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# Forecasting Swedish Inflation and Policy Rates Using Random Forests and Bullard's Modernized Taylor Rule

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## Abstract

This paper examines whether the Riksbank could have predicted the historic inflationary surge in Sweden in the aftermath of the Covid-19 pandemic and warned the Swedish public prior to embarking on the most aggressive policy rate-hike cycle since the global financial crisis. I study the matter in two steps. First, I generate true out-of-sample, monthly inflation forecasts for the period beginning June 2018 and ending September 2022 using traditional econometric models as well as a modern machine learning method called Random Forest as proposed by Medeiros et al. (2021) and Araujo & Gaglianone (2023). Then, I approximate the Riksbank's policy rule using Bullard's modernized Taylor rule and generate policy rate forecasts for the entire period. Results indicate that the Riksbank could have both predicted the historic surge in inflation and warned the Swedish public about the looming rate hikes sooner, especially if it had used forecasts generated by a Random Forest algorithm. Variable importance figures reported by the Random Forest algorithms show that changes in the U.S. Federal Funds Rate might be more important than changes in the Swedish policy rate "Styrräntan" in forecasting inflation in Sweden, indicating that the Riksbank might have less control over inflation than is generally assumed.

**Keywords:** Inflation Forecasting, Interest Rate Forecasting, Modernized Taylor Rule, Random Forest

**JEL Codes:** E31, E37, E43, E47

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# 1 Introduction

In the aftermath of the Covid-19 pandemic, the world was infected with yet another virus, only this time a monetary one: inflation. Reaching levels not seen in almost half a century and with complete disregard for national borders, inflation proliferated across continental Europe, the United Kingdom, the Nordics, and North America. It eroded the purchasing power of households, it plunged businesses into sudden financial distress, and it piled pressure on political and financial institutions during a time of geopolitical turmoil and war.

The sudden rise in inflation came as a surprise to most observers. At the beginning of 2021, the consensus end-of-year inflation forecasts for the U.S. and Euro area were below the 2% target. In June that same year, forecasts were revised up, with inflation in the U.S. and Euro area forecast to reach just over 4% and 2% by year-end, respectively (Bank for International Settlements, 2022). However, observers insisted that this would at worst be a modest and temporary overshoot of the target rate. At the end of 2021, inflation reached 7% in the U.S. and 5% in the Euro area (Bureau of Labor Statistics, 2022; Eurostat, 2022). It peaked at 9.1% in the U.S. in June 2022 and at 10.6% in the Euro area in October 2022 (Bureau of Labor Statistics, 2023; Eurostat, 2023).

Of course, economic forecasts are often wrong. However, the forecast errors in 2021 and 2022 were unusually large, and, in many countries, beyond what “[...] many regarded as plausible” (Bank for International Settlements, 2022). Moreover, because inflation forecasts are used by central banks to project and determine policy rates, the failure in forecasting inflation led to erroneous policy rate forecasts. The ensuing upheaval of policy rates put households—who were carrying unprecedented levels of debt (Federal Reserve, 2023; IMF, 2023; SCB, 2023)—businesses, and financial institutions under considerable financial stress. The financial stress on by financial institutions culminated in the collapse of a global systemically important bank in Credit Suisse, partially triggered by the failure of the regional American lender Silicon Valley Bank (SVB), which failed specifically because of its bet that policy rate forecasts by the Federal Reserve were accurate (Financial Times, 2023).

The situation in Sweden was no exception to the wider global trend. Inflation in Sweden peaked at 10.2% as measured by KPIF<sup>1</sup> in December 2022, despite the Riksbank forecasting as late as February 2022 that inflation would be lower than 2.5% by October that same year (Riksbanken, 2022). In February 2022, the Riksbank also projected a 0% policy rate for the remainder of the year. In December 2022, the policy rate was 2.5% and, as of May 3 2023, the policy rate was 3.5%, with further hikes projected (Riksbanken, 2023).

In the wake of the rapid rate hikes, the Riksbank was subject to intense public scrutiny by labor leaders and business representatives alike (Dagens Industri, 2023). In response, the Riksbank Governor Erik Thedéen, referring to the Riksbank’s inaccurate inflation and policy rate forecasts, stated: “I think it is worrisome that people trust our forecasts.” (SVT, 2023)<sup>2</sup>

However, it is *essential* that the public trusts the forecasts by the Riksbank, considering the 2% inflation target only anchors inflation expectations *because* the public trusts the Riksbank (Ascari et al., 2017; Christelis et al., 2020; Svensson, 1997). Forecast errors of this magnitude risk undermining the credibility of the Riksbank, which, because it enables economic stability and consequently common prosperity, is a linchpin of a healthy democracy. Fundamentally, this raises the question: Could the Riksbank have predicted the historic surge in inflation in the aftermath of the Covid-19 pandemic? And, if so, could the Riksbank have warned the Swedish public about impending rate hikes sooner?

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<sup>1</sup>KPIF is Swedish CPI with fixed interest rates.

<sup>2</sup>Translated from the direct quote in Swedish: “Jag tycker det är bekymmersamt att folk litar på våra prognoser.”

To answer these questions, I generate true out-of-sample, monthly inflation forecasts beginning June 2018 and ending September 2022 using two traditional econometric models—the Autoregressive Moving Average (ARMA) and the Vector Autoregression (VAR)—and one modern machine learning model called Random Forest (RF). Recent research suggests that RF models can significantly and consistently outperform forecasts generated by traditional models (Araujo & Gaglianone, 2023; Medeiros et al., 2021). Model performance is evaluated by comparing generated inflation forecasts with those issued by the Riksbank and real KPIF observations. Next, the policy rule followed by the Riksbank is approximated using Bullard’s modernized Taylor rule, with the help of which, using the inflation forecasts generated by the models, I create alternative policy rate forecasts and compare them to those issued by the Riksbank and the real policy rate.

My main findings indicate that the answer to the two fundamental questions posed in this paper are in the affirmative. With the exception of one configuration of the VAR model, all models outperformed inflation forecasts issued by the Riksbank, with the two RF model configurations collectively outperforming all other models across all 12 forecast horizons. On average, the best performing RF model configuration outperformed the Riksbank by over 100% in terms of  $R^2$ . Furthermore, when adjusted for potentially erroneous policy rule approximations, all models outperformed the policy rate forecasts issued by the Riksbank, on average reducing forecast errors by 14.3% as measured by Root Mean Squared Error (RMSE). However, models that were better able to forecast inflation generally underperformed weaker inflation forecasting models when forecasting policy rates. This is primarily explained by the fact that the generated policy rate forecasts are not in fact forecasting how the Riksbank *will* set the policy rate, but rather how it *should* set the policy rate given the current policy rate and forecast rates of inflation.

The remainder of this paper is structured as follows. Section 2 details relevant literature and research, and outlines this paper’s contribution to the literature. Section 3 provides an introduction to the methods used. Section 4 details the data and the required pre-processing. Section 5 presents the results. Section 6 concludes.

## 2 Literature

### 2.1 Overview of Related Literature

The central purpose of Swedish monetary policy is to keep inflation low and steady while maintaining confidence in the 2% inflation target (Riksbanken, 2023). A credible inflation target acts as a *nominal anchor*—a benchmark for price and wage trajectories in the economy—and alters the inflation expectations of households, companies, and all other economic agents in such a way that a common and consistent view of how prices will develop in the future emerges. Common inflation expectations simplify the creation of long-term economic plans for all agents, creating auspicious conditions for strong, stable, and equitable economic growth.

The idea that the inflation target acts as a nominal anchor is widely recognized in the literature (Jahan, 2018; Mishkin, 1999). However, the anchoring effect of the inflation target does not emanate from the target itself, but rather from its perceived validity. Ascari et al. (2017) found that the degree to which the central bank is transparent in its communications helps in anchoring inflation expectations. However, they also found that the importance of being transparent diminishes as the target rate increases, and that explicitly altering the target rate could unanchor inflation expectations. In addition, they found that central bank communication is an essential part of the inflation targeting regime, and that as long as economic agents trust the monetary authority and know the policy rule, they will use communicated information to form their own inflation expectations. Similarly, Christelis et al. (2020) found that higher trust in the ECB induced anchoring of inflation expectations around the medium term inflation target and reduced consumers’ uncertainty surrounding future rates of inflation. Overall, these findings imply that the effectiveness of monetary policy hinges on the credibility of the central bank in question.

Unfortunately, real-life implementation of the inflation target will always be imperfect for the simple reason that central banks have no direct control over inflation. Current inflation is determined by decisions and events that the central bank may or may not have had any control over and that occurred in previous months or years, and any monetary policy decisions taken by the central bank today will only affect inflation at some uncertain time in the future. Svensson (1997) argued that this imperfect and lagged control over inflation could, in the long-term, harm the credibility of central banks because they can, if they so wish, easily deflect any accountability by claiming that current deviations from the target rate are due to factors outside their control. To remedy this potential issue, Svensson showed that inflation targeting implies *forecast targeting* and proposed that central banks pursue forecast targeting explicitly, wherein inflation forecasts become medium-term targets. This approach would be more transparent than the opaque long-term inflation target of 2%, it would increase the accountability of central banks, and it would enhance public understanding of monetary policy.

However, inflation forecasting has been a challenging and unrewarding endeavor historically. There is scant evidence that traditional methods—which include variations on the standard ARMA, VAR, and Phillips curve models—can consistently outperform naive models such as a Random Walk or basic univariate methods such as a simple autoregression (Stock & Watson, 2008).

The most popular forecasting method among observers and academics alike is considered to be the Phillips curve model (Bishop & Greenland, 2021; Eser et al., 2020; Forbes, 2019). Phillips curve models are generally expressed as an equation that relates the unemployment rate, or some other kind of proxy for economic activity, to some measure of inflation. Despite its popularity, Atkeson & Ohanian (2001) found that out of 132 different configurations of the Phillips curve model none were able to forecast inflation on a quarterly basis between 1984 and 1999 more accurately than a simple

coin flip. Despite these findings, Phillips curve models are still in use by professional observers, major international institutions, and central banks.

In practice, central banks rely on a variety of formal and informal methods to forecast inflation. Former Chairman of the Board of Directors of the Federal Reserve System Ben Bernanke (2007), detailed how the American Federal Reserve relies on both structural and purely statistical models in its forecasting and described inflation forecasting as combining “[...] model-based projections, anecdotal and other ‘extra-model’ information, and professional judgement.” The Federal Reserve’s forecasts for longer-term horizons are mostly based on various versions of the new Keynesian Phillips curve. However, Bernanke acknowledged that “[...] for all the advances that have been made in modeling and statistical analysis, practical forecasting continues to involve art as well as science.” Because of this, inflation forecasts by the Federal Reserve inevitably rely on and reflect a considerable amount of expert judgement.

The Bank of England similarly utilizes a suite of models to guide its forecasts (Harrison et al., 2005). This suite of models acts as the “primary organizational framework” through which the Monetary Policy Committee processes its expert judgement and assumptions concerning major macroeconomic issues. One of the models in the aforementioned suite of models is the Structural VAR, which is a kind of hybrid model that enables the committee to incorporate theoretically derived identification structures while fitting the data according to statistical metrics.

The Swiss National Bank has historically relied on different configurations of VAR models to forecast inflation (Lack, 2006), making it the most quantitative of the central banks heretofore mentioned. More specifically, the Swiss National Bank has used a variety of VAR models with different input variables to produce forecasts, and then aggregated those results into a single forecast using a simple average. An especially interesting part of this method is the variable selection process involved. The Swiss National Bank initially compiled a pool of 10 macroeconomic variables selected based on a priori theoretical knowledge, and then specified a total of 512 VAR models, which consisted of three to five variable combinations of the pre-selected macroeconomic variables.

What is particularly interesting is that all three central banks mentioned above—the Swiss National Bank in particular—aggregate results of various models to improve the accuracy of their forecasts. In fact, this idea is prevalent in the machine learning literature today—it is called *ensemble learning*—and it is the cornerstone of many modern forecasting algorithms. Recent literature suggests that modern algorithms utilizing ensemble learning techniques can generate significantly and consistently more accurate inflation forecasts than both older statistical models and central banks, with the strongest of the candidate models to emerge being Random Forest (RF) (Medeiros et al., 2021; Araujo & Gaglianone, 2023).

The RF algorithm holds many advantages over the aforementioned traditional econometric methods (Cutler et al., 2012; Medeiros et al., 2021). Because of its non-parametric nature, the RF algorithm is intrinsically adept at dealing with skewed data distributions and requires no assumptions about the distribution of the input variables. RF is also an ensemble of decision trees, meaning the algorithm is inherently non-linear. In general, the RF algorithm is especially good at capturing non-linear relationships in high-dimensional data characterized by the so-called “curse of dimensionality”, which simply means that there are relatively few observations of the dependent variable and relatively many potential variables to predict the dependent variable with (Evangelista et al., 2006).

Medeiros et al. (2021) specifically, argue that there are many theoretical arguments justifying non-linear relationships between inflation and other macroeconomic factors. For example, Medeiros et al. bring up that the relationship between inflation and unemployment depends on the level of

slack in the economy. Medeiros et al. further highlight that uncertainty associated with black-swan events and their consequences can also induce non-linearities.

Finally, RF requires no major assumptions about what drives or predicts inflation (Cutler et al., 2012; Medeiros et al., 2021). The algorithm self-selects variables based on how much accuracy is lost when the values of said variables are randomly permuted among each other. Once an RF model is trained, it can return the relative importance of all variables, allowing the researcher to understand which variables drive the performance of the model.

Both Medeiros et al. (2021) and Araujo & Gaglianone (2023) found that the RF algorithm consistently outperformed all other traditional and machine learning algorithms in forecasting inflation, especially for forecast horizons of 6 months or greater. These longer-term inflation forecasts are of special interest to policy makers because they are a key part of the policy rules followed by central banks when deciding the appropriate policy rate.<sup>3</sup> The simplest and most widely known policy rule is the Taylor rule (Taylor, 1993), commonly defined as

$$i_t = \pi_t + r_t^* + \phi_\pi \pi_t^{GAP} + \phi_y y_t^{GAP} \quad (1)$$

where  $i_t$  is the appropriate policy rate,  $\pi_t$  is the current rate of inflation,  $r_t^*$  is the assumed natural interest rate,  $\pi_t^{GAP}$  is the difference between the current rate of inflation and the inflation target,  $y_t^{GAP}$  is the output gap, and  $\phi_\pi$  and  $\phi_y$  are positive coefficients. However, the traditional Taylor rule tends to recommend a relatively conservative policy stance. As a result, recent analysis indicates that major central banks such as the Federal Reserve do not adhere to the Taylor rule, especially in the period following the 2008 financial crisis (Kliesen, 2019). To explain the policy rules followed by central banks in modern times various modified Taylor rules have been proposed. Among them, Bullard’s modernized Taylor rule (Bullard, 2018a) has been shown to be able to reliably explain policy rates set by the Federal Reserve since the 2008 financial crisis (Kliesen, 2019). Its formulation is similar to the traditional Taylor rule and can be written as

$$i_t = \rho i_{t-1} + (1 - \rho)(\pi^* + r_t^* + \phi_\pi \pi_t^{GAP} + \phi_u u_t^{GAP}) \quad (2)$$

where  $i_{t-1}$  is the policy rate for the previous period and  $r_t^*$  is a measure of the natural interest rate, which is currently estimated by Bullard to be zero. Next,  $\pi^*$  is the inflation target and  $\pi_t^{GAP}$  is the forecast inflation overshoot, meaning the difference between the forecast rate of inflation and the target rate. Finally,  $u_t^{GAP}$  is a measure of excess unemployment, calculated as the difference between the current unemployment rate and the assumed natural rate of unemployment (NAIRU).  $\rho$ ,  $\phi_\pi$ , and  $\phi_u$  are all coefficients and estimated by Bullard to be 0.85, 1.5, and 0.1, respectively. The low value of  $\phi_u$  is intended to reflect the currently observed flatness of the Phillips curve.

## 2.2 Contribution to the Literature

This paper builds upon the methodology developed by Medeiros et al. (2021) and Araujo & Gaglianone (2023) and applies it to the Swedish economy in order to answer the first of the two fundamental questions asked in this paper: Could the Riksbank have predicted the historic surge in inflation in the aftermath of the Covid-19 pandemic? I expand the methodology by investigating how the performance of RF models changes based on the underlying temporal structure of inputs and how such changes alter the relative importance of variables. Further, I extend the analysis by quantifying and discussing the impact of inflation forecasting using RF on policy rate forecasts by

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<sup>3</sup>These are for example called the Federal Funds Rate in the U.S. and “Styrränta” in Sweden.

creating approximations of the Riksbank's policy rule using Bullard's modernized Taylor rule and answering the second fundamental question posed: Could the Riksbank have warned the Swedish public about impending rate hikes sooner?

### 3 Methodology and Theory

All forecasts generated using autoregressive methods are generated by implementing an iterative forecasting method as recommended by Marcellino et al. (2004). RF model forecasts are generated using direct forecasting in order to keep computational requirements manageable. All models are implemented in R using open-source packages. Model performance is measured by the Root Mean Squared Error (RMSE) and explained variance in the out-of-sample data calculated as  $R^2$ . RMSE is the measure preferred by Medeiros et al. (2021) and can be interpreted as the standard deviation of residuals or errors.

#### 3.1 ARMA

The ARMA model is one of the most common econometric models used for time series analysis, popularized by Box and Jenkins (1970). The model is commonly specified as a function of  $(p, q)$ —written as  $\text{ARMA}(p, q)$ —where  $p$  is the number of past observations included in the regression and  $q$  is the number of past errors included. The past errors are those produced when predicting observations using a simple autoregression, which is a special case of ARMA and denoted  $\text{ARMA}(p, 0)$ . Mathematically the  $\text{ARMA}(p, q)$  model can be written as

$$y_t = \sum_{i=1}^p \phi_i y_{t-i} + \sum_{i=1}^q \psi_i \xi_{t-i} \quad (3)$$

where  $y_t$  is the observed variable in the current period predicted using  $p$  lagged values of itself  $y_{t-i}$  and  $q$  lagged values of errors  $\xi_{t-i}$ .  $\phi_i$  and  $\psi_i$  are coefficients.

The ARMA model’s strengths lie in its ease of use and interpretability. However, as it is a univariate method, it can only use previous observations of the dependent variable as inputs, significantly restricting the domain of possible predictors. Additionally, ARMA models require that underlying data conform to certain assumptions, most notably stationarity, meaning that the mean and variance of the time series must be constant across time (Mills, 2019).<sup>4</sup>

#### 3.2 VAR

The VAR model is a generalization of the  $\text{AR}(p, 0)$  model and denoted  $\text{VAR}(p)$ . The model consists of  $k$  endogenous variables, allowing the user to model multiple time series at the same time using lagged values of all variables. VAR models are very flexible in terms of the ways in which they can be structured, meaning that variable selection plays a vital role in maximizing the inherent performance potential of any VAR model. As an example, a  $\text{VAR}(2)$  model with two endogenous variables can be written as

$$\begin{cases} x_t &= a_{11}x_{t-1} + a_{12}y_{t-1} + b_{11}x_{t-2} + b_{12}y_{t-2} + c_1 \\ y_t &= a_{21}x_{t-1} + a_{22}y_{t-1} + b_{21}x_{t-2} + b_{22}y_{t-2} + c_2 \end{cases}$$

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<sup>4</sup>Worth noting is that inflation data post 2021 is so strongly non-stationary that it would require as many as four first-differencing iterations in order to make it stationary, significantly reducing the interpretability of the model, and eliminating one of the primary reasons to use it in the first place.

where  $x$  and  $y$  are the endogenous variables,  $a_{ij}$  and  $b_{ij}$  are coefficients, and  $c_i$  are constants. Using vector notation, a general VAR( $p$ ) model can be written as

$$\vec{y}_t = \sum_{i=1}^p A_i \vec{y}_{t-i} + \vec{c} \quad (4)$$

where  $\vec{y}_t$  is the vector containing the current values of the endogenous variables,  $A_i$  is the matrix of coefficients,  $\vec{y}_{t-i}$  is the vector containing the  $i$ :th lagged values of the endogenous variables, and  $\vec{c}$  is a constant vector.

VAR models require a priori knowledge of which features affect—or at least are hypothesized to affect—each other over time. Furthermore, VAR requires weak stationarity of all endogenous variables and no perfect multicollinearity between predictor variables. However, even the presence of non-perfect multicollinearity is a well recognized issue in the literature (Vatcheva et.al, 2016). First, multicollinearity is strongly associated with unstable and biased standard errors, leading to unstable p-values and eroding the interpretability of the model. Second, even though multicollinearity does not bias the fit of the model, it does create a situation in which it becomes “practically impossible” to interpret the coefficients of the model, leading to misleading conclusions as regards the role of each collinear predictor.

Because the performance of a VAR model is dependent on the selection of lags and variables, I have chosen to configure two VAR models in an attempt to investigate the inherent performance of the model itself.

### 3.2.1 Traditional Configuration

The first of the two models is a traditionally configured VAR model—denoted VAR-TRD—and it is primarily inspired by the kind of models historically used at the Swiss National Bank. The model is configured using the following five variables selected on the basis of traditional economic theory:

1. Industrial Output
2. Unemployment
3. Policy Rate (Styrräntan)
4. M3 Money Supply
5. KPIF

### 3.2.2 Granger Configuration

The second VAR model—denoted VAR-GRG—is specified using variables selected through a Granger causality test. The reasoning behind this approach is as follows. It is a well known fact that ordinary regressions reflect correlation, not causation. However, Granger (1969) argued that causality can be tested by measuring the ability of lagged values of a time series  $X$  to predict future values of a time series  $Y$ . As such, we say that  $X$  Granger-causes  $Y$  if future values of  $Y$  can be more accurately predicted using lagged values of both  $X$  and  $Y$  than only using lagged values of  $Y$ . The intuition behind Granger causality as presented is relatively simple, however, the technical details are quite intricate and beyond the scope of this paper.

Thus, the idea in this paper is to select input variables for a VAR model based on them Granger-causing inflation. Once the Granger-causal variables are identified, strongly correlated variables are excluded to avoid issues induced by collinear predictors, and the remaining variables are used to configure the VAR-GRG model.

### 3.3 Random Forest

RF is a supervised machine learning algorithm first introduced by Breiman (2001). Formally, RF is a non-parametric (meaning it does not require any assumptions about the distribution of the input data), supervised (meaning it needs labeled training data), ensemble learning algorithm that utilizes decision trees, bagging, and the Strong Law of Large Numbers to construct predictions based on a set of inputs. The introduction to the RF algorithm as presented below is primarily inspired by the chapter on Random Forests by Cutler et al. (2012).

#### 3.3.1 Decision Trees

The principal component of the RF algorithm is the decision tree, more specifically the classification and regression tree—or CART—as defined by Breiman (1984). All decision trees begin with a root node and end in leaf nodes. Non-leaf nodes are always split into two descendant nodes based on the value of one of the predictor variables (called *features*). Each non-leaf node in a tree contains a *splitting criteria*, which is used to divide the data into smaller, more homogeneous groups. The most common splitting criteria for regression trees is the Sum of Squared Errors (SSE), formulated as

$$SSE = \sum_{i \in S_1} (y_i - \bar{y}_1)^2 + \sum_{i \in S_2} (y_i - \bar{y}_2)^2 \quad (5)$$

where  $S_1$  and  $S_2$  are the two sets that result from splitting the data into two partitions,  $y_i$  are the observations of the variable of interest in each set, and  $\bar{y}_j$  are the mean values of the variable of interest in each set. This means that at each node, the algorithm attempts to minimize the SSE in the variable of interest (in our case the KPIF). This splitting criteria carries with it the added benefit of being very similar to the fitting algorithm employed by, for example, the ordinary least square regression (OLS). This is the splitting criteria used in both RF models in this paper.

CARTs are in and of themselves non-parametric learning algorithms capable of tackling many kinds of problems. However, as a standalone approach, CARTs are fundamentally limited in their applicability because of two major issues (Zorman et al., 1997). First, because of their complexity, CARTs are easy to overfit, meaning they will capture both the information and the random noise in the data, leading to poor performance on out-of-sample data. Second, CARTs are notoriously unstable, leading to entirely dissimilar trees for only slightly different training data, heavily restricting interpretability.

#### 3.3.2 Strong Law of Large Numbers, Ensemble Methods, and Bagging

The Strong Law of Large Numbers (SLLN) is a mathematical theorem closely related to the more well-known Law of Large Numbers (LLN). In general terms, the LLN states that when the same experiment is conducted a large number of times  $n$ , the average result of the experiments  $\bar{X}_n$  will tend to be close to the expected value of the experiment  $\mu$ . The SLLN is a more stringent formulation of the LLN, stating that as  $n$  goes to infinity the average result of the experiments  $\bar{X}_n$  will almost

surely converge to the expected value of the experiment  $\mu$ . In mathematical terms the SLLN is commonly expressed as (Spanos, 2012)

$$P\left(\lim_{n \rightarrow \infty} \bar{X}_n = \mu\right) = 1 \quad (6)$$

The SLLN is the backbone of the RF algorithm for two specific reasons. First, it guarantees that the model does not become overfitted as the number of trees in the forest increases. Second, it guarantees that as the number of trees in the forest increases, the error of the forecast almost surely converges to zero (Breiman, 2001).

The idea of ensemble learning is related to the LLN. Ensemble methods aggregate predictions made by multiple algorithms in order to maximize predictive performance, yielding better results than any one method alone (Rokach, 2010). In order to maximize the benefits of ensemble learning, the methods must also be sufficiently diverse (Kuncheva & Whitaker, 2003; Sollich & Krogh, 1995). The idea of RF is to grow a sufficient number of uncorrelated decision trees in order to produce a strong ensemble of models.

RF also utilizes *bagging*, which is a special kind of sampling algorithm introduced by Breiman (1996) to improve the stability and accuracy of predictions. Given a training set  $D$  consisting of  $N$  elements, the bagging algorithm will sample  $N$  elements from  $D$  with replacement, producing what is known as the *bootstrap sample*. This means that the same element might show up multiple times in the same bootstrap sample, while some elements are not included at all. The data that do not make the bootstrap sample are called *out-of-bag* data and are later used to measure variable importance. The bootstrap sample is the first of two sources of randomness that allow RF to grow uncorrelated trees, maximizing ensemble learning effects.

### 3.3.3 RF Algorithm

It is beyond the scope of this paper to detail all theoretical intricacies of the RF algorithm.<sup>5</sup> However, in order to understand how it produces better predictions and is able to capture more complex relationships than traditional models, it is necessary to understand the method broadly.

RF begins by creating  $k$  bootstrap samples of training data: one bootstrap sample for each tree. Then, RF randomly selects the features to be considered for each splitting criteria in each tree. For regression trees Hastie et al. (2009) recommend that one select  $m = \frac{p}{3}$  different features to be considered at any given split for each tree, where  $p$  is the total number of features in the data. This is the second source of randomness that helps RF create uncorrelated trees.

The splitting criteria in each non-leaf node in each tree is then determined by comparing almost all<sup>6</sup> possible splitting criteria for all randomly selected features, and picking the one which minimizes the SSE as defined in Eq. (5).

Once a tree has reached the maximum allowed number of leaf nodes, the value of each leaf node is set to the average value of the variable of interest in the set that is contained in said node. When a prespecified number of trees has been grown the model is complete. Predictions are made on

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<sup>5</sup>For an in-depth pedagogical presentation of the algorithm I refer to Cutler et al. (2012). For a detailed and technical presentation see Breiman (2001).

<sup>6</sup>The formulation “almost all” refers to the fact that the considered splitting criteria for any given feature will depend on the number of observations in the training set and the range of values that the feature spans. The default number of splits considered is  $n - 1$  where  $n$  is the number of samples in the data. As an example, given that a feature has a maximum value of 10 and minimum value of 1 in a given training set consisting of 5 observations, the 4 considered split criteria values at a node will be 2, 4, 6, and 8.

out-of-sample data by feeding the data through each tree and then taking a simple average of the outputs from each tree.

### 3.3.4 Feature Importance

One of the key benefits of using RF is that it can provide a measure of feature importance. The importance of any given feature  $F$  is defined by its *permutation importance* (Cutler et al., 2012). Permutation importance is measured by taking the out-of-bag data for each tree and feeding it through the trained model, generating predicted values  $y^*$ . The values of  $F$  are then randomly permuted among each other in the out-of-bag sample, with all other data kept unchanged, and fed through the model again, generating a second set of predicted values denoted  $\hat{y}$ . The importance of  $F$  is then defined as

$$Imp(F) = \frac{1}{J} \left[ \sum_{i \in \mathcal{J}} (y_i - y_i^*)^2 - \sum_{i \in \mathcal{J}} (y_i - \hat{y}_i)^2 \right] \quad (7)$$

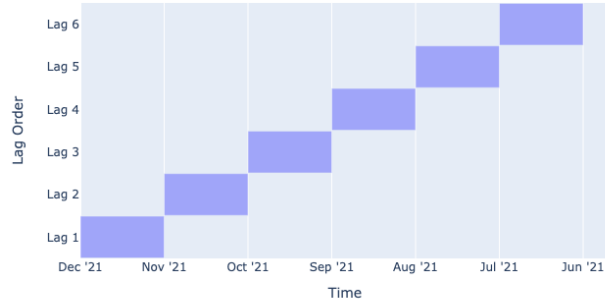
where  $J$  is number of observations in the out-of-bag set  $\mathcal{J}$  and  $y_i$  are the individual observations of the variable of interest (again, the KPIF) in the out-of-bag data. Permutation importance is thus a measure of how much the Mean Squared Error (MSE) increases when the observations of feature  $F$  in an out-of-bag set are randomly permuted.

To summarize, RF is a very attractive method because it has the ability to capture very complex relationships, and, when it does, it can identify the most important features by evaluating how much predictive power is lost when their values are randomly permuted.

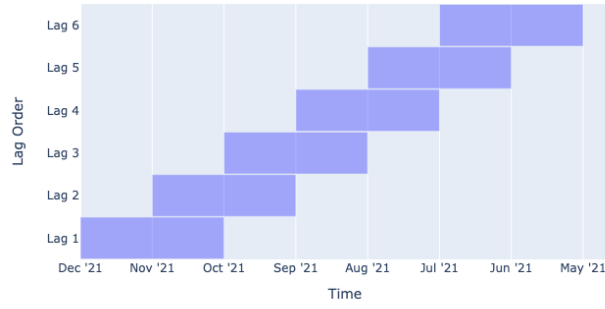
### 3.3.5 RF-STP and RF-CUM

To investigate the dynamics behind inflation I set up two different RF models, both using six lagged observations of each feature as inputs. The first—denoted RF-STP—is configured in such a way that it only uses month-on-month differences in each feature as inputs. As an example, Figure 1a displays the temporal data structure used by the RF-STP model when forecasting inflation on a 3 month horizon, in this example for the end of March 2022 from the end of December 2021. The RF-STP model uses six lagged month-on-month changes in each feature as inputs, and outputs the forecasted cumulative change in inflation from December 2021 to March 2022. This cumulative change is then added onto the rate of inflation in December 2021 to establish the final forecast.

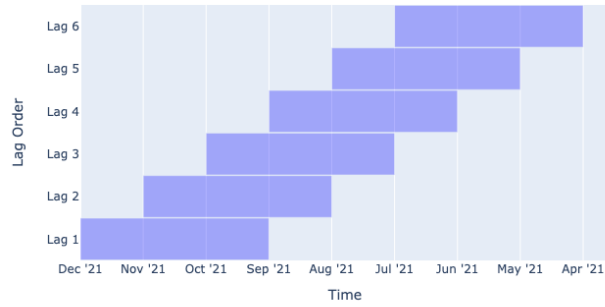
The second model—denoted RF-CUM—is configured to use lagged cumulative changes in features as inputs. RF-CUM also uses six lagged values of each feature, however, the temporal data structure used by RF-CUM is somewhat complicated because it changes based on the forecast horizon. As an example, the changes in temporal structure when forecasting inflation in December 2021 for February and March 2022, respectively, are displayed in Figures 1b and 1c. Figure 1b shows that when RF-CUM forecasts inflation for February 2022—a 2 month forecast horizon—the Lag 1 inputs are the changes in each feature between October and December 2021; the Lag 2 inputs are the changes in each feature between September and November 2021; and so on. Figure 1c shows that when RF-CUM forecasts inflation for March 2022—a 3 month forecast horizon—the Lag 1 inputs are the changes in each feature between September and December 2021; the Lag 2 inputs are the changes in each feature between August and November 2021; and so on. The final inflation forecasts by the RF-CUM model are generated in the same way as they are for the RF-STP model.



(a) RF-STP: all forecast horizons



(b) RF-CUM: 2 month forecast horizon



(c) RF-CUM: 3 month forecast horizon

Figure 1: Visualization of the temporal data structure used in the two RF models. Figure (a) displays the temporal data structure used by the RF-STP model for *all* forecast horizons. Figure (b) displays the temporal structure used by the RF-CUM model *specifically* for the 2 month forecast horizon. Figure (c) displays the temporal structure used by the RF-CUM model *specifically* for the 3 month forecast horizon. *Source: Author's own illustration.*

### 3.4 Bullard's Modernized Taylor Rule

Bullard's rule as originally specified in Eq. (2) has specific coefficient values associated with it. However, those coefficients are approximations for the policy rule of the Federal Reserve, meaning they do not necessarily reflect the policy rule followed by the Riksbank. Because of this I re-write Bullard's rule in a more general form,

$$i_t = \rho i_{t-1} + \psi_\pi \pi^* + \phi_\pi \pi_t^{GAP} + \phi_u u_t^{GAP} \quad (8)$$

and estimate the coefficients  $\rho$ ,  $\psi_\pi$ ,  $\phi_\pi$ , and  $\phi_u$  using a simple OLS regression in order to approximate the policy rule of the Riksbank. The  $r^*$  term has been eliminated from the expression because, as stated earlier, Bullard approximates that it is currently around zero for most developed economies.

Worth noting before concluding this section is that when written in this form the estimated coefficients  $\psi_\pi$ ,  $\phi_\pi$ , and  $\phi_u$  for the policy rule of the Federal Reserve equate to 0.15, 0.225, and 0.015, respectively.

## 4 Data

All data used to train the models and evaluate their performance consist of 124 variables (including the KPIF measure itself) totaling 258 observations, beginning March 2001 and ending September 2022. 88 of the variables were originally reported in monthly intervals and 29 were reported in quarterly intervals. The quarterly data are extended to monthly data using cubic spline interpolation. Seven of the variables were reported annually through 2005 and quarterly from 2006 onward. These have also been extended to monthly data using cubic splines. The data are categorized according to the variable categorization scheme proposed by McCracken & Ng (2016) and used by Medeiros et al. (2021).<sup>7</sup>

Once the data are consolidated in monthly format they are pre-processed according to the needs of each model. For the ARMA model all data are first-differenced only. The reason for this is that the model assumes that data are stationary. In this case, the data are the KPIF time series, which after being first-differenced are KPSS tested by the `auto.arima()` function in R to ensure stationarity during the training period. Since all inputs are by definition of the same order of magnitude there is no need to standardize them.

For both VAR models, all data are first-differenced and then standardized by subtracting from each variable its sample mean and dividing by its sample standard deviation. These steps are done primarily for two reasons. First, the VAR requires its data to be stationary. Second, in order for the coefficients in the VAR models to be interpretable, the variables need to be of the same magnitude. Standardizing the variables in this fashion does not make them normally distributed because it leaves the inherent skew of the distribution unchanged. However, it does center the distribution around a zero-mean and standardizes the standard deviation to 1, making the data comparable in terms of magnitude.<sup>8</sup>

The data for the RF-STP model are first-differenced in the same way as they are for the VAR models. For the RF-CUM model, data are first-differenced using a lag equivalent to the forecast horizon as detailed in Section 3.3.5. The data for both RF models are then standardized in the same way as they are for VAR models. Worth highlighting is that RF does not technically require that data be standardized. However, there is evidence in the medical literature that if features vary in scale the variable importance measure of RF could be unreliable (Strobl et al., 2007). Because of this, data are standardized for both RF models as well.

Data are then split into a training and a testing set according to the 80/20 rule inspired by the Pareto Principle. This is not the most advanced way of splitting the data, but it is the simplest and most common way of doing so (Gholamy et al., 2018).

In order to create Bullard rule approximations of the policy rule followed by the Riksbank, data on the estimated natural rate of unemployment in Sweden (the NAIRU) is also collected. Prior to the Covid-19 pandemic NAIRU was estimated at around 6.8% (Konjunkturinstitutet, 2019). Today it is approximated at around 7.5% (Sveriges Kommuner och Regioner, 2022). Because of this I have chosen to structure the data in such a way that NAIRU is set to 6.8% through December 2019 and to 7.5% from January 2020 onward.

Finally, data on inflation and policy rate forecasts by the Riksbank are taken directly from the Riksbank’s monetary policy reports.<sup>9</sup>

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<sup>7</sup>The full list of variables used in this paper, their categorization, and their sources can be found in Appendix A.

<sup>8</sup>Differencing is not only a statistical requirement for some of the models. It is also useful insofar as it makes the data more closely reflect the phenomenon of inflation: It is not the absolute value of any variable that determines the rate of inflation, rather it is the change in variables that might impact prices of goods, in turn affecting inflation.

<sup>9</sup>The official name of the report is “Penningpolitisk Rapport”.

## 5 Analysis

### 5.1 Autoregressive Model Configurations and Coefficients

The ARMA model is specified using the `auto.arima()` function in R, which automatically conducts a KPSS test to check whether the data are stationary, takes the appropriate number of first-differencing steps if the data are non-stationary, and determines the optimal number of lags and moving average terms by minimizing the AIC criterion. The optimal ARMA model specified in this manner on the training data set used herein contains 3 lags of the KPIF variable and 2 lagged error terms.

Table 1 displays the regression coefficients for the ARMA model. The third lag of the KPIF variable is the only lagged KPIF term significant at the 95% level or greater. However, both moving average terms are estimated to be of greater magnitude and they are both significant at the 99.9% level. The moving average coefficients are negative reflecting the corrective nature of the error terms in the model.

Table 1: Regression coefficients for the ARMA model

| Parameter   | Estimate             |
|-------------|----------------------|
| $\pi_{t-1}$ | 0.002<br>(0.069)     |
| $\pi_{t-2}$ | -0.061<br>(0.069)    |
| $\pi_{t-3}$ | -0.164*<br>(0.070)   |
| $\xi_{t-1}$ | -0.603***<br>(0.068) |
| $\xi_{t-2}$ | -0.295***<br>(0.072) |

Note: Coefficients are interpreted as changes in the dependent variable KPIF given a one unit increase in the coefficient term. Standard errors reported in parentheses. Significance levels reported: \*\*\*  $p < 0.001$ , \*  $p < 0.05$ .  
Source: Author-generated figures in R using data from the Riksbank.

Next, the VAR-GRG model is specified. The variables identified as Granger-causing inflation are reported in Table 2. The most surprising Granger-causing variable is the U.S. Federal Funds Rate (the F.F.R)—a strictly foreign variable— which traditionally is not considered when forecasting Swedish inflation. Furthermore, conspicuous in its absence is the Swedish policy rate “Styrräntan”, which is the main lever through which the Riksbank attempts to control inflation. These findings are all the more interesting because this test is run on data that end in May 2018, so there should be no obvious relationship between the F.F.R. and Swedish rate of inflation.

Finally, the two energy related goods variables are highly correlated, so the weaker one (Exports) is excluded .

Table 2: Results of Granger causality test

| Parameter                     | p-value |
|-------------------------------|---------|
| Domestic Energy Demand        | 0.051   |
| Exports: Energy Related Goods | 0.015   |
| Imports: Energy Related Goods | 0.009   |
| Swedish M3 Money Supply       | <0.001  |
| U.S. Federal Funds Rate       | 0.027   |
| BoP: Financial Derivatives    | 0.040   |
| Industrial Capacity Utilized  | 0.028   |

Note: Only parameters which returned p-values below 0.1 are reported. *Source: Author-generated figures in R using data from the Riksbank, the SCB, and the Federal Reserve Bank.*

Both VAR models are specified with the help of the `VARselect()` function in R, where I have imposed a maximum 12 lag restriction. The function recommends using 12 lags for both models based on the AIC criterion, four lags for VAR-TRD and three lags for VAR-GRG based on the HQ criterion, and two lags for VAR-TRD and three lags for VAR-GRG based on the SC criterion. Because the recommendations based on different information criterion vary significantly, I have chosen to use the average of the recommended lags—in this case six lags—for both models based on the approach recommended by Ayalew et al. (2012).

Table 3 presents the parameters in the VAR-TRD model whose coefficients are significant at or above the 95% level for at least one of the lags. We see that only two of the five parameters in the VAR-TRD model are significant at any lag. SWE M3 is significant at lags one and six at the 99% and 95% levels, respectively. Because of the way the data are structured, the interpretation of the coefficients is that there is a 0.212 and 0.182 standard deviation increase in KPIF given a one standard deviation increase in SWE M3 at lag one and lag six, respectively. KPIF is significant at lag three at the 99% level and the coefficient indicates that a one standard deviation increase in KPIF at lag three is associated with a 0.222 standard deviation decrease in KPIF.

Table 3: VAR-TRD regression coefficients for statistically significant parameters across lags

| Lag | SWE M3             | KPIF                |
|-----|--------------------|---------------------|
| 1   | 0.212**<br>(0.080) | —                   |
| 3   | —                  | −0.222**<br>(0.077) |
| 6   | 0.182*<br>(0.080)  | —                   |

Note: Only parameters with a significant coefficient for at least one lag are reported. Coefficients are interpreted as standard deviation changes in the dependent variable KPIF given a one standard deviation increase in their associated parameters. Significance levels reported: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ . *Source: Author-generated figures in R using data from the Riksbank and the SCB.*

Table 4 displays the parameters in the VAR-GRG model whose coefficients are significant at or above the 95% level for at least one of the lags. For the VAR-GRG model five of the seven variables in the model are statistically significant for at least one lag. All significant SWE M3 coefficients are positive, ranging from 0.251 to 0.199 decreasing in lag, and significant at lag one at the 99% level and at lags five and six at the 95% level. Again, the third KPIF lag is significant at the 95% level, but of slightly smaller magnitude than it is in the VAR-TRD model.

The third lag of the U.S. Federal Funds Rate is negative and significant at the 95% level. The coefficient -0.243 indicates that a one standard deviation increase in the U.S. F.F.R decreases KPIF in Sweden by 0.243 standard deviations after three months. This is very interesting because this is the role one would expect the Swedish policy rate to play, not the F.F.R.

In terms of magnitude, the most important variable is the Utilized Industrial Capacity, with which one standard deviation increases at lag one and lag two are associated with almost a one standard deviation increase and a two standard deviation decrease in KPIF, respectively. However, the Utilized Industrial Capacity coefficients have by far the biggest standard errors as well.

Finally, it is important to keep in mind that, in this paper, we cannot compare the magnitudes of coefficients between ARMA and VAR models because of the way the data are structured. The ARMA model coefficients tell us the change in inflation given a one unit increase in an input variable, while the VAR models, in order to be internally interpretable, yield results that indicate how KPIF changes in terms of standard deviations given a one standard deviation increase in a given input variable.

Table 4: VAR-GRG regression coefficients for statistically significant parameters across lags

| Lag | Energy: Demand      | SWE M3             | Utilized Ind.Cap.  | U.S. F.F.R         | KPIF               |
|-----|---------------------|--------------------|--------------------|--------------------|--------------------|
| 1   | -0.243**<br>(0.093) | 0.251**<br>(0.081) | 0.984**<br>(0.346) | —<br>—             | —<br>—             |
| 2   | —<br>—              | —<br>—             | -1.905*<br>(0.868) | —<br>—             | —<br>—             |
| 3   | 0.202*<br>(0.093)   | —<br>—             | —<br>—             | -0.243*<br>(0.118) | -0.191*<br>(0.083) |
| 5   | —<br>—              | 0.210*<br>(0.081)  | —<br>—             | —<br>—             | —<br>—             |
| 6   | —<br>—              | 0.199*<br>(0.080)  | —<br>—             | —<br>—             | —<br>—             |

Note: Only parameters with a significant coefficient for at least one lag are reported. Coefficients are interpreted as standard deviation changes in the dependent variable KPIF given a one standard deviation increase in their associated parameters. Significance levels reported: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ . *Source: Author-generated figures in R using data from the Riksbank, the SCB, and the Federal Reserve Bank.*

## 5.2 Summary of Inflation Forecasts

Table 5: Inflation forecast summary for the out-of-sample period starting in June 2018

|                           | (1)          | (2)           | (3)                 | (4)             |
|---------------------------|--------------|---------------|---------------------|-----------------|
| <b>Benchmark Model</b>    | mean<br>RMSE | mean<br>$R^2$ | %<br>RMSE Reduction | %<br>$R^2$ Gain |
| Riksbanken                | 1.913        | 0.246         |                     |                 |
| <b>Proprietary Models</b> |              |               |                     |                 |
| ARMA                      | 1.857        | 0.288         | 2.9%                | 16.7%           |
| VAR-TRD                   | 2.114        | 0.088         | -10.5%              | -64.3%          |
| VAR-GRG                   | 1.784        | 0.364         | 6.7%                | 47.8%           |
| RF-STP                    | 1.683        | 0.409         | 12.0%               | 66.1%           |
| RF-CUM                    | 1.553        | 0.493         | 18.8%               | 100.1%          |
| Mean                      | 1.798        | 0.329         | 6.0%                | 33.3%           |
| Median                    | 1.784        | 0.364         | 6.7%                | 47.8%           |

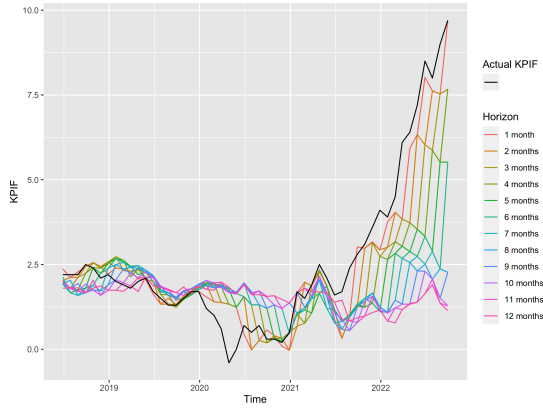
Note: Columns (1) and (2) report the forecast horizon average RMSE and  $R^2$ . Columns (3) and (4) report the percentage reduction in RMSE and percentage increase in  $R^2$  compared to the Riksbank benchmark model. Mean and Median figures only pertain to the proprietary models. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

Table 5 presents a summary of the inflation forecast results. On average, the Riksbank’s inflation forecasts explain 24.6% of the variation in the out-of-sample data as measured by  $R^2$ , with an average RMSE of 1.913. Among the proprietary models, the VAR-TRD is by far the worst performing model, underperforming the Riksbank’s forecasts by an average of 10.5% in terms of RMSE and 64.3% in terms of  $R^2$ . At the other end of the spectrum, the RF-CUM model is the best performing model, on average reducing RMSE by 18.8% and increasing  $R^2$  by 100.1% compared to the Riksbank. On average, the proprietary models reduced RMSE by 6.0% and increased  $R^2$  by 33.3% compared to the Riksbank.

These results provide a clear answer to the first question posed in this paper: The Riksbank could have predicted the historic surge in inflation in the aftermath of the Covid-19 pandemic. The matter is made all the more somber by the fact that a primitive ARMA model outperformed the Riksbank by 2.9% in terms of RMSE and 16.7% in terms of  $R^2$  in the out-of-sample period.

## 5.3 Inflation Forecasts in Depth

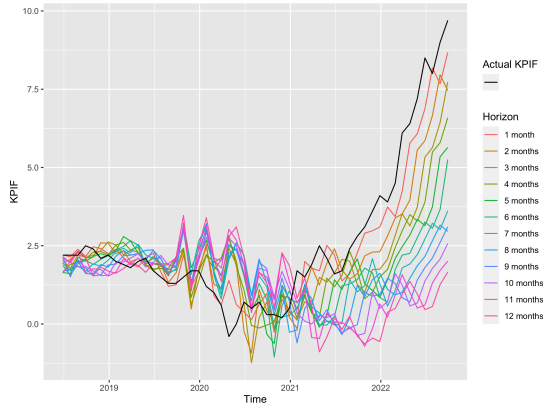
Figure 2 displays the inflation forecasts generated by all models across all 12 forecast horizons as well as the actual KPIF observations for the out-of-sample period. Figures 2a and 2b provide a possible indication as to why the performance metrics of the Riksbank are so similar to those of the ARMA model. We can see that the Riksbank’s forecasts across all horizons are very similar to those generated by the ARMA model, with a minor exception during the onset of the Covid-19 pandemic in early 2020. Furthermore, the Riksbank and the ARMA model are the only two models whose



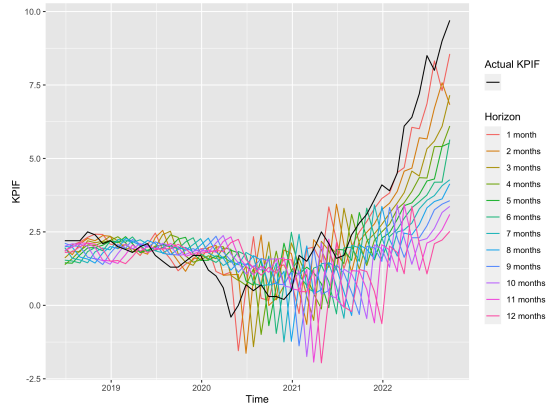
(a) Riksbanken



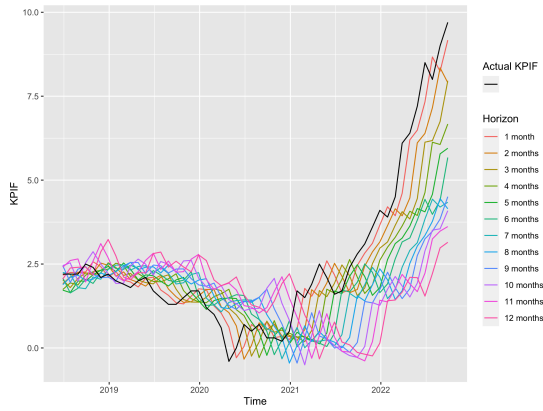
(b) ARMA



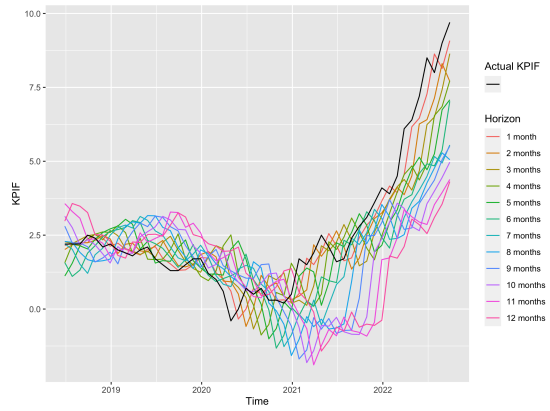
(c) VAR-TRD



(d) VAR-GRG



(e) RF-STP



(f) RF-CUM

Figure 2: Inflation forecasts by all models across all forecast horizons. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

forecasts converge to the actual KPIF value around April 2021, while forecasts by all other models diverge significantly across forecast horizons at that specific time.

The VAR model forecasts displayed in Figures 2c and 2d indicate that VAR models are fundamentally sensitive to volatility in the underlying data, best exemplified by the unstable forecasts in early 2020. A possible explanation for this could be that VAR models treat all their input variables as endogenous. This means that in order to generate longer-horizon inflation forecasts they also have to generate their own forecasts for the other input variables and then use those as inputs. During a period of high volatility this could lead to unstable results and perhaps indicates that the iterative forecasting method recommended by Marcellino et al. (2004) is substandard during such periods. Considering this, the VAR-GRG model still performs very well. It is remarkably stable prior to 2020, when inputs are relatively stable, and it is able to recover its predictive performance faster than its sister VAR-TRD model in the aftermath of the Covid-19 induced volatility.

Figures 2e and 2f display the forecasts generated by the RF models. The RF models are less stable than their counterparts in the period preceding 2020, with greater variance among forecast horizons. However, after the onset of Covid-19, the RF models perform much better than any other model. Comparing the forecasts generated by the two RF models, we can also see the importance of cumulative effects. This is most noticeable from the beginning of 2021 until the end of 2021, when the longer-horizon forecasts generated by RF-CUM gained accuracy much quicker than those generated by RF-STP.

Horizon specific performance is presented in Tables 6 and 7, where the dominance of the RF models is made explicit. The two RF models collectively outperformed all other models across all 12 forecast horizons both in terms of RMSE and  $R^2$ . Tables 6 and 7 also showcase for which horizons the benefits from including cumulative effects in the RF-CUM model are the greatest. We can see that the RF-CUM model loses slightly less performance in terms of both RMSE and  $R^2$  than its sister RF-STP model for horizons 1–4. However, horizons 5 and 6 are major outliers, with the RF-CUM model losing much less performance than the RF-STP model, signalling that changes accumulated over five and six months can have relatively large effects on inflation. Horizons 7–12, on the other hand, have the RF-CUM model on average incrementally lose more performance than the RF-STP model, indicating that there might be little to be gained by including changes accumulated over more than six months.

Finally, Table 7 highlights the fact that no model was able to beat a simple sample mean beyond at best the 10 month forecast horizon. The Riksbank and the VAR-TRD model performed the worst in this regard, with their forecasts going into negative  $R^2$  territory after the 7 month forecast horizon. However, even the RF-CUM model, which could still explain 15.3% of the variance in KPIF for the 10 month forecast horizon, could not outperform the sample mean for forecast horizons 11 and 12. This finding is especially important because it highlights the difficulty in forecasting inflation beyond a year, especially during highly uncertain and volatile times.

Table 6: Inflation forecast accuracy for all models across all horizons as measured by RMSE.  $\% \Delta$  represents the percentage change in RMSE between consecutive forecast horizons. Bold figures represent best performance at each horizon. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

| Horizon | Riksbank |             | ARMA  |             | VAR-TRD |             | VAR-GRG |             | RF-STP       |             | RF-CUM       |             |
|---------|----------|-------------|-------|-------------|---------|-------------|---------|-------------|--------------|-------------|--------------|-------------|
|         | RMSE     | $\% \Delta$ | RMSE  | $\% \Delta$ | RMSE    | $\% \Delta$ | RMSE    | $\% \Delta$ | RMSE         | $\% \Delta$ | RMSE         | $\% \Delta$ |
| 1       | 0.658    |             | 0.564 |             | 0.714   |             | 0.777   |             | <b>0.489</b> |             | 0.501        |             |
| 2       | 0.926    | +40.6       | 0.906 | +60.6       | 1.140   | +59.6       | 1.104   | +42.0       | <b>0.812</b> | +65.9       | 0.819        | +63.6       |
| 3       | 1.141    | +23.2       | 1.184 | +30.7       | 1.455   | +27.6       | 1.281   | +16.1       | 1.062        | +30.9       | <b>1.008</b> | +23.1       |
| 4       | 1.452    | +27.3       | 1.467 | +23.8       | 1.670   | +14.8       | 1.465   | +14.4       | 1.320        | +24.3       | <b>1.215</b> | +20.5       |
| 5       | 1.762    | +21.3       | 1.684 | +14.8       | 1.922   | +15.0       | 1.600   | +9.2        | 1.519        | +15.1       | <b>1.280</b> | +5.4        |
| 6       | 2.012    | +14.2       | 1.905 | +13.2       | 2.126   | +10.6       | 1.727   | +8.0        | 1.686        | +11.0       | <b>1.391</b> | +8.7        |
| 7       | 2.266    | +12.6       | 2.114 | +10.9       | 2.317   | +9.0        | 1.867   | +8.1        | 1.875        | +11.2       | <b>1.620</b> | +16.5       |
| 8       | 2.368    | +4.5        | 2.271 | +7.4        | 2.488   | +7.4        | 2.000   | +7.2        | 2.002        | +6.8        | <b>1.825</b> | +12.7       |
| 9       | 2.474    | +4.5        | 2.404 | +5.9        | 2.647   | +6.4        | 2.191   | +9.5        | 2.141        | +7.0        | <b>1.964</b> | +7.6        |
| 10      | 2.583    | +4.4        | 2.517 | +4.7        | 2.811   | +6.2        | 2.317   | +5.7        | 2.294        | +7.2        | <b>2.153</b> | +9.6        |
| 11      | 2.638    | +2.1        | 2.608 | +3.6        | 2.976   | +5.9        | 2.463   | +6.3        | 2.412        | +5.2        | <b>2.379</b> | +10.5       |
| 12      | 2.672    | +1.3        | 2.662 | +2.1        | 3.105   | +4.3        | 2.620   | +6.3        | 2.584        | +7.1        | <b>2.487</b> | +4.5        |

Table 7: Inflation forecast accuracy for all models across all horizons as measured by  $R^2$ .  $\% \Delta$  represents the percentage change in  $R^2$  between consecutive forecast horizons. Bold figures represent best performance at each horizon. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

| Horizon | Riksbank |             | ARMA   |             | VAR-TRD |             | VAR-GRG |             | RF-STP       |             | RF-CUM       |             |
|---------|----------|-------------|--------|-------------|---------|-------------|---------|-------------|--------------|-------------|--------------|-------------|
|         | $R^2$    | $\% \Delta$ | $R^2$  | $\% \Delta$ | $R^2$   | $\% \Delta$ | $R^2$   | $\% \Delta$ | $R^2$        | $\% \Delta$ | $R^2$        | $\% \Delta$ |
| 1       | 0.921    |             | 0.942  |             | 0.907   |             | 0.890   |             | <b>0.956</b> |             | 0.954        |             |
| 2       | 0.843    | -8.4        | 0.850  | -9.8        | 0.763   | -15.9       | 0.777   | -12.6       | <b>0.880</b> | -8.0        | 0.877        | -8.0        |
| 3       | 0.762    | -9.6        | 0.744  | -12.5       | 0.613   | -19.6       | 0.700   | -10.0       | 0.794        | -9.8        | <b>0.814</b> | -7.2        |
| 4       | 0.615    | -19.3       | 0.607  | -18.4       | 0.490   | -20.1       | 0.608   | -13.2       | 0.681        | -14.2       | <b>0.730</b> | -10.3       |
| 5       | 0.433    | -29.6       | 0.482  | -20.6       | 0.325   | -33.7       | 0.532   | -12.4       | 0.578        | -15.1       | <b>0.701</b> | -4.1        |
| 6       | 0.260    | -39.9       | 0.337  | -30.1       | 0.174   | -46.4       | 0.455   | -14.6       | 0.481        | -16.9       | <b>0.646</b> | -7.8        |
| 7       | 0.062    | -76.2       | 0.184  | -45.5       | 0.019   | -88.9       | 0.363   | -20.1       | 0.358        | -25.6       | <b>0.520</b> | -19.5       |
| 8       | -0.024   | —           | 0.058  | -68.4       | -0.131  | —           | 0.269   | -26.0       | 0.268        | -25.1       | <b>0.391</b> | -24.8       |
| 9       | -0.118   | —           | -0.056 | —           | -0.280  | —           | 0.123   | -54.3       | 0.163        | -39.4       | <b>0.295</b> | -24.5       |
| 10      | -0.219   | —           | -0.158 | —           | -0.444  | —           | 0.019   | -84.3       | 0.038        | -76.5       | <b>0.153</b> | -48.1       |
| 11      | -0.271   | —           | -0.242 | —           | -0.618  | —           | -0.109  | —           | -0.063       | —           | -0.034       | —           |
| 12      | -0.305   | —           | -0.295 | —           | -0.761  | —           | -0.254  | —           | -0.220       | —           | -0.130       | —           |

## 5.4 Opening the Black Box: Random Forest Variable Importance

Figure 3 displays the relative feature importance in the RF-STP model for forecast horizons 1, 3, 6, and 9. The third lag of KPIF is the most important parameter for the 1 month forecast. However, what is striking about these results is the fact that across four different forecast horizons strictly foreign features such as U.S. M1, E.U. 5Y, and the U.S. Federal Funds Rate are very important when it comes to forecasting Swedish inflation. As mentioned previously, these figures are based on the *training data*, which ended May 2018, meaning there should be no obvious relationship between Swedish inflation and these foreign features.

We can see that it takes a relatively long time for changes in foreign features to affect Swedish inflation in the RF-STP model. In Figure 3b we see that the fifth lag of E.U. 5Y, and the fifth and first lags of the F.F.R. are the first, second, and third most important features in the RF-STP model, respectively, when generating 3 month horizon forecasts. This means that it takes around 4–8 months for changes in foreign features to affect inflation in Sweden. Further, in Figure 3d, lags 4, 5, and 6 of the F.F.R. are considered most important, meaning that it can take between 13–15 months for monthly changes in the F.F.R. to exert their full influence on KPIF.

Because of the special data structures used in the RF-CUM model, I remind the reader that the interpretation of each lag changes based on the forecast horizon as detailed in Section 3.3.5 and Figure 1. However, for the 1 month forecast horizon, the features can be interpreted in the exact same way as they can for the RF-STP model. This is because the 1 month forecast horizon RF-CUM and RF-STP models are trained on the exact same data. The reason why results differ between them is randomness. Even though they are trained on the exact same data set, they are extremely unlikely to be trained on the exact same data *points* given the RF algorithm’s use of bootstrap sampling and its random selection of features for each individual tree. The difference in performance between models trained on the same data is generally quite small: in our case it is approximately 2.4% in terms of RMSE. Because of this randomness, feature importance can also differ slightly between two models trained on the same data. However, the difference in terms of  $(\Delta MSE)\%$  are also usually small.<sup>10</sup>

Figure 4 displays the relative feature importance in the RF-CUM model for forecast horizons 1, 3, 6, and 9. Interestingly, forecast horizons 3, 6, and 9 are no longer characterized by the importance of foreign features, but rather by the high importance of the lagged cumulative effects of KPIF. For the 3 month forecast horizon, the RF-CUM model loses almost 18% of its performance when the out-of-bag KPIF  $t-1$  values are randomly permuted. For the 6 month and 9 month forecast horizons the drop in performance is even greater at around 25%. However, foreign features still retain some relevance. Figure 4b indicates that cumulative changes in the U.S. 3M, the F.F.R., and E.U. 3M are three of the five most important features for the 3 month forecast horizon, and Figure 4d indicates that cumulative changes in the F.F.R. are the third most important feature for the 9 month forecast horizon.

One important finding is worth reiterating before concluding this section: The reported RF variable importance figures indicate that strictly foreign features such as the U.S. Federal Funds Rate have a significant effect on Swedish inflation. This hints at the fact that the Riksbank might have less control over inflation in Sweden than is commonly assumed. This finding is in accord with Reade & Voltz (2009), who found that despite its nominal monetary policy autonomy, Sweden is “[...] de facto not master in its own house”.<sup>11</sup>

<sup>10</sup>See Appendices B and C for extended feature importance figures for the two models.

<sup>11</sup>Reade & Voltz (2009) investigated traditional arguments against Sweden joining the euro. They concluded that if



Figure 3: Five most important features in the RF-STP model for selected forecast horizons. Importance of each feature is scaled by the feature specific out-of-bag standard error. Colors reflect feature categories as proposed by McCracken & Ng (2016). *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

Sweden was to adopt the euro and give up its monetary sovereignty, the loss of monetary policy autonomy would in practice be “negligible” and would be outweighed by Sweden gaining influence in European monetary policy making.

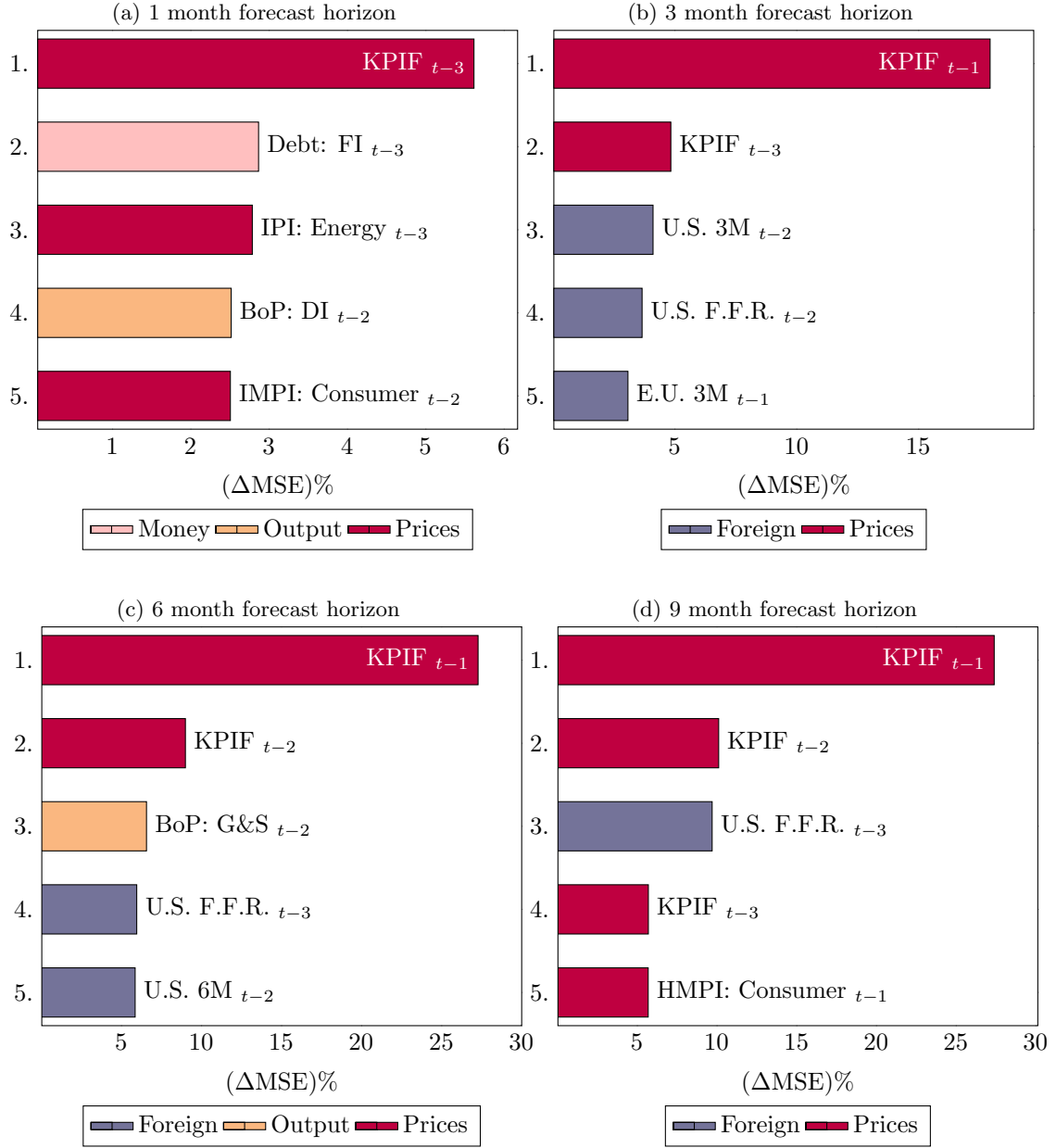


Figure 4: Five most important features in the RF-CUM model for selected forecast horizons. Importance of each feature is scaled by the feature specific out-of-bag standard error. Colors reflect feature categories as proposed by McCracken & Ng (2016). *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

## 5.5 Bullard’s Rule Approximation of the Riksbank’s Policy Rule

Table 8 shows the Bullard rule approximations of the Riksbank’s policy rule across all twelve forecast horizons. The current rate coefficient  $\rho$  is significant at the 99.9% level across all horizons. This confirms Bullard’s finding that the current policy rate is extraordinarily important in determining the policy rate for the next period. Next, the coefficient for the inflation target  $\psi_\pi$  is statistically significant for 10 out of 12 forecast horizons, and greatest in magnitude and significance around lags 6–9.

The two most interesting findings relate to the importance of inflation forecasts and excess unemployment. As regards the importance of inflation forecasts, we see that  $\phi_\pi$  is statistically significant until forecast horizon 9. This indicates that the Riksbank does not take inflation forecasts much into consideration beyond that point, possibly indicating that the Riksbank knows that inflation forecasts beyond this point are highly unreliable. This hypothesis is supported by the findings in Section 5.3. As regards the importance of excess unemployment, we can see that the  $\phi_u$  coefficient is the correct sign (negative), indicating that the Riksbank would lower the policy rate if excess unemployment were to rise. However, the  $\phi_u$  coefficient is not statistically significant for any of the 12 forecast horizons, indicating that the Riksbank is in agreement with the statements made by Bullard regarding the flatness of the Phillips curve (Bullard, 2018b).

## 5.6 Summary of Policy Rate Forecasts

Table 9 presents a summary of the policy rate forecast performance of all models. The Riksbank’s forecasts explain 48.0% of the variation in the policy rate measured as  $R^2$ , with an RMSE of 0.250, which is exactly equivalent to a quarter point change in the policy rate. However, the so-called Riksbank-BLR model—the forecasts generated using the Riksbank’s estimated policy rule in tandem with the Riksbank’s own inflation forecasts—yielded better forecasts than the Riksbank, on average reducing RMSE by 17.6% and increasing  $R^2$  by 29.8%. The most likely explanation for this is that the Riksbank-BLR forecasts are generated more often than the official forecasts by the Riksbank.

Next, we can see that on average, the ARMA model is best able to forecast the policy rate, on average explaining 69.4% of the policy rate variation since June 2018 in terms of  $R^2$ , with an average RMSE of 0.191. Interestingly, the RF-CUM model, which yielded the best inflation forecasting performance, underperforms the policy rate forecasts issued by the Riksbank by an average of 0.6% in terms of RMSE and 7.9% in terms of  $R^2$ . The reasons for this are discussed in the following section.

Table 8: Bullard’s rule approximations of the Riksbank’s policy rules across all forecast horizons

| Horizon | Current Rate        | Targ. Inflation     | Proj. Inflation     | Unemployment      | Adj. $R^2$ | RMSE  |
|---------|---------------------|---------------------|---------------------|-------------------|------------|-------|
|         | $\rho$              | $\psi_\pi$          | $\phi_\pi$          | $\phi_u$          |            |       |
| 1       | 1.121***<br>(0.112) | 0.023<br>(0.020)    | 0.036*<br>(0.015)   | −0.015<br>(0.039) | 0.868      | 0.126 |
| 2       | 1.319***<br>(0.100) | 0.064***<br>(0.018) | 0.045**<br>(0.013)  | −0.067<br>(0.034) | 0.901      | 0.110 |
| 3       | 1.165***<br>(0.182) | 0.054<br>(0.031)    | 0.103***<br>(0.021) | −0.024<br>(0.056) | 0.769      | 0.167 |
| 4       | 1.163***<br>(0.161) | 0.064*<br>(0.027)   | 0.149***<br>(0.020) | −0.013<br>(0.049) | 0.821      | 0.147 |
| 5       | 1.233***<br>(0.214) | 0.094*<br>(0.036)   | 0.197***<br>(0.032) | −0.029<br>(0.065) | 0.691      | 0.193 |
| 6       | 1.404***<br>(0.198) | 0.139***<br>(0.034) | 0.254***<br>(0.035) | −0.062<br>(0.059) | 0.728      | 0.181 |
| 7       | 1.664***<br>(0.265) | 0.202***<br>(0.047) | 0.238**<br>(0.068)  | −0.144<br>(0.076) | 0.528      | 0.239 |
| 8       | 1.692***<br>(0.269) | 0.223***<br>(0.049) | 0.316***<br>(0.083) | −0.131<br>(0.077) | 0.536      | 0.237 |
| 9       | 1.634***<br>(0.284) | 0.227***<br>(0.054) | 0.343**<br>(0.099)  | −0.101<br>(0.081) | 0.505      | 0.245 |
| 10      | 1.396***<br>(0.318) | 0.172**<br>(0.063)  | 0.110<br>(0.128)    | −0.094<br>(0.093) | 0.380      | 0.274 |
| 11      | 1.285***<br>(0.313) | 0.152*<br>(0.062)   | 0.071<br>(0.161)    | −0.067<br>(0.105) | 0.373      | 0.275 |
| 12      | 1.173***<br>(0.311) | 0.136*<br>(0.065)   | 0.075<br>(0.208)    | −0.023<br>(0.115) | 0.373      | 0.275 |

Note: Highlighted rows indicate suspected anomalous policy rule approximations. Standard errors reported in parentheses. Significance levels reported: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ . *Source: Author-generated figures in R using data from the Riksbank, the SCB, Konjunkturinstitutet, and Sveriges Kommuner och Regioner.*

Table 9: Policy rate forecast summary for the out-of-sample period starting in June 2018

|                            | (1)   | (2)   | (3)            | (4)        |
|----------------------------|-------|-------|----------------|------------|
|                            | mean  | mean  | %              | %          |
| Benchmark Models           | RMSE  | $R^2$ | RMSE Reduction | $R^2$ Gain |
| Riksbanken-OFF             | 0.250 | 0.480 |                |            |
| Riksbanken-BLR             | 0.206 | 0.623 | 17.6%          | 29.8%      |
| <b>Bullard Rule Models</b> |       |       |                |            |
| ARMA                       | 0.191 | 0.694 | 23.4%          | 44.6%      |
| VAR-TRD                    | 0.205 | 0.647 | 17.7%          | 34.9%      |
| VAR-GRG                    | 0.217 | 0.614 | 13.2%          | 28.1%      |
| RF-STP                     | 0.210 | 0.639 | 16.0%          | 33.1%      |
| RF-CUM                     | 0.251 | 0.442 | -0.6%          | -7.9%      |
| Mean                       | 0.215 | 0.607 | 13.9%          | 26.6%      |
| Median                     | 0.210 | 0.639 | 16.0%          | 33.1%      |

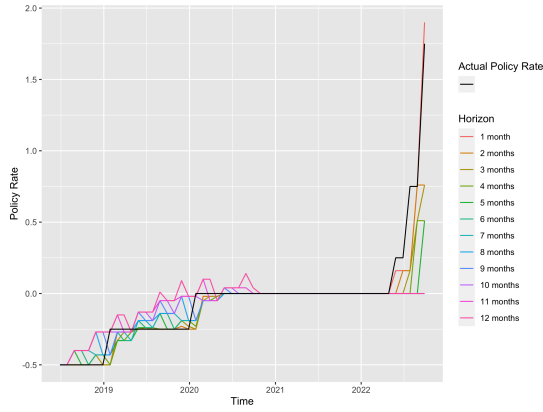
Note: Columns (1) and (2) report the forecast horizon average RMSE and  $R^2$ . Columns (3) and (4) report the percentage reduction in RMSE and percentage increase in  $R^2$  compared to the Riksbank-OFF benchmark model. Mean and Median figures only pertain to the Bullard rule models. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

## 5.7 Policy Rate Forecasts in Depth

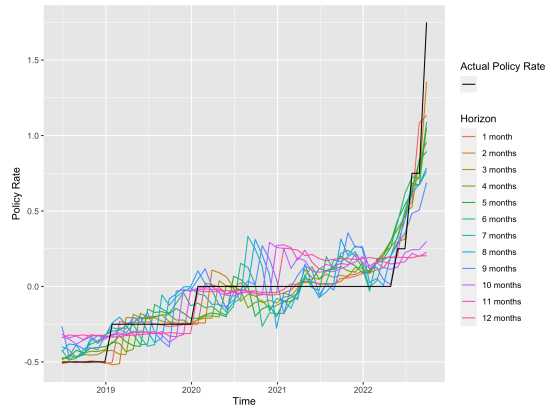
Figure 5 displays the policy rate forecasts generated by all models across all horizons using their own inflation forecasts in tandem with Bullard rule approximations of the Riksbank’s policy rule.

As identified in the previous section, the most accurate inflation forecasting model RF-CUM underperformed the Riksbank in forecasting the policy rate. The reason for this is likely twofold. First, neither the RF-CUM model nor any other proprietary model is actually attempting to forecast the policy rate path that *will* be pursued by the Riksbank. Rather, they generate the policy rate path that the Riksbank *should* pursue, given their own inflation forecasts and the current policy rate. Second, some of the Bullard rule approximations of the Riksbank’s policy rule might be inducing anomalous forecasts. As evident in Figures 5c–5f, the policy rate forecasts generated by all proprietary models for horizons 6–9, with the exception of the ARMA model, are uncharacteristically volatile. This observation is made explicit in Tables 11 and 12, where the anomalous horizons are highlighted. In Table 11 we see that with the exception of the ARMA model, the RMSE measures for the proprietary models increase significantly for the highlighted periods, only to decrease by as much 46.3% in the case of the RF-CUM model for horizon 10. This anomaly is even more stark in Table 12, where we can see that, for example, the RF-CUM model loses almost 50% of its explanatory power at horizon 6 and a full 100% of its explanatory power at horizon 8, only to recover to an  $R^2$  value of 0.589 at horizon 10 and stay above an  $R^2$  value of 0.5 for horizons 11 and 12.

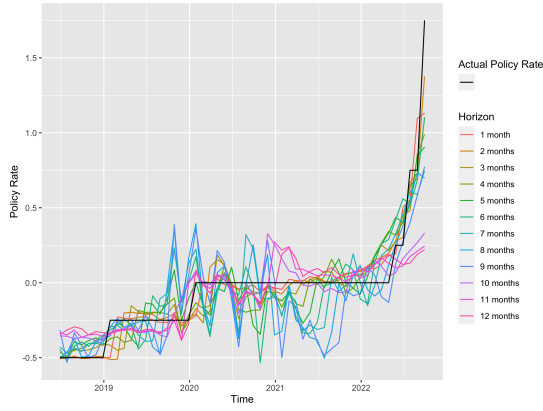
In Table 8, we can see that the horizons for which the policy rule approximations yield anomalous results are also those for which estimated coefficients change significantly. The current rate coefficient  $\rho$  estimate increases by 13.9% from horizon 5 to horizon 6, and decreases by 16.5% from horizon 9 to horizon 10.



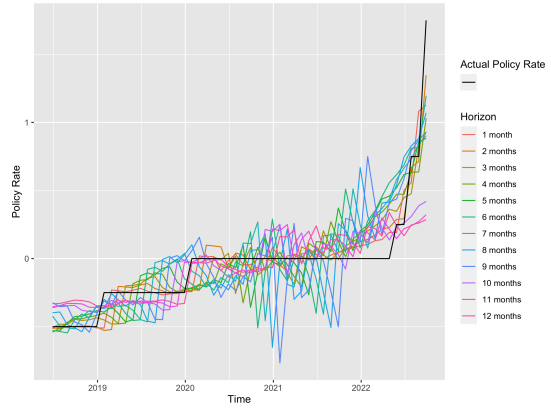
(a) Riksbanken



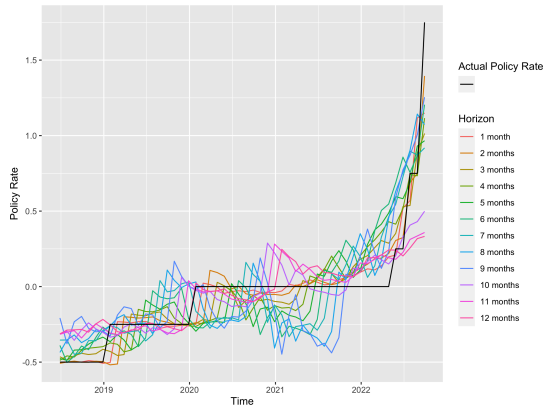
(b) ARMA



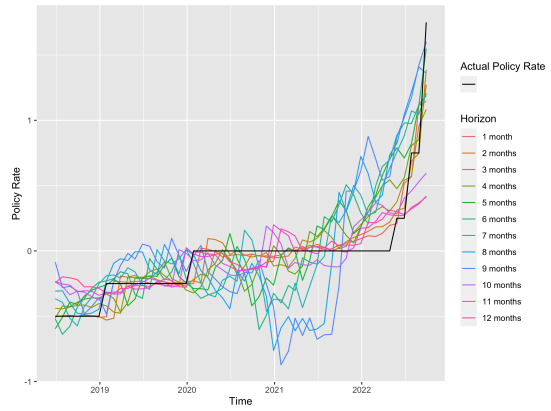
(c) VAR-TRD



(d) VAR-GRG



(e) RF-STP



(f) RF-CUM

Figure 5: Policy rate forecasts by all models across all forecast horizons. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

The inflation target coefficient  $\psi_\pi$  increases by 47.9% from horizon 5 to horizon 6, continually increases for horizons 6–9, and drops 24.2% from horizon 9 to horizon 10. The most significant irregularity stems from the projected inflation overshoot coefficient  $\phi_\pi$  estimate, which jumps 28.9% from horizon 5 to horizon 6, increases a further 35.0% through the 6–9 horizon span, and drops by 67.9% from horizon 9 to horizon 10.

Table 10: Policy rate forecast summary adjusted for anomalous Bullard rule policy rule approximations

|                                     | (1)   | (2)   | (3)            | (4)        |
|-------------------------------------|-------|-------|----------------|------------|
|                                     | mean  | mean  | %              | %          |
| <b>Adjusted Benchmark Models</b>    | RMSE  | $R^2$ | RMSE Reduction | $R^2$ Gain |
| Riksbanken-OFF                      | 0.226 | 0.562 |                |            |
| Riksbanken-BLR                      | 0.196 | 0.647 | 13.3%          | 15.1%      |
| <b>Adjusted Bullard Rule Models</b> |       |       |                |            |
| ARMA                                | 0.191 | 0.684 | 15.5%          | 21.7%      |
| VAR-TRD                             | 0.189 | 0.696 | 16.4%          | 23.8%      |
| VAR-GRG                             | 0.199 | 0.671 | 11.9%          | 19.4%      |
| RF-STP                              | 0.191 | 0.694 | 15.5%          | 23.5%      |
| RF-CUM                              | 0.198 | 0.673 | 12.4%          | 19.8%      |
| Adjusted Mean                       | 0.194 | 0.684 | 14.3%          | 21.6%      |
| Adjusted Median                     | 0.191 | 0.684 | 15.5%          | 21.7%      |

Note: Columns (1) and (2) report the forecast horizon average RMSE and  $R^2$ . Columns (3) and (4) report the percentage reduction in RMSE and percentage increase in  $R^2$  compared to the Riksbank-OFF benchmark model. Mean and Median figures only pertain to the Bullard rule models. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

Table 10 presents the adjusted policy rate forecast summary, where the anomalous policy rule forecasts have been removed. With the exception of the ARMA model, all models, including the Riksbank, gain performance by excluding the anomalous horizons. With said adjustments, the proprietary models outperform the policy rate forecasts by the Riksbank by an average of 21.6% in terms of  $R^2$ , reducing the RMSE by an average of 14.3%.

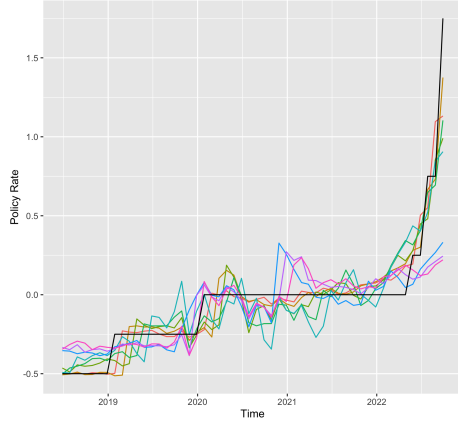
Figure 6 displays the policy rate forecasts generated by the proprietary models—with the exception of the ARMA model—with the anomalous policy rule forecasts removed. This provides a clearer view of how different inflation forecasts affect policy rate forecasts and, incidentally, an answer to the second fundamental question posed in this paper: Could the Riksbank have warned the Swedish public about impending rate hikes sooner? The answer is clearly yes. Figure 6d indicates that if the Riksbank had used the inflation forecasts generated by the RF-CUM model it could have warned the public about the first quarter point rate hike as much as a year in advance and the following half point rate hike as much as five months in advance. An alternative interpretation of the same figure is that the Riksbank should have slowly started raising the policy rate as early as late 2021 or early 2022.

Table 11: Bullard’s rule policy rate forecast accuracy for all models across all horizons as measured by RMSE. % $\Delta$  represents the percentage change in RMSE between consecutive forecast horizons. Highlighted rows indicate suspected anomalous policy rule approximations. Bold figures represent best performance at each horizon *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

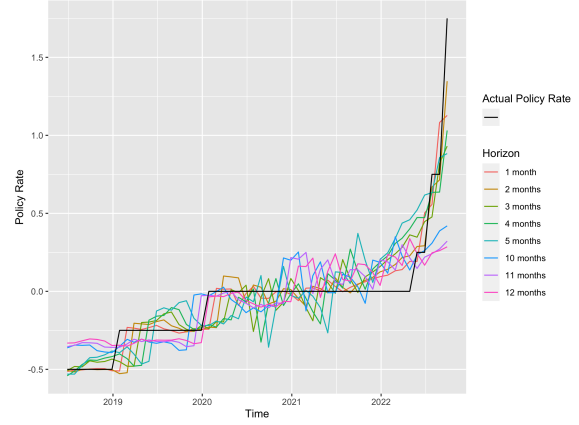
| Horizon | Riksbank-OFF |            | Riksbank-BLR |            | ARMA         |            | VAR-TRD      |            | VAR-GRG |            | RF-STP       |            | RF-CUM       |            |
|---------|--------------|------------|--------------|------------|--------------|------------|--------------|------------|---------|------------|--------------|------------|--------------|------------|
|         | RMSE         | % $\Delta$ | RMSE         | % $\Delta$ | RMSE         | % $\Delta$ | RMSE         | % $\Delta$ | RMSE    | % $\Delta$ | RMSE         | % $\Delta$ | RMSE         | % $\Delta$ |
| 1       | <b>0.099</b> |            | 0.126        |            | 0.126        |            | 0.126        |            | 0.129   |            | 0.128        |            | 0.128        |            |
| 2       | 0.171        | +72.3      | 0.110        | -12.7      | <b>0.108</b> | -14.1      | <b>0.108</b> | -13.8      | 0.115   | -10.6      | 0.109        | -14.3      | 0.110        | -13.7      |
| 3       | 0.178        | +4.1       | 0.167        | +51.8      | <b>0.158</b> | +46.2      | 0.160        | +47.5      | 0.181   | +56.7      | 0.168        | +53.4      | 0.171        | +55.1      |
| 4       | 0.216        | +21.3      | <b>0.147</b> | -12.0      | 0.154        | -2.7       | 0.151        | -5.5       | 0.188   | +3.9       | 0.181        | +8.1       | 0.202        | +18.1      |
| 5       | 0.237        | +9.6       | 0.193        | +31.3      | <b>0.179</b> | +16.1      | 0.189        | +25.1      | 0.222   | +18.6      | 0.222        | +22.5      | 0.262        | +29.5      |
| 6       | 0.293        | +23.6      | 0.181        | -6.2       | <b>0.172</b> | -4.0       | 0.207        | +9.7       | 0.239   | +7.5       | 0.247        | +10.9      | 0.313        | +19.5      |
| 7       | 0.294        | +0.2       | 0.239        | +32.0      | <b>0.195</b> | +13.5      | 0.229        | +10.6      | 0.244   | +2.3       | 0.237        | -4.0       | 0.294        | -5.9       |
| 8       | 0.297        | +1.1       | 0.237        | -0.8       | <b>0.194</b> | -0.4       | 0.259        | +12.9      | 0.260   | +6.2       | 0.254        | +7.4       | 0.395        | +34.3      |
| 9       | 0.301        | +1.5       | 0.245        | +3.4       | <b>0.203</b> | +4.2       | 0.262        | +1.5       | 0.268   | +3.4       | 0.247        | -3.1       | 0.428        | +8.3       |
| 10      | 0.300        | -0.3       | 0.274        | +11.8      | 0.258        | +27.4      | 0.248        | -5.4       | 0.240   | -10.4      | <b>0.227</b> | -7.8       | 0.230        | -46.3      |
| 11      | 0.302        | +0.6       | 0.275        | +0.4       | 0.271        | +5.0       | 0.262        | +5.6       | 0.255   | +6.0       | 0.246        | +8.4       | <b>0.240</b> | +4.7       |
| 12      | 0.306        | +1.3       | 0.275        | 0          | 0.275        | +1.5       | 0.265        | +1.2       | 0.259   | +1.6       | 0.249        | +1.3       | <b>0.241</b> | +0.2       |

Table 12: Bullard’s rule policy rate forecast accuracy for all models across all horizons as measured by  $R^2$ . % $\Delta$  represents the percentage change in  $R^2$  between consecutive forecast horizons. Highlighted rows indicate suspected anomalous policy rule approximations. Bold figures represent best performance at each horizon. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

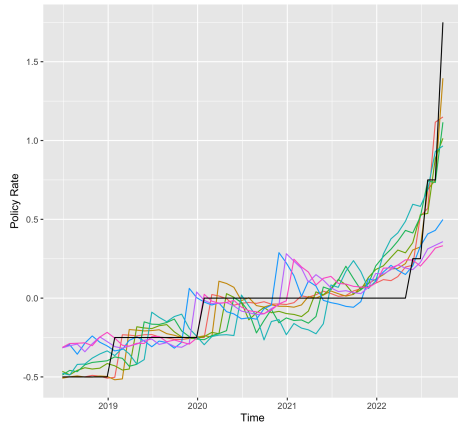
| Horizon | Riksbank-OFF |            | Riksbank-BLR |            | ARMA         |            | VAR-TRD      |            | VAR-GRG |            | RF-STP       |            | RF-CUM       |            |
|---------|--------------|------------|--------------|------------|--------------|------------|--------------|------------|---------|------------|--------------|------------|--------------|------------|
|         | $R^2$        | % $\Delta$ | $R^2$        | % $\Delta$ | $R^2$        | % $\Delta$ | $R^2$        | % $\Delta$ | $R^2$   | % $\Delta$ | $R^2$        | % $\Delta$ | $R^2$        | % $\Delta$ |
| 1       | <b>0.923</b> |            | 0.868        |            | 0.876        |            | 0.877        |            | 0.870   |            | 0.873        |            | 0.873        |            |
| 2       | 0.771        | -16.5      | 0.901        | +3.8       | 0.908        | +3.7       | <b>0.909</b> | +3.6       | 0.897   | +3.0       | 0.906        | +3.9       | 0.905        | +3.7       |
| 3       | 0.752        | -2.5       | 0.769        | -14.7      | <b>0.804</b> | -11.5      | 0.801        | -11.8      | 0.746   | -16.8      | 0.780        | -13.9      | 0.772        | -14.8      |
| 4       | 0.635        | -15.5      | 0.821        | +6.8       | 0.814        | +1.3       | <b>0.823</b> | +2.7       | 0.725   | -2.7       | 0.743        | -4.7       | 0.681        | -11.7      |
| 5       | 0.562        | -11.5      | 0.691        | -15.8      | <b>0.750</b> | -7.9       | 0.722        | -12.2      | 0.614   | -15.3      | 0.614        | -17.3      | 0.466        | -31.6      |
| 6       | 0.330        | -41.2      | 0.728        | +5.4       | <b>0.769</b> | +2.6       | 0.666        | -7.8       | 0.554   | -9.8       | 0.526        | -14.5      | 0.238        | -49.0      |
| 7       | 0.327        | -0.9       | 0.528        | -27.5      | <b>0.703</b> | -8.6       | 0.591        | -11.2      | 0.534   | -3.7       | 0.562        | +7.0       | 0.325        | +36.8      |
| 8       | 0.313        | -4.3       | 0.536        | +1.5       | <b>0.705</b> | +0.3       | 0.479        | -19.0      | 0.475   | -11.1      | 0.495        | -12.0      | -0.217       | -100       |
| 9       | 0.292        | -6.6       | 0.505        | -5.8       | <b>0.680</b> | -3.6       | 0.463        | -3.3       | 0.439   | -7.6       | 0.526        | +6.2       | -0.427       | –          |
| 10      | 0.296        | +1.4       | 0.380        | -24.8      | 0.480        | -29.4      | 0.519        | +12.3      | 0.549   | +25.2      | <b>0.597</b> | +13.6      | 0.589        | –          |
| 11      | 0.287        | -3.0       | 0.373        | -1.8       | 0.427        | -11.1      | 0.464        | -10.6      | 0.493   | -10.2      | 0.527        | -11.7      | <b>0.549</b> | -6.7       |
| 12      | 0.268        | -6.6       | 0.373        | 0          | 0.409        | -4.1       | 0.451        | -2.8       | 0.477   | -3.2       | 0.515        | -2.3       | <b>0.548</b> | -0.3       |



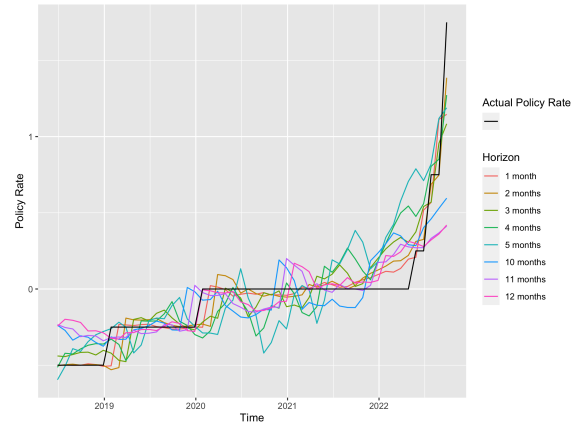
(a) VAR-TRD



(b) VAR-GRG



(c) RF-STP



(d) RF-CUM

Figure 6: Policy rate forecasts generated by the proprietary models across forecast horizons 1–5 and 10–12, excluding the ARMA model. *Source: Author-generated figures in R using data from sources detailed in Appendix A.*

## 5.8 Limitations and Future Research

This paper is primarily limited by its scope. The purpose of the paper is to investigate whether or not inflation forecasts *could* have been better for the period beginning June 2018 and ending September 2022. As such, I do not attempt to find the *optimal* inflation forecasting model, leaving ample room for future research, which could improve on some of the following points.

To begin with, the hyperparameters of the RF models used in this paper are the default values built into the R-package `randomForest`, so the natural next step would be to fine-tune the hyperparameters of the RF models. This can be done by, for example, changing the number of trees in the forest, changing the maximum number of nodes in each tree, or altering the weights associated with the predictions generated by each tree. RF is generally considered to deliver good results out-of-the-box, but there is considerable evidence in the literature that indicates that even though hyperparameter tuning is not as important for RF as it is for other machine learning algorithms, it can still generate considerable performance gains (Probst et.al, 2019; Probst & Boulesteix, 2018).

Another natural next step would be to incorporate additional features into the data set, especially fiscal features and features that contain estimates of the future. As regards the former, it is well established in the literature that fiscal policy influences the way in which monetary policy interacts with the economy (Kloosterman, 2022). As such, there is good a priori theoretical reasons for including this kind of features. As regards the latter, the possible utility of including estimates of the future is best illustrated by an example. The progressive step-like decline of longer-horizon inflation forecasts generated by the RF-CUM model immediately after the onset of Covid-19 is displayed in Figure 2f. The forecasts are generated around March and April 2020, meaning that the information available to the model includes the shocks that have just occurred, but not the announced global stimulus packages. Once the effects of the stimulus packages begin to show up in the data, the RF-CUM model recovers its predictive performance quickly. This indicates that if the RF-CUM model had access to this information when it was announced, but prior to its effects showing up in lagged data, it could have delivered more accurate forecasts for the period immediately after the onset of Covid-19.

Next, one of the main findings in this paper is that cumulative effects are very important when forecasting inflation using RF. However, the data structures used in this paper are not fully optimized to reflect this fact or maximize its effects. Recall Figures 1b and 1c in Section 3.3.5 which visualized the temporal structure of the data used for the RF-CUM models. This kind of structure is perhaps ideal if ones purpose is to study how long it takes for various changes in features to propagate through the economy and affect inflation. However, it is likely suboptimal for inflation forecasting as such for two main reasons. First, this kind of structure does not allow for cumulative effects to vary in length across lags – recall, every lagged input looks back at the same number of months and the number of months is determined by the forecast horizon – limiting the span of information incorporated into each lag. Because of this, the RF-CUM model as specified in this paper might be bottlenecked by its data structure. Second, this kind of temporal structure makes it more difficult to interpret the variable importance reported by the RF-CUM model, as evident in Section 5.4.

Figure 7 presents an alternative temporal data structure for the RF-CUM model. In this kind of structure each lag contains information on the cumulative change in each feature going back 1 month, 2 months, 3 months, and so on. Using this structure the model gains new information for each lag without losing any of its previous information. Furthermore, the variable importance figures become more intuitive, allowing the model to be extended with more lags without their inclusion changing the way in which the output of the model is to be interpreted. Considering these benefits, any continued work on forecasting inflation using RF should strongly consider using this kind of

temporal data structure.

Finally, the real time availability and continuity of data are not fully controlled for. I have attempted to exclude any data that are explicitly reported with a lag or routinely revised post publication. However, the data for which it is not explicitly stated whether they are published with a lag or routinely revised are still included. Because of this, there is a risk that the proprietary models used in this paper benefit from more accurate data or data that are simply not available to the Riksbank in real time.

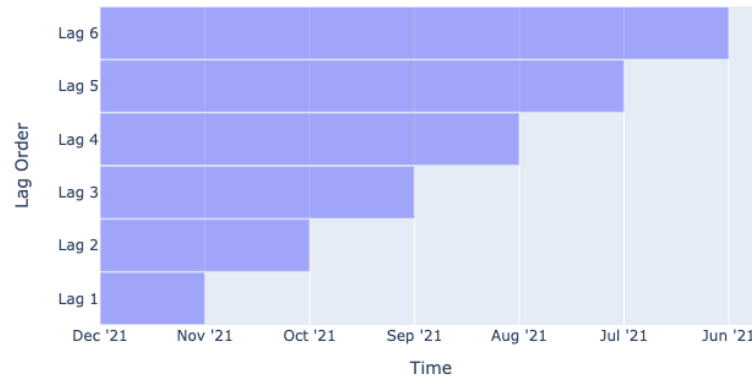


Figure 7: Proposed temporal data structure for the RF-CUM model for all horizons. *Source: Author's own illustration.*

## 6 Conclusions

The surge in inflation in the aftermath of the Covid-19 pandemic left major monetary institutions in disarray, unable to predict the biggest inflationary surge the developed world has seen in modern times. The failure in forecasting inflation led to sudden policy rate hikes, heaping financial pressure on households, businesses, and financial institutions during a time of geopolitical turmoil and war. Forecasts by the Riksbank were no exception, with the Swedish central bank making 7.7 and 2.5 *percentage point* errors in its 2022 end-of-year inflation and policy rate forecasts<sup>12</sup>, respectively.

With these failures in mind, the purpose of this paper is to answer the following fundamental questions: Could the Riksbank have predicted the historic surge in inflation in the aftermath of the Covid-19 pandemic? And, if so, could the Riksbank have warned the Swedish public about impending rate hikes sooner?

The findings in this paper indicate that the answer to both questions is yes. On average, the five proprietary models used to forecast inflation on the out-of-sample data set beginning June 2018 and ending September 2022 reduced forecast errors as measured by RMSE by 6.0% and increased  $R^2$  by 33.3% compared to the Riksbank. Among the proprietary models, the RF model which uses cumulative changes in features as inputs—denoted RF-CUM—was the top-performer, outperforming the Riksbank by an average of 18.8% in terms of RMSE and 100.1% in terms of  $R^2$ .

With regard to the performance of each model for each specific forecast horizon, the two RF models collectively outperformed all other models for all 12 forecast horizons, both in terms of RMSE and  $R^2$ . Furthermore, inflation forecasts generated by the simple ARMA model outperformed the Riksbank by 2.9% in terms of RMSE, 16.7% in terms of  $R^2$ , and were by far the most similar to the forecasts issued by the Riksbank, both in terms of trajectory and accuracy.

The feature importance figures reported by the two RF models hint at the fact that the Riksbank might have less control over inflation in Sweden than is generally assumed, lending tacit support for the conclusion by Reade & Voltz (2009) that Sweden is “[...] de facto not master in its own house” in terms of monetary policy. Both RF models reported that changes in the U.S. Federal Funds Rate play a more important role in forecasting inflation in Sweden than the Swedish policy rate “Styrräntan”. Both the RF model using lagged monthly changes in features as inputs—denoted RF-STP—and the RF-CUM model lost as much as 9.0% and 9.7% in terms of forecast accuracy as measured by MSE, respectively, when changes in the U.S. Federal Funds Rate in the out-of-bag data were randomly permuted.

Using Bullard modernized Taylor rule approximations of the Riksbank’s policy rule, I find that the proprietary models on average reduce policy rate forecast errors by 13.9% in terms of RMSE and explain 26.6% more of the policy rate variance in terms of  $R^2$  compared to the Riksbank. The ARMA model delivered the best policy rate forecasts, on average reducing policy rate forecast errors by 23.4% in terms of RMSE and explaining 44.6% more of the policy rate variance as measured by  $R^2$  compared to the Riksbank. Surprisingly, the RF-CUM model on average performed worse than any other model, increasing policy rate forecast errors by 0.6% as measured by RMSE and explaining 7.9% less of the policy rate variance as measured by  $R^2$  compared to the Riksbank.

However, I identify two possible reasons why models that performed comparatively worse when forecasting inflation performed comparatively better when forecasting policy rates. The first reason is that Bullard rule approximations of the Riksbank’s policy rule for forecast horizons 6–9 might be erroneous. The unexplained magnitudinous changes in the regression coefficients for the aforementioned forecast horizons led to volatile outlier-forecasts for all models except the

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<sup>12</sup>Recall, these were published in February 2022.

ARMA model. Consequently, when policy rate forecasts for horizons 6–9 were excluded, the average performance of the ARMA model remained unchanged, but the performance of all other models improved. With this change implemented, the proprietary models on average reduced policy rate forecast errors by 14.3% in terms of RMSE and explained 21.6% more of the policy rate variance in terms of  $R^2$  compared to the Riksbank. However, this change led to the VAR-TRD model—the only model that performed worse than the Riksbank in forecasting inflation—being the best performing model when forecasting policy rates, reducing policy rate forecast errors by 16.4% in terms of RMSE and explaining 23.8% more of the policy rate variance as measured by  $R^2$  compared to the Riksbank.

The second reason relates to the interpretation of the policy rate forecasts themselves. The proprietary models are not forecasting how the Riksbank *will* set the policy rate, but rather how the Riksbank *should* set the policy rate given the current policy rate and forecast rates of inflation. Because the models that performed better when forecasting inflation predicted a rise in inflation earlier than worse-performing models, the better-performing models generally recommended higher policy rates sooner. Since the Riksbank held the policy rate at 0% until April 2022, the relatively early rate hike recommendations made by the better-performing models generated larger forecast “errors” early in the rate–hike cycle.

Finally, this paper also discusses and highlights the importance of the temporal structure of the underlying data when forecasting inflation using RF. The RF-CUM model outperformed the RF-STP model for 10 out of 12 forecast horizons, highlighting the importance of cumulative changes in features in forecasting inflation. This paper also touches on the fact that the temporal data structure used for the RF-CUM model in this paper might have been suboptimal and recommends an alternative temporal structure, depicted in Figure 7, for future research.

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## Appendices

### Appendix A: Full list of variables, categories, and sources used

| Variable                                                   | Category                            | Source     |
|------------------------------------------------------------|-------------------------------------|------------|
| BoObl 2Y                                                   | Interest and exchange rates         | Riksbanken |
| BoObl 5Y                                                   | Interest and exchange rates         | Riksbanken |
| Byggekostnadsindex (BKI)                                   | Prices                              | SCB        |
| Total Energy Demand                                        | Consumption, orders and inventories | SCB        |
| Energy Exports                                             | Consumption, orders and inventories | SCB        |
| Domestic Energy Demand                                     | Consumption, orders and inventories | SCB        |
| Total Energy Supply                                        | Consumption, orders and inventories | SCB        |
| Energy Imports                                             | Consumption, orders and inventories | SCB        |
| EU 3M                                                      | Foreign                             | Riksbanken |
| EU 6M                                                      | Foreign                             | Riksbanken |
| EU 5Y                                                      | Foreign                             | Riksbanken |
| EU 10Y                                                     | Foreign                             | Riksbanken |
| EUR/SEK                                                    | Interest and exchange rates         | Riksbanken |
| EXPI: All Products                                         | Prices                              | SCB        |
| EXPI: Total Index excl. Food. Beverages. and Tobacco       | Prices                              | SCB        |
| EXPI: Total Index excl. Energy                             | Prices                              | SCB        |
| EXPI: Investment Goods                                     | Prices                              | SCB        |
| EXPI: Consumption Goods                                    | Prices                              | SCB        |
| EXPI: Consumption Goods excl. Food. Beverages. and Tobacco | Prices                              | SCB        |
| EXPI: Durable Consumer Goods                               | Prices                              | SCB        |
| EXPI: Input and Capital Goods                              | Prices                              | SCB        |
| EXPI: Non-Durable Consumer Goods                           | Prices                              | SCB        |
| EXPI: Energy Related Goods                                 | Prices                              | SCB        |
| GB 3M                                                      | Foreign                             | Riksbanken |
| GB 6M                                                      | Foreign                             | Riksbanken |
| GB 5Y                                                      | Foreign                             | Riksbanken |
| GB 10Y                                                     | Foreign                             | Riksbanken |
| GBP/SEK                                                    | Interest and exchange rates         | Riksbanken |
| HMPI: All Products                                         | Prices                              | SCB        |
| HMPI: Total Index excl. Food. Beverages. and Tobacco       | Prices                              | SCB        |
| HMPI: Total Index excl. Energy                             | Prices                              | SCB        |
| HMPI: Investment Goods                                     | Prices                              | SCB        |
| HMPI: Consumption Goods                                    | Prices                              | SCB        |
| HMPI: Consumption Goods excl. Food. Beverages. and Tobacco | Prices                              | SCB        |
| HMPI: Durable Consumer Goods                               | Prices                              | SCB        |
| HMPI: Input and Capital Goods                              | Prices                              | SCB        |
| HMPI: Non-Durable Consumer Goods                           | Prices                              | SCB        |
| HMPI: Energy Related Goods                                 | Prices                              | SCB        |
| Hours Worked                                               | Labor Market                        | SCB        |
| IMPI: All Products                                         | Prices                              | SCB        |

| Variable                                                   | Category                            | Source                   |
|------------------------------------------------------------|-------------------------------------|--------------------------|
| IMPI: Total Index excl. Food. Beverages. and Tobacco       | Prices                              | SCB                      |
| IMPI: Total Index excl. Energy                             | Prices                              | SCB                      |
| IMPI: Investment Goods                                     | Prices                              | SCB                      |
| IMPI: Consumption Goods                                    | Prices                              | SCB                      |
| IMPI: Consumption Goods excl. Food. Beverages. and Tobacco | Prices                              | SCB                      |
| IMPI: Durable Consumer Goods                               | Prices                              | SCB                      |
| IMPI: Input and Capital Goods                              | Prices                              | SCB                      |
| IMPI: Non-Durable Consumer Goods                           | Prices                              | SCB                      |
| IMPI: Energy Related Goods                                 | Prices                              | SCB                      |
| In Labor Force                                             | Labor Market                        | SCB                      |
| Industrial Orders: Domestic Production and Mining          | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Domestic Input Goods excl. Energy       | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Domestic Investment Goods               | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Domestic Non-Durable Consumer Goods     | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Export Production and Mining            | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Export Input Goods excl. Energy         | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Export Investment Goods                 | Consumption, orders and inventories | SCB                      |
| Industrial Orders: Export Non-Durable Consumer Goods       | Consumption, orders and inventories | SCB                      |
| IPI: Input Goods excl. Energy                              | Prices                              | SCB                      |
| IPI: Investment Goods                                      | Prices                              | SCB                      |
| IPI: Non-Durable Consumer Goods                            | Prices                              | SCB                      |
| IPI: Durable Consumer Goods                                | Prices                              | SCB                      |
| IPI: Mining and Related                                    | Prices                              | SCB                      |
| IPI: Production Goods                                      | Prices                              | SCB                      |
| IPI: Energy                                                | Prices                              | SCB                      |
| KPIF                                                       | Prices                              | SCB                      |
| S&P500                                                     | Stock Market                        | Swedish House of Finance |
| OMXS30                                                     | Stock Market                        | Swedish House of Finance |
| Out of Labor Force                                         | Labor Market                        | SCB                      |
| SWE M1                                                     | Money and Credit                    | SCB                      |
| SWE M3                                                     | Money and Credit                    | SCB                      |
| SE GVB 2Y                                                  | Interest and exchange rates         | Riksbanken               |
| SE GVB 5Y                                                  | Interest and exchange rates         | Riksbanken               |
| SE GVB 10Y                                                 | Interest and exchange rates         | Riksbanken               |
| Styrränta                                                  | Interest and exchange rates         | Riksbanken               |
| Total Employed                                             | Labor Market                        | SCB                      |
| Unemployed                                                 | Labor Market                        | SCB                      |
| Unused Labor Hours                                         | Labor Market                        | SCB                      |
| US 3M                                                      | Foreign                             | Riksbanken               |
| US 6M                                                      | Foreign                             | Riksbanken               |
| US 5Y                                                      | Foreign                             | Riksbanken               |
| US 10Y                                                     | Foreign                             | Riksbanken               |

| Variable                                                     | Category                    | Source                            |
|--------------------------------------------------------------|-----------------------------|-----------------------------------|
| US FFR                                                       | Foreign                     | Federal Reserve Bank of St. Louis |
| US M1                                                        | Foreign                     | Federal Reserve Bank of St. Louis |
| US M2                                                        | Foreign                     | Federal Reserve Bank of St. Louis |
| USD/SEK                                                      | Interest and exchange rates | Riksbanken                        |
| USD/SEK FRWD-3M                                              | Interest and exchange rates | Riksbanken                        |
| USD/SEK FRWD-6M                                              | Interest and exchange rates | Riksbanken                        |
| BoP: Trade in Goods and Services                             | Output and Income           | SCB                               |
| BoP: Primary Income                                          | Output and Income           | SCB                               |
| BoP: Secondary Income                                        | Output and Income           | SCB                               |
| BoP: Capital Balance                                         | Output and Income           | SCB                               |
| BoP: Direct Investments                                      | Output and Income           | SCB                               |
| BoP: Portfolio Investments                                   | Money and Credit            | SCB                               |
| BoP: Financial Derivatives                                   | Money and Credit            | SCB                               |
| BoP: Other Investments                                       | Output and Income           | SCB                               |
| BoP: Currency Reserves                                       | Money and Credit            | SCB                               |
| BoP: Residual Post                                           | Output and Income           | SCB                               |
| BS: Financial Assets                                         | Money and Credit            | SCB                               |
| BS: Financial Debts                                          | Money and Credit            | SCB                               |
| BS: Debt Issued                                              | Money and Credit            | SCB                               |
| Credit Rates: Non-Financial Companies                        | Interest and exchange rates | SCB                               |
| Credit Rates: Households                                     | Interest and exchange rates | SCB                               |
| Households: Net Disposable Income. Annualized Change         | Output and Income           | SCB                               |
| Households: Net Savings as % of Disposable Income            | Output and Income           | SCB                               |
| Households: Financial Savings as % of Disposable Income      | Output and Income           | SCB                               |
| Households: Net Debt as % of Disposable Income               | Output and Income           | SCB                               |
| Households: Interest Rate Costs as % of Disposable Income    | Output and Income           | SCB                               |
| Industrial Capacity Utilized (%): Input Goods excl. Energy   | Output and Income           | SCB                               |
| Industrial Capacity Utilized (%): Investment Goods           | Output and Income           | SCB                               |
| Industrial Capacity Utilized (%): Non-Durable Consumer Goods | Output and Income           | SCB                               |
| Industrial Capacity Utilized (%): Durable Consumer Goods     | Output and Income           | SCB                               |
| Industrial Capacity Utilized (%): Mining and Related         | Output and Income           | SCB                               |
| Industrial Capacity Utilized (%): Production Goods           | Output and Income           | SCB                               |
| Job Openings: Total                                          | Labor Market                | SCB                               |
| Job Openings: Public Sector                                  | Labor Market                | SCB                               |
| New Homes Constructed: Apartments                            | Housing                     | SCB                               |
| New Home Constructed: Houses                                 | Housing                     | SCB                               |
| National Debt: Public Sector                                 | Money and Credit            | SCB                               |
| National Debt: Central Bank                                  | Money and Credit            | SCB                               |
| National Debt: Monetary Financial Institutions               | Money and Credit            | SCB                               |
| National Debt: Other Financial Institutions                  | Money and Credit            | SCB                               |
| National Debt: Non-Financial Corporations                    | Money and Credit            | SCB                               |
| National Debt: Direct Investments                            | Money and Credit            | SCB                               |

## Appendix B: Extended Importance Figures: RF-STP

Table 13: The 25 most important features: RF-STP, 1 month forecast horizon

| Feature                                                        | ( $\Delta$ MSE)% |
|----------------------------------------------------------------|------------------|
| KPIFLag3                                                       | 4.60             |
| US.M1Lag5                                                      | 3.61             |
| EU.5YLag6                                                      | 2.86             |
| IMPI..Durable.Consumer.GoodsLag2                               | 2.61             |
| BoP..Capital.BalanceLag2                                       | 2.61             |
| New.Home.Constructed..HousesLag2                               | 2.61             |
| GB.6MLag6                                                      | 2.29             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag2    | 2.29             |
| National.Debt..Public.SectorLag5                               | 2.26             |
| BoP..Primary.IncomeLag1                                        | 2.21             |
| Industrial.Orders..Domestic.Investment.GoodsLag4               | 2.16             |
| National.Debt..Monetary.Financial.InstitutionsLag4             | 2.15             |
| HMPI..Durable.Consumer.GoodsLag5                               | 2.14             |
| BoObl.5YLag6                                                   | 2.13             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag5          | 2.13             |
| IPI..Investment.GoodsLag2                                      | 2.12             |
| BoP..Direct.InvestmentsLag4                                    | 2.12             |
| BoP..Other.InvestmentsLag5                                     | 2.06             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag4    | 2.06             |
| US.3MLag4                                                      | 2.05             |
| GB.5YLag6                                                      | 2.04             |
| Households..Net.Debt.as...of.Disposable.IncomeLag3             | 2.01             |
| HMPI..Consumption.Goods.excl..Food..Beverages..and.TobaccoLag5 | 1.99             |
| BoP..Financial.DerivativesLag4                                 | 1.99             |
| GB.6MLag1                                                      | 1.96             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.

Table 14: The 25 most important features: RF-STP, 3 month forecast horizon

| Feature                                                     | ( $\Delta$ MSE)% |
|-------------------------------------------------------------|------------------|
| EU.5YLag5                                                   | 5.36             |
| US.FFRLag5                                                  | 4.61             |
| US.FFRLag1                                                  | 3.67             |
| BoP..Currency.ReservesLag4                                  | 3.23             |
| BoP..Trade.in.Goods.and.ServicesLag1                        | 3.06             |
| Households..Net.Disposable.Income..Annualized.ChangeLag4    | 3.05             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag6 | 3.02             |
| EU.3MLag1                                                   | 2.91             |
| BoObl.5YLag4                                                | 2.85             |
| Households..Net.Debt.as...of.Disposable.IncomeLag1          | 2.63             |
| BS..Financial.AssetsLag6                                    | 2.60             |
| SE.GVB.2YLag6                                               | 2.51             |
| IMPI..Durable.Consumer.GoodsLag6                            | 2.36             |
| EU.5YLag4                                                   | 2.34             |
| BoP..Currency.ReservesLag2                                  | 2.33             |
| StyrräntaLag6                                               | 2.31             |
| BoP..Residual.PostLag5                                      | 2.29             |
| EXPI..Non.Durable.Consumer.GoodsLag6                        | 2.24             |
| BoP..Capital.BalanceLag1                                    | 2.24             |
| BS..Debt.IssuedLag4                                         | 2.22             |
| HMPI..Total.Index.excl..Food..Beverages..and.TobaccoLag6    | 2.18             |
| EXPI..Investment.GoodsLag6                                  | 2.13             |
| Households..Net.Debt.as...of.Disposable.IncomeLag2          | 2.09             |
| HMPI..Investment.GoodsLag3                                  | 2.08             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag2 | 2.01             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.

Table 15: The 25 most important features: RF-STP, 6 month forecast horizon

| Feature                                                     | ( $\Delta$ MSE)% |
|-------------------------------------------------------------|------------------|
| US.FFRLag5                                                  | 9.03             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag6 | 6.37             |
| US.FFRLag4                                                  | 4.76             |
| EU.5YLAG2                                                   | 4.13             |
| BoP..Financial.DerivativesLag6                              | 4.05             |
| SE.GVB.2YLAG1                                               | 3.89             |
| Households..Net.Debt.as...of.Disposable.IncomeLag1          | 3.88             |
| New.Homes.Constructed..ApartmentsLag6                       | 3.86             |
| US.FFRLag6                                                  | 3.71             |
| BS..Financial.DebtsLag6                                     | 3.36             |
| BoP..Secondary.IncomeLag4                                   | 2.99             |
| BoP..Trade.in.Goods.and.ServicesLag1                        | 2.96             |
| BoP..Currency.ReservesLag4                                  | 2.87             |
| Households..Net.Debt.as...of.Disposable.IncomeLag2          | 2.87             |
| Industrial.Capacity.Utilized.....Production.GoodsLag1       | 2.81             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag6       | 2.69             |
| Job.Openings..TotalLag1                                     | 2.66             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag1 | 2.56             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag3       | 2.45             |
| Industrial.Orders..Export.Non.Durable.Consumer.GoodsLag1    | 2.42             |
| National.Debt..Other.Financial.InstitutionsLag3             | 2.38             |
| US.3MLag3                                                   | 2.37             |
| US.3MLag4                                                   | 2.35             |
| Households..Net.Disposable.Income..Annualized.ChangeLag1    | 2.35             |
| IMPI..Energy.Related.GoodsLag6                              | 2.32             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.

Table 16: The 25 most important features: RF-STP, 9 month forecast horizon

| Feature                                                     | ( $\Delta$ MSE)% |
|-------------------------------------------------------------|------------------|
| US.FFRLag4                                                  | 6.43             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag4       | 5.74             |
| US.FFRLag5                                                  | 5.37             |
| US.FFRLag6                                                  | 5.17             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag5       | 5.10             |
| BS..Debt.IssuedLag1                                         | 5.04             |
| BS..Debt.IssuedLag5                                         | 4.91             |
| BS..Debt.IssuedLag4                                         | 4.84             |
| New.Homes.Constructed..ApartmentsLag6                       | 4.22             |
| US.FFRLag3                                                  | 3.91             |
| EU.6MLag6                                                   | 3.46             |
| US.6MLag6                                                   | 3.44             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag3       | 3.39             |
| National.Debt..Monetary.Financial.InstitutionsLag1          | 3.34             |
| BS..Financial.DebtsLag4                                     | 3.32             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag5 | 3.32             |
| SE.GVB.2YLag1                                               | 3.22             |
| BS..Debt.IssuedLag6                                         | 3.15             |
| BoP..Trade.in.Goods.and.ServicesLag2                        | 3.14             |
| Households..Net.Debt.as...of.Disposable.IncomeLag3          | 3.13             |
| US.FFRLag1                                                  | 2.98             |
| EU.6MLag5                                                   | 2.95             |
| Industrial.Capacity.Utilized.....Production.GoodsLag5       | 2.94             |
| Industrial.Capacity.Utilized.....Investment.GoodsLag6       | 2.93             |
| National.Debt..Other.Financial.InstitutionsLag3             | 2.76             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.

## Appendix C: Extended Importance Figures: RF-CUM

Table 17: The 25 most important features: RF-CUM, 1 month forecast horizon

| Feature                                                  | ( $\Delta$ MSE)% |
|----------------------------------------------------------|------------------|
| KPIFLag3                                                 | 5.62             |
| National.Debt..Monetary.Financial.InstitutionsLag3       | 2.87             |
| IPI..EnergyLag3                                          | 2.79             |
| BoP..Direct.InvestmentsLag2                              | 2.52             |
| IMPI..Durable.Consumer.GoodsLag2                         | 2.51             |
| Industrial.Capacity.Utilized.....Mining.and.RelatedLag2  | 2.39             |
| Industrial.Orders..Export.Production.and.MiningLag2      | 2.37             |
| HMPI..Total.Index.excl..EnergyLag1                       | 2.34             |
| EUR.SEKLAG3                                              | 2.27             |
| SE.GVB.2YLAG1                                            | 2.23             |
| SE.GVB.5YLAG1                                            | 2.20             |
| EXPI..All.ProductsLag2                                   | 2.19             |
| Job.Openings..TotalLag3                                  | 2.19             |
| BoP..Trade.in.Goods.and.ServicesLag2                     | 2.15             |
| BS..Financial.AssetsLag3                                 | 2.14             |
| S.P500LAG1                                               | 1.96             |
| SE.GVB.5YLAG2                                            | 1.95             |
| Unused.Labor.HoursLag3                                   | 1.87             |
| EXPI..Total.Index.excl..EnergyLag3                       | 1.82             |
| USD.SEKLAG3                                              | 1.82             |
| IPI..Non.Durable.Consumer.GoodsLag1                      | 1.80             |
| Households..Net.Disposable.Income..Annualized.ChangeLag2 | 1.78             |
| IMPI..Non.Durable.Consumer.GoodsLag3                     | 1.76             |
| Industrial.Orders..Export.Investment.GoodsLag2           | 1.75             |
| Households..Net.Savings.as...of.Disposable.IncomeLag3    | 1.74             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.

Table 18: The 25 most important features: RF-CUM, 3 month forecast horizon

| <b>Feature</b>                                              | <b>(<math>\Delta</math>MSE)%</b> |
|-------------------------------------------------------------|----------------------------------|
| KPIFLag1                                                    | 17.95                            |
| KPIFLag3                                                    | 4.85                             |
| US.3MLag2                                                   | 4.12                             |
| US.FFRLag2                                                  | 3.67                             |
| EU.3MLag1                                                   | 3.09                             |
| IMPI..Energy.Related.GoodsLag1                              | 3.08                             |
| US.3MLag1                                                   | 3.08                             |
| BoP..Trade.in.Goods.and.ServicesLag1                        | 2.92                             |
| Households..Net.Debt.as...of.Disposable.IncomeLag2          | 2.83                             |
| National.Debt..Public.SectorLag1                            | 2.72                             |
| US.6MLag2                                                   | 2.67                             |
| USD.SEK Lag1                                                | 2.63                             |
| US.M2Lag2                                                   | 2.62                             |
| S.P500Lag1                                                  | 2.57                             |
| HMPI..Consumption.GoodsLag3                                 | 2.52                             |
| Job.Openings..TotalLag3                                     | 2.51                             |
| BoObl.2Y Lag2                                               | 2.50                             |
| BoP..Financial.DerivativesLag3                              | 2.47                             |
| BoP..Primary.IncomeLag3                                     | 2.44                             |
| EU.3MLag2                                                   | 2.34                             |
| USD.SEK Lag2                                                | 2.34                             |
| US.FFRLag3                                                  | 2.33                             |
| SE.GVB.5Y Lag1                                              | 2.31                             |
| Households..Financial.Savings.as...of.Disposable.IncomeLag1 | 2.30                             |
| SWE.M1Lag3                                                  | 2.27                             |

*Source: Author-generated figures in R using data from sources detailed in Appendix A.*

Table 19: The 25 most important features: RF-CUM, 6 month forecast horizon

| Feature                                                     | ( $\Delta$ MSE)% |
|-------------------------------------------------------------|------------------|
| KPIFLag1                                                    | 27.30            |
| KPIFLag2                                                    | 9.02             |
| BoP..Trade.in.Goods.and.ServicesLag2                        | 6.59             |
| US.FFRLag3                                                  | 5.98             |
| US.6MLag2                                                   | 5.88             |
| EXPI..Energy.Related.GoodsLag1                              | 5.81             |
| US.3MLag1                                                   | 4.90             |
| New.Home.Constructed..HousesLag1                            | 4.86             |
| US.3MLag2                                                   | 4.52             |
| Industrial.Capacity.Utilized.....Durable.Consumer.GoodsLag3 | 4.43             |
| Households..Net.Debt.as...of.Disposable.IncomeLag1          | 4.28             |
| BS..Financial.AssetsLag2                                    | 4.25             |
| EXPI..Energy.Related.GoodsLag2                              | 4.16             |
| US.FFRLag1                                                  | 4.15             |
| SWE.M1Lag3                                                  | 4.10             |
| US.6MLag1                                                   | 4.09             |
| BoP..Capital.BalanceLag2                                    | 3.83             |
| HMPI..Consumption.GoodsLag2                                 | 3.54             |
| BoP..Trade.in.Goods.and.ServicesLag1                        | 3.48             |
| HMPI..Consumption.GoodsLag1                                 | 3.47             |
| US.3MLag3                                                   | 3.45             |
| IMPI..Energy.Related.GoodsLag3                              | 3.38             |
| Households..Net.Disposable.Income..Annualized.ChangeLag2    | 3.36             |
| SWE.M3Lag1                                                  | 3.35             |
| GB.10YLag2                                                  | 3.24             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.

Table 20: The 25 most important features: RF-CUM, 9 month forecast horizon

| Feature                                                  | ( $\Delta$ MSE)% |
|----------------------------------------------------------|------------------|
| KPIFLag1                                                 | 27.41            |
| KPIFLag2                                                 | 10.13            |
| US.FFRLag3                                               | 9.72             |
| KPIFLag3                                                 | 5.72             |
| HMPI..Consumption.GoodsLag1                              | 5.71             |
| National.Debt..Direct.InvestmentsLag1                    | 5.68             |
| EXPI..Energy.Related.GoodsLag1                           | 4.88             |
| National.Debt..Direct.InvestmentsLag3                    | 4.88             |
| Households..Net.Debt.as...of.Disposable.IncomeLag1       | 4.78             |
| National.Debt..Direct.InvestmentsLag2                    | 4.70             |
| EXPI..Energy.Related.GoodsLag2                           | 4.63             |
| US.5YLAG1                                                | 4.49             |
| US.FFRLag2                                               | 4.43             |
| IMPI..Energy.Related.GoodsLag3                           | 4.35             |
| IMPI..Energy.Related.GoodsLag2                           | 4.30             |
| SWE.M3Lag3                                               | 4.25             |
| US.6MLag1                                                | 4.24             |
| SWE.M1Lag1                                               | 3.97             |
| Job.Openings..TotalLag1                                  | 3.94             |
| US.3MLag1                                                | 3.88             |
| HMPI..Non.Durable.Consumer.GoodsLag1                     | 3.85             |
| EU.3MLag3                                                | 3.81             |
| HMPI..Investment.GoodsLag3                               | 3.78             |
| IMPI..Total.Index.excl..Food..Beverages..and.TobaccoLag2 | 3.76             |
| US.3MLag3                                                | 3.59             |

Source: Author-generated figures in R using data from sources detailed in Appendix A.