Staff memo

AI-based fore-casting in Sweden

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Summary

This paper explores the application of machine learning models, specifically random forests and neural networks, for forecasting Swedish GDP and inflation using a comprehensive dataset of 120 Swedish macroeconomic and financial variables. We compare the forecasting performance of these AI-based models with traditional benchmark models such as the random walk (RW) and autoregressive (AR) models, as well as widely used forecasting models including static and dynamic factor models. The results indicate that the AI-based forecasting models, random forests and neural networks, outperform the benchmark time series models, especially when forecasting CPI inflation.

Our findings suggest that incorporating nonlinear modelling techniques through machine learning methods can significantly improve forecasting accuracy for macroeconomic indicators. The study highlights the importance of model nonlinearity over the mere expansion of datasets and suggests that AI-based models like random forests offer valuable enhancements to benchmark models in economic forecasting.

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1 Introduction

In the rapidly evolving landscape of economic analysis, central banks are increasingly seeking innovative tools to enhance their forecasting capabilities. Forecasting − the practice of predicting future economic indicators using the most recent available data − is a critical component in the policymaking process. Accurate forecasts of e.g. GDP growth and inflation allow central banks to make timely decisions to stabilise economies in pursuit of their monetary policy goals.

Traditionally, central banks have relied on classical econometric models and economic theories in their forecasting efforts. These models often utilize a combination of leading indicators and simple regression techniques to estimate current economic conditions. While these methods have provided valuable insights, they may not fully capture the complexity and dynamism of modern economies. The explosion of available data in recent years provides possibilities for improvements.

The past decade has witnessed a significant expansion in both the volume and variety of data sources relevant to economic forecasting. Non-traditional data—such as transaction-level financial data, social media activity, real-time consumer sentiment, and even satellite imagery—offer a wealth of information that can enhance the understanding of economic trends, see e.g. Jain (2019) and Löf and Stockhammar (2024). However, extracting meaningful signals from these rich and complex datasets poses significant analytical challenges.

This is where advanced machine learning (ML) and artificial intelligence (AI) models come into play. Techniques such as random forests (Breiman, 2001), deep learning models (including convolutional neural networks and recurrent neural networks, see e.g. Goodfellow et al. (2016)), and transformer architectures have shown great promise in handling large, unstructured datasets and uncovering intricate patterns that traditional models might miss.

There are several potential benefits of ML models in forecasting. One is that these models can process vast amounts of data and identify nonlinear relationships, potentially leading to more accurate forecasts, see e.g. Jönsson (2020) and Chen et al. (2023). They are also adept at handling high-frequency data and non-traditional data, allowing central banks to update their forecasts more frequently as new data become available, see e.g. Lenza et al. (2023) and Goulet Coulombe (2024).

A critical aspect of integrating machine learning into central bank practices is ensuring that these models complement rather than replace traditional econometric approaches. By comparing and benchmarking ML models against state-of-the-art time series models, central banks can assess their relative performance and identify areas where AI provides added value. Furthermore, understanding the inner workings of ML models through explainability techniques allows economists to extract economic insights from complex algorithms. This alignment ensures that policy decisions remain grounded in sound economic reasoning, see the discussions in e.g. Mullainathan and Spiess (2017) and Rudin (2019).

In this memo, we use ML models for forecasting the monthly Swedish GDP indicator and CPI inflation. As explanatory variables we use a dataset of 120 Swedish and foreign macroeconomic and financial variables. The results demonstrate that some ML type models, specifically the random forest (RF) and neural network (NN) models, generate the most accurate inflation forecasts across all horizons, outperforming the random walk benchmark model by 10–40 percent. The RF model exhibits superior forecasting precision for the GDP indicator, though the differences are smaller in comparison. A key conclusion drawn from this analysis is that the determining factor for forecasting accuracy is not the breadth of the information set, but the nonlinearity of the model.[2] The study underscores that AI techniques, with their ability to handle complexity, large datasets, and dynamic real-time information, offer substantial potential to yield new insights and augment the toolkit for time series forecasting.

The findings in this memo are consistent with similar exercises from other studies using data from the United States, the United Kingdom, Canada, and other European countries, see for instance Goulet Coulombe (2022, 2024) and Anesti et al. (2024).

In Chapter 2, we describe all the forecasting models used and evaluated in our analysis, including simple benchmark models. Chapter 3 looks at the data used and how they are transformed for analysis. In Chapter 4, we report the results of our forecasting exercises, comparing the performance of the different models using metrics like the Root Mean Squared Error (RMSE) to assess their predictive accuracy. Finally, Chapter 5 concludes.

2 Models

In this chapter we will describe all the models used and evaluated in this memo. Throughout we will compare the forecasting performance of the AI-based models with simple benchmarks described in Section 2.1 and with widely employed forecasting models described in Section 2.2. Sections 2.3 and 2.4 describe the AI-based random forests and neural network models.

2.1 Simple benchmark models

The **random walk** (RW) and the **autoregressive** (AR) models are fundamental concepts in the field of time series analysis and are used as benchmark models when evaluating the forecasting performance of the more complex models suggested in this paper.

[2] The random forest is a nonlinear model because it combines many decision trees that divide data into separate regions with different predictions instead of following a straight line. By using multiple trees with different dividing points, random forests create complex patterns that cannot be described by a simple linear relationship.

A random walk model is a stochastic process where each step is determined by a random draw. It is expressed as:

$$Y_t = Y_{t-1} + e_t,$$

where Y_t is the current value of the variable of interest, Y_{t-1} is the value at the previous time step, and e_t is a white noise error term uncorrelated with previous observations of Y. In a random walk, the best prediction for the next observation is simply the current observation, since the changes from one step to another are completely random. A random walk is non-stationary, as its properties (mean, variance) change over time due to the cumulative effect of the random components.

In contrast, an Autoregressive model of order p, or AR(p) model, is a simple type of time series model that uses a linear function of the previous value to predict the current value. It is represented as:

$$Y_t = c + \sum_p \phi_p Y_{t-p} + e_t,$$

where c is a constant and ϕ_p is the autoregressive coefficient matrix for each lag. The AR(p) model is stationary if all roots of its characteristic polynomial lie outside the unit circle, meaning that its properties do not change over time. This makes it a suitable model for many time series that exhibit some form of autocorrelation.

Both the random walk and AR model are often used as benchmarks in model evaluation. If the more complex models used in this paper cannot outperform these simple models in terms of forecasting accuracy, it would indicate that the additional complexity of the model is not justified. In other words, the random walk and AR model provide a baseline against which other models' performance can be judged.

The random walk and AR models provide a straightforward benchmark to assess the added value of more complex models.

2.2 Benchmark forecasting models

In this section we will describe a couple of widely used forecasting models which we use for comparison in this memo.

One of these is **factor models** which are good at handling and interpreting large, complex datasets. By focusing on common factors that explain the shared variance among variables, these models streamline analysis and enhance forecasting capabilities. The determination of the number of factors and lagged terms through information criteria ensures that models remain both accurate and parsimonious. This approach has become a cornerstone in econometric modelling and has broad applications in finance, economics, and other fields that involve high-dimensional data analysis.

In this paper, we employ two types of factor models, **static** (or ordinary) and **dynamic**. Both are making use of principal components (PCs) derived through a statistical technique known as Principal Component Analysis (PCA). This method transforms the original correlated variables into a new set of uncorrelated variables called principal components. Each principal component is a linear combination of the original variables and constructed to capture as much variance in the data as possible. The first principal component accounts for the highest variance, the second captures the next highest variance while remaining uncorrelated with the first, and this process continues for subsequent components. By focusing on principal components, we effectively summarize the information contained in a large number of variables into a few key factors. This reduction not only simplifies the data but also helps highlight the most influential patterns and relationships inherent in the dataset.

The fundamental difference between static and dynamic factor models lies in the handling of time dynamics. Static factor models are designed to capture the common variation among a set of observed variables using a smaller number of unobserved latent factors. The term "static" refers to the fact that these models consider relationships at a single point in time, without explicitly modelling the temporal dynamics of the factors or idiosyncratic components. Static factor models thus provide a snapshot analysis suitable for static data. An early text about (static) factor models is Lawley and Maxwell (1971) while e.g. Ng (2006) and Gianonne et al. (2008) have popularized the method on macroeconomic data. On the other hand, dynamic factor models (DFMs) offer a framework to model and predict time-dependent behaviours in complex datasets. DFMs are statistical models designed to extract common latent factors that drive the co-movements among a large number of time series variables. In macroeconomic forecasting, DFMs are particularly advantageous due to their ability to condense information from numerous economic indicators into a few unobserved factors, thereby reducing dimensionality and capturing the underlying economic structure. The factors are then conceptualized as representing a few unobserved processes related to the state of the economy that drive a large set of underlying macroeconomic variables. See Geweke (1977) for an early reference on dynamic factor models and Forni et al. (2000) and Bańbura et al. (2011) for later well cited papers.

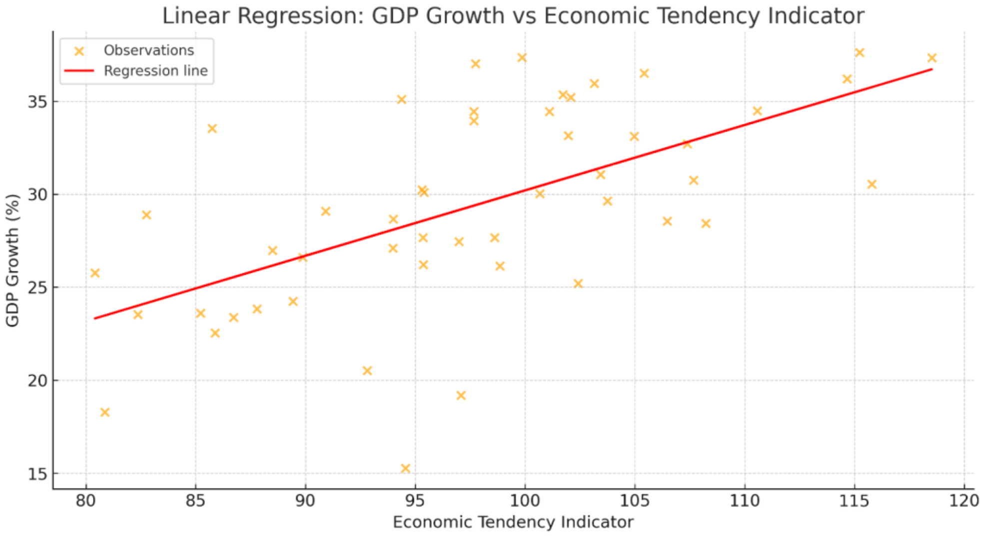
A common challenge in both static and dynamic factor models is selecting the appropriate number of factors. The choice is crucial for model accuracy and interpretability. Including too many factors can lead to overfitting, where the model becomes excessively complex and captures random noise rather than meaningful patterns. Conversely, too few factors may result in underfitting, failing to capture essential information. We refer to the dedicated section on hyperparameter selection to clarify how we address this process within our framework for all models.

2.3 Random forest models

Random forest (RF) is an ensemble learning method introduced by Breiman in 2001 to improve predictive accuracy and reduce the variance often seen in traditional decision trees. Single decision trees tend to overfit training data, especially with complex and volatile data like macroeconomic time series. RF addresses this by creating a "forest" of decision trees, each trained on a randomly bootstrapped subset of the data. By aggregating predictions across all trees in the forest, RF reduces variability and provides more stable, accurate forecasts, see e.g. Biau and Scornet (2016).

Suppose we are trying to predict GDP growth with one indicator, the economic tendency indicator.[3] The parametric approach would be to run a regression of GDP growth on the indicator. See Figure 1 for an illustration of the simple regression problem.

Figure 1. Example of a simple linear regression

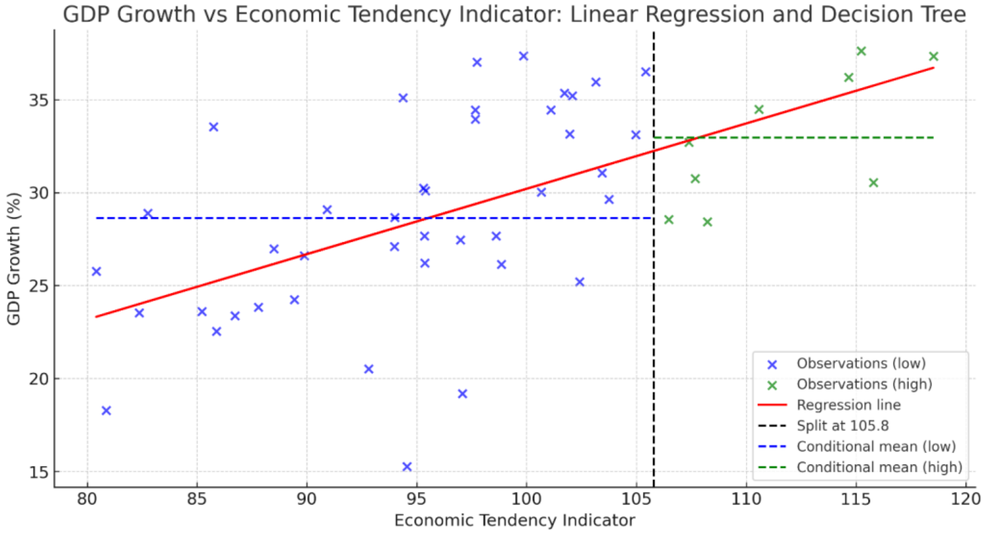


Note: Artificial data.

Now, instead, the idea is to split the feature or predictor, the indicator, data space into two regions. When we want to make a prediction, we find the region where the current indicators are located. Then, we look into our dataset and compute the average of previous outcomes for GDP growth rate for this region and use this as our prediction. Figure 2 illustrate the idea of the decision tree in comparison with a linear regression model.

[3] The economic tendency indicator is a monthly indicator of the present economic situation published by the National Institute of Economic Research (NIER).

Figure 2. Example of a simple decision tree for forecasting

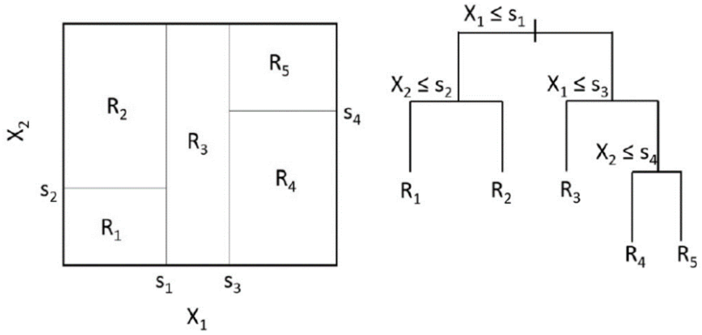


Note: Artificial data.

The question is how to select the split of the regions optimally when estimating the model. This is achieved by adjusting the binary split that maximizes the fit (minimal squared forecast errors) for the training data. In the example of Figure 2, it shows that we split the economic tendency indicator by 105.8, then we have the high and low GDP expected growth rate (in blue and green crosses, separately).

It's helpful to further consider the concept of a Regression Tree when there is more than one predictor. The regression tree is a nonparametric model that recursively splits the data space, spanned by multiple predictors, into regions using binary divisions. Each split is determined by a threshold on one of the predictor variables that minimizes prediction errors within the resulting regions. To illustrate how a regression tree functions, let us consider an example from Hastie (2009). Imagine a simplified regression problem where X1 and X2 are predictor variables and Y is the dependent variable. The tree might first split the data at X1 = s1, creating two regions based on this threshold. Then, the left region (where X1 < s1) is split based on X2=s2, while the right region is split at X1=s3. Finally, the region on the right side of X1 (i.e., X1> s3) is further divided at X2=s4. Hence, the final structure divides the predictor space into five regions, with the model's prediction for Y in each region set as the average of values within that region. The following figure summarizes this regression tree model, see Medeiros et al. (2021):

Figure 3. Example of a regression tree



This structure creates a nonlinear model, as it approximates an unknown nonlinear function by using local predictions based on averages in these segmented regions. At each step, the model determines the optimal split by selecting the variable and threshold that minimize the sum of squared errors within each resulting node.

However, despite being simple and interpretable, a single decision tree suffers from overfitting. Each branch of a tree represents a highly specific pattern, which often reflects the noise or random fluctuations in the training data rather than the underlying trends. As a result, the model performs well on training data but poorly on unseen data.

RF tackles this issue by generating a “forest” of decision trees, each trained on a unique sample of the dataset obtained through bootstrapping (random sampling with replacement). This ensures that each tree is trained on a different subset of the data, capturing different aspects of the relationships between variables. Each tree makes its own prediction, and RF aggregates these predictions by taking an average, resulting in a more stable and accurate outcome.

As a nonlinear model, RF is especially effective for capturing complex relationships between variables without making assumptions about their functional forms. In summary, RF is a crucial model for forecasting tasks, as it minimizes variance and enhances predictive accuracy compared to individual trees, particularly in high-variability or noisy contexts like economic time series. Thanks to its ability to capture complex, nonlinear patterns, RF provides a powerful tool for predicting future economic trends, helping to reduce the risk of overfitting and improve forecast reliability.

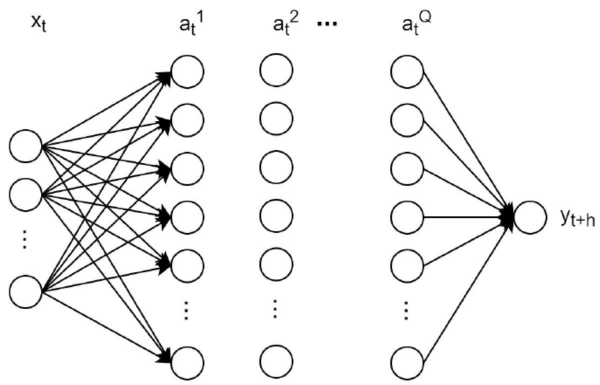
We configured 500 trees on bootstrapped samples, by randomly sampling the data with replacement. This setup allows the model to average over a large number of estimates, reducing prediction variance without an excessive computational load. Additionally, to further ensure diversity among trees, the model randomly selects one-third of the predictor variables to perform each split in each tree. This strategy prevents any single variable from dominating the splits and strengthens the model’s robustness by promoting diverse tree structures. Each tree grows until every leaf (the final split sample) has a minimum of 5 observations, limiting overfitting by avoiding overly narrow, specific partitions that could capture noise rather than meaningful patterns in the data.

On the other hand, our RF model can be trained with different combinations of predictor variables, enabling it to accommodate multiple forecasting perspectives. Specifically, the model can use either (1) only the lagged values of Principal Components (PCs), (2) the lagged values of all variables in the dataset, or (3) a combination of both PCs and lagged variables (potentially including only autoregressive terms of the target variable). The third approach is generally preferred, as combining both PCs and lagged variables has shown to yield the best forecasting accuracy. This finding highlights the importance of using a wide range of information alongside the model's nonlinear structure to maximize predictive power. However, the model's performance with only PCs or only lagged variables also remains competitive, outperforming standard benchmark models. Once again, this demonstrates that the key factor in improving forecasting performance is the nonlinearity of the model rather than merely increasing the number of variables considered.

2.4 Neural network models

Another ML model that has received much interest in forecasting exercises due to its flexibility and power is the neural network (NN). One of the earliest comprehensive studies on the use of neural networks in macroeconomic forecasting is Kuan and Liu (1995) but NNs are still frequently used, see e.g. Schmidt-Hieber (2020), Farell et al. (2021), Chronopoulos et al. (2024). Like the RFs, NNs can capture complex nonlinear relationships among variables without requiring explicit assumptions about their functional form. In this project, we focus primarily on the fully connected feed-forward neural network (FFNN), which is one of the simplest but still effective architectures. This model is inspired by the functioning of the human brain. Indeed, it consists of multiple layers of interconnected nodes, or neurons. Each neuron in a given layer receives signals from the neurons in the previous layer, processes this information, and sends a new signal to the next neurons in the subsequent layer. The signal received by each neuron is a weighted sum of the outputs from the preceding layer, plus a bias term. This linear combination is then passed through a nonlinear activation function, which determines the neuron's output. Figure 4 illustrates a general schematic representation of such a network.

Figure 4. Example of Feed-forward neural network



The structure of the FFNN includes three types of layers: (i) an input layer that processes raw data (x_t), (ii) one or more hidden layers where the data undergo transformations, and (iii) an output layer that delivers the model's prediction (y_{t+h}).

Each node in a hidden layer is connected to all nodes in the subsequent layer. This means that each node receives as input a linear combination of the outputs (*a*) from the previous layer, represented as *w'a+b*, where *w* is the vector of weights, and *b* is the bias term. This linear transformation is then passed through a nonlinear activation function, such as *σ(w'a+b)*, to produce the node's output. The inclusion of the nonlinear transformation enables the network to approximate intricate relationships in the data, which are often not captured by linear models.

For our implementation, we employ the Rectified Linear Unit (ReLU) as the activation function for the hidden layers. This is defined as: ReLU(z)=max(0,z). In other words, this activation function outputs the input value itself if it is positive and 0 otherwise. ReLU has become the standard in modern deep learning due to its computational efficiency and superior performance in practice, see e.g. Goodfellow et al. (2016). It also facilitates faster convergence during training compared to other functions. For the output layer, instead, we employ a linear activation function to produce continuous-valued predictions appropriate for forecasting.

As with other models in this project, the input vector x_t contains the macroeconomic predictors and their lags. However, in accordance with standard practices for neural networks, the data is first normalized to fall within a range of -1 to 1. This normalization ensures that all covariates are treated with equal importance *a priori*, preventing variables with larger scales from exerting greater influence on the model.

The task of training the FFNN involves estimating the weights and the bias for each node of each layer. So given an initialization for *w* and *b* (using the Glorot initialization method in our case), the objective is to minimize the network's loss function. The loss function is the quadratic mean squared errors (MSE), which measures the in-sample mean-squared difference between the predicted values and the actual values, and the optimization algorithm is the gradient descent. This consists of iteratively adjusting the weights and biases by taking steps negatively proportional to the partial derivative of the loss function with respect to *w* and *b*. The gradients of the loss function are computed using a process called backpropagation. Backpropagation calculates the gradient layer by layer, starting from the output layer and moving backwards to the input layer.

In conclusion, the FFNN model provides a powerful framework for forecasting macroeconomic variables, leveraging its ability to learn complex nonlinear relationships. The combination of ReLU activations, robust initialization methods, and gradient-based optimization makes it particularly well-suited for high-dimensional and volatile datasets. By capturing the intricate dynamics inherent in macroeconomic data, FFNNs serve as a valuable tool for enhancing predictive accuracy.

2.5 Hyperparameters selection

The selection of hyperparameters plays a crucial role in ensuring the accuracy and stability of macroeconomic forecasting models.[4] Different models require different approaches for selecting these parameters, balancing complexity, interpretability, and forecasting performance.

For autoregressive models, the only hyperparameter to be determined is the number of lags. Lags capture the dynamic relationships and temporal dependencies within the data. This is selected using the Bayesian Information Criterion (BIC), which balances model fit and parsimony by penalizing excessive complexity. The BIC is particularly suitable for time series models as it discourages overfitting by favouring models with fewer parameters while still capturing essential dynamics.

In the factor model, two key hyperparameters need to be selected: the number of principal components (PCs) and the number of lags. The optimal number of PCs is determined using the Bai and Ng (2007) criteria, which are specifically designed for factor models by accounting for both the cross-sectional and time series dimensions of the data. Among the three criteria proposed by Bai and Ng, we adopt the second one, as it provides a more reliable trade-off between information retention and model simplicity. For additional discussion on alternative approaches, see Den Reijer et al. (2021). The number of lags in factor models is selected using the BIC criterion, as in the AR model case.

When moving to Machine Learning models, traditional criteria like BIC or AIC become unsuitable because they rely on likelihood-based estimations, which are not directly applicable in complex, nonparametric settings. Instead, we use Cross-Validation (CV), which is more appropriate for tuning hyperparameters in ML models as it evaluates predictive performance directly rather than relying on theoretical approximations, see e.g. Hastie et al. (2009) for discussions.

[4] A hyperparameter is a value that must be set before model training begins and cannot be learned from the data itself, such as the number of lagged observations in an autoregressive model, the seasonality period in decomposition, or smoothing factors in exponential smoothing methods.

In particular, we implement a 5-fold CV procedure, which splits the dataset into five equal parts (folds). The model is trained on four folds and validated on the remaining one, and this process is repeated five times so that each fold serves as a validation set once. The optimal parameters are those that minimize the MSE across all folds, ensuring a robust selection process that generalizes well to unseen data.

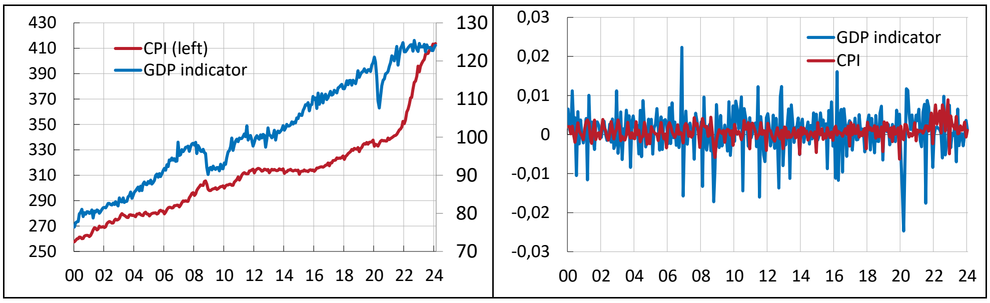
For random forest models, both the number of lags and the number of principal components (when using PCs) are selected via 5-fold CV. Similarly, for neural networks, the hyperparameters include not only the number of lags but also the number of hidden layers and the number of nodes per layer. Given the computational intensity of tuning multiple hyperparameters simultaneously, the CV procedure for NNs is performed using a grid search. In this approach, a set of potential values for each hyperparameter is predefined, and CV is conducted only on the combinations of these values rather than over an unrestricted search space, significantly reducing computational costs.

For all models, hyperparameter selection is performed once over the entire dataset, rather than separately for each rolling-window forecasting step. While tuning parameters dynamically for each forecasting window might be theoretically more precise, it would be computationally prohibitive and introduce unnecessary volatility in model structure across time. Given that the primary goal of this study is to develop a framework that is practically applicable for real-world forecasting operations within the bank, and since our results indicate that selecting hyperparameters once over the full sample does not significantly alter forecasting performance, we adopt this more stable and computationally efficient approach.

3 Data

In this paper we forecast the diff log GDP indicator and CPI. Figure 5 shows the seasonally adjusted level series and the transformed series on the left and right panels respectively.

Figure 5. The GDP indicator and CPI, Jan 2000-Feb 2024[5]



Note: Both series are seasonally adjusted.

We forecast the GDP indicator and CPI by making use of 120 Swedish macroeconomic and financial variables. All the variables are listed in Appendix A. Trending variables are made stationary by first differences or diff logs.

4 Results

In this Section we will show the results from the different model exercises. The random forests (RF) results are shown in Section 4.1 and the neural networks (NN) results in Section 4.2. The comparison with the benchmark models is included in each subsection.

4.1 Results from random forests and neural networks

The main out-of-sample forecasting exercise we employ in this paper is that we train the models using data from January 2000 until December 2016 and then evaluate the model performance on data from January 2017 until February 2024 (86 monthly observations). This means that about 70 percent of the observations are used in the training sample and the remaining 30 percent are used in the evaluation sample. The models are estimated using a rolling window using 86 observations.[6]

The results at horizons 1, 2, 6 and 12 months are shown in Tables 1 and 2 where the Root Mean Squared Error (RMSE) is the preferred forecast accuracy metric. The panels on the right show the RMSE's relative to the random walk (RW) benchmark, where

[5] The GDP Indicator is produced by Statistics Sweden (SCB and published monthly about 30 days after the reference month to provide an early picture of GDP development based on preliminary data. The calculation of the GDP Indicator largely mirrors the regular quarterly GDP compilation but adapts methods in areas where standard data sources are not yet available, often utilizing preliminary or alternative data.

[6] We also tried to use an expanding window with similar results.

a value below 1 means that the competing model performs better than a RW and vice versa.

Table 1. Forecasting performance of CPI inflation

	RMSE				RMSE/RMSE(RW)			
	1m	2m	6m	12m	1m	2m	6m	12m
RW	0.0086	0.0073	0.0007	0.0056	1	1	1	1
AR	0.0055	0.0055	0.0051	0.0054	0.6338	0.7507	0.7350	0.9703
FACTOR	0.0056	0.0053	0.0063	0.0062	0.6534	0.7336	0.9049	1.1227
RF	0.0049	0.0050	0.0049	0.0050	0.5707	0.6844	0.7012	0.9052
NN	0.0053	0.0057	0.0058	0.0059	0.6142	0.7786	0.8224	1.0565

Table 2. Forecasting performance of the GDP indicator

	RMSE				RMSE/RMSE(RW)			
	1m	2m	6m	12m	1m	2m	6m	12m
RW	0.0176	0.0202	0.0185	0.0199	1	1	1	1
AR	0.0149	0.0136	0.0135	0.0136	0.8469	0.6723	0.7303	0.6819
FACTOR	0.0131	0.0139	0.0155	0.0135	0.7445	0.6880	0.8367	0.6812
RF	0.0132	0.0139	0.0129	0.0135	0.7486	0.6861	0.6983	0.6778
NN	0.0146	0.0136	0.0146	0.0149	0.8282	0.6725	0.7886	0.7494

From Table 1 it is clear that RF produce the most accurate inflation forecasts at all horizons and 10 to 40 percent better forecasts than the random walk benchmark. On average, the RF model has superior forecasting precision for the GDP indicator, see Table 2, but here the differences were smaller. The AR, factor and RF models are 15-30 percent more accurate than the RW over all horizons. Here the NN model is only 5-20 percent more accurate than the RW benchmark. Figures B1 to B12 in Appendix B show cascade plot comparisons of the different models. The results suggest that the target variables, the GDP indicator and the CPI inflation, are significantly influenced by other variables or by nonlinear relationships captured through machine learning methods.

In our RF analysis, we found that the combined approach—utilizing both principal components (PCs) and lagged variables—consistently yielded lower RMSEs. This outcome implies that leveraging a broader and more diverse information set, along with RF's ability to detect nonlinear relationships, leads to the most accurate forecasts.

Interestingly, even the simplified RF models that used only PCs or only raw variables outperformed traditional linear models on average. This finding underscores the effectiveness of RF in forecasting tasks, as their inherent structure naturally accommodates complex interactions and nonlinearities that linear models typically cannot handle.

A key conclusion from our analysis is that the decisive factor for forecasting accuracy is not the breadth of the information set but the nonlinearity of the model. We observed that performance deteriorated when moving from an autoregressive (AR) model to more complex linear models like factor models. However, performance improved when employing a nonlinear model such as random forest, emphasizing the importance of capturing nonlinear relationships.

4.2 Diebold-Mariano test

The Diebold-Mariano (DM) test is a commonly used procedure for comparing predictive accuracy between two forecasting methods. In essence, it checks whether the difference between the performances of two competitive models is statistically different from zero, using a specified loss function (the mean squared error in our case). In addition, the DM test applies a Newey-West–type correction that accounts for possible autocorrelation in the forecast errors, which is particularly relevant for multi-step-ahead predictions. Under the null hypothesis of equal predictive accuracy, the resulting DM statistic is approximately standard-normally distributed, so we can assess significance by comparing the test statistic to critical values of the normal distribution or, equivalently, by computing p-values.

We applied the DM test only to the three models—AR, RF, and factor models—that have shown competitive advantage compared to others (lower RMSEs) in at least one horizon in our forecasting exercise. Based on the test outcomes and the p-values calculated for both variables across the four horizons, we can conclude the following:

For CPI, AR versus RF shows only borderline evidence at horizons 1 and 2 (with p-values of 0.0999 and 0.1018, respectively), suggesting no strong difference at a 5% significance level. AR versus the factor model presents a similar pattern: weaker evidence of divergence around horizon 6 (p=0.0512) and horizon 12 (p=0.0844). By contrast, RF versus the factor model reveals clear significance for several horizons. For example, the p-values at horizon 1 (p=0.0141), 6 (p=0.0093), and 12 (p=0.0001), indicate a more pronounced gap in accuracy between these two models. However, the overall assessment from DM test statistics confirms the finding that the RF model performs better.

Turning to GDP, the differences in forecasting precision between the models were found to be too small to be statistically significant.

Overall, these results imply that any performance gap strongly depends on the combination of model and forecast horizon. In line with the RMSE findings, random forests outperform the other models for CPI and this difference is often statistically significant. On the other hand, for GDP no single method stands out.

5 Conclusions

In this memo, we take a comprehensive approach to evaluate the forecasting performance of AI and machine learning techniques in forecasting macroeconomic time series in Sweden.

AI models, with their ability to handle complexity, large datasets, and dynamic real-time information, offer significant potential to provide new insights, and add a new toolkit to time series forecasting. Their ability to capture nonlinear relationships, adapt to new data, and automate forecasting processes presents a considerable advantage over traditional models, particularly in fields like macroeconomic forecasting and financial time series analysis.

As AI techniques mature and become more integrated into forecasting systems, we can expect them to increasingly complement and, in some cases, outperform traditional statistical methods, providing more accurate, adaptable, and scalable predictions in the macroeconomic forecasting experiments. In particular, we show that the improvement is significant in comparison with the classical time series models. The model and parameter choices are important, but not a determining factor in the performance gains.

References

Anesti, N., Kalamara, E. and Kapetanios, G. (2024), “Forecasting with machine learning methods and multiple large datasets”, *Econometrics and Statistics*, in press.

Baffigi, A., Golinelli, R. and Parigi, G. (2004), “Bridge models to forecast the Euro Area GDP", *International Journal of Forecasting*, 20(3), 447–460.

Bai, J. and Ng, S. (2007), “Determining the number of primitive shocks in factor models”, *Journal of Business & Economic Statistics*, 25(1), 52–60.

Bańbura, M., Giannone, D. and Reichlin, L. (2011), “*Forecasting*”. In: Oxford Handbook on Economic Forecasting, Clements, M.P. and Hendry, D.F. (eds.). Oxford University Press: Oxford.

Biau, G. and Scornet, E. (2016), “A random forest guided tour”, *TEST*, 25, 197–227.

Breiman, L. (2001), “Random forests”, *Machine Learning*, 45, 5–32.

Chen, H., Cheng, Y., Liu, Y. and Tang, K. (2023), “Teaching economics to the machines”, Available at SSRN: https://ssrn.com/abstract=4642167.

Chronopoulos, I., Raftapostolos, A. and Kapetanios, G. (2024), “Forecasting value-at-risk using deep neural network quantile regression”, *Journal of Financial Econometrics*, 22, 636–669.

Den Reijer, A., Jacobs, J. and Otter, P. (2021), “A criterion for the number of factors”, *Communications in Statistics – Theory and Methods*, 50(18), 4293–4299.

Farrell, M. H., Liang, T. and Misra, S. (2021), “Deep neural networks for estimation and inference”, *Econometrica*, 89, 181–213.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2000), “The generalized dynamic factor model: Identification and estimation”, *The Review of Economics and Statistics*, 82(4), 540–554.

Geweke, J. (1977), “The dynamic factor analysis of economic time series models”, In: *Latent variables in socio-economic models*, edited by Aigner, D. J. and Goldberger A. S., pp. 365–383. Amsterdam: North-Holland Publishing Company.

Giannone, D., Reichlin, L. and Small, D. (2008), “Forecasting: The real-time informational content of macroeconomic data”, *Journal of Monetary Economics*, 55(4), 665–676.

Goodfellow, I., Bengio, Y. and Courville, A. (2016), “*Deep learning*”. MIT Press.

Goulet Coulombe, P. (2024), “The macroeconomy as a random forest”, *Journal of Applied Econometrics*, 39(3), 401–421.

Goulet Coulombe, P. (2022), “How is machine learning useful for macroeconomic forecasting?”, *Journal of Applied Econometrics*, 37(5), 920–964.

Hastie, T., Tibshirani, R. and Friedman, J. (2009), “The elements of statistical learning”, *Springer Series in Statistics, Springer*.

Jain, A. (2019), “Macro forecasting using alternative data”, *Handbook of US Consumer Economics*, Academic Press.

Jönsson, K. (2020), “Machine learning and forecasts of Swedish GDP”, *Journal of Business Cycle Research*, 16, 123–134.

Kuan, C. M. and Liu, T. (1995), “Forecasting exchange rates using feedforward and recurrent neural networks”, *Journal of Applied Econometrics*, 10(4), 347–364.

Lawley, D. N. and Maxwell, A. E. (1971), *“Factor analysis as a statistical method”* (2nd ed.). Butterworths, London.

Lenza, M., Moutachaker, I. and Paredes, J. (2023), “Density forecasts of inflation: A quantile regression forest approach”, *ECB Working Paper No. 2830*.

Löf, M. and Stockhammar, P. (2024), “Indicators for short-term forecasting”, *Staff memo*, October 2024, Sveriges Riksbank.

Masini, Ricardo P., Marcelo C. Medeiros, and Eduardo F. Mendes. “Machine learning advances for time series forecasting.” *Journal of Economic Surveys*, 37, 76–111.

McCracken, M. and Ng, S. (2016), “FRED-MD: A monthly database for macroeconomic research”, *Journal of Business & Economic Statistics*, 34(4), 574–589.

Medeiros, M., Vasconcelos, G., Veiga. Á., and Zilberman, E. (2021) “Forecasting inflation in a data-rich environment: The benefits of machine learning methods”, *Journal of Business & Economic Statistics*, 39(1), 98–119.

Mullainathan, S. and Spiess, J. (2017), “Machine learning: An applied econometric approach”, *Journal of Economic Perspectives*, 31(2), 87–106.

Ng, S. (2006), “Testing cross-section correlation in panel data using spacings”, *Journal of Business & Economic Statistics*, 24(1), 12–23.

Rudin, C. (2019), “Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead”, *Nature Machine Intelligence*, 1(5), 206–215.

Schmidt-Hieber, J. (2020), “Nonparametric regression using deep neural networks with ReLU activation function”, *The Annals of Statistics*, 48, 1875–1897.

Wallis, K.F. (1986), “Forecasting with an econometric model: the ‘ragged edge’ problem”, *Journal of Forecasting*, 51(1), 1–12.

APPENDIX A – The data

For the purpose of macroeconomic forecasting and policy making in Sweden, a large database of time series variables sampled at a monthly frequency is constructed. The data collection is based on the same principles as the US oriented McCracken and Ng (2016) FRED-MD database. The data set consists of *T*=300 monthly observations starting from January 2000 onwards for *N*=131 time series variables, which is considered a *data-rich environment* for macroeconomic forecasting. Collecting more time series variables is possible, but not necessarily desirable unless the data are informative about the economic variables we seek to explain. For our purpose, we assembled a balanced database that contains both coincident and leading indicators. The coincident indicators, or hard data, measure economic activity on a timely available basis. The leading indicators, or soft data, contain the forward looking signals about economic activity and price setting that we aim to exploit. The data set can be further classified into eight different categories: prices, production, financial, foreign, labour market, trade, purchasing managers index (PMI) and the economic tendency survey as published by the Swedish National Institute of Economic Research (*Konjunkturbarometern*). The data is listed in Table A1 below.

The observations for the variables in the different categories become available with a varying publication lag. Obviously, most financial series are being observed in real-time. Soft data contained in surveys tend to become available at the end of the corresponding period. Hard data like monthly industrial production typically only becomes available with a delay of six weeks after the end of the corresponding month. As the availability pattern of the observations differs across the categories, the data set contains a *ragged-edge,* cf. Wallis (1986) at the end of the sample period. The ragged-edge availability pattern differs for each vintage of the data set.

Finally, the data is transformed to remove outliers and, possibly, remove trends. The stationarity inducing transformations consists of taking logarithms (log), temporal differences of the variables (diff) and, potentially, summation. For instance, the coding "log=1, diff=1" for the prices implies taking the first difference of the logarithm of the price index, which approximately corresponds to month-on-month growth rates. The coding "log=1, diff=1, sum=11" then moreover sums over the latest 11 months leading to approximately year-on-year growth rates, hence, inflation rates. Finally, note that the "sum=2" approximates quarter-on-quarter growth rates for monthly variables. This specific transformation turns out to be very useful to smooth out noisy behaviour. Table A1 below lists the codes from the data provider Macrobond.[7] The codes, their categorization, description and stationarity inducing transformations.

[7] Macrobond Financial, see http://www.macrobond.com.

Table A1. The data

	LOG	DIFF	SUM	Category	Macrobond name	Description
1	1	1	2	Prices	sepric1091	Sweden, Consumer Price Index, CPIF, Index
2	0	1	2	Konj	kibt_binve201m	Sweden, Business Surveys, Konjunkturinstitutet (KI), Investment Goods, Volume of Production, Expectations
3	0	1	2	Konj	kibt_btvi201msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacturing, Volume of Production, Expectations, SA
4	0	1	2	Konj	kibt_b41000201msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction of Buildings, Building Activity, Expectations, SA
5	0	1	2	Konj	kibt_totf203msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction, Order Books, Expectations, SA
6	0	1	2	Konj	kibt_bdhan201msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Retail Trade, Selling Volumes, Expectations, SA
7	0	1	2	Konj	kibt_b45000201msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Wholesale & Retail Trade & Repair of Motorwheels & Motorcycles, Selling Volumes, Expectations, SA
8	0	1	2	Konj	kibt_b46300201msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Wholesale of Food, Beverages & Tobacco, Selling Volumes, Expectations, SA
9	0	1	2	Konj	kibt_btotsysamsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Total Industry, Number of Employees, Expectations, SA
10	0	1	2	Konj	kibt_totf204msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction, Number of Employees, Expectations, SA
11	0	1	2	Konj	kibt_bdhan204msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Retail Trade, Number of Employees, Expectations, SA
12	0	1	2	Konj	kibt_indikatorm	Sweden, Business Surveys, Konjunkturinstitutet (KI), Indicators, Economic Tendency Indicator
13	0	1	2	Konj	kibt_b46300conmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Wholesale of Food, Beverages & Tobacco, Confidence Indicator, SA
14	0	1	2	Konj	kibt_binveconmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Investment Goods, Confidence Indicator, SA
15	0	1	2	Konj	kibt_btviconmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacturing, Confidence Indicator, SA
16	0	1	2	Konj	kibt_bconsconmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Consumer Goods, Confidence Indicator, SA
17	0	1	2	Konj	kibt_bintmconmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Intermediate Goods, Confidence Indicator, SA

18	0	1	2	Konj	kibt_totfconmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction, Confidence Indicator, SA
19	0	1	2	Konj	kibt_bdhanconmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Retail Trade, Confidence Indicator, SA
20	0	1	2	Konj	kibt_b29000conmsa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacture of Motor Vehicles, Trailers & Semi-Trailers, Confidence Indicator, SA
21	0	1	2	Konj	kibt_binve101msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Investment Goods, Volume of Production, Outcome, SA
22	0	1	2	Konj	kibt_binve102msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Investment Goods, Inflow of New Orders on the Domestic Market, Outcome, SA
23	0	1	2	Konj	kibt_binve103msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Investment Goods, Inflow of New Orders on the Export Market, Outcome, SA
24	0	1	2	Konj	kibt_binve104msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Investment Goods, Overall Order Books, Present Situation Assessment, SA
25	0	1	2	Konj	kibt_btvi101msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacturing, Volume of Production, Outcome, SA
26	0	1	2	Konj	kibt_btvi102msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacturing, The Inflow of New Orders on The Domestic Market, Outcome, SA
27	0	1	2	Konj	kibt_btvi103msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacturing, The Inflow of New Orders on The Export Market, Outcome, SA
28	0	1	2	Konj	kibt_btvi104msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Manufacturing, Overall Order Books, Present Situation Assessment, SA
29	0	1	2	Konj	kibt_totf101msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction, Building Activity, Outcome, SA
30	0	1	2	Konj	kibt_totf104msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction, Order Books, Present Situation Assessment, SA
31	0	1	2	Konj	kibt_totf103msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Construction, Order Books, Outcome, SA
32	0	1	2	Konj	kibt_b4711x101msa	Sweden, Business Surveys, Konjunkturinstitutet (KI), Retail Sale of Non-Durable Goods, Selling Volumes, Outcome, SA
33	0	1	2	Konj	kics_bhusconmsa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Indicators, All Consumers, The Consumer Confidence Indicator (CCI), SA
34	0	1	2	Konj	kics_bhusmakromsa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Indicators, All Consumers, The Macro Index, SA
35	0	1	2	Konj	kics_bhusmikromsa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Indicators, All Consumers, The Micro Index, SA

36	0	1	2	Konj	kics_q020msa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Financial Situation of the Household, Over the next 12 Months, SA
37	0	1	2	Konj	kics_q010msa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Financial Situation of the Household, Compared to 12 Months Ago, SA
38	0	1	2	Konj	kics_q070msa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Unemployment, Over the next 12 Months, SA
39	0	1	2	Konj	kics_q080msa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Major Purchases, Now, SA
40	0	1	2	Konj	kics_q090msa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Major Purchases, Over the next 12 Months, SA
41	0	1	2	Konj	kics_q040msa	Sweden, Consumer Surveys, Konjunkturinstitutet (KI), Swedish Economy, General Economic Situation over the next 12 Months, SA
42	0	1	2	PMI	sesurv0242	Sweden, Business Surveys, Swedbank, Services PMI, Total, SA, Index
43	0	1	2	PMI	sesurv0178	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, New Orders, SA, Index
44	0	1	2	PMI	sesurv0179	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Production, SA, Index
45	0	1	2	PMI	sesurv0180	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Employment, SA, Index
46	0	1	2	PMI	sesurv0181	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Delivery Times, SA, Index
47	0	1	2	PMI	sesurv0182	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Inventories, SA, Index
48	0	1	2	PMI	sesurv0195	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Export Orders, Index
49	0	1	2	PMI	sesurv0184	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Domestic Orders, SA, Index
50	0	1	2	PMI	sesurv0197	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Back-Log of Orders, Index
51	0	1	2	PMI	sesurv0187	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Import (Forecast), SA, Index
52	0	1	2	PMI	sesurv0186	Sweden, Business Surveys, Swedbank, Purchasing Managers' Index, Prices (Forecast), SA, Index
53	0	1	2	PMI	sesurv0620	Sweden, Business Surveys, Konjunkturinstitutet (KI), Economic Tendency Survey, Retail Trade, Confidence Indicator, SA, Index
54	1	1	2	Production	seprod0095	Sweden, Industrial Production, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index

55	1	1	2	Production	seprod0104	Sweden, Manufacturing, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index
56	1	1	2	Production	seprod0109	Sweden, Manufacturing, Wood & Wood Products, Cork, Cane etc., excl. Furniture, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index
57	1	1	2	Production	seprod0112	Sweden, Manufacturing, Paper & Paper Products, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index
58	1	1	2	Production	seprod1897	Sweden, Manufacturing, Chemical, Chemical Products & Pharmaceutical Products, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index
59	1	1	2	Production	seprod0121	Sweden, Manufacturing, Rubber & Plastic Products, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index
60	1	1	2	Production	seprod0123	Sweden, Manufacturing, Basic Metals, Total, Calendar & Seasonally Adjusted, Constant Prices, Chained, Index
61	1	1	2	Production	setrad0868	Sweden, Domestic Trade, Services Trade, Service Production Index, Total, Calendar Adjusted, Constant Prices, SA, Index
62	1	1	2	Production	seprod0816	Sweden, New Orders, Whole Economy, Goods, Intermediate Goods Industry, Calendar & Seasonally Adjusted, Constant Prices, Index
63	1	1	2	Production	seprod0817	Sweden, New Orders, Whole Economy, Goods, Energy-Related Goods excl. Electricity, Calendar & Seasonally Adjusted, Constant Prices, Index
64	1	1	2	Production	seprod0818	Sweden, New Orders, Whole Economy, Goods, Capital Goods Industry, Calendar & Seasonally Adjusted, Constant Prices, Index
65	1	1	2	Production	seprod0819	Sweden, New Orders, Whole Economy, Goods, Non-Durable Consumer Goods Industry, Calendar & Seasonally Adjusted, Constant Prices, Index
66	1	1	2	Production	seprod0820	Sweden, New Orders, Whole Economy, Goods, Durable Consumer Goods Industry, Calendar & Seasonally Adjusted, Constant Prices, Index
67	1	1	2	Production	seprod0857	Sweden, New Orders, Domestic, Total, Calendar & Seasonally Adjusted, Constant Prices, Index
68	1	1	2	Production	seprod0899	Sweden, New Orders, Non-Domestic, Total, Calendar & Seasonally Adjusted, Constant Prices, Index
69	1	1	2	Labour Market	selama0281	Sweden, Employment, Employed & Self Employed at Work, Males & Females, Total 15-74 Years
70	1	1	2	Labour Market	selama3135	Sweden, Productivity, Costs & Hours Worked, Actual Working Hours per Week, Employed & Self Employed, Males & Females, Total, 15-74 Years, SA
71	1	1	2	Labour Market	selama11493	Sweden, Unemployment, Unemployed Persons, Males & Females, By Duration, Average Weeks, 15-74 Years, Total

72	1	1	2	Labour Market	selama0001	Sweden, Labor Turnover, New Vacancies, Total (PES)
73	1	1	2	Trade	setrad6487	Sweden, Foreign Trade, Export (Goods), Constant Prices, Index, SEK
74	1	1	2	Trade	setrad6453	Sweden, Foreign Trade, Import (Goods), Constant Prices, Index, SEK
75	0	1	2	Financial	se2ygov	Sweden, Government Benchmarks, Macrobond, 2 Year, Yield
76	0	1	2	Financial	se5ygov	Sweden, Government Benchmarks, Macrobond, 5 Year, Yield
77	1	1	2	Financial	sek	Sweden, FX Spot Rates, Macrobond, SEK per USD
78	1	1	2	Financial	sekeur	Sweden, FX Spot Rates, Macrobond, SEK per EUR
79	1	1	2	Financial	omxspi	Sweden, Equity Indices, Nasdaq OMX, All-Share, OMX Stockholm Index, Price Return, Close, SEK
80	1	1	2	Financial	semost0024	Sweden, Monetary Statistics, Monetary Aggregates, M3, Total, SEK
81	0	1	2	Foreign	ussurv1055	United States, Business Surveys, ISM, Report on Business, Manufacturing, Purchasing Managers', SA, Index
82	0	1	2	Foreign	ussurv1046	United States, Business Surveys, ISM, Report on Business, Services, NMI/PMI, New Orders, SA, Index
83	0	1	2	Foreign	ussurv1057	United States, Business Surveys, ISM, Report on Business, Manufacturing, PMI, Production, SA, Index
84	1	1	2	Foreign	uslama1060	United States, Employment, Payroll, Nonfarm, Payroll, Total, SA
85	0	1	2	Foreign	bls_eiuirexfdfls	United States, BLS, Import/Export Price Indexes, IPI, BEA End Use, All Imports Excluding Food & Fuels
86	0	1	2	Foreign	uslama1849	United States, Unemployment, National, 16 Years & Over, Rate, SA
87	1	1	2	Foreign	uspric2156	United States, Consumer Price Index, All Urban Consumers, U.S. City Average, All Items, SA, Index
88	0	1	2	Foreign	ussurv6195	United States, Investor Surveys, AAII, Sentiment Survey, Bull-Bear Spread
89	0	1	2	Foreign	deprod2198	Germany, New Orders, Manufacturing, Euro Area, Total, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDe-metra+), Index
90	0	1	2	Foreign	deprod2218	Germany, New Orders, Manufacturing, Euro Area, Goods Category, Capital Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index

91	0	1	2	Foreign	deprod2228	Germany, New Orders, Manufacturing, Euro Area, Goods Category, Consumer Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index
92	0	1	2	Foreign	deprod2208	Germany, New Orders, Manufacturing, Euro Area, Goods Category, Intermediate Goods, Calendar Adjusted (X13 JDemetra+), Constant Prices, SA (X13 JDemetra+), Index
93	1	1	2	Foreign	prdb_dscai21ea19pm	Euro Area 19, Eurostat, Production in Industry, Mining & Quarrying; Manufacturing; Electricity, Gas, Steam & Air Conditioning Supply (B-D), 2021=100, Calendar Adjusted, SA, Index
94	1	1	2	Foreign	prdcscai21ea19pm	Euro Area 19, Eurostat, Production in Industry, Manufacturing (C), 2021=100, Calendar Adjusted, SA, Index
95	1	1	2	Foreign	prdmigcogscai21ea19pm	Euro Area 19, Eurostat, Production in Industry, MIG - Consumer Goods, 2021=100, Calendar Adjusted, SA, Index
96	1	1	2	Foreign	prdfscai21ea19co	Euro Area 19, Eurostat, Production in Construction, Production (volume), Construction (F), 2021=100, Calendar Adjusted, SA, Index
97	1	1	2	Foreign	prdmigdcogscai21ea19pm	Euro Area 19, Eurostat, Production in Industry, MIG - Durable Consumer Goods, 2021=100, Calendar Adjusted, SA, Index
98	1	1	2	Foreign	prdmigingscai21ea19pm	Euro Area 19, Eurostat, Production in Industry, MIG - Intermediate Goods, 2021=100, Calendar Adjusted, SA, Index
99	1	1	2	Foreign	prdmigndcogscai21ea19pm	Euro Area 19, Eurostat, Production in Industry, MIG - Non-Durable Consumer Goods, 2021=100, Calendar Adjusted, SA, Index
100	0	1	2	Foreign	pcactsalm_un_t_totea20hr	Euro Area 20, Eurostat, Employment & Unemployment, Unemployment, Harmonized Unemployment Rates, Unemployment According to ILO Definition - Total, Percentage of Active Population, SA
101	0	1	2	Foreign	euzew0002	Euro Area, Economic Surveys, ZEW, Financial Market Report, Current Economic Situation, Balance
102	0	1	2	Foreign	bs_ici_balsaea20ib	Euro Area 20, Eurostat, Business Surveys, Eurostat, Sentiment Indicators, Industrial Confidence Indicator, SA
103	1	1	2	Foreign	eupric0001	Euro Area, HICP, All-Items, Index
104	1	1	2	Foreign	uscaes0302	United States, Crude Oil, Brent Europe Spot Price FOB, USD
105	1	1	2	Financial	sx7530pi	Sweden, Equity Indices, Nasdaq OMX, ICB Sector, Electricity, Index, Price Return, Close, SEK
106	1	1	2	Foreign	wocaes0456	World, Commodity Indices, FAO, Food Price Index
107	1	1	2	Foreign	wocaes0091	World, Gold, New York, Close, USD
108	1	1	2	Financial	sx0001pi	Sweden, Equity Indices, Nasdaq OMX, ICB Industry, Oil & Gas, Index, Price Return, Close, SEK

109	1	1	2	Prices	sepric3773	Sweden, PPI Domestic Market, By Products, Consumer Goods, Index
110	1	1	2	Prices	sepric3775	Sweden, PPI Domestic Market, By Products, Consumer Goods (Except Food, Beverages & Tobacco), Index
111	1	1	2	Prices	sepric3778	Sweden, PPI Domestic Market, By Products, Intermediate Goods, Index
112	1	1	2	Prices	sepric3771	Sweden, PPI Domestic Market, By Products, Capital Goods, Index
113	1	1	2	Prices	sepric3776	Sweden, PPI Domestic Market, By Products, Durable Consumer Goods, Index
114	1	1	2	Prices	sepric4469	Sweden, Import Prices, Terms of Trade, By Product, Capital Goods, Index
115	1	1	2	Prices	sepric4471	Sweden, Import Prices, Terms of Trade, By Product, Consumer Goods, Index
116	1	1	2	Prices	sepric4474	Sweden, Import Prices, Terms of Trade, By Product, Durable Consumer Goods, Index
117	1	1	2	Prices	sepric4476	Sweden, Import Prices, Terms of Trade, By Product, Intermediate Goods, Index
118	1	1	2	Prices	sepric4105	Sweden, Export Prices, Terms of Trade, By Product, Capital Goods, Index
119	1	1	2	Prices	sepric4107	Sweden, Export Prices, Terms of Trade, By Product, Consumer Goods, Index
120	1	1	2	Prices	sepric4110	Sweden, Export Prices, Terms of Trade, By Product, Durable Consumer Goods, Index
121	1	1	2	Prices	sepric4112	Sweden, Export Prices, Terms of Trade, By Product, Intermediate Goods, Index
122	1	1	2	Prices	sepric4115	Sweden, Export Prices, Terms of Trade, By Product, Non-Durable Consumer Goods, Index
123	1	1	2	Prices	sepric5529	Sweden, Inflation, CPIF, Services, Index
124	1	1	2	Prices	sepric5530	Sweden, Inflation, CPIF, Food, Index
125	1	1	2	Prices	sepric5531	Sweden, Inflation, CPIF, Capital Stock, Index
126	1	1	2	Prices	sepric5532	Sweden, Inflation, CPIF, Energy, Index
127	1	1	2	Prices	sepric5528	Sweden, Inflation, CPIF, Goods (Excluding Food), Index

128	1	1	2	Prices	serbcpi999	Sweden, Consumer Price Index (Riksbank Classification), Total, Index
129	1	1	2	Production	senaac4900	Sweden, GDP Indicator, Activity Indicator, SA, Index
130	1	1	2	Financial	seexri0001	Sweden, FX Indices, Riksbanken, KIX Index, Index
131	0	1	2	Financial	serate0001	Sweden, Policy Rates, Central Bank of Sweden, Policy Rate (Effective Dates)

APPENDIX B – Graphs[8]

Figure B1. AR forecasts at different horizons for CPI inflation

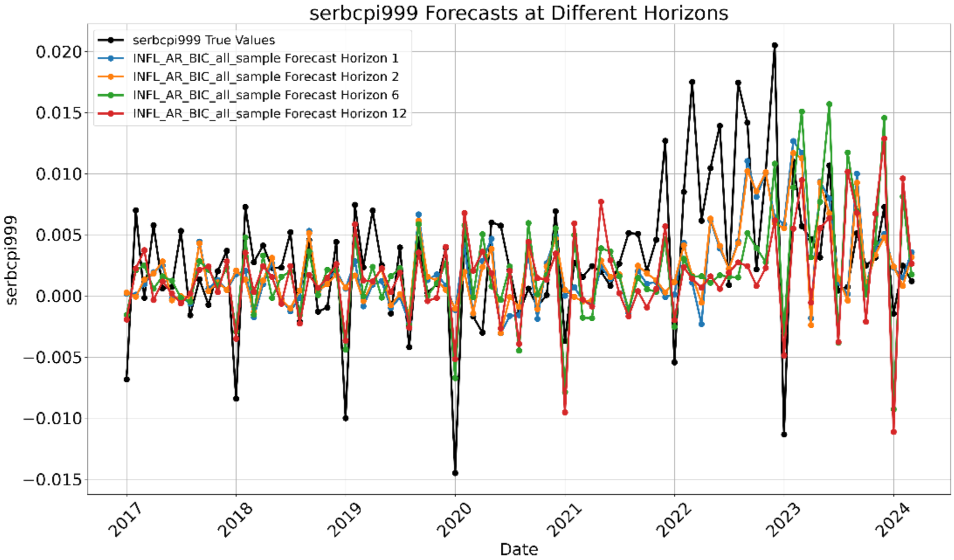
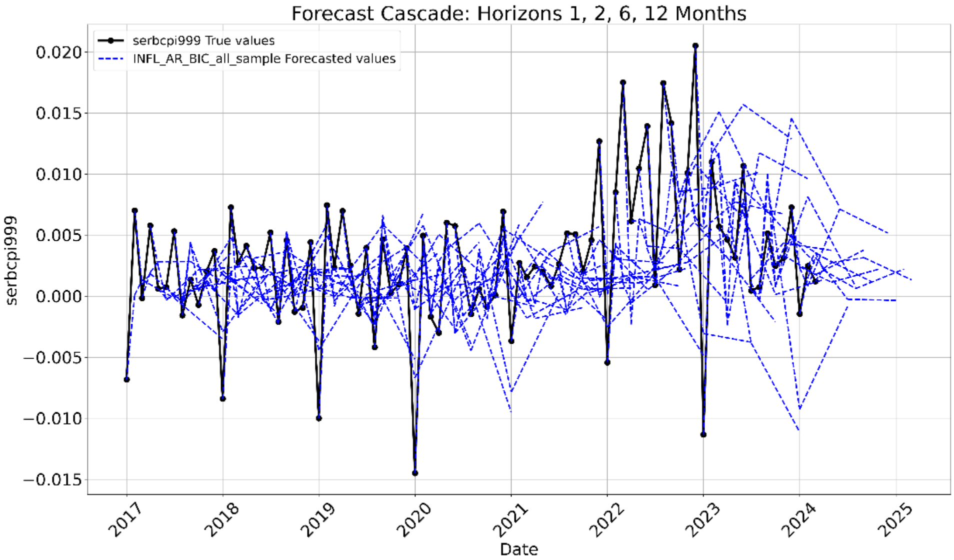


Figure B2. Cascade plot AR forecasts for CPI inflation



[8] The legends are using the Macrobond names in Table A1.

Figure B3. Static factor model forecasts at different horizons for CPI inflation

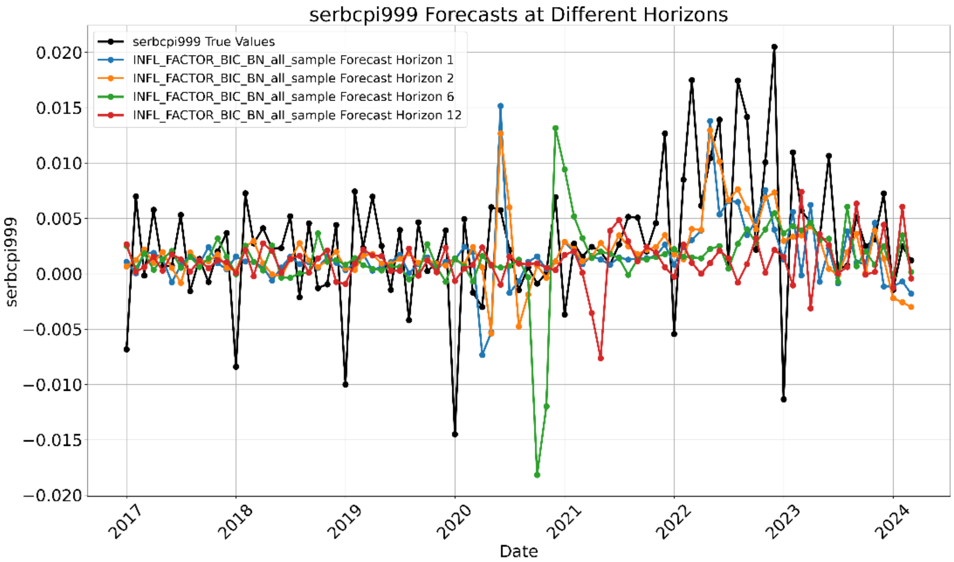


Figure B4. Cascade plot static factor model forecasts for CPI inflation

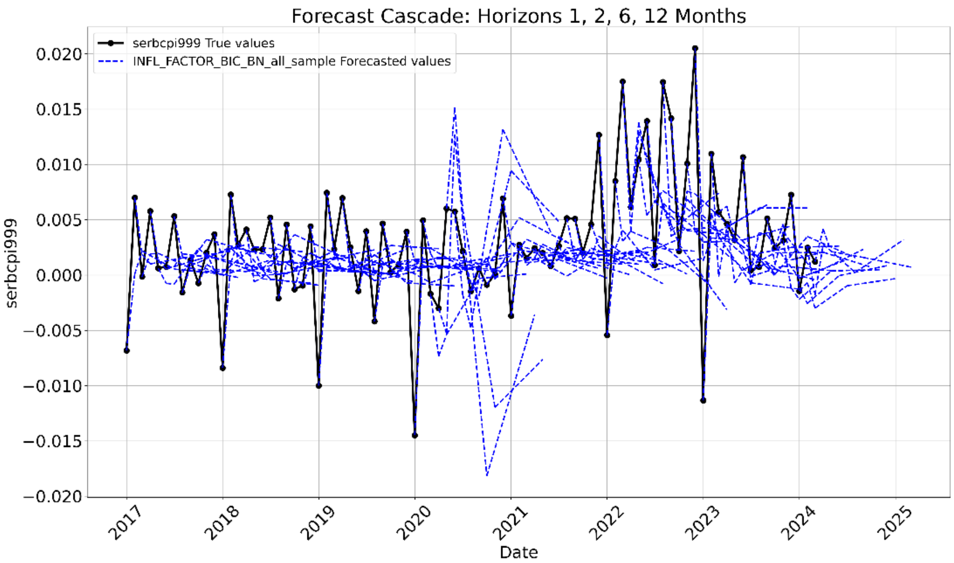


Figure B5. Random forest forecasts at different horizons for CPI inflation

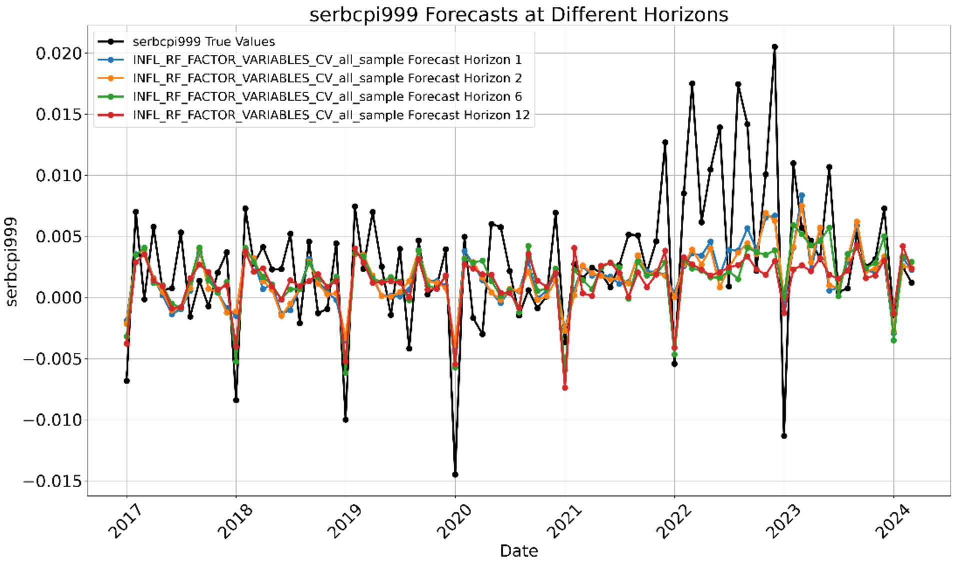


Figure B6. Cascade plot random forest forecasts for CPI inflation

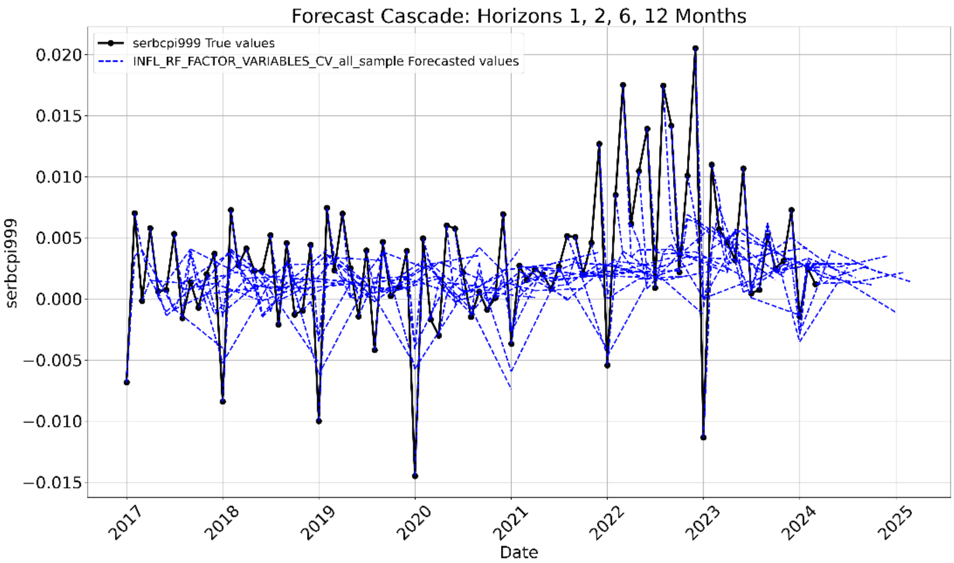


Figure B7. AR model forecasts at different horizons for the GDP indictor

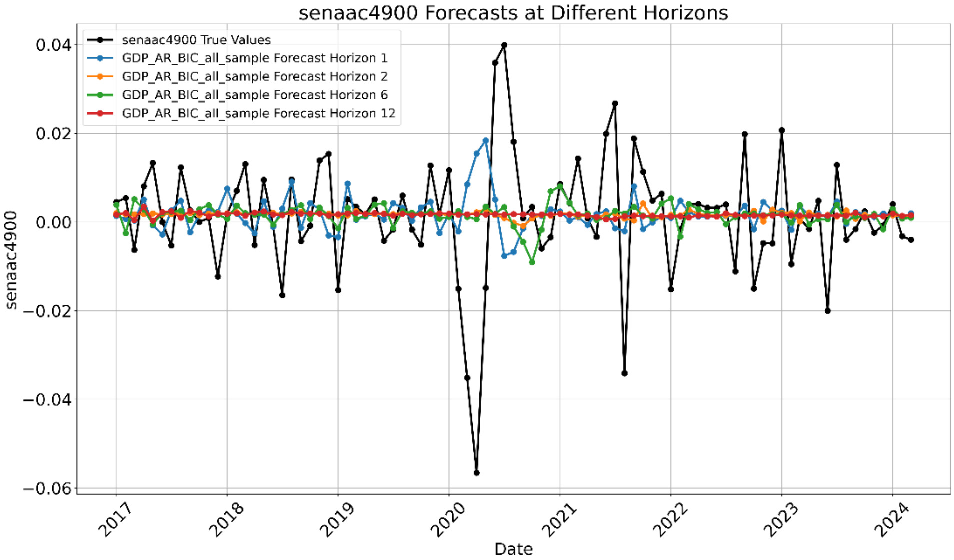


Figure B8. Cascade plot AR model forecasts for the GDP indicator

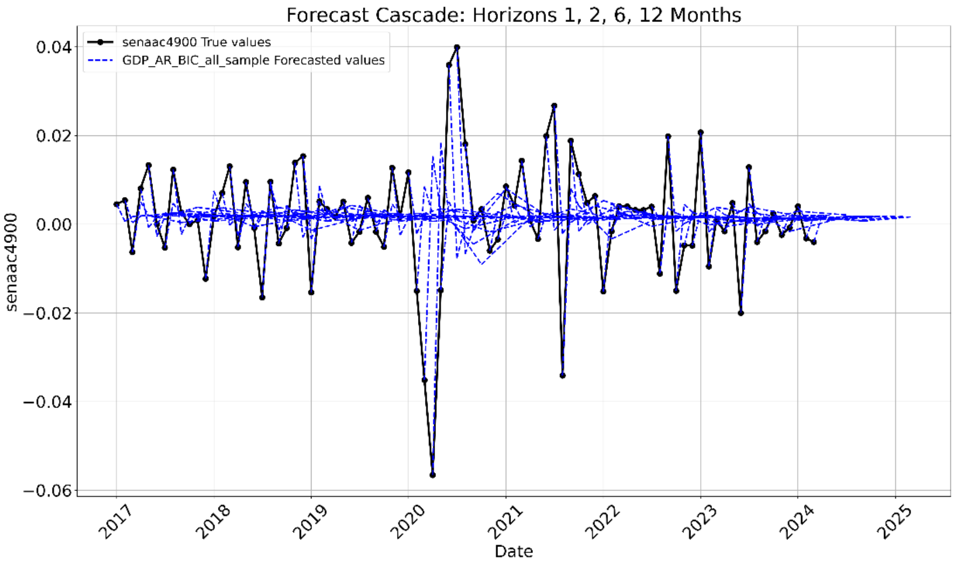


Figure B9. Static factor model forecasts at different horizons for the GDP indictor

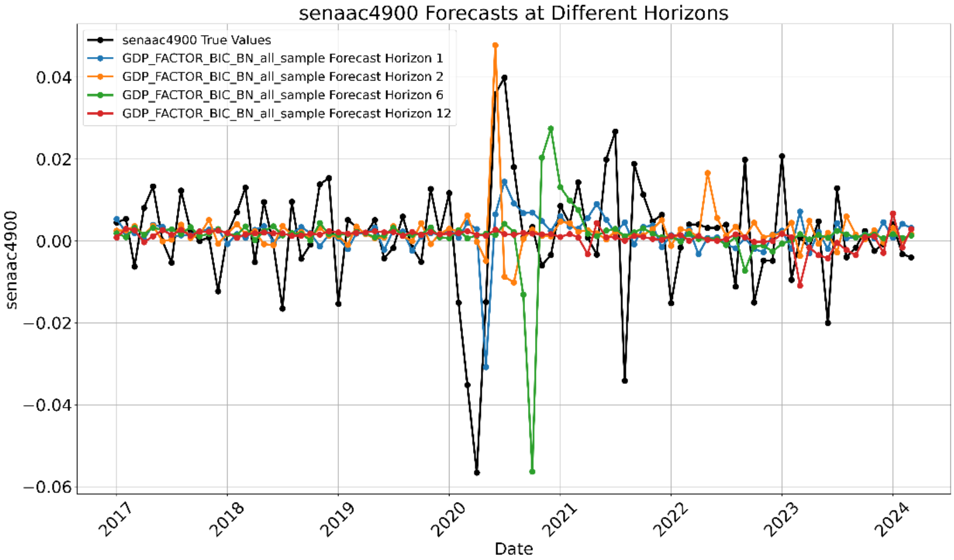


Figure B10. Cascade plot static factor model forecasts for the GDP indicator

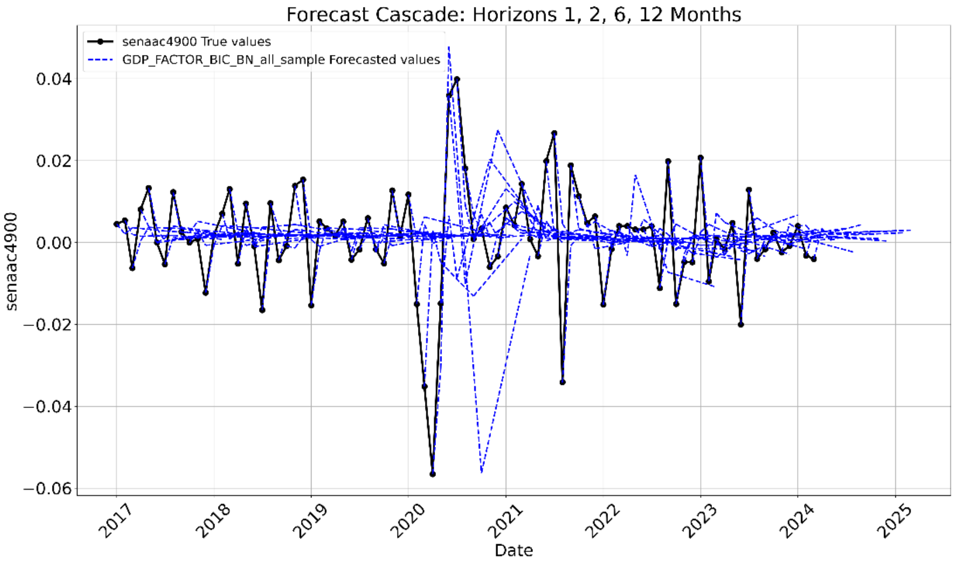


Figure B11. Random forest model forecasts at different horizons for the GDP indictor

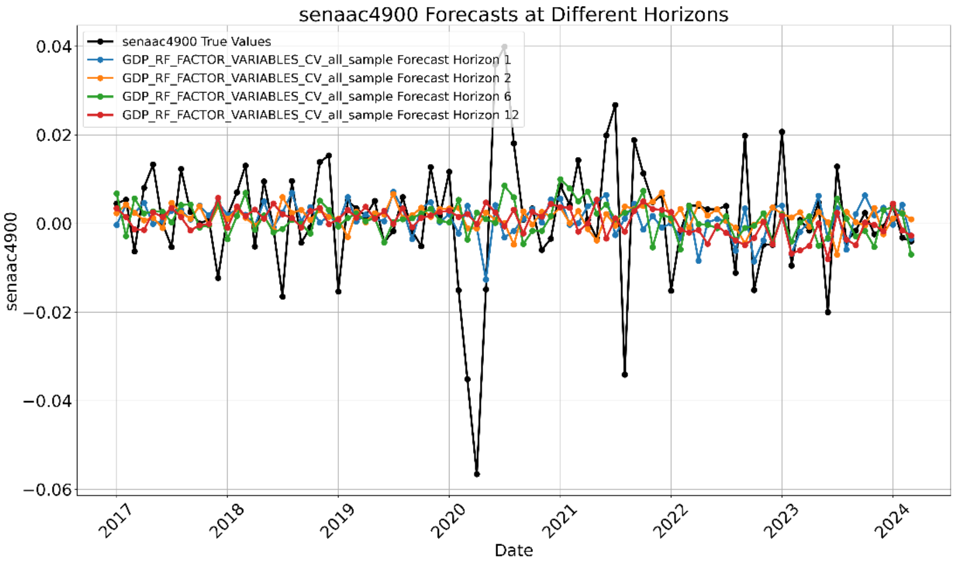
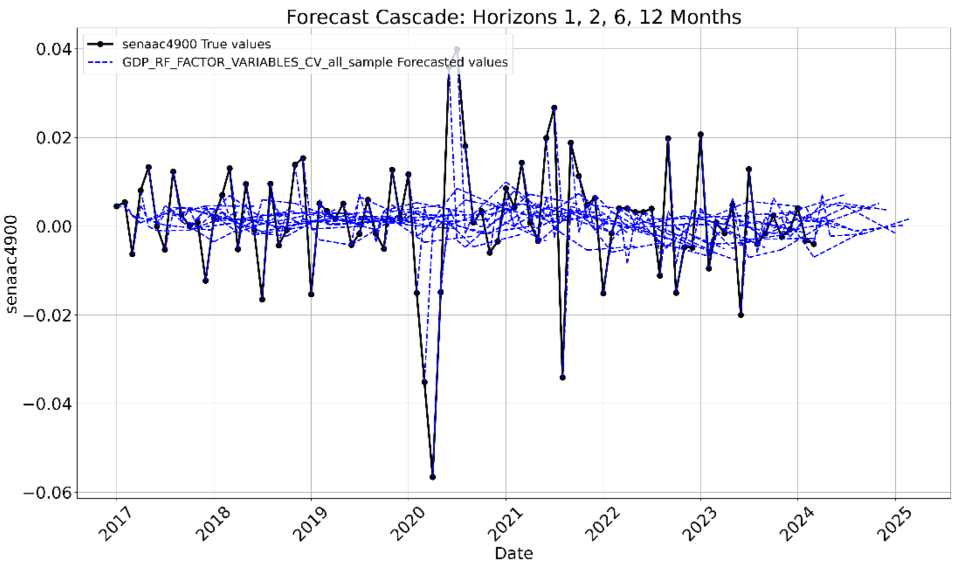


Figure B12. Cascade plot static random forest forecasts for the GDP indicator



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