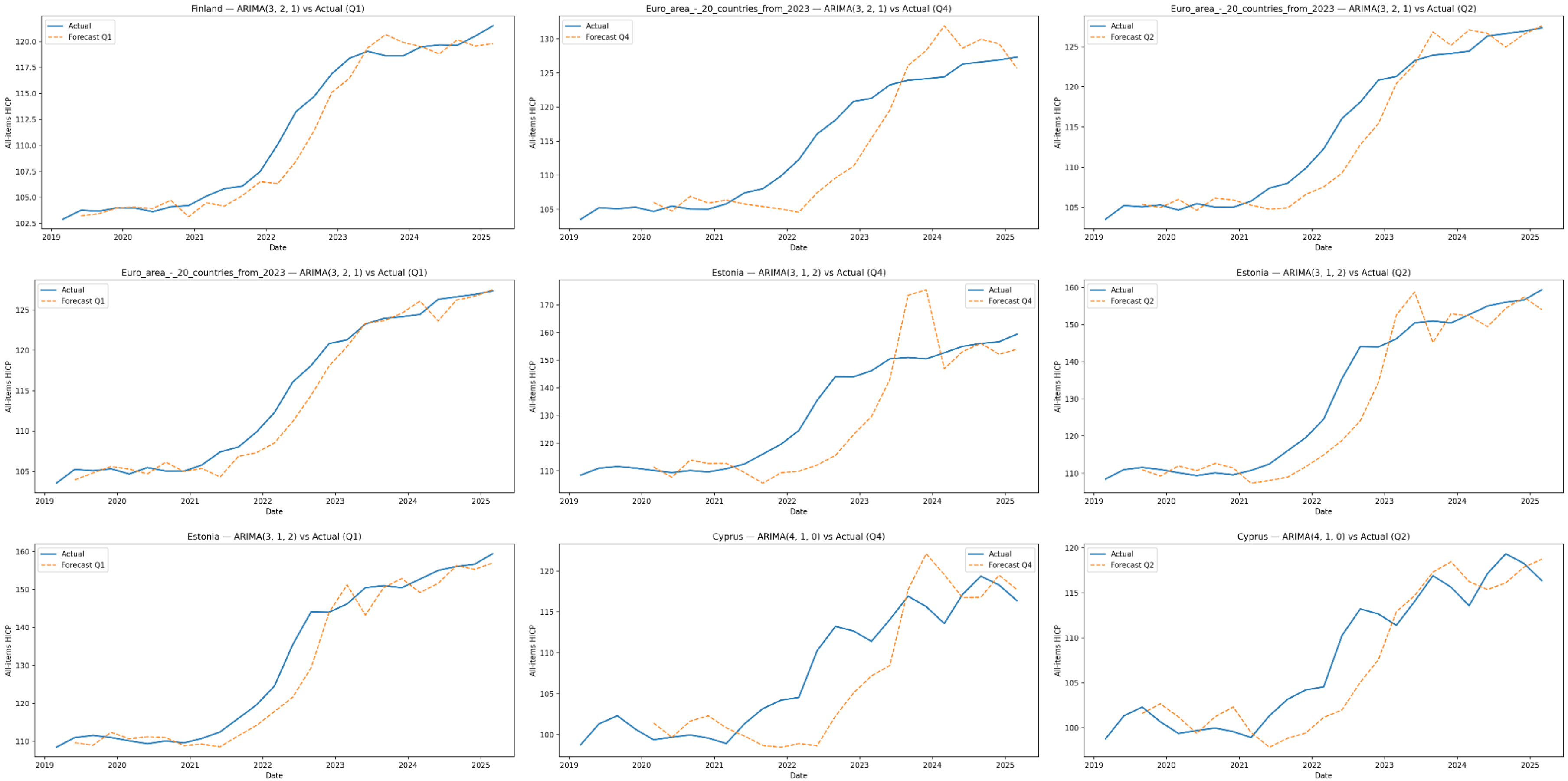
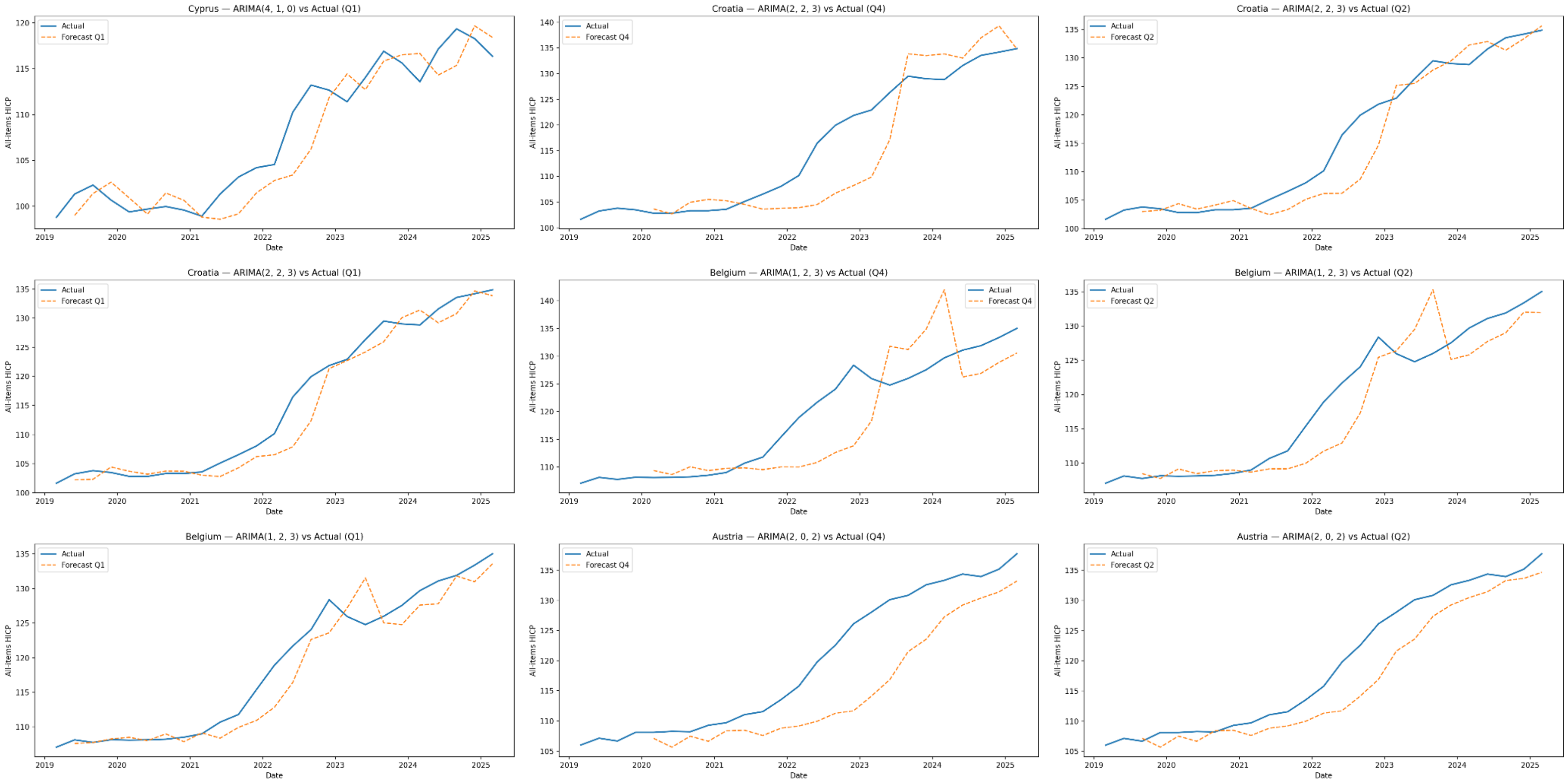

XGBoost - Estonia (Q4)
XGBoost - Estonia (Q2)
XGBoost - Estonia (Q1)
XGBoost - Cyprus (Q4)
XGBoost - Cyprus (Q2)
XGBoost - Cyprus (Q1)
XGBoost - Croatia (Q4)
XGBoost - Croatia (Q2)
XGBoost - Croatia (Q1)
Actual
Forecast Q4
Forecast Q2
Forecast Q1
All-items HICP
Date
2020
2021
2022
2023
2024
2025

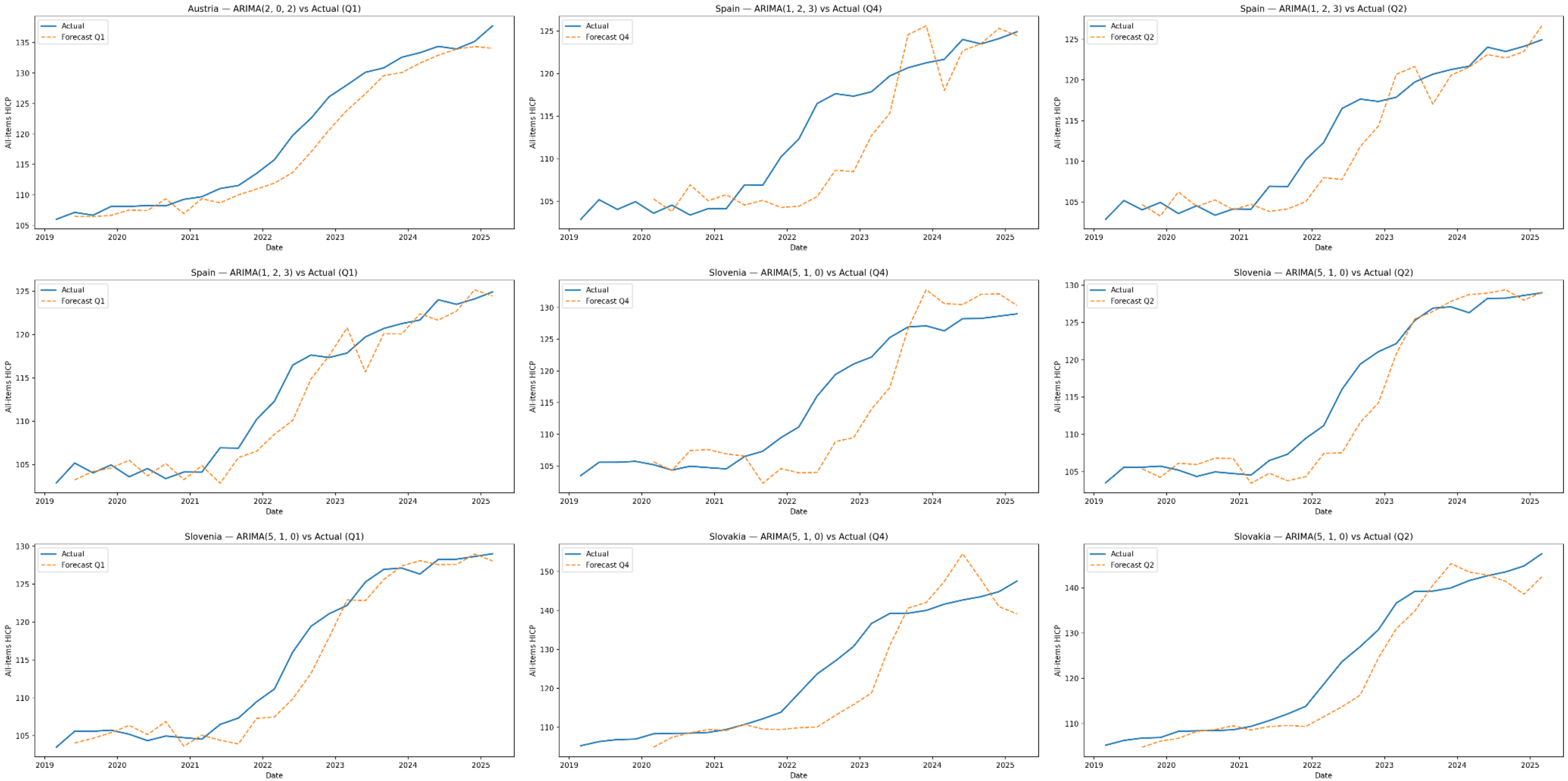
Figure A3. ARIMA model: Actual vs Forecasts (Eurozone counties plus EA-20

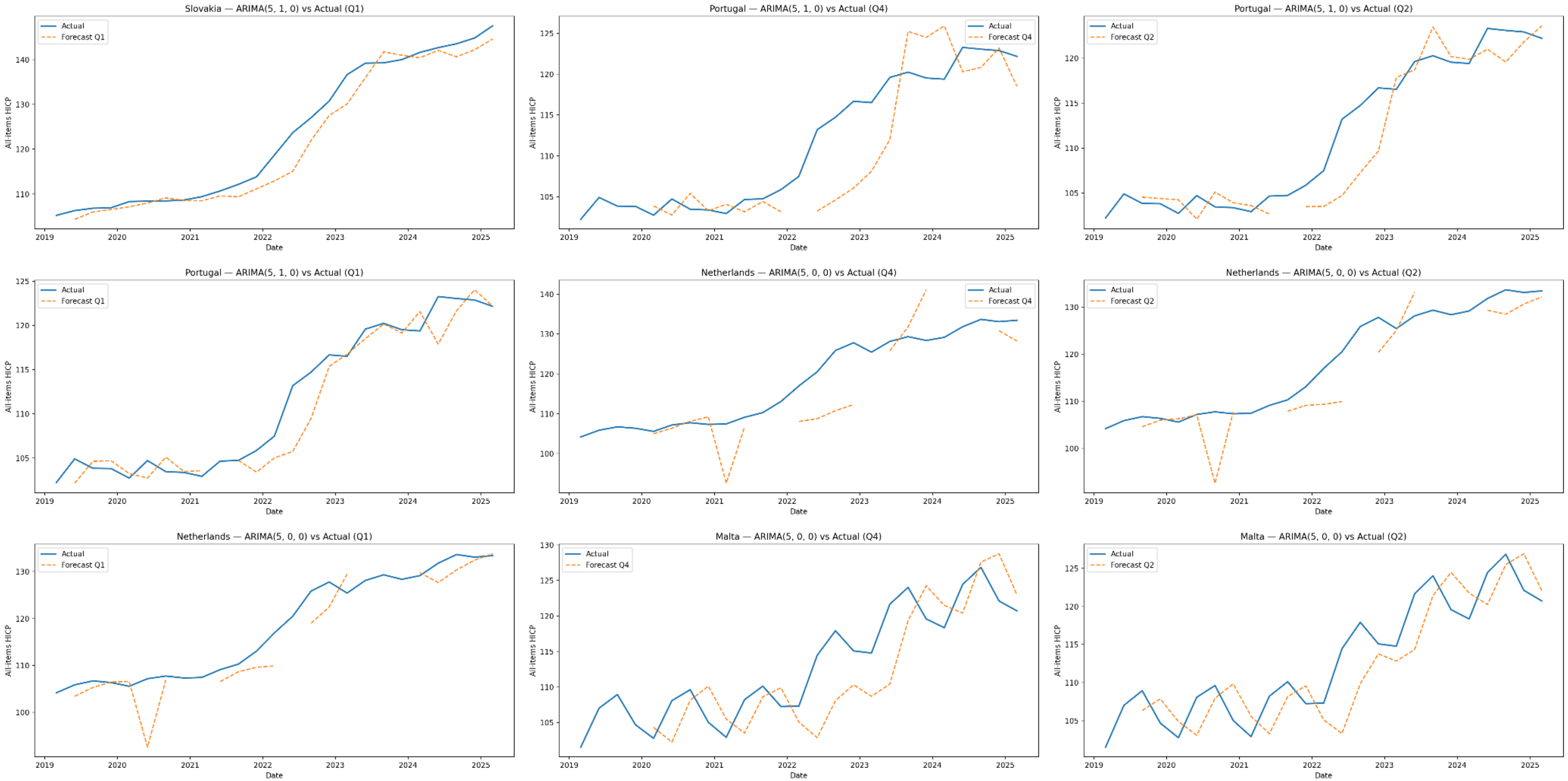



Greece — ARIMA(3, 2, 2) vs Actual (Q1)
Germany — ARIMA(5, 0, 0) vs Actual (Q4)
Germany — ARIMA(5, 0, 0) vs Actual (Q2)
Germany — ARIMA(5, 0, 0) vs Actual (Q1)
France — ARIMA(5, 1, 0) vs Actual (Q4)
France — ARIMA(5, 1, 0) vs Actual (Q2)
France — ARIMA(5, 1, 0) vs Actual (Q1)
Finland — ARIMA(3, 2, 1) vs Actual (Q4)
Finland — ARIMA(3, 2, 1) vs Actual (Q2)
Actual
Forecast Q1
Forecast Q4
Forecast Q2
All-items HICP
Date


Finland — ARIMA(3, 2, 1) vs Actual (Q1)
Euro_area_-_20_countries_from_2023 — ARIMA(3, 2, 1) vs Actual (Q4)
Euro_area_-_20_countries_from_2023 — ARIMA(3, 2, 1) vs Actual (Q2)
Euro_area_-_20_countries_from_2023 — ARIMA(3, 2, 1) vs Actual (Q1)
Estonia — ARIMA(3, 1, 2) vs Actual (Q4)
Estonia — ARIMA(3, 1, 2) vs Actual (Q2)
Estonia — ARIMA(3, 1, 2) vs Actual (Q1)
Cyprus — ARIMA(4, 1, 0) vs Actual (Q4)
Cyprus — ARIMA(4, 1, 0) vs Actual (Q2)
Actual
Forecast Q1
Forecast Q2
Forecast Q4
All-items HICP
Date


Cyprus — ARIMA(4, 1, 0) vs Actual (Q1)
Croatia — ARIMA(2, 2, 3) vs Actual (Q4)
Croatia — ARIMA(2, 2, 3) vs Actual (Q2)
Croatia — ARIMA(2, 2, 3) vs Actual (Q1)
Belgium — ARIMA(1, 2, 3) vs Actual (Q4)
Belgium — ARIMA(1, 2, 3) vs Actual (Q2)
Belgium — ARIMA(1, 2, 3) vs Actual (Q1)
Austria — ARIMA(2, 0, 2) vs Actual (Q4)
Austria — ARIMA(2, 0, 2) vs Actual (Q2)
Actual
Forecast Q1
Forecast Q4
Forecast Q2
All-items HICP
Date


Austria — ARIMA(2, 0, 2) vs Actual (Q1)
Spain — ARIMA(1, 2, 3) vs Actual (Q4)
Spain — ARIMA(1, 2, 3) vs Actual (Q2)
Spain — ARIMA(1, 2, 3) vs Actual (Q1)
Slovenia — ARIMA(5, 1, 0) vs Actual (Q4)
Slovenia — ARIMA(5, 1, 0) vs Actual (Q2)
Slovenia — ARIMA(5, 1, 0) vs Actual (Q1)
Slovakia — ARIMA(5, 1, 0) vs Actual (Q4)
Slovakia — ARIMA(5, 1, 0) vs Actual (Q2)
Actual
Forecast Q1
Forecast Q4
Forecast Q2
All-items HICP
Date


Slovakia — ARIMA(5, 1, 0) vs Actual (Q1)
Actual
Forecast Q1
Portugal — ARIMA(5, 1, 0) vs Actual (Q4)
Actual
Forecast Q4
Portugal — ARIMA(5, 1, 0) vs Actual (Q2)
Actual
Forecast Q2
Portugal — ARIMA(5, 1, 0) vs Actual (Q1)
Actual
Forecast Q1
Netherlands — ARIMA(5, 0, 0) vs Actual (Q4)
Actual
Forecast Q4
Netherlands — ARIMA(5, 0, 0) vs Actual (Q2)
Actual
Forecast Q2
Netherlands — ARIMA(5, 0, 0) vs Actual (Q1)
Actual
Forecast Q1
Malta — ARIMA(5, 0, 0) vs Actual (Q4)
Actual
Forecast Q4
Malta — ARIMA(5, 0, 0) vs Actual (Q2)
Actual
Forecast Q2
All-items HICP
Date

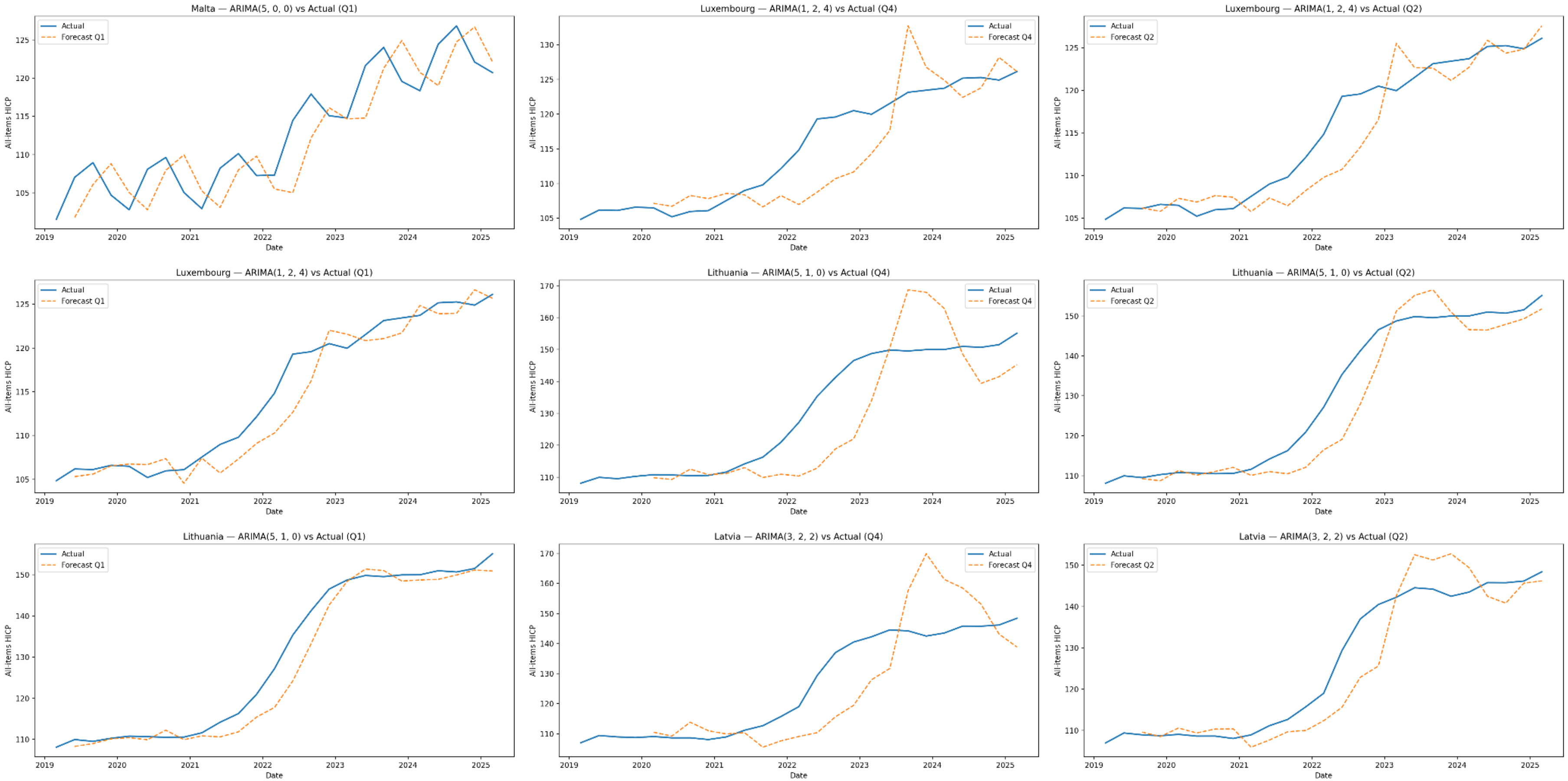
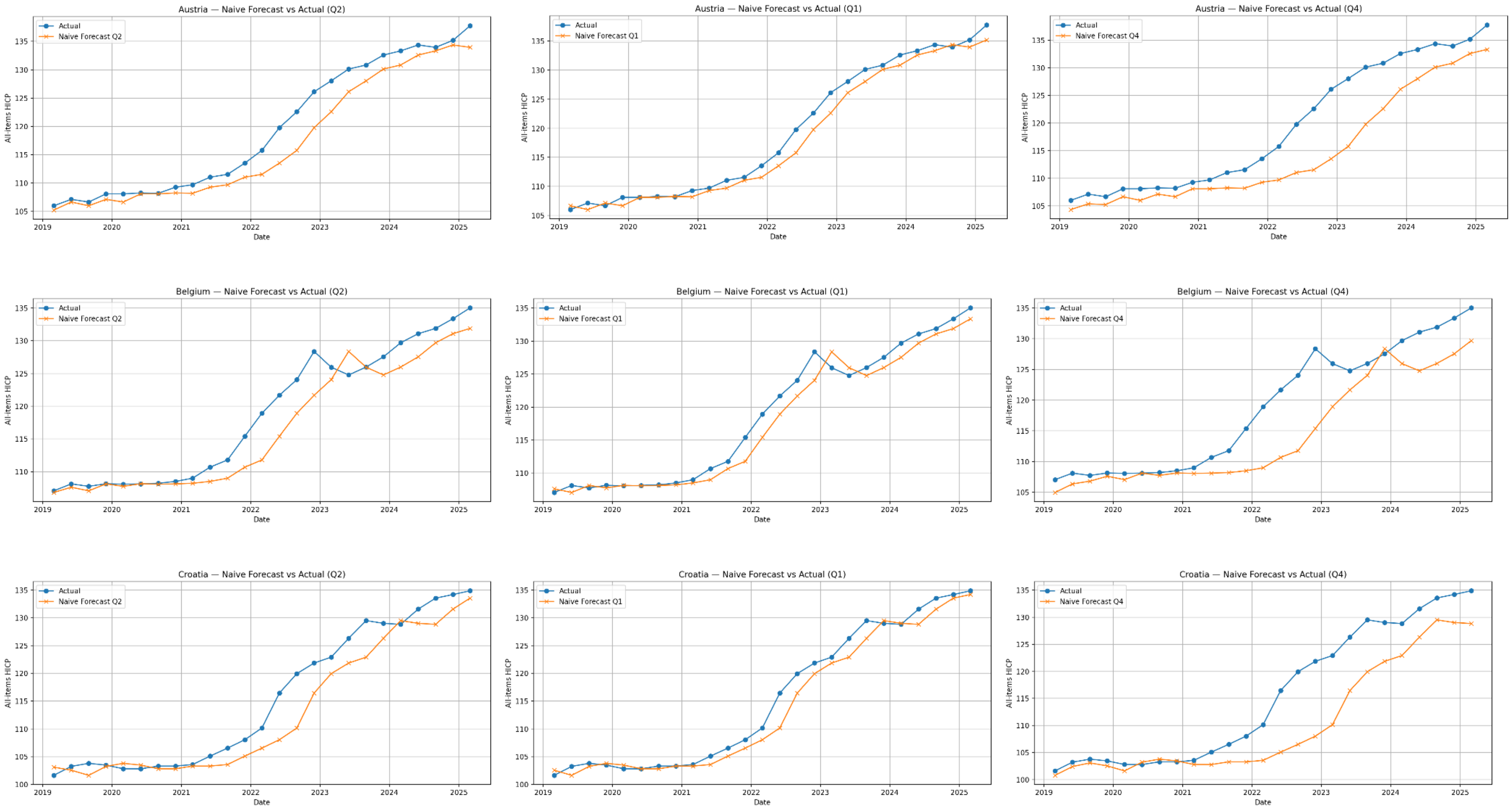
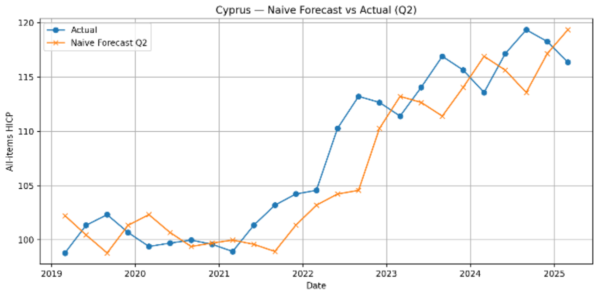
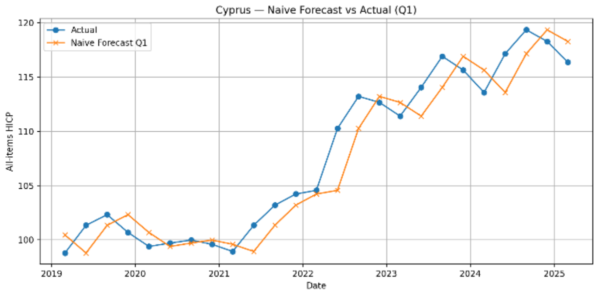
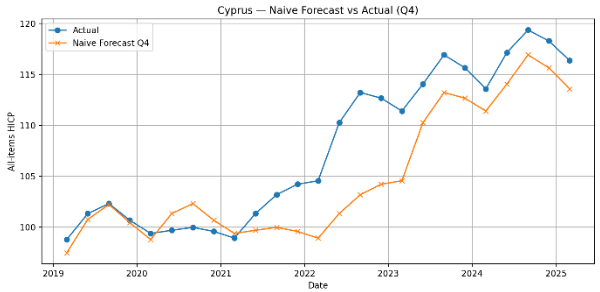

Malta — ARIMA(5, 0, 0) vs Actual (Q1)
Luxembourg — ARIMA(1, 2, 4) vs Actual (Q4)
Luxembourg — ARIMA(1, 2, 4) vs Actual (Q2)
Luxembourg — ARIMA(1, 2, 4) vs Actual (Q1)
Lithuania — ARIMA(5, 1, 0) vs Actual (Q4)
Lithuania — ARIMA(5, 1, 0) vs Actual (Q2)
Lithuania — ARIMA(5, 1, 0) vs Actual (Q1)
Latvia — ARIMA(3, 2, 2) vs Actual (Q4)
Latvia — ARIMA(3, 2, 2) vs Actual (Q2)
Actual
Forecast Q1
Forecast Q2
Forecast Q4
All-items HICP
Date

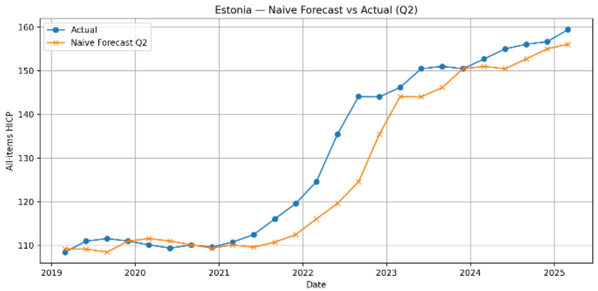
Figure A4. NAIVE model: Actual vs Forecasts (Eurozone counties plus EA-20)

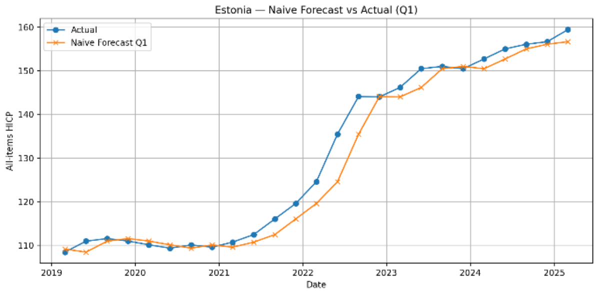


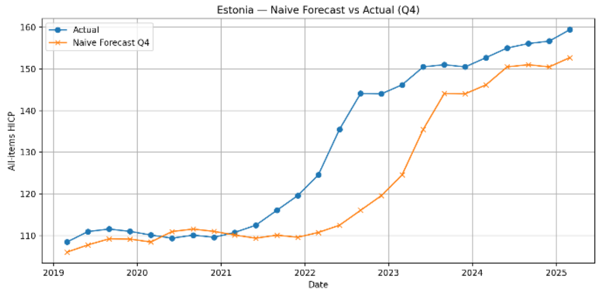

Cyprus — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date

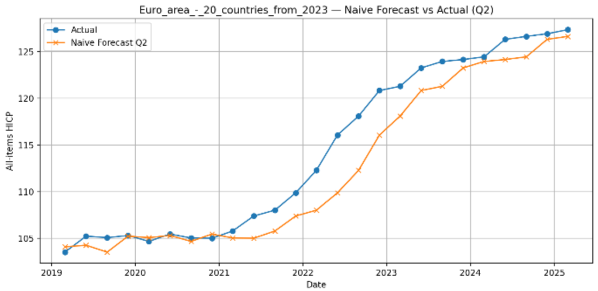

Cyprus — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date


Cyprus — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date


Estonia — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date


Estonia — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date


Estonia — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date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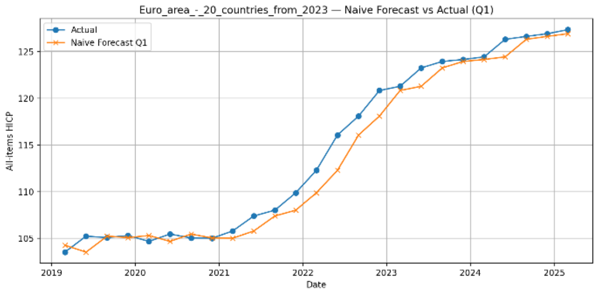
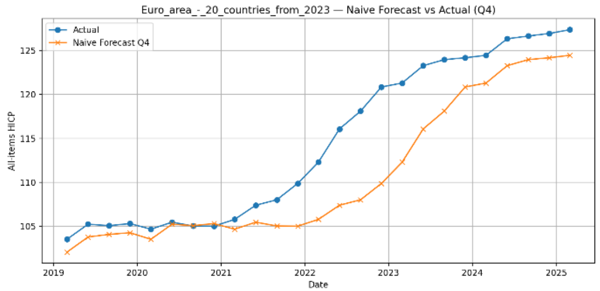
Actual
Naive Forecast Q2
All-items HICP
Date


Euro_area_-_20_countries_from_2023 — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date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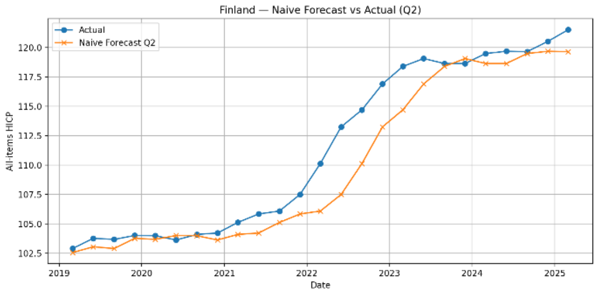
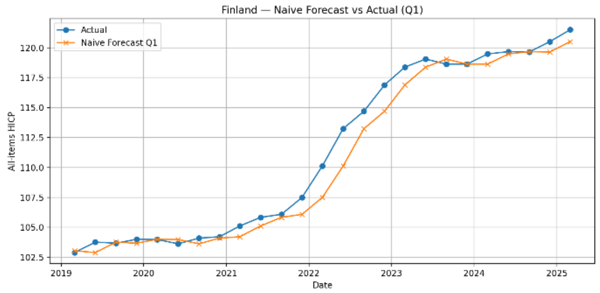
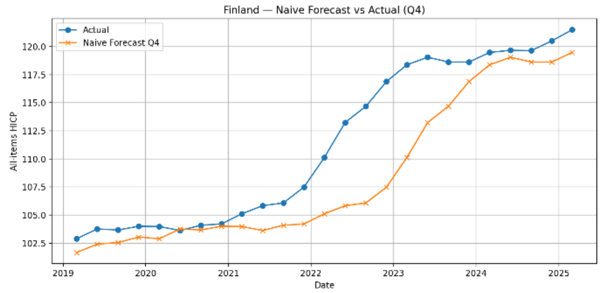
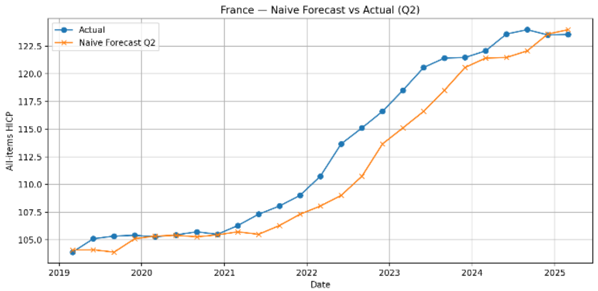
Actual
Naive Forecast Q4
All-items HICP
Date


Finland — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date
102.5
105.0
107.5
110.0
112.5
115.0
117.5
120.0
2019
2020
2021
2022
2023
2024
2025


Finland — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date
102.5
105.0
107.5
110.0
112.5
115.0
117.5
120.0
2019
2020
2021
2022
2023
2024
2025


Finland — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date
102.5
105.0
107.5
110.0
112.5
115.0
117.5
120.0
2019
2020
2021
2022
2023
2024
2025


France — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date
105.0
107.5
110.0
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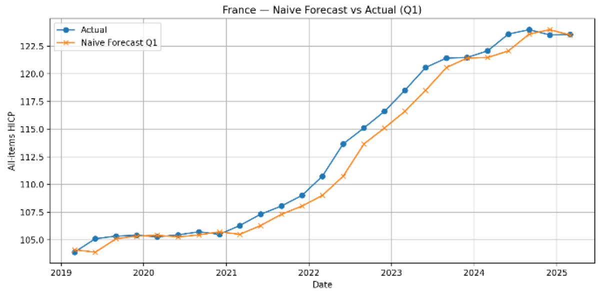
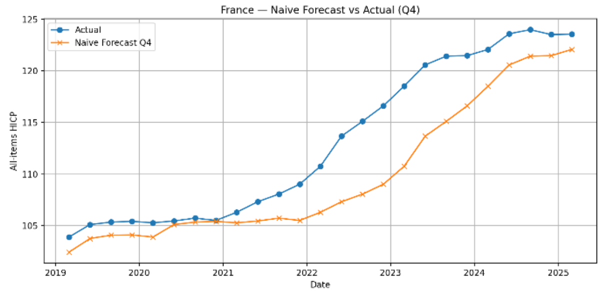
115.0
117.5
120.0
122.5
2019
2020
2021
2022
2023
2024
2025


France — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date
105.0
107.5
110.0
112.5
115.0
117.5
120.0
122.5
2019
2020
2021
2022
2023
2024
2025


France — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date
105
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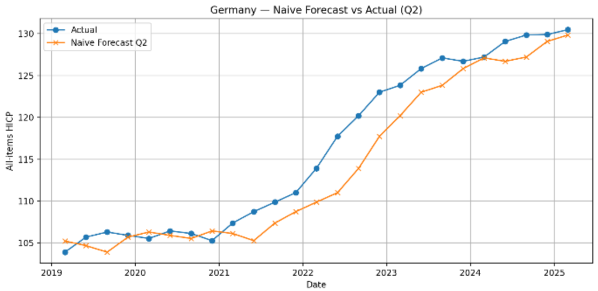
2020
2021
2022
2023
2024
2025


Germany — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date
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120
125
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2020
2021
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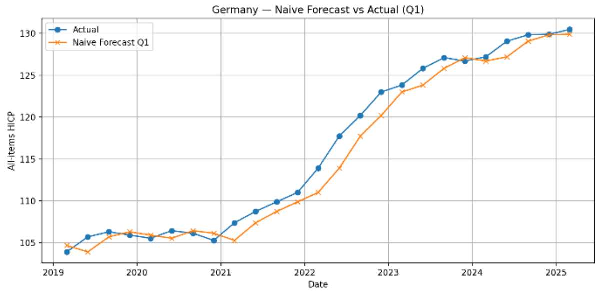
2023
2024
2025


Germany — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
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2020
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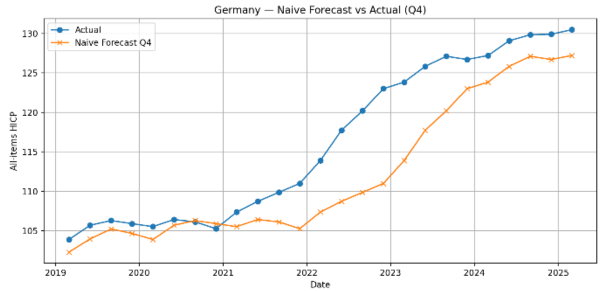
Germany — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date
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120
125
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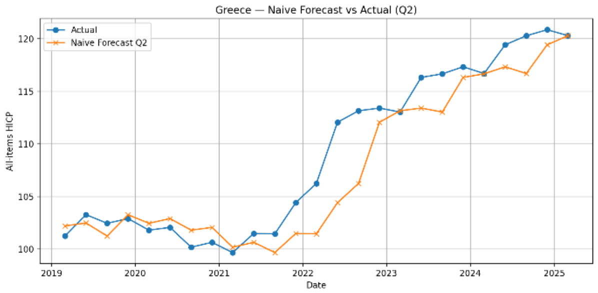
2019
2020
2021
2022
2023
2024
2025


Greece — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
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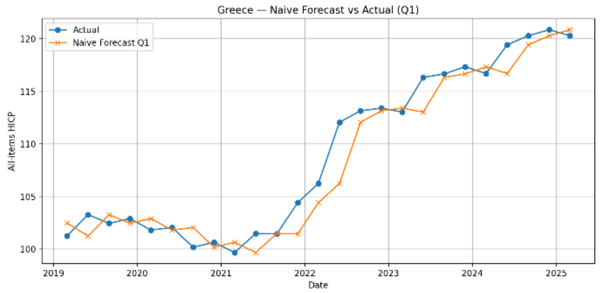
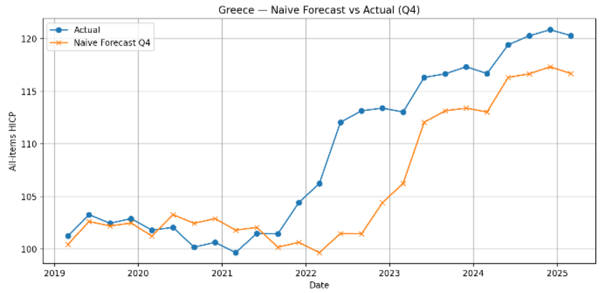

Greece — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date


Greece — Naive Forecast vs Actual (Q4)
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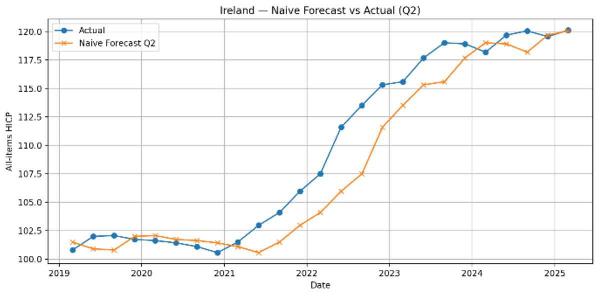
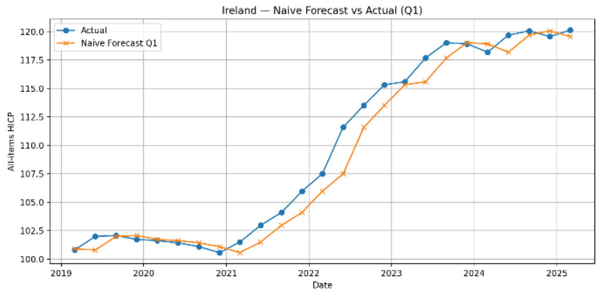
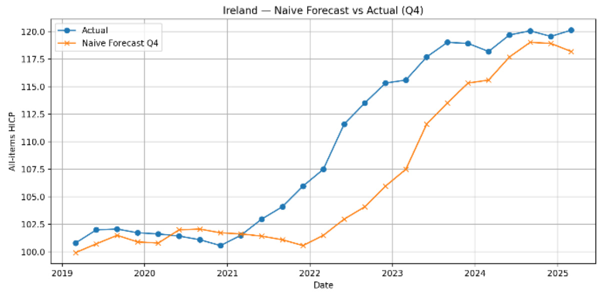
Naive Forecast Q4
All-items HICP
Date


Ireland — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date


Ireland — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date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Actual
Naive Forecast Q4
All-items HICP
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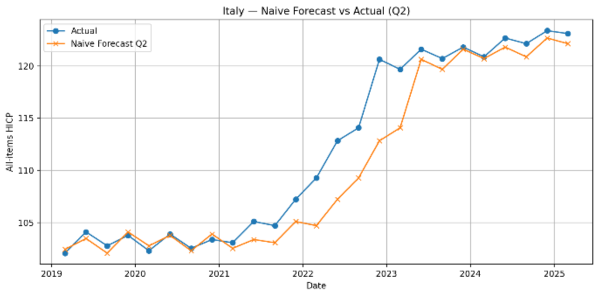
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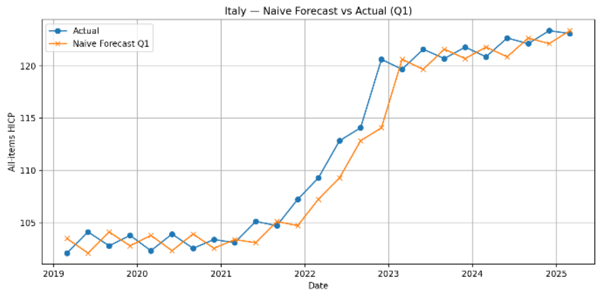
Actual
Naive Forecast Q2
All-items HICP
Date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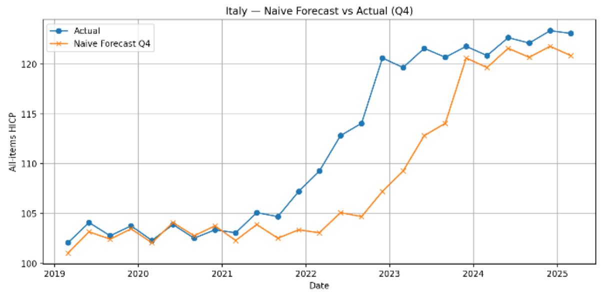
Actual
Naive Forecast Q1
All-items HICP
Date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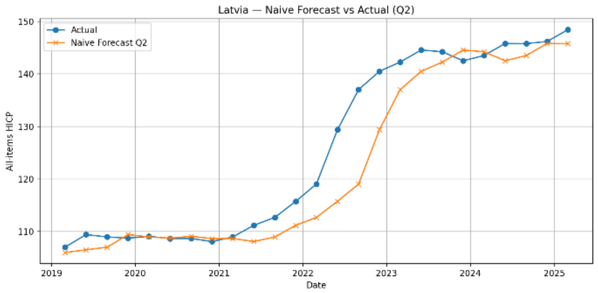
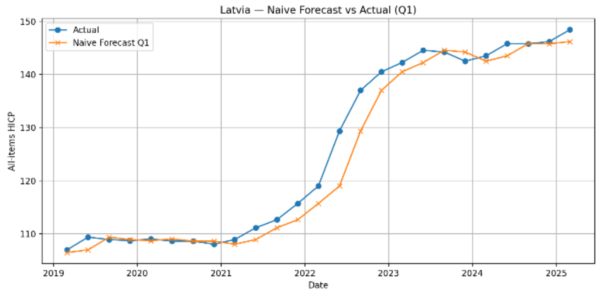
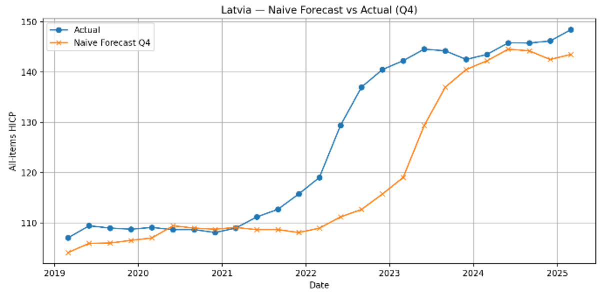
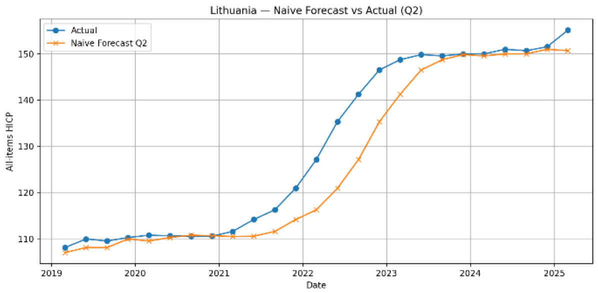
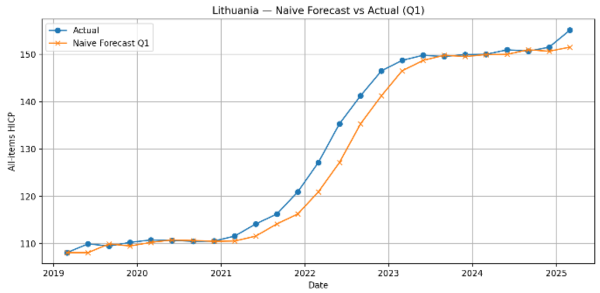
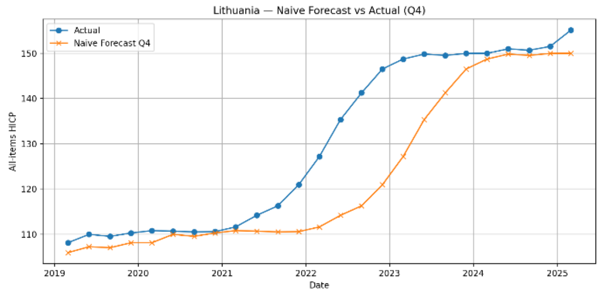
Naive Forecast Q4
All-items HICP
Date


Latvia — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date

Latvia — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date

Latvia — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date

Lithuania — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date

Lithuania — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date

Lithuania — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
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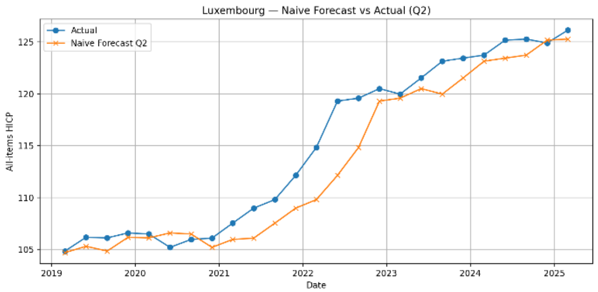
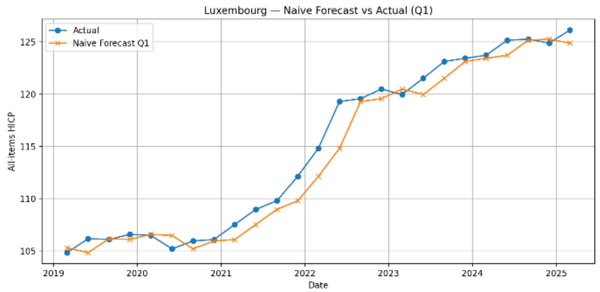
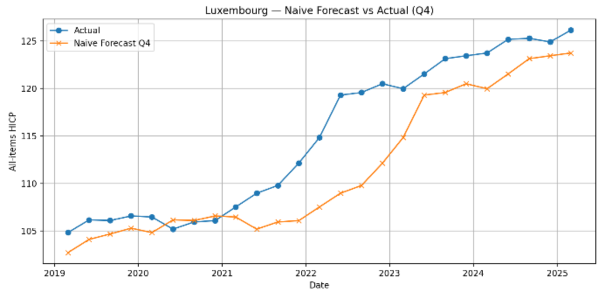
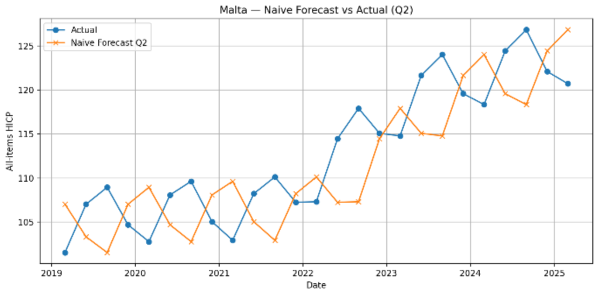
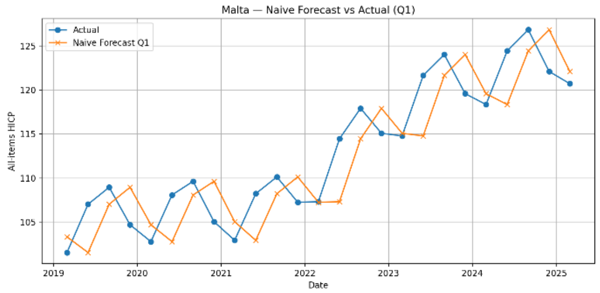

Luxembourg — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date

Luxembourg — Naive Forecast vs Actual (Q1)
Actual
Naive Forecast Q1
All-items HICP
Date

Luxembourg — Naive Forecast vs Actual (Q4)
Actual
Naive Forecast Q4
All-items HICP
Date


Malta — Naive Forecast vs Actual (Q2)
Actual
Naive Forecast Q2
All-items HICP
Date


Malta — Naive Forecast vs Actual (Q1)
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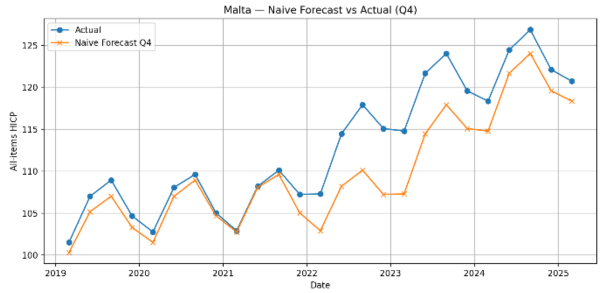
Naive Forecast Q1
All-items HICP
Date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Naive Forecast Q4
All-items HICP
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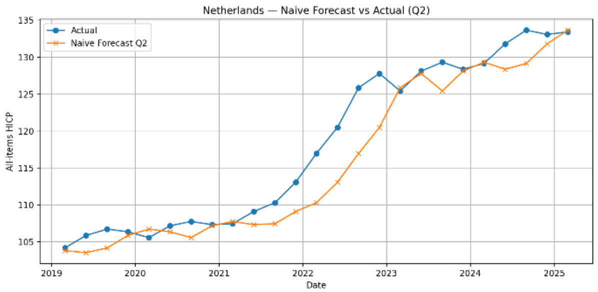
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All-items HICP
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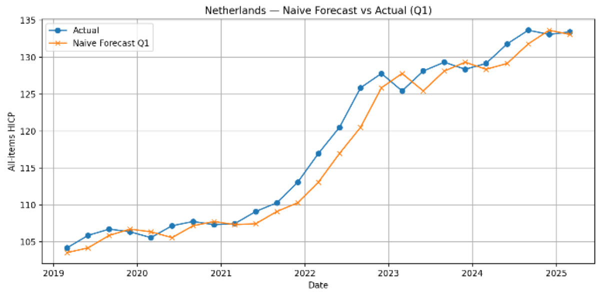
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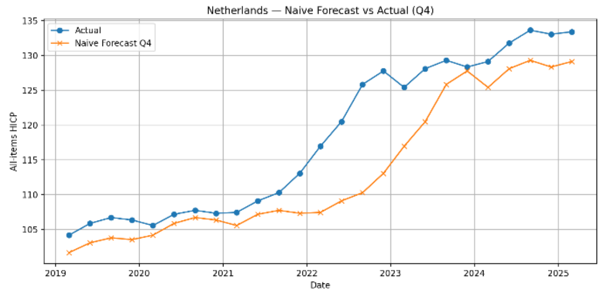
Actual
Naive Forecast Q1
All-items HICP
Date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Naive Forecast Q4
All-items HICP
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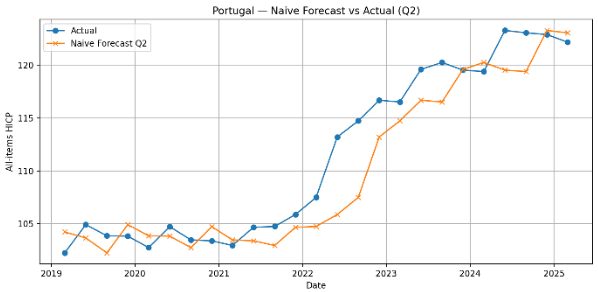
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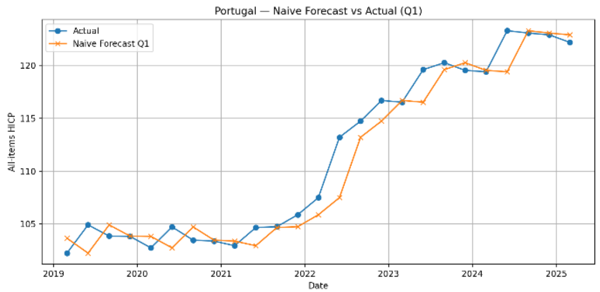
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Naive Forecast Q1
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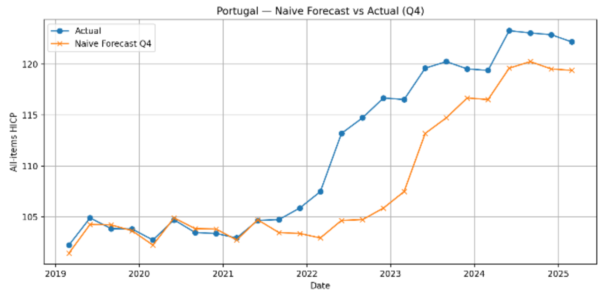
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Naive Forecast Q4
All-items HICP
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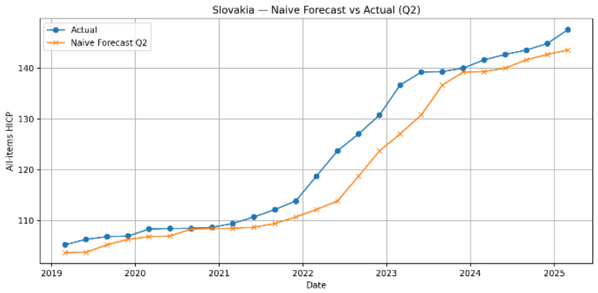
Slovakia — Naive Forecast vs Actual (Q2)
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Naive Forecast Q2
All-items HICP
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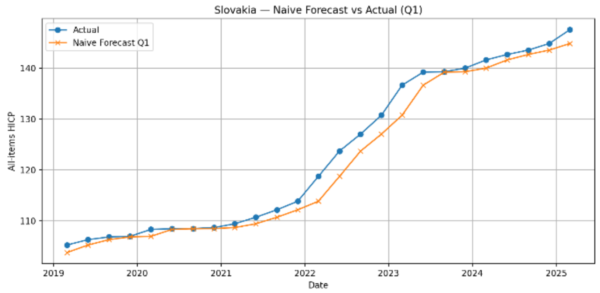
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All-items HICP
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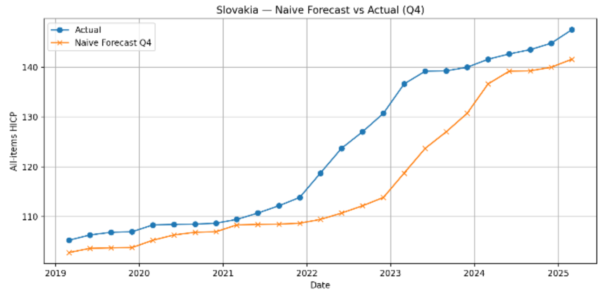
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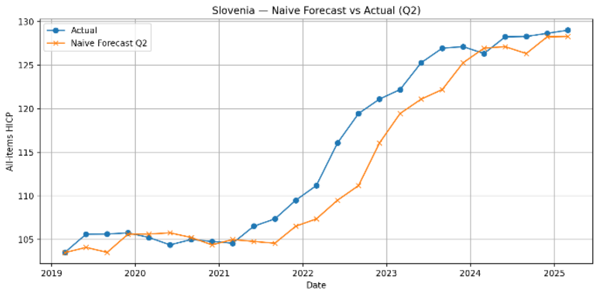
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Naive Forecast Q2
All-items HICP
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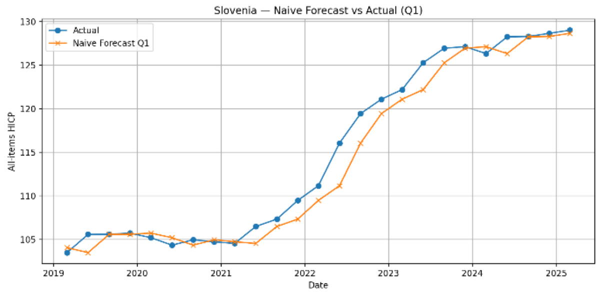
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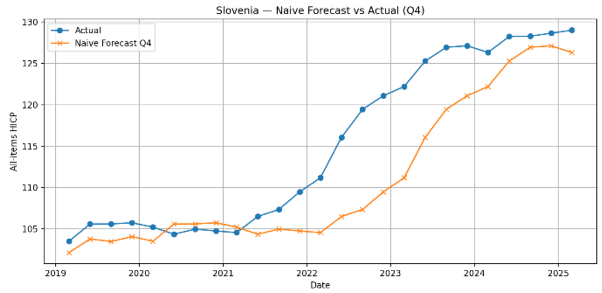
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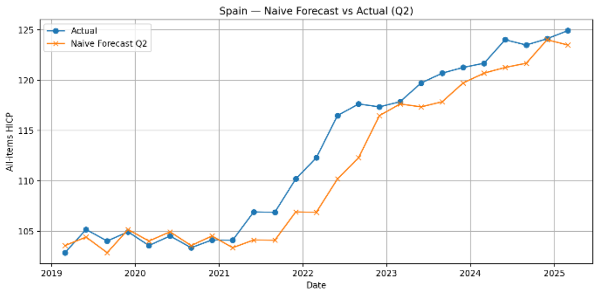
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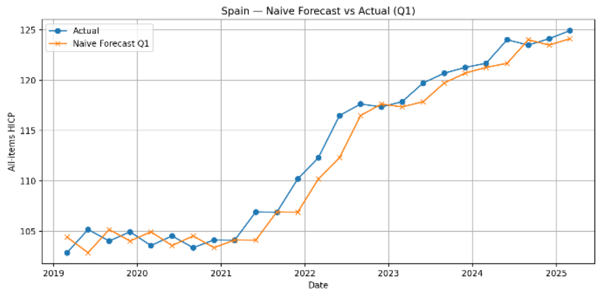
Naive Forecast Q2
All-items HICP
Date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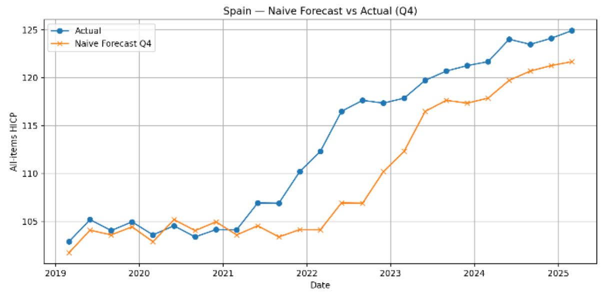
Naive Forecast Q1
All-items HICP
Date


Spain — Naive Forecast vs Actual (Q4)
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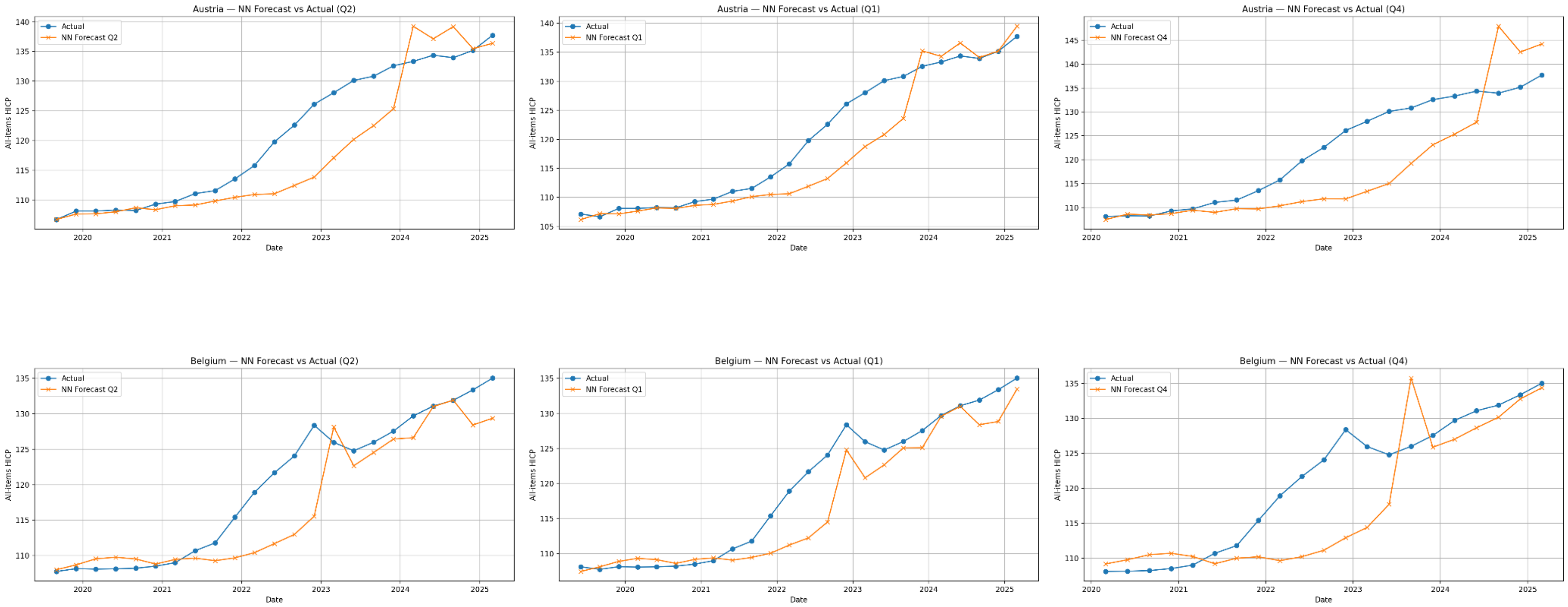
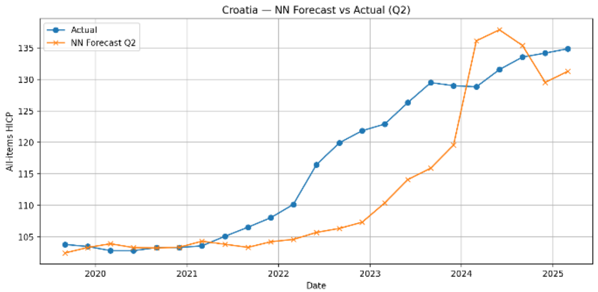
Naive Forecast Q4
All-items HICP
Date

Figure A5. NN (Neural Networks) model: Actual vs Forecasts (Eurozone counties plus EA-20)




Croatia — NN Forecast vs Actual (Q2)
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NN Forecast Q2
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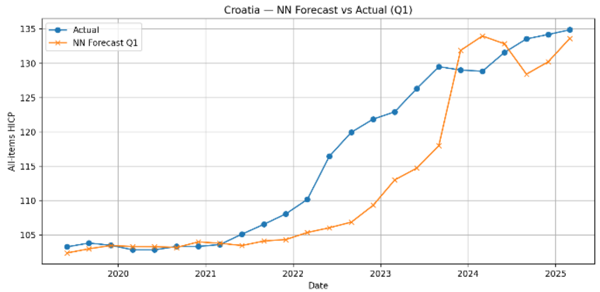
Croatia — NN Forecast vs Actual (Q1)
Actual
NN Forecast Q1
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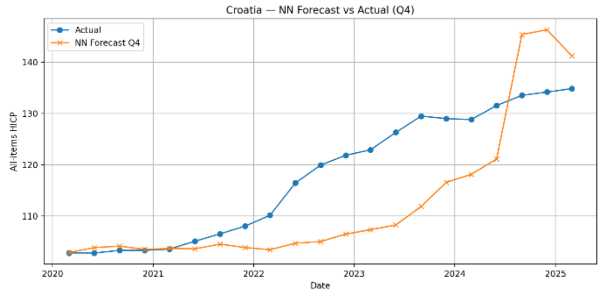
Croatia — NN Forecast vs Actual (Q4)
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NN Forecast Q4
All-items HICP
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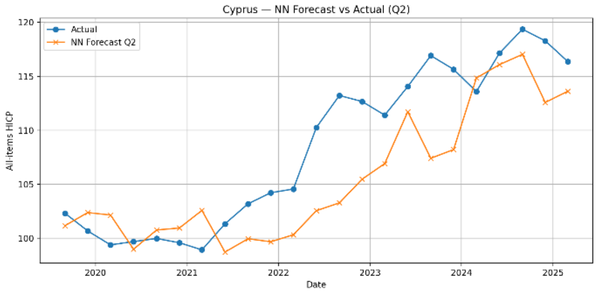
Cyprus — NN Forecast vs Actual (Q2)
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NN Forecast Q2
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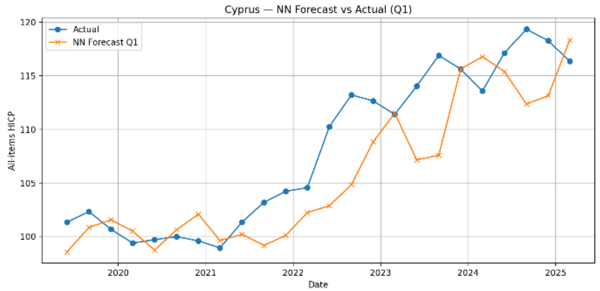
Cyprus — NN Forecast vs Actual (Q1)
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NN Forecast Q1
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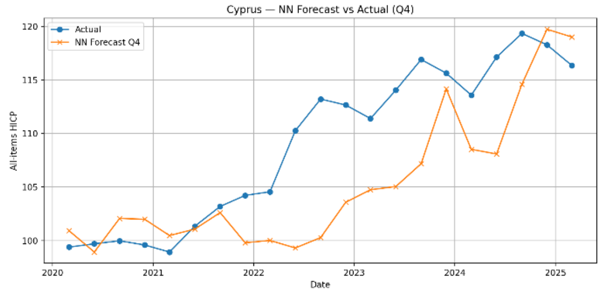
Cyprus — NN Forecast vs Actual (Q4)
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NN Forecast Q4
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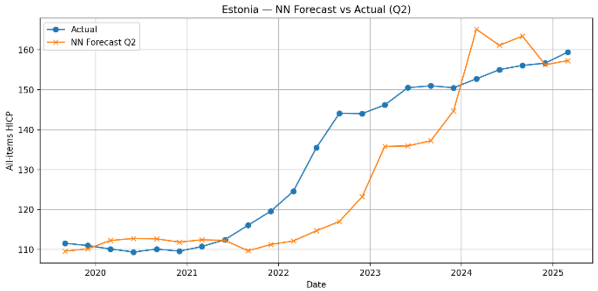
Estonia — NN Forecast vs Actual (Q2)
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NN Forecast Q2
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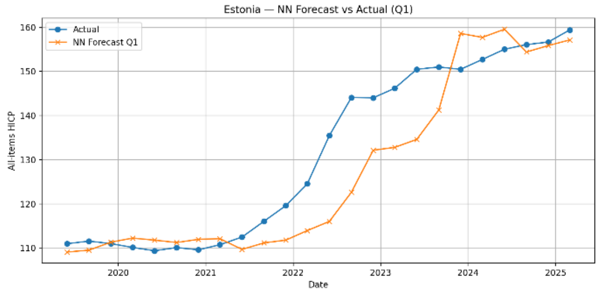
Estonia — NN Forecast vs Actual (Q1)
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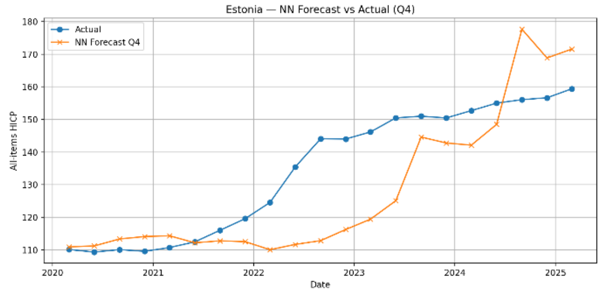
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NN Forecast Q4
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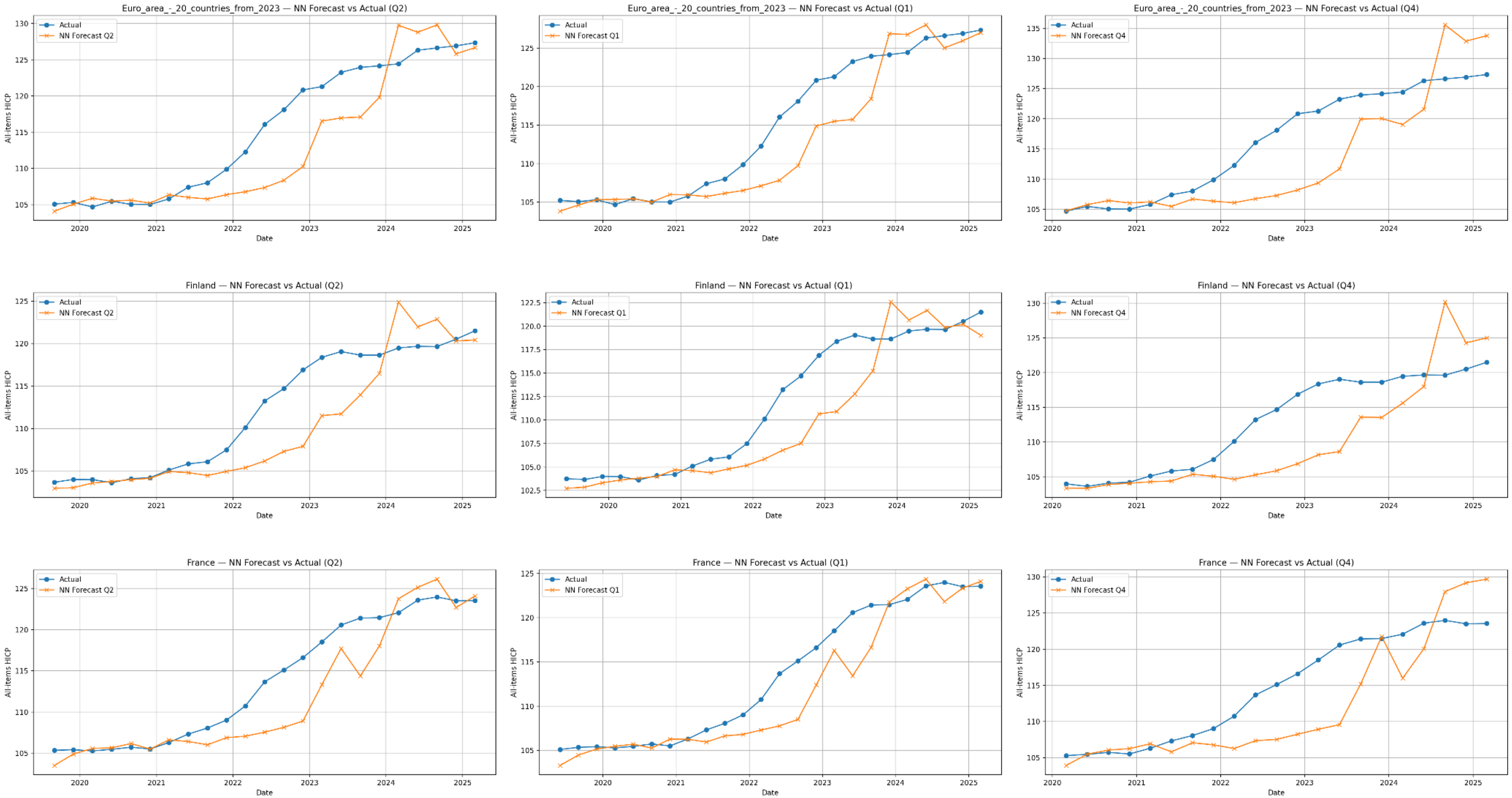
Euro_area_-_20_countries_from_2023 — NN Forecast vs Actual (Q2)
Actual
NN Forecast Q2
All-items HICP
Date
Euro_area_-_20_countries_from_2023 — NN Forecast vs Actual (Q1)
Actual
NN Forecast Q1
All-items HICP
Date
Euro_area_-_20_countries_from_2023 — NN Forecast vs Actual (Q4)
Actual
NN Forecast Q4
All-items HICP
Date
Finland — NN Forecast vs Actual (Q2)
Actual
NN Forecast Q2
All-items HICP
Date
Finland — NN Forecast vs Actual (Q1)
Actual
NN Forecast Q1
All-items HICP
Date
Finland — NN Forecast vs Actual (Q4)
Actual
NN Forecast Q4
All-items HICP
Date
France — NN Forecast vs Actual (Q2)
Actual
NN Forecast Q2
All-items HICP
Date
France — NN Forecast vs Actual (Q1)
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France — NN Forecast vs Actual (Q4)
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All-items HICP
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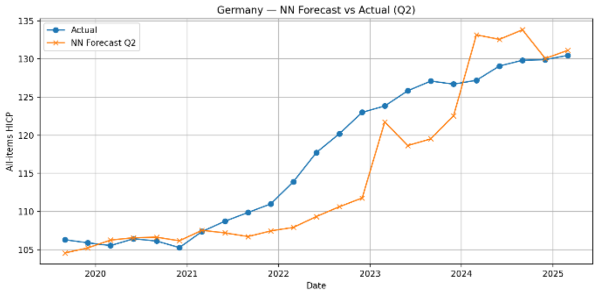
Germany — NN Forecast vs Actual (Q2)
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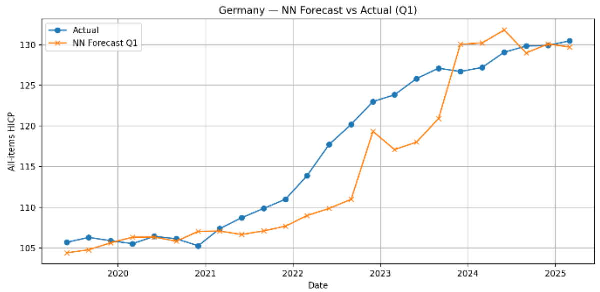
Germany — NN Forecast vs Actual (Q1)
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NN Forecast Q1
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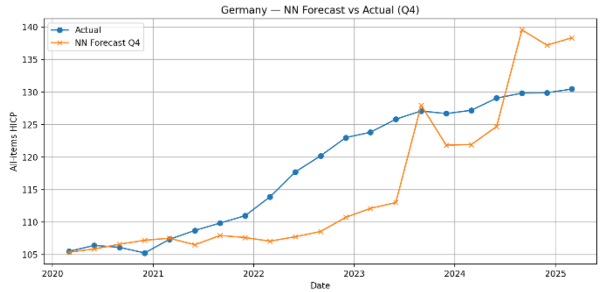
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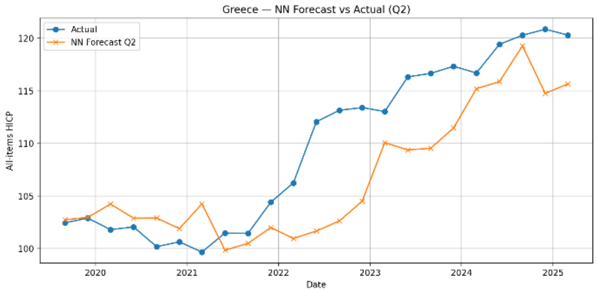
Greece — NN Forecast vs Actual (Q2)
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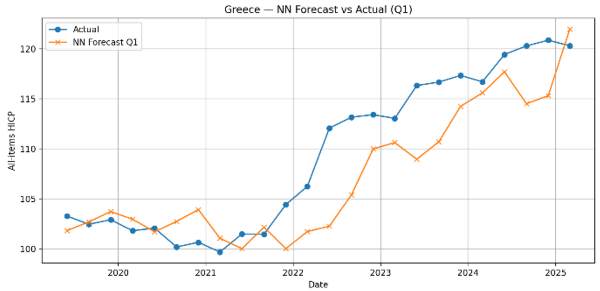
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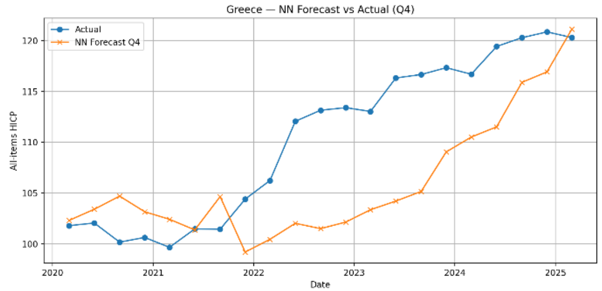
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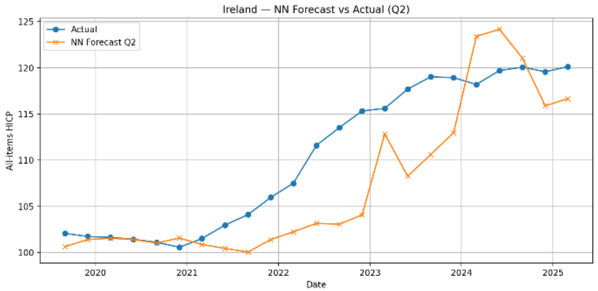
Ireland — NN Forecast vs Actual (Q2)
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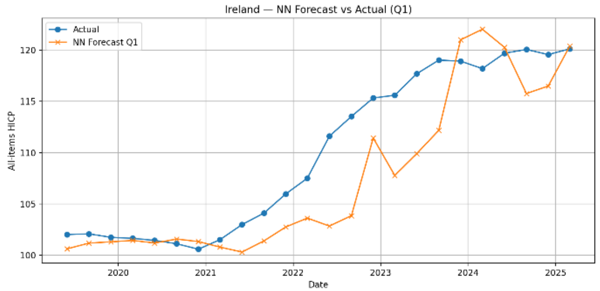
Ireland — NN Forecast vs Actual (Q1)
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NN Forecast Q1
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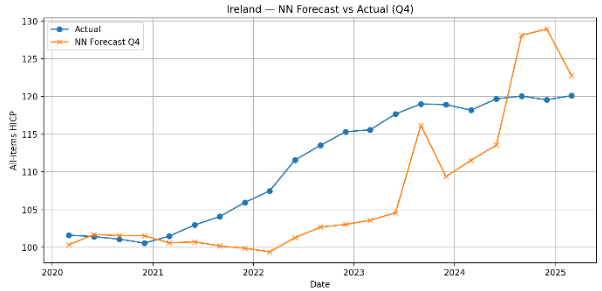
Ireland — NN Forecast vs Actual (Q4)
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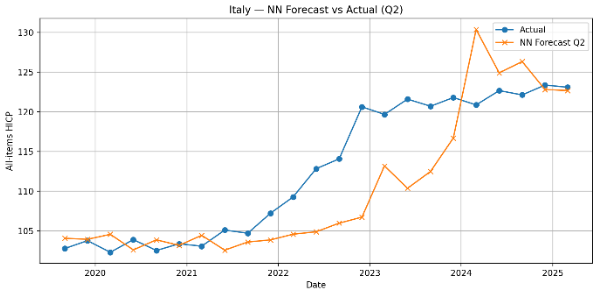
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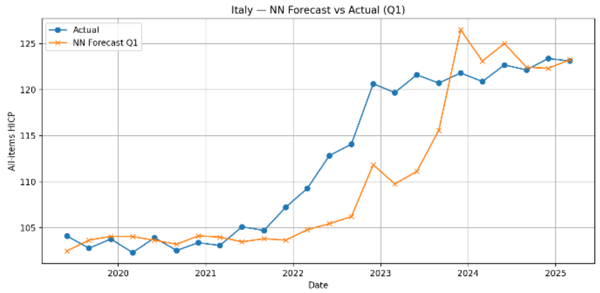
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NN Forecast Q1
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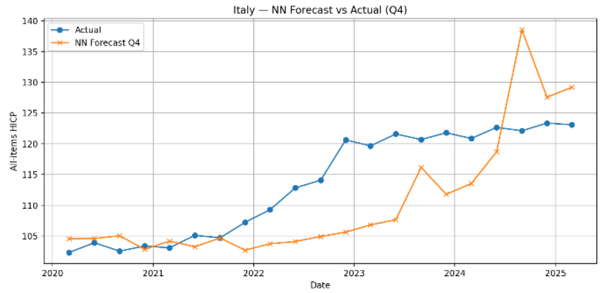
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NN Forecast Q4
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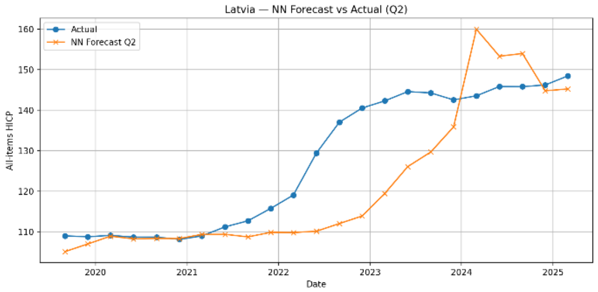
Latvia — NN Forecast vs Actual (Q2)
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NN Forecast Q2
All-items HICP
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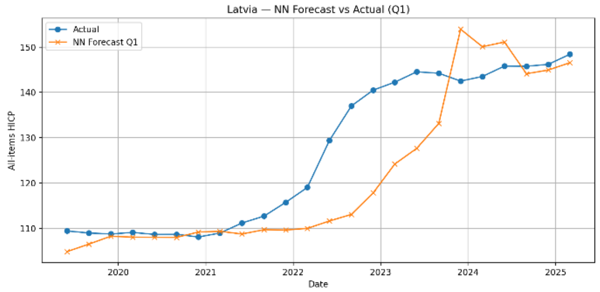
Latvia — NN Forecast vs Actual (Q1)
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NN Forecast Q1
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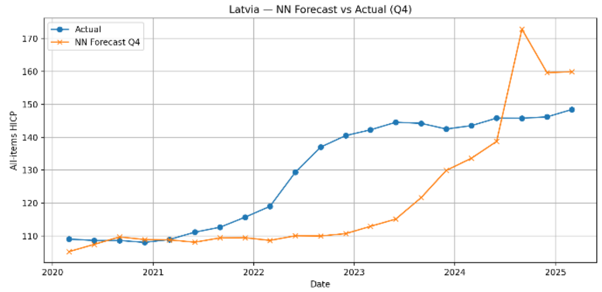
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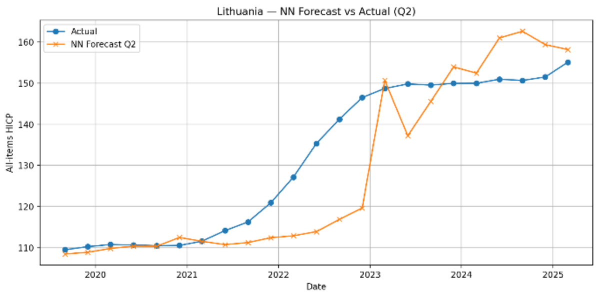
NN Forecast Q4
All-items HICP
Date


Lithuania — NN Forecast vs Actual (Q2)
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NN Forecast Q2
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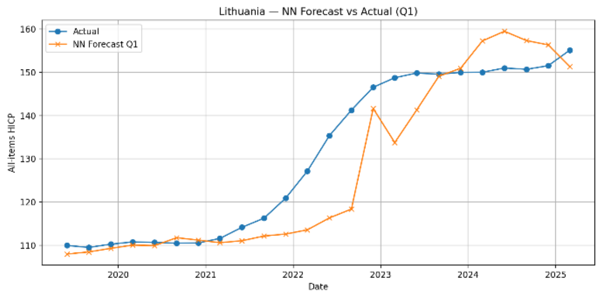
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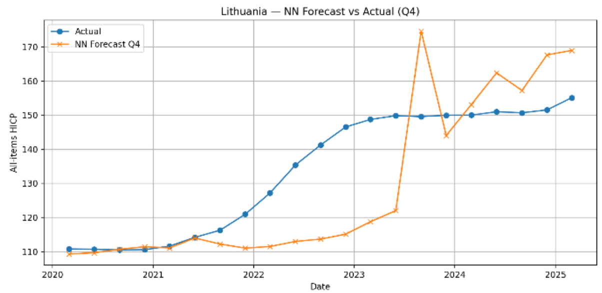
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NN Forecast Q4
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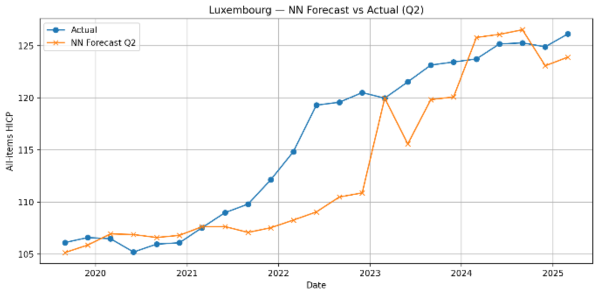
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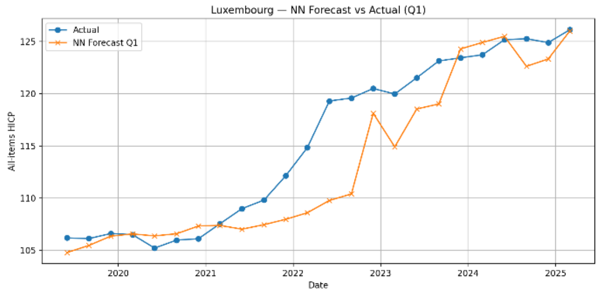
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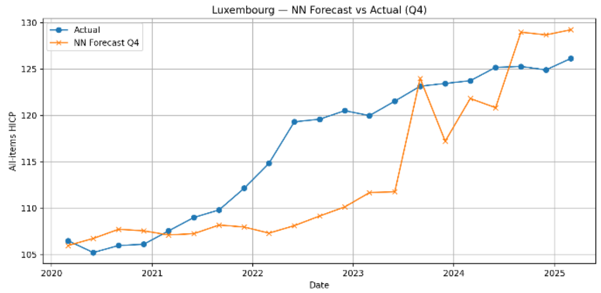
Luxembourg — NN Forecast vs Actual (Q4)
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NN Forecast Q4
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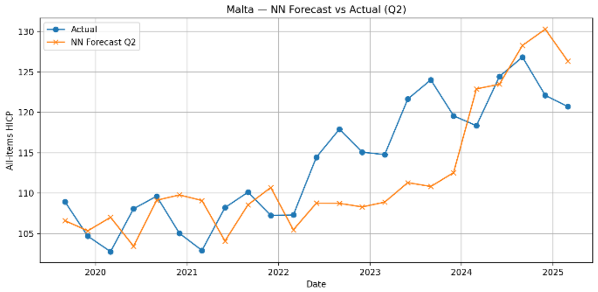
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Actual
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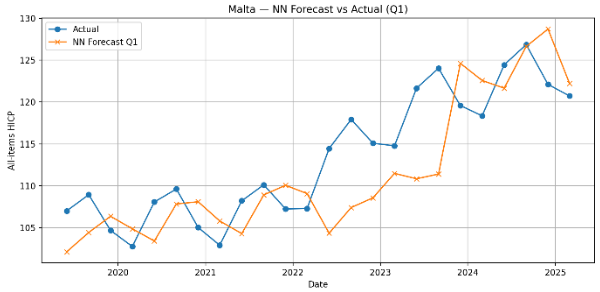
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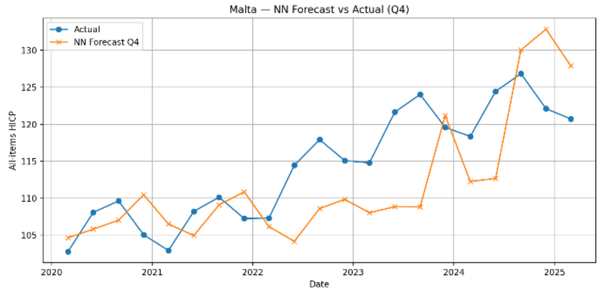
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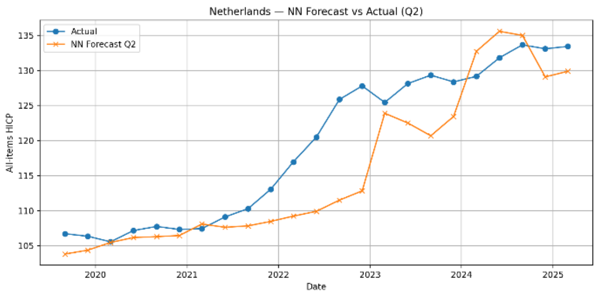
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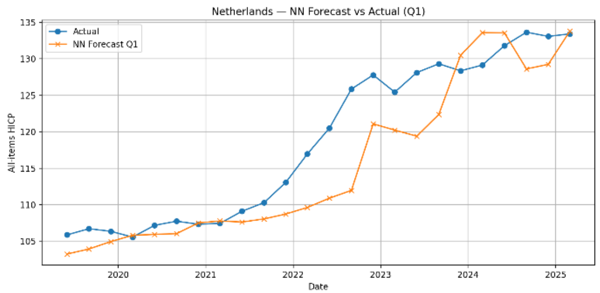
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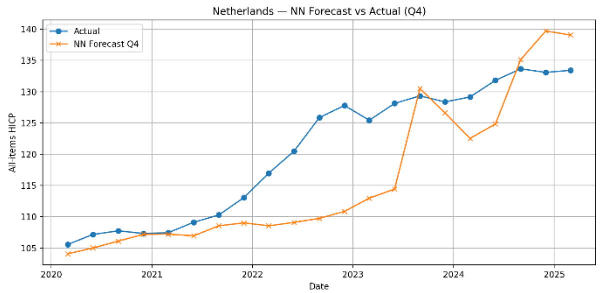
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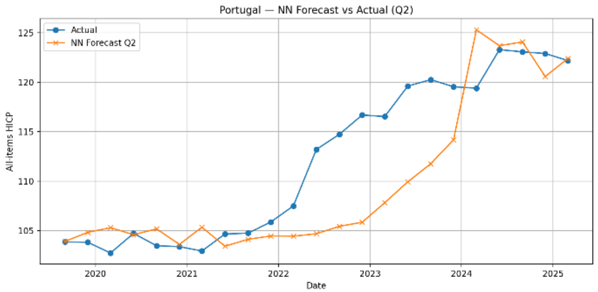
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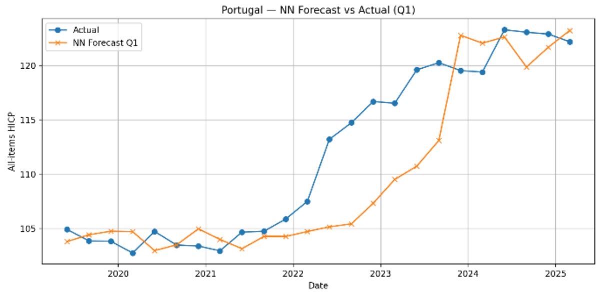
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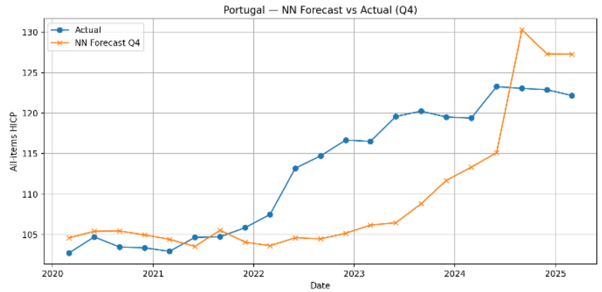
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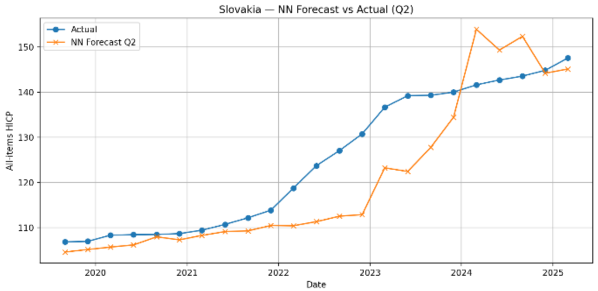
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NN Forecast Q2
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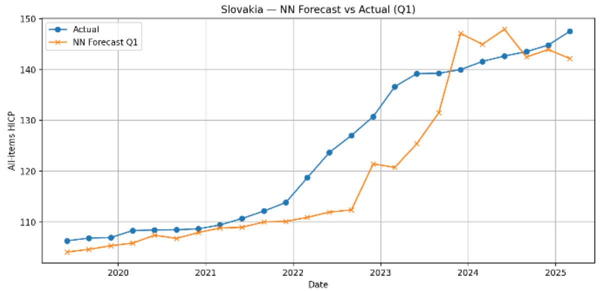
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NN Forecast Q1
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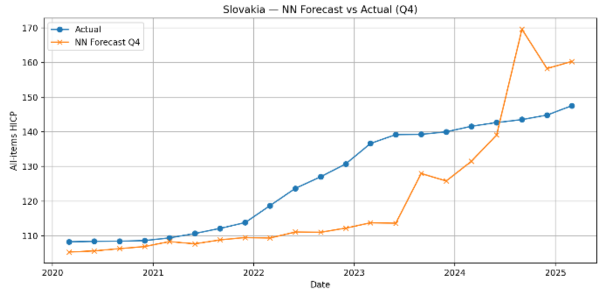
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Actual
NN Forecast Q4
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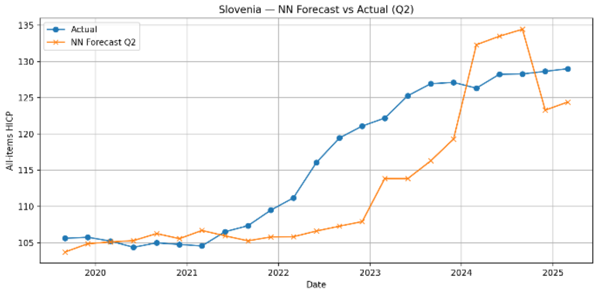
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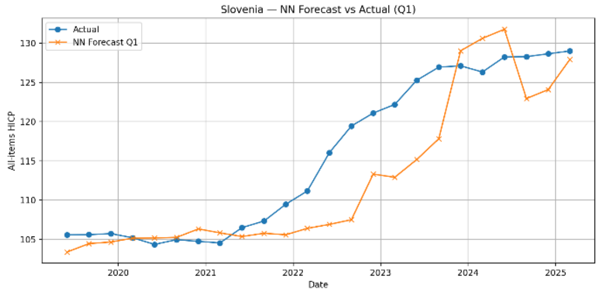
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NN Forecast Q1
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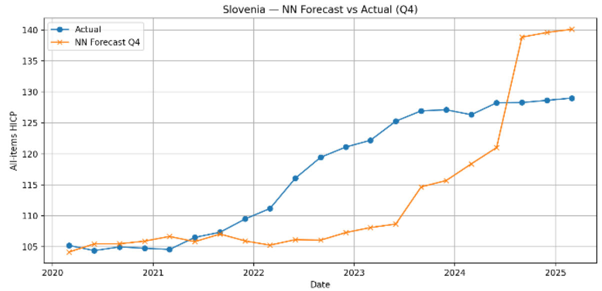
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NN Forecast Q4
All-items HICP
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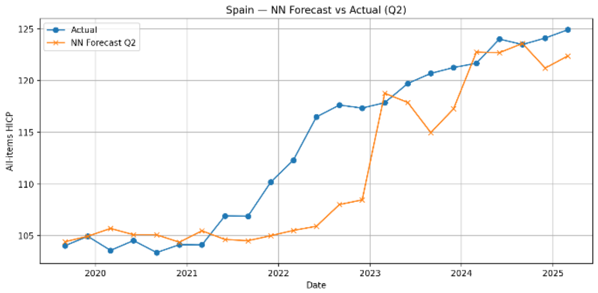
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NN Forecast Q2
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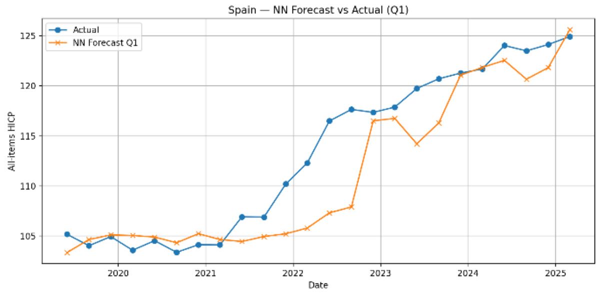
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NN Forecast Q1
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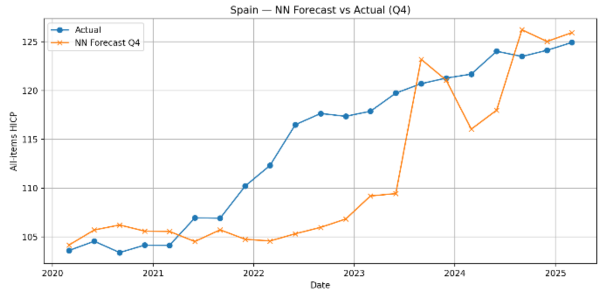
Spain — NN Forecast vs Actual (Q4)
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All-items HICP
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