BORRADORES DE
ECONOMÍA

Check for updates

Instantaneous Inflation as a Predictor of Inflation

By:
Wilmer Mart²nez-Rivera
Edgar Caicedo-Garc²a
Juan Bonilla-P®rez

Núm. 1296
2025

BANCO DE LA REPÚBLICA
COLOMBIA

Instantaneous Inflation as a Predictor of Inflation*

The opinions contained in this document are the sole responsibility of the authors and do not commit Banco de la República nor its Board of Directors.

Wilmer Martínez-Rivera[1*], Edgar Caicedo-García[2], Juan Bonilla-Pérez[3]

[1*]Departamento de Inflación, Banco de la República, Bogotá, Colombia.
[2]Departamento de Inflación, Banco de la República, Bogotá, Colombia.
[3]Confederation of retail distributors of fuels and energy, Bogotá, Colombia.

*Corresponding author(s). E-mail(s): wmartiri@banrep.gov.co;
Contributing authors: Ecaicega@banrep.gov.co;
jbonilla@comce-soldicom.com;

Abstract

This article studies the relationship between instantaneous and year-on-year inflation and the benefit of the forecast performance using instantaneous as a predictor. Instantaneous inflation is a transformation of year-on-year inflation, assigning different weights to each month of the Consumer Price Index (CPI) used to calculate the year-on-year inflation. We study the relationship using the Coincident Profile, which allows us to determine whether instantaneous inflation is coincident or anticipates the dynamic of year-on-year inflation. This finding establishes the lag order of the VAR, VECM, and ARIMAX models. Once we fit these models, we forecast year-on-year inflation and evaluate the predictive capacity. We found that instantaneous inflation helps to improve the forecast performance, beating the performance of an ARIMA model and more complex models that use a large set of predictors in several evaluation periods in the near and medium term. We developed three empirical exercises using data from Colombia, the United States, and the United Kingdom to evaluate this approach; in the three cases, we found betterment using instantaneous inflation as a predictor.

Keywords: Instantaneous Inflation, Coincident Profile, Forecast Evaluation

Clasificación JEL: C52 , E17 , E31

*We want to thank the comments from some of the attendees of the International Symposium of Forecasting (ISF), Dijon, France, 2024, and the comments and suggestions provided by the audience of the Internal Seminar at the Central Bank of Colombia. We are especially grateful to Manuel Hernandez-Bejarano and Juan Ospina-Tejeiro for their careful reading and suggestions that helped to improve the current version.

Inflación instantánea como predictor de la inflación

Las opiniones contenidas en el presente documento son responsabilidad exclusiva de los autores y no comprometen al Banco de la República ni a su Junta Directiva

Wilmer Martínez-Rivera[1*], Edgar Caicedo-García[2], Juan Bonilla-Pérez[3]

[1*]Departamento de Inflación, Banco de la República, Bogotá, Colombia.
[2]Departamento de Inflación, Banco de la República, Bogotá, Colombia.
[3]Confederación de distribuidores minoristas de combustibles y energéticos, Bogotá, Colombia.

*Autor corresponsal. E-mail(s): wmartiri@banrep.gov.co;
Coautores: Ecaicega@banrep.gov.co; jbonilla@comce-soldicom.com;

Resumen

En este documento estudiamos la relación entre la inflación instantánea y la inflación anual y las ventajas de incluir la inflación instantánea como predictor en el desempeño de pronóstico de la inflación anual. La inflación instantánea ofrece una perspectiva más dinámica sobre la inflación, asignando pesos variables al Índice de Precios al Consumidor (IPC) en los usados para el cálculo de la inflación anual. Nosotros estudiamos la relación por medio del Perfil Coincidente, el cual permite establecer si la inflación instantánea y anual son contemporáneos o si una antecede la dinámica de la otra. Este hallazgo es usado para establecer el orden autorregresivo de modelos VAR, VECM y ARIMAX. Una vez estos modelos son ajustados, pronosticamos la inflación anual y evaluamos su capacidad predictiva. Nosotros encontramos que la inflación instantánea ayuda a mejorar los pronósticos de la inflación anual mejorando el desempeño de modelos como el ARIMA y modelos más complejos que incluyen un conjunto amplio de predictores a horizontes de corto y mediano plazo. Nosotros desarrollamos tres ejercicios empíricos para evaluar la metodología propuesta incluyendo datos para Colombia, Estados Unidos y Reino Unido. Los resultados de la evaluación de pronósticos en los tres casos muestran que la inflación instantánea como predictor ayuda a mejorar los pronósticos de la inflación anual.

Keywords: Inflación instantánea, Perfil coincidente, Evaluación de pronósticos

Clasificación JEL: C52 , E17 , E31

1 Introduction

Improving near and medium-term forecast performance is essential for most monetary authorities. Central banks periodically release consumer price inflation forecasts, which contribute to a more precise evaluation of the economic conditions and business decisions appropriate for policy decisions. Furthermore, accurate inflation forecasting helps anchor inflation expectations, which is fundamental for effective monetary policy decision-making. This leads to controlling prices and anchoring inflation at levels consistent with the inflation target. That is why central banks must continue to assess their forecast procedures and look for predictors that support the inflation dynamic and drive more accurate forecasts.

Eeckhout (2023) proposed the concept of "instantaneous inflation" to correct the bias generated in calculating official inflation (year-on-year inflation) when it is weighted equally every month. In particular, when calculating instantaneous inflation, more weight is assigned to current events, recognizing that recent news has a more significant impact on inflationary behavior than events in the past. This measurement form allows us to capture changes in the prices of goods and services more accurately in real time, providing an updated image of inflationary dynamics. With instantaneous inflation, a better adaptation of monetary policy and more informed decision-making are achieved to control the unwanted effects of price increases.

In this article, we utilize instantaneous inflation as a predictor of year-on-year inflation to enhance its forecast performance for horizons ranging from 1 to 12 months ahead. We focused on the headline and core inflation for three economies: Colombia (CO), the United States (US), and the United Kingdom (UK). We use monthly data from the CPI index to calculate instantaneous and year-on-year inflation in the following periods: January 1982 to December 2023 for CO, January 1980 to December 2023 for the US, and January 1988 to December 2023 for the UK. Since calculating instantaneous inflation allows for changing the weights assigned to the CPI values used to calculate year-on-year inflation, we explore a wide range of weights for instantaneous inflation calculations to evaluate their predictive capacity.

We contribute to this article as follows. First, we employ the Coincident Profile (CP) Martínez-Rivera et al. (2016) to determine the potential predictive capacity of instantaneous, year-on-year inflation. The CP tool enables the identification of the relationship between two time series based on their turning points. Thus, using the CP, we can establish whether a time series coincides with a second or one leads to another. In this sense, we obtain a lag value (l) depending on the relationship found; for instance, if the two time series are coincident, $l = 0$. Second, we utilize the l value as an alternative method for identifying the lag order in a bivariate VAR or VECM model, based on the stationarity conditions, and for an ARIMAX model. Third, to evaluate the forecast performance, we propose a simple scheme to identify a subset of better forecasters by comparing all the forecast models with a benchmark.

Given that we explore different weights for calculating instantaneous inflation, we obtain a collection of fitted models and forecasts; thus, the evaluation is split into two parts. The first part compares forecasts from a bivariate VAR or VECM and a benchmark forecast from an ARIMA model. In the second part, we compare two types of forecasts: one from a bivariate VAR or VECM that utilizes the result from CP as the lag order, and another that uses information criteria to determine the lag order. In addition, we compare the forecast performance with the forecast from an ARIMAX and a collection of more complex models. We apply the proposed methodology with data from three countries, CO, the US, and the UK, which cover different sample sizes.

Our findings suggest that although we can not identify a unique set of weights for calculating instantaneous inflation, we discover a range of values that allow us to calculate a reasonable predictor of year-on-year inflation. In this sense, we identified a small set of predictors that helped improve the forecast performance in several periods, thereby significantly enhancing the benchmark's forecast accuracy. This result also indicates that instantaneous inflation is causal in the Granger sense, as it helps reduce the root mean squared forecast error (RMSFE). The proposed evaluation scheme also enables us to identify a subset of models whose forecasts exhibit equally significant behavior compared to the benchmark. This result suggests a simple forecast combination, such as the mean or the median from this subset of forecasters. This subset was established for each out-of-sample time and each forecast horizon. Furthermore, we developed a collection of plots to visualize the forecast performance from all the implemented models throughout the evaluation period. Finally, our findings contribute to the forecasting literature by demonstrating the utility of a simple calculation, such as instantaneous inflation, as a predictor alongside the usual battery of predictors. This finding is supported by the three empirical applications that we developed here.

The first section includes an introduction and a literature review. Section 2 covers the methodology adopted in this research for calculating instantaneous inflation and evaluating this indicator with different bandwidth parameter values. Sections 3 and 4 contain the data used, the results, its forecasting capacity, and the discussion. Finally, it concludes.

2 Methodology

Eeckhout (2023) defines instantaneous inflation as a kernel-based measure that puts more weight on recent observations and less on foretime observations. This measure is a polynomial-weighted kernel indexed with a bandwidth parameter regulating average smoothing. To clarify the definition of instantaneous inflation, we present some previous concepts. Let p_t be the price level at time t. Based on the time series $p_{1:T} = \{y_1, y_2, ..., y_T\}$, where T denotes the sample size, we can calculate several measures of the variation or changes of the prices. Under the assumption that $p_{1:T}$ represents the CPI, some traditional measures of price changes are the inflation measure. For instance, following the notation used in Eeckhout (2023), month-on-month inflation rate i_t^m, annualized monthly inflation rate i_t^{am}, and the year-on-year price changes i_t^y as we define in (1) to (3).

$$i_t^m = \frac{p_t - p_{t-1}}{p_{t-1}}, \tag{1}$$

$$i_t^{am} = (1 + i_t^m)^{12} - 1, \tag{2}$$

$$i_t^y = \frac{p_t - p_{t-12}}{p_{t-12}} = \prod_{\tau=0}^{11}(1 + i_{t-\tau}^m) - 1. \tag{3}$$

Now, the instantaneous inflation, i_t^κ, is defined as we show in 4, where $\kappa(\tau)$ is a polynomial weighted kernel[1] given in (5) where a is the bandwidth parameter.

$$i_t^\kappa = \prod_{\tau=0}^{11}(1 + i_{t-\tau}^m)^{\kappa(\tau,a)} - 1, \tag{4}$$

$$\kappa(\tau, a) = (M - \tau)^a \frac{M}{\sum_{\tau=0}^{M-1}(M - \tau)^a}, \ \forall a \geq 0. \tag{5}$$

[1]According to Eeckhout (2023), other kernel functions could be used.

The instantaneous inflation with the kernel function defines in (5), and $M = 12$ has the following properties:

1. If $a = 0$, $\kappa(\tau) = 1$ for all τ, then $i_t^{\kappa} = i_t^{y}$.
2. If $a \to \infty$, $\kappa(\tau) = 12$ for $\tau = 0$, and $\kappa(\tau) = 0$ otherwise, then $i_t^{\kappa} = i_t^{am}$.

The proof of these properties is available in the Appendix. In the figures in 1, we illustrate these properties using data from Colombia and the United States. We remark on some facts. First, the year-on-year price changes (YoY), or year-on-year inflation, is the geometric average of the last 12 month-on-month price changes (MoM) with equal weight, while the instant inflation (II) is also a geometric average of the last 12 MoM with higher weights for the most recent MoM according to the value of the a parameter in (5) as the a increases most weight is provided the most recent MoM. On the contrary, the annualized monthly inflation (A_MoM) puts all the weight on the current MoM. Second, the II as a increases highlights the changes of the YoY; see Figures in 1.

From these remarks, we pose the following question: Can instantaneous inflation serve as a predictor of year-on-year price changes? Answering this question is the main goal of this document. Thus, for a given value of a we calculate the values of κ in (5) then we calculate i_t^{κ} from (4). Here, we have a couple of questions: Is there any specific value of a that optimizes the forecast in the sense that it reduces the root mean squared forecast error (RMSFE)? Would this value work for all the horizons? These two questions are summarized in (6).

$$a = argmin\left\{ f\left(i_{T+h}^{y} - \hat{i}_{T+h}^{\kappa}(\kappa(\tau, a)) \right) \right\}, \tag{6}$$

where T is the sample size, i_{T+h}^{y} is the year-on-year inflation in the period $T + h$, $\hat{i}_{T+h}^{\kappa}(\kappa(\tau, a))$ is the instantaneous inflation forecast $h - steps - ahead$ and $f(\cdot)$ any function that evaluates forecast performance, particularly here it represents the RMSFE. To explore the relationship between every i_t^{κ}, and i_t^{y}, we use the *Coincident Profile* proposed by Martínez-Rivera et al. (2016). This tool allows us to determine if a couple of time series based on their turning points are coincident (contemporary) or leading (one variable leads to the other)[2]. For a similar purpose, this tool has also been used by Martínez-Rivera et al. (2013). In Figure 2, we show the CP that compare i_t^{y} and $i_t^{\kappa}(\kappa(\tau, a))$ on the sample period Jan 1983 - Jun 2023. We use two values for the a parameter ($a = 0.25$ left panel and $a = 3$ right panel). The highest bar in each plot tells us what the potential lag value is that leads $i_t^{\kappa}(\kappa(\tau, a))$ to i_t^{y}.

Once we establish the potential relationship between i_t^{y} and $i_t^{\kappa}(\kappa(\tau, a))$, for a given a, on a specific period, we use this information as the order of a bivariate vector autoregressive (VAR) model as in (7) if we have stationarity conditions or a vector error correction model (VECM) as in (8) if in addition to have non-stationarity we confirm cointegration, see Lütkepohl (1987) or Tsay (2013), additionally, we fit an Autoregressive Integrated Moving Average (ARIMA) with explanatory variables (ARIMAX), see Cryer and Chan (2008).

Forecasting with VAR, VECM and ARIMAX models

We model the relationship between the year-on-year inflation, i_t^{y}, and the instantaneous inflation, $i_t^{\kappa}(\kappa(\tau, a))$, as a bivariate vector autoregression, VAR(p) with order p, whose close-form expression is:

[2]This tool is available on the R package Coinprofile

$$Y_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{\Phi_i} Y_{t-1} + \boldsymbol{\epsilon}_t, \tag{7}$$

where $Y_t = (i_t^y, i_t^\kappa)'$ is a 2×1 vector, $\mathbf{c}$ is a 2×1 vector of intercepts, $\mathbf{\Phi_i}$, $i = 1, ..., p$, are 2×2 coefficient matrices with p denoting the number of lags or the order of the model, and $\boldsymbol{\epsilon}_t$ are normally-distributed with covariance matrix $\mathbf{\Sigma}$. Likewise, under the assumptions that Y_t is a vector of integrated -I(1)- and cointegrated time series, a vector error correction model, VECM(p), has the form:

$$\Delta Y_t = \mathbf{\Pi} Y_{t-1} + \sum_{i=1}^{p-1} \mathbf{\Phi_i} \Delta Y_{t-1} + \boldsymbol{\epsilon}_t, \tag{8}$$

where $\Delta Y_t = Y_t - Y_{t-1}$, $\mathbf{\Pi}$ is a 2×2 matrix, that contains the cointegration relations; the other terms are defined similarly as in expression (7). Also, we fit an ARIMAX model to capture the relationship between i_t^y and i_t^κ as follows in (9):

$$i_t^y = c + \sum_{j=1}^{p_0} \phi_j i_{t-j}^y + \sum_{j=1}^{q_0} \theta_j \epsilon_{t-j} + \sum_{j=1}^{p} \alpha_j i_{t-j}^\kappa + \epsilon_t, \tag{9}$$

where c is a constant, ϕ_j the autoregressive parameters, θ_j the moving average parameters, p_0 and q_0 are the autoregressive and moved average orders, respectively, α_j are the parameters of the explanatory variables and p is the maximum lag of the explanatory variable determined according to the coincident profile analysis.

Thus, based on the fitted VAR, VECM, and ARIMAX models, we forecast the year-on-year inflation, i_t^y. In cases where the potential lag value is 0 or positive, we fix that lag to 1. According to stationarity conditions, and given the evaluation scheme proposed here (see section 2.1 below), we fit only one of the models, VAR or VECM; thus, from now on, we will refer to it interchangeably as the VECM model for simplicity. Additionally, to determine the order of VECM, we use the information criterion.

Now, we describe the proposed methodology step by step.

1. From $p_{1:T}$ adjusted by seasonal factors, calculate i_t^m, i_t^{am}, and i_t^y.
2. Using values for a from 0.25 to 6, jumping each 0.25, from 7 to 12, jumping each unit, and $a = 100$, in (5), calculate i_t^κ in (4).
3. Use Martínez-Rivera et al. (2016)'s *CP* to study the relationship between i_t^y and every i_t^κ and determine the lag in the case i_t^κ leads i_t^y.
4. a) Based on step 3, fix the order of a bivariate VAR or VECM model (previously confirmed stationarity or non-stationarity conditions and cointegration) and the lags for the predictor variable to be included in an ARIMAX model. To fit the relationship between i_t^y and i_t^κ.
   b) Use the information criterion to determine the order of VECM.
5. Based on step 4, forecast i_t^y for horizons $h = 1, 2, ..., 12$.
6. Use Diebold and Mariano (1995)'s test to evaluate the forecast performance.

To apply this sequence of steps, we define a sample period from January 1983 for CO, January 1981 for the US, and January 1989 for the UK, extending to December 2017. We then forecast from horizon 1 to 12. Therefore, we repeat this process by expanding the sample period by one month until we arrive at the end of the sample, December 2023. Thus, we build out-sample predictions for each horizon to use the Diebold and Mariano (1995)'s test to measure the forecast performance.

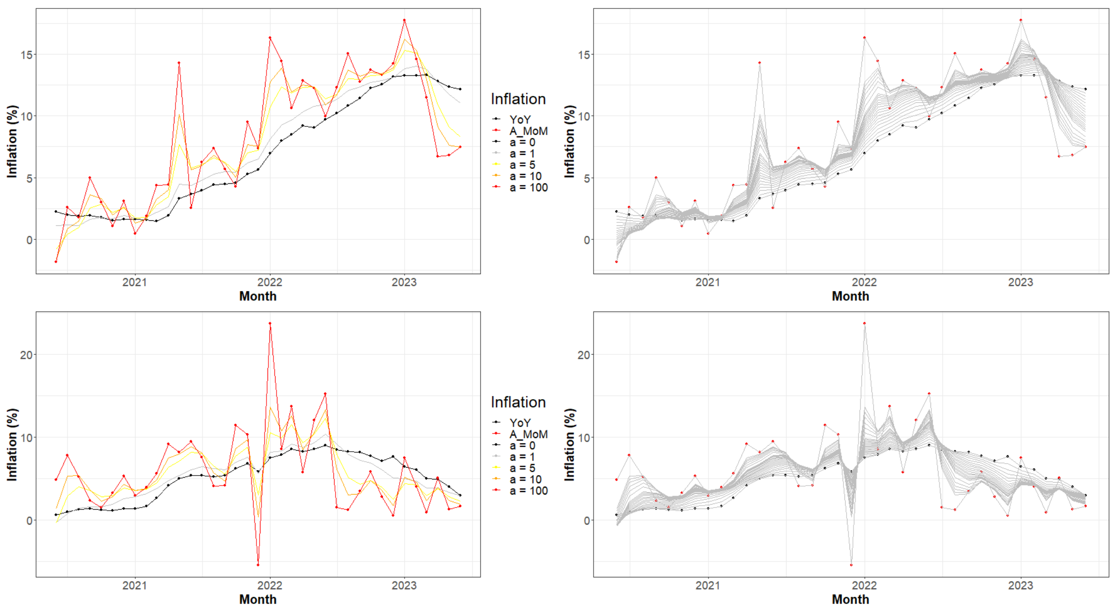


Figure 1: **Instantaneous Inflation.** Top panel for headline inflation for the Colombian case and bottom panel for headline inflation for the US case, from Jun 2020 to Jun 2023. Year-on-year price changes (YoY, black dots), annualized monthly inflation (A_MoM, red dots), and instant inflation (II, coloring lines) with different values for the a parameter. Plots on the right, the gray lines represent II with a moving from 0 to 4, jumping each 0.25, then by taking the values 5, 6, 7, 8, 9, 10, and 100.

2.1 Evaluation scheme

We use sample data from a different beginning point, depending on the availability of the data used (monthly data for Colombia, the United States, and the United Kingdom), to December 2017. For each a value considered for calculating the instantaneous inflation, we establish the potential relationship between instantaneous inflation and inflation based on the CP. Once we fix each model, VECM or ARIMAX, for each instantaneous inflation, we forecast for horizons 1 to 12. Then, we add the following observation, corresponding to January 2018. Thus, we expand the sample, and again, we apply the CP by identifying the potential lag used to fix both the VECM and ARIMAX models. Now, we forecast up to 12 steps ahead. Repeating this procedure until December 2018, we complete an out-sample of size 12 for each horizon. We calculate the RMSFE for each horizon by identifying the model with the minimum RMSFE value and the

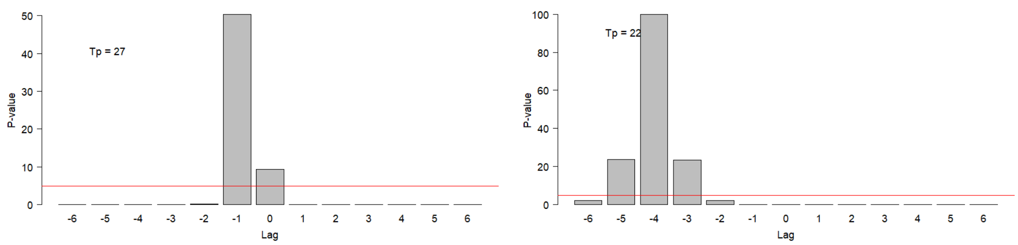


Figure 2: **Coincident profile**. Comparison between i_t^y and $i_t^\kappa(\kappa(\tau, a))$ on the sample period Jan 1983 - Jun 2023. We use $a = 0.25$ (left panel) and $a = 3$. (right panel)

significant difference compared to a Benchmark model; this model is termed, for this out-of-sample size, "the best model." The other models are compared to the best using the Diebold and Mariano (1995)'s test to measure the forecast performance. This evaluation allows us to identify a subset of models with a similar performance or whose forecast performance is not statistically different. We will continue this process to complete the sample until December 2023.

Following this evaluation scheme, we can identify a subset of models with equal performance month-by-month from January 2019 to December 2023. Thus, we report the percentage of times each model was classified in the subset of best models; see Table 2. This report is available only for the VECM model and the benchmark model, the Best ARIMA model, which is fitted considering the AIC criterion. In addition, in Figure 5, we report a comparison between the forecast (gray dots) and the observed headline inflation (black line) for given horizons. These plots also include the mean and median for all the forecasts, the best forecaster (in red), and the mean and median, considering only the forecast classified as the best. These last three lines are printed from December 2018.

According to the proposed evaluation scheme, the best model changes with each evaluation period; consequently, the subset of better models also changes. Therefore, we create a couple of plots that allow us to check the historical behavior of the best model and the subset of the better models. In Figures 3 and 4, for instance, we include the sequence of the best model (model with the minimum RMSFE each evaluation period) and the sequence of the subset models (gray dots), respectively. The numbers in the plots on Figure 3 refer to the a parameter used to calculate the instantaneous inflation used in the bivariate VECM model; they are in red when their performance is statistically better than the benchmark model.

2.2 Comparing with other models

In Martínez-Rivera et al. (2025) developed a comparison between forecasting aggregated components of inflation, such as headline and core, and forecasting disaggregated data by aggregating those. They implemented various models for both aggregate and disaggregated data. The implemented models include Autoregressive Moving Average models, Threshold Autoregressive models, and dimension reduction models (via principal components analysis), where the components are used as covariates in an Autoregressive Moving Average model with exogenous variables (ARIMAX). Additionally, selection variable models such as Ridge, Lasso, and Random Forest are employed. These models are summarized in Table 1 and briefly described as follows.

The models implemented by Martínez-Rivera et al. (2025) include aggregate and disaggregate data of the CPI index. Thus, letting y_t^a an aggregate of inflation and letting $\{y_{1t}, y_{2t}, \ldots, y_{nt}\}$ a

Model	Description	Forecast method
M0	Best ARIMA model according to AIC criterion	Iterative
ARp	AR(12) model	Direct
TAR	Threshold autoregressive model (two regimes)	Iterative
PY0	PCA of the set of 181 CPI item series (Ys), fitted using ARIMAX	Iterative
RFY[a]	Random Forest with the sets Ys	Direct
RidY[a]	Ridge with the sets Ys	Direct
LasY[a]	Lasso with the sets Ys	Direct

Table 1: Fitted models in Martínez-Rivera et al. (2025): Principal components analysis (PCA), dynamic factor model (DFM). [a] For the Aggregates correspond to the full set of CPI item series, and the disaggregates correspond to the lags 1 to 12 of the fitted time series itself.

set of n disaggregated inflation index such that for each t

$$y_t^a = \sum_{i=1}^{n} w_i y_{it} \quad \text{where} \quad \sum_{i=1}^{n} w_i = 1, \tag{10}$$

where $\{w_1, w_2, \ldots, w_n\}$ is a set of fixed weights. Every model in Table 1 is fitted to forecast using the aggregate response variable y_t^a. Additionally, each model is also fitted for each individual response y_{it}, where $i = 1, 2, ..., n$. The forecasts obtained from these individual models are then aggregated using equation (10). As a result, each model produces two types of forecasts: one generated from modeling the aggregate and another from modeling the individual components and then aggregating those forecasts. These are denoted as $M0.A$ for the aggregate model and $M0.D$ for the disaggregate model, for example.

The $M0$, ARp, and TAR are univariate models that utilize past information of the response variable as predictors. $PY0$ model employs principal components analysis on the disaggregate set as a dimension reduction technique, using the resulting components as exogenous variables in an Autoregressive Moving Average model (ARIMAX). Additionally, the selection variable models Random Forest (RFY), Ridge (RidY), and Lasso (LasY) use the set of disaggregates as covariates for the aggregate and the own disaggregate lags from 1 to 12 to fit every disaggregate case. Finally, two forecast methods were considered: iterative and direct. For further details, see Martínez-Rivera et al. (2025).

They also considered data from Colombia, the United States, and the United Kingdom. The sample period is from January 2011 to December 2017, and the out-of-sample period is from January 2018 to June 2023. Here, we compared the forecast performance between the aggregate and disaggregate results and the results developed in this document for both the VECM and ARIMAX approaches for each country data set. The comparison is made by using a couple of plots of the best historical performance and the historical forecast behavior of a subset of better forecasters, for example, Figures on 6 and 7. These plots allow us to identify a subset of better forecasters and the potential advantages of forecasting inflation using Instantaneous Inflation as a predictor.

3 Data and application description

To evaluate the proposed methodology, we use data from the CPI for three countries: the United Kingdom, the United States, and Colombia. We use the Consumer Price Index (CPI) for both the aggregate Headline and Core, adjusted for seasonal effects. The sample sizes for each country are as follows: CO, from January 1982 to December 2023; the US, from January 1980 to December 2023; and the UK, from January 1988 to December 2023.

4 Results and discussion

We apply the proposed methodology for each data set from the UK, the US, and CO, and aggregate headline and core inflation. We consider two sample sizes: one from the beginning according to the availability for each country (see section 3) to December 2017 (S1), and a second from January 2010 to December 2017 (S2). Using the two samples, we forecast up to horizon 12 and then expand month by month until December 2023, making forecasts for 12 steps as each month is added. Thus, we obtained a forecast sample size of 73. Using sample S1, we evaluate the historical performance of the a parameter used for calculating the Instantaneous Inflation, first using the forecast from the VAR or VECM model that uses the result from the CP analysis as the lag input order ($VECM\_CP$). Table 3 summarizes the frequency with which VAR or VECM models were fitted. For instance, a VECM model for the UK and its headline inflation was fitted only twice. Secondly, we compare three approaches, $VECM\_CP$, the VAR or VECM model that uses as lag input order the result from the information criteria ($VECM\_IC$), and an ARIMAX model that uses the lag input for the predictor variable (Instantaneous Inflation), again, the lag input for the predictor variable (Instantaneous Inflation) uses the result from CP(ARX). With S2, in addition to comparing the three approaches, we also compare them with a forecast from the aggregated and disaggregated components of inflation, as obtained by Martínez-Rivera et al. (2025). They employed several models, including ARIMA, reduction dimension models, and selection and machine learning models; a summary of these models is provided in Table 1.

Now, we apply the proposed methodology. Firstly, we calculate the Instantaneous Inflation (i_t^κ) for different values of a, and we compare the potential relationship between each i_t^κ and the yearly inflation (i_t^y) by using the CP. These results are available, using S1 and the $VECM\_CP$ approach, for CO in Table 2 for headline inflation, as described in Section 2.

In Table 2, we can see that Instantaneous Inflation for a values 0.25, 0.5, and 0.75, almost all the time i_t^κ leads i_t^y by one month. From $a = 1$ to $a = 6$, the leads increase from 2 to 5. From $a = 7$ to $a = 100$, the leads decrease. Thus, we identify the potential leads for each sample, which are usually stable for specific a values. Also, this table shows the forecast performance under a bivariate VECM model. Thus, for instance, the forecasts from the Instantaneous Inflation with a values of 0.25, 2.25, 3.75, and 3.5 are part of the subset of better forecasters for all horizons and all evaluation periods. In addition, these cases outperform the benchmark (BAR model) for horizons 1, 3, and 6 more than 50% of the time, and 30% for horizon 9. Also, we can see that from horizon 6, all the models, except for $a = 100$, have the same performance, and basically, we can not find any difference among them. It can be checked more clearly in plots in Figure 3. To visualize the best model throughout the evaluation period, we create a plot with the a parameter values corresponding to the best model, which we refer to as the *best model historical performance.*

Thus, in Figure 3, we show for horizons 1, 3, 6, 9, and 12 during the period 2019-2023, a sequence of the best forecaster, according to our description in section 2.1. We highlight in red the cases where the best $VECM\_CP$ model is statistically significantly better than the benchmark. Accordingly, for horizon 1, we can identify that a $VECM\_CP$ model with instantaneous inflation and $a = 2$, $a = 1.25$, $a = 2.25$, and $a = 0.25$ mainly at the end of the period improves their forecast compared to the BAR model. Similarly, we can observe the other horizons. Although the best model is a $VECM\_CP$ with $a = 0.25$ in most cases for horizons 1 and 3, we can not generalize since other $VECM\_CP$ models with other a values have an equivalent performance, as we show in Table 2. Therefore, to visualize the subset of models that exhibit similar performance, we create a plot, per horizon, that allows us to identify which models through the evaluation period have equal performance; we called this *historical performance plot*, for example, see plots in Figure 4. In this Figure, for horizons 1 and 3 (upper and down panel, respectively), we mark with a gray dot if the model $VEC\_CP(a)$ (a values in the y-axis) is part of the subset of models with similar performance to the best model identified in Figure 3. Thus, on the upper panel, for the BAR model (benchmark), the sub-periods with gray dots coincide with the period of black values in Figure 3, for horizon 1. This implies that the sections with missing dots coincide with the period of red values in Figure 3. In this sense, the sequence of gray dots in Figure 4 tells us what models are equivalent or have a similar performance through the evaluation period, or simply the subset of better forecasters at each time point. For example, in January 2023, the models $VEC\_CP(a)$ with $a = 0.25, 2.25, 2.5, 2.75, 3.25, 3.5, 5.5$ represent the subset of better forecasters.

Plots in Figure 5 show the comparison between the forecast with $VEC\_CP(a)$ (gray dots) and the observed Head inflation (black line, Obs). In these plots, we also include four measures from the forecast. These measures are the mean and the median (Mean hi and Median hi, respectively, where $i = 1, 3, 6, 9$ which refers to the horizon), and mean and median of the forecast from the subset of better forecasters, see Figure 4 (MeanB hi and MedianB hi, respectively, where $i = 1, 3, 6, 9$ which refers to the horizon). Furthermore, we add the forecast from the best forecaster; see Figure 3 (in red, labeled 'Best hi'). Thus, these plots allow us to see the forecast behavior for different horizons and their simple combinations using the mean and median measures. Additionally, we constructed combinations from the subset of the better forecaster; however, graphically, we cannot identify any improvement compared to the measure with all the forecasters.

Finally, with S2, in Figure 6, we compare the performance of the four approaches BAR, $VECM\_CP$, $VECM\_CI$ and $ARIMAX$ with a set of models that include aggregate and disaggregate index, according to Martínez-Rivera et al. (2025), see Table 1. From top to bottom, we present the historical performance of each model's $VECM\_CP$, $VECM\_CI$, and $ARIMAX$ models, which include instantaneous inflation. The plot at the bottom illustrates the historical performance of some aggregate and disaggregated models. In all cases, we use the benchmark (BAR) as a reference to select the best model; see Figure 6. Firstly, the plot for the $VECM\_CP$ approach shows that most models exhibit similar behavior until October 2021. From November 2022, models with $a \leq 4$ have better performance than BAR, and from May 2023, the only model with good performance is the one with $a = 0.25$. Secondly, although the plot for $VECM\_CI$ shows that all models have the same performance for the whole period and are statistically better than the BAR from November 2022, we cannot identify a smaller subset of better models. Thirdly, the plot for $ARIMAX$ shows that most of their models had good performance before 2023; however, none had a good performance after December 2021. Something similar to the ARIMAX models we observed for the aggregates and disaggregated models from early 2022.

We split the results as follows: First, we used core inflation, using S1 and S2, for the Colombian case. Second, the headline uses S1 and S2 for the United States, and third, the headline uses S1 and S2 for the United Kingdom. Comments on these results are available in the following sections, and supporting results, including tables and plots, are presented in the Appendix section. We omit the results for core inflation in the United States and the United Kingdom; however, these results will be available upon request.

4.1 Colombia core inflation using S1 and S2

Following a similar discussion to the one in the previous section, Table 4 summarizes the results for sample S1. The optimum lag primarily depends on the CP, which ranges from 1 to 5. The forecast obtained with $a = 0.25$ is consistent for all the horizons and equivalent to the performance of the benchmark model at horizon 1. We notice a meaningful improvement from horizon 3 and, more remarkably, from horizon 6, where all the models that use the instantaneous inflation have significantly better performance than the benchmark, ranging from 60% to 34%. This result is also seen in Figure 8. In this Figure, we show the subset of better forecasters. For horizon 1 from 2021, this subset is small for some values of a. For horizon 3, the only model in the subset of the better models is the one with $a = 0.25$; it happens mainly from November 2021.

Using sample S2 and comparing with aggregates and disaggregated models in most of the cases where the best models were statistically superior to the benchmark model, which happened with $VECM\_CP$ using $a = 0.25$ and $a = 4.25$, see Figure 9. Regarding the subset of better forecasters, Figure 10, we notice that from 2022, a few models $VECM\_CP$ are part of this subset, although most $VECM\_CI$ models are. ARIMAX models show good behavior until mid-2020, but after December 2021, none of these models exhibit good performance. Notably, several aggregate and disaggregated models are part of the subset of better forecasters during the evaluation period.

4.2 The United States headline inflation using S1 and S2

The results for the Headline inflation in the US using S1 are available in Table 5, and Figure 11. From Table 5, we notice an increasing lag as the value of a increases in blocks; for example, for values of a between 0.25 and 1.25, the optimum lag is 1, then this value increases until 3. Then, the optimum lag jumps between 2 and 4. Regarding the predictive capacity, we note an improvement for most of the $VECM\_CP(a)$ models compared to the benchmark for horizons 1 and 3. In the top plot in Figure 11, we can see that, for horizons 1 and 3, there is a significant improvement in the forecast performance during the beginning and the end of the evaluation period. This improvement happens for $a = 0.25, 0.5, 1.5$, and $a = 2.25$. The middle and bottom plots in Figure 11 show the behavior of the better subset of forecasters. We can not identify any specific winner between the a values from these results.

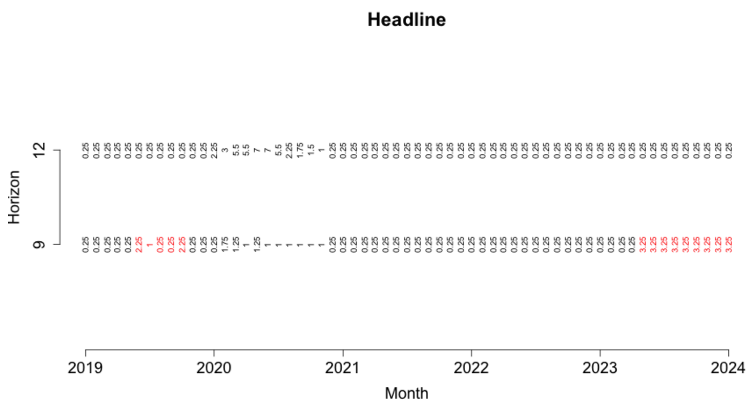
Using sample S2, in Figures 12 and 13, we show the behavior of the best model and the changes of the better subset forecasters, respectively. From plots in Figure 13, we can see that the models $VECM\_CP(a)$ and $VECM\_CI(a)$ exhibit good behavior, particularly during 2020, when only a few models, specifically $VECM\_CP(a)$, are part of the better subset. The ARIMAX models, in general, have poor behavior at horizon 1. Additionally, several aggregate and disaggregated models demonstrate good forecast performance.

4.3 The United Kingdom Headline inflation using S1 and S2

The results for the Headline inflation in the UK using S1 are available in Table 6, and Figure 14. From Table 6, we observe an increase in the lag as the value of a increases, from lag 2 to lag 4; however, for $a = 4.75$, most of the models exhibit an optimum lag of 1. Regarding the predictive capacity, the improvement for most of the $VECM\_CP(a)$ models compared to the benchmark is around 10% for horizons 1 and 3. In the top plot in Figure 14, we can see a few red values, which confirm the low percentage of the improvement on the forecast performance, as Table 6 shows. The middle and bottom plots in Figure 14 show the behavior of the better subset of forecasters. Since 2022, we have observed a decrease in the size of the subset of better forecasters.

Using sample S2, we notice a substantial improvement in the forecast performance; see Figure 15. Using this sample, we find that one of the best models is $M0A$ for horizons 1 and 3. For horizon 6, however, there are multiple best models throughout the period. Regarding the historical behavior of the better subset, plots on Figure 16, $VECM\_CP$ models behave similarly until May 2021. Still, from June, a small set of models with a between 2.5 and 4.25 and $a = 100$ are part of the better subset. $VECM\_CI$ models exhibit a similar behavior from July 2019 to January 2021; during the remainder of the evaluation period, models with a between 2.25 and

4.25 are primarily part of the better subset. Most ARIMAX models from 2019 to April 2020 and from July 2020 to January 2021 exhibit similar behavior, while models with a between 2.5 and 4.5 from February 2021 and November 2022 are part of the better subset. Finally, most aggregate and disaggregated models from 2019 to December 2020 have similar behavior, while from January 2023 to June 2023, only six models are part of the better subset.



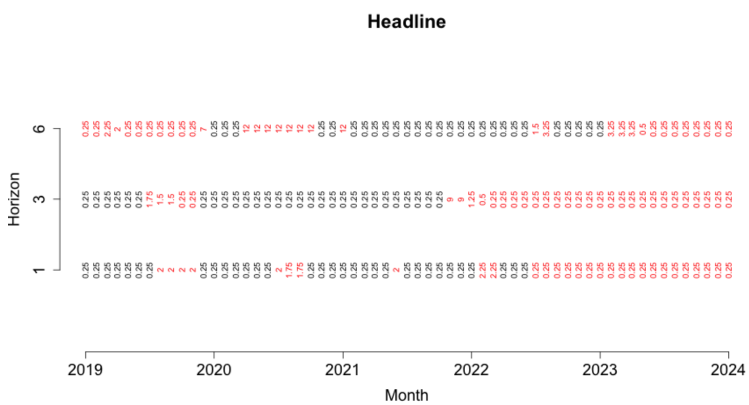


Figure 3: **CO Results. Best forecasts** $VECM(a)$ -a value refers to instantaneous inflation used by the bivariate $VECM\_CP$ model- behavior through time, corresponding to the model with the minimum RMSFE and significant difference compared to the BAR model. The red values of the parameter a indicate that, when instantaneous inflation is 5%, it is significantly better than the benchmark model, an ARIMA model, according to the Diebold and Mariano (1995) test. Missing values indicate that the best model was the benchmark.

5 Synthesis and Conclusions

Year-on-year inflation is an indicator that is closely tied to the sum of monthly price changes over an entire year, where each month has equal importance. However, when inflation changes rapidly, as it often does in Colombia, a calculation bias can be generated, affecting monetary policy decisions that are not well-calibrated to the economy's current situation. One way to overcome a

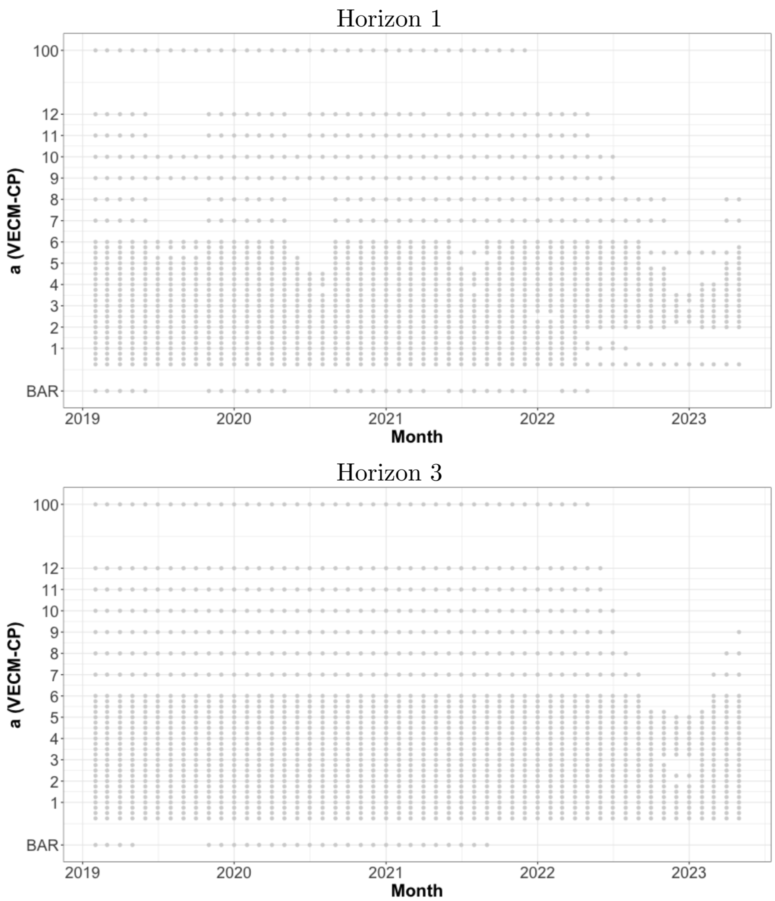


Figure 4: **CO Results (Historical performance). The subset of the better forecasters** $VECM\_CP(a)$ -a value refers to instantaneous inflation used by the bivariate $VECM\_CP$ model through time (gray dots).

calculation bias is by using instantaneous inflation, which allows us to incorporate changes in consumer prices more quickly and more adequately reflect current demand, market conditions, and price trends. Instantaneous inflation has the advantage of helping to better guide the formation of inflation expectations and the indexation of contracts, which can contribute to more informed decision-making by monetary authorities and a more stable and predictable economy. Instantaneous inflation is calculated using the kernel approach, which assigns a higher weight to recent events and a lower weight to more distant observations. Likewise, an optimal value of the bandwidth parameter (value a) that minimizes the model's RMSFE, where the instantaneous inflation indicator is a predictor, was calculated. From the analysis using instantaneous inflation as a predictor, we concluded that this measure is more sensitive to recent changes, being more volatile than official year-on-year inflation, but with the significant advantage of providing a more up-to-date view of the price situation. However, in this document, instantaneous inflation was calculated from the CPI seasonally adjusted, eliminating much of the volatility inherent in

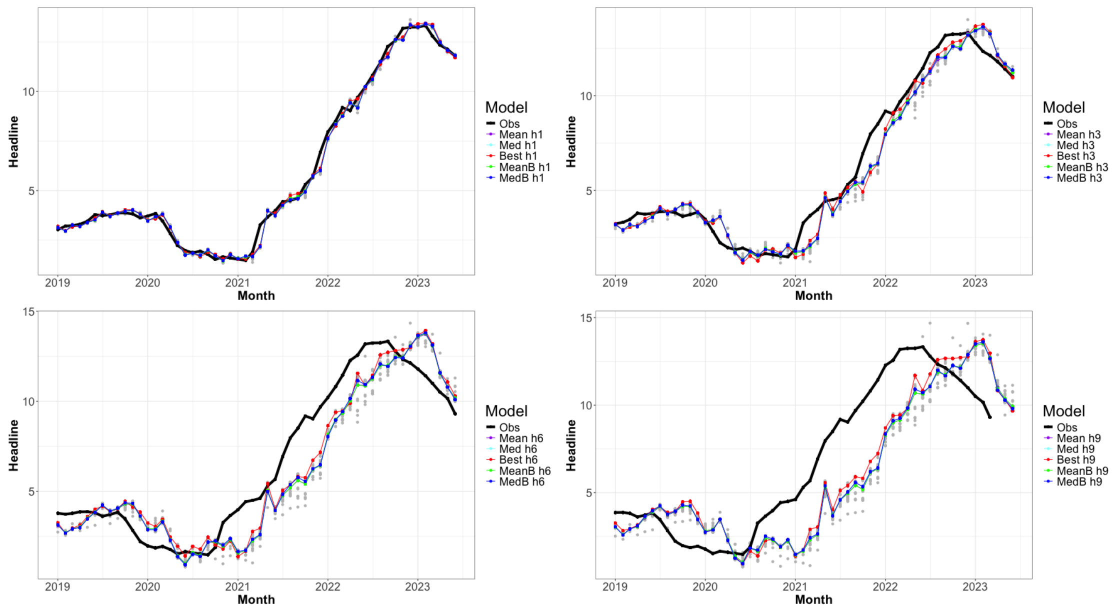


Figure 5: **Forecasts for the headline CPI inflation in Colombia using $VECM\_CP(a)$ approaches** (gray dots) compared to the observed headline inflation (black line), lagged by h months. Mean hi and Med hi refer to the mean and the median of the forecast given by the gray dots (where $i = 1, 3, 6, 9$ refer to the forecast horizon), Best hi refers to the forecast given by the model that exhibits the minimum RMSFE per evaluation period, and MeanB hi and MedB hi refer to the mean and the median from the subset of better forecasters, see Figure 4.

its calculation, and then, with matching profile tests, it was concluded that this measure operates as a leading indicator of conventional observed inflation, anticipating its inflection points consistently for headline and core inflation in the three countries analyzed.

The forecast analysis using the instantaneous inflation as a predictor in a bivariate VECM or VAR models ($VECM\_CP(a)$, and $VECM\_CI(a)$ with CP and AIC criterion as support of the order, respectively), and $ARIMAX(a)$ models with a sample S1 and three data sets (Colombia, the United States, and the United Kingdom), shows an improvement of the forecast accuracy using a traditional ARIMA model as benchmark. The findings suggest that Instantaneous Inflation works as a predictor of Inflation. Although we cannot identify a unique a value, we found a collection of values that provide appropriate Instantaneous Inflation predictors, which differ for each horizon. For example, in the case of Colombian headline inflation, the values of a fluctuate around 0.25 and 5. For the United States and the United Kingdom, this happens for a between 0.25 and 2.25 and 0.25 and 1, respectively.

Using sample S2 for the headline inflation, we identify similar results for Colombia and the United States: models $VECM\_CP(a)$ and $VECM\_CI(a)$ exhibit good behavior. In contrast, for the United Kingdom application, some models from the four groups exhibit good forecast performance. In most of the applications presented here, we conclude that instantaneous inflation is valuable for anticipating the dynamics of year-on-year inflation. Additionally, incorporating this information into the models is straightforward, and it does not require any extra information

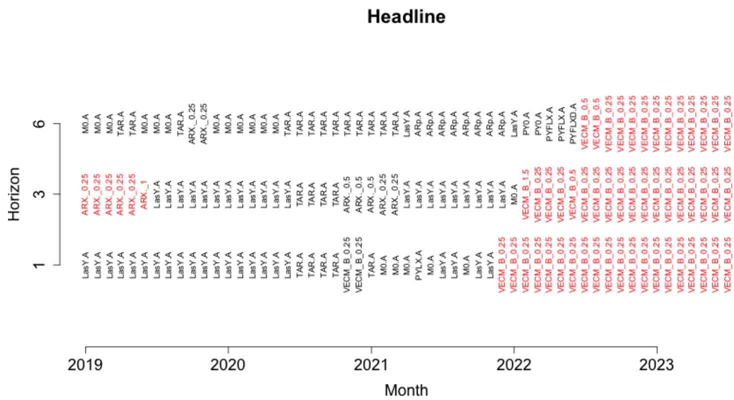


Figure 6: **CO Results. Best forecaster comparison using S2**. Acronyms refer to the best model behavior through time, corresponding to the model with the minimum RMSFE and significant difference compared to the BAR model. The red acronyms indicate that the improvement is significantly (at 5%) better than the benchmark model, an ARIMA model, according to the Diebold and Mariano (1995) test. Missing values indicate that the best model was the benchmark. The description of the acronyms is available in Table 1. $VECM\_B$ and $VECM\_C$ refer to $VECM\_CP(a)$ and $VECM\_CI(a)$, respectively. $ARX\_$ refers to the ARIMAX model that uses instantaneous inflation.

beyond the price index.

Data availability The developed R code and the data set for the Colombian applications are available at https://github.com/WilmerMartinezR/InflaInstV0.git. This material corresponds to the results in sub-section 4.1.

a	Opt Lag CP					Horizon (%)				
	-5	-4	-3	-2	-1	1	3	6	9	12
0.25	0	0	0	0	73	100	100	100	100	100
0.5	0	0	0	0	73	67	100	98	100	100
0.75	0	0	0	0	73	67	100	98	100	100
1	0	0	0	72	1	74	100	100	100	100
1.25	0	0	0	72	1	70	100	100	100	100
1.5	0	0	37	36	0	67	100	100	100	100
1.75	0	0	73	0	0	67	100	100	100	100
2	0	27	46	0	0	97	97	100	100	100
2.25	0	71	2	0	0	100	100	100	100	100
2.5	2	70	1	0	0	97	97	100	100	100
2.75	0	72	1	0	0	100	97	100	100	100
3	0	72	1	0	0	98	95	100	100	100
3.25	24	49	0	0	0	100	100	100	100	100
3.5	29	44	0	0	0	100	100	100	100	100
3.75	72	1	0	0	0	93	100	100	100	100
4	67	6	0	0	0	97	100	100	100	100
4.25	67	6	0	0	0	93	100	100	100	100
4.5	67	6	0	0	0	93	100	100	100	100
4.75	71	2	0	0	0	87	100	100	100	100
5	69	4	0	0	0	80	100	100	100	100
5.25	70	3	0	0	0	74	97	100	100	100
5.5	39	34	0	0	0	89	92	98	100	100
5.75	69	4	0	0	0	74	92	100	100	100
6	69	4	0	0	0	72	92	100	100	100
7	32	41	0	0	0	82	92	98	100	100
8	32	41	0	0	0	80	89	98	100	100
9	0	71	2	0	0	80	77	100	100	100
10	0	71	2	0	0	72	72	100	100	100
11	10	25	38	0	0	61	70	97	100	100
12	9	25	39	0	0	59	70	98	100	100
100	0	0	0	3	70	61	69	87	100	100
BAR						52	48	44	77	100

Table 2: **CO results Headline inflation**. Instantaneous inflation, $i_t^\kappa(\kappa(\tau,a))$, compared to Headline inflation by using the CP, columns 2 to 6 -Opt Lag CP-. We compared the data using a sample period from January 1983 to December 2017, and then extended the sample month by month until December 2023, resulting in a total of 73 comparisons. The negative values of Opt Lag CP indicate that $i_t^\kappa(\kappa(\tau,a))$ leads to year-on-year inflation, i_t^y. Horizon means the number of times (in percentage) the model $VECM\_CP$ was classified in the subgroup of the best forecasters compared with the benchmark, columns 7 to the end. BAR refers to the benchmark model as the best ARIMA model according to the AIC criterion.

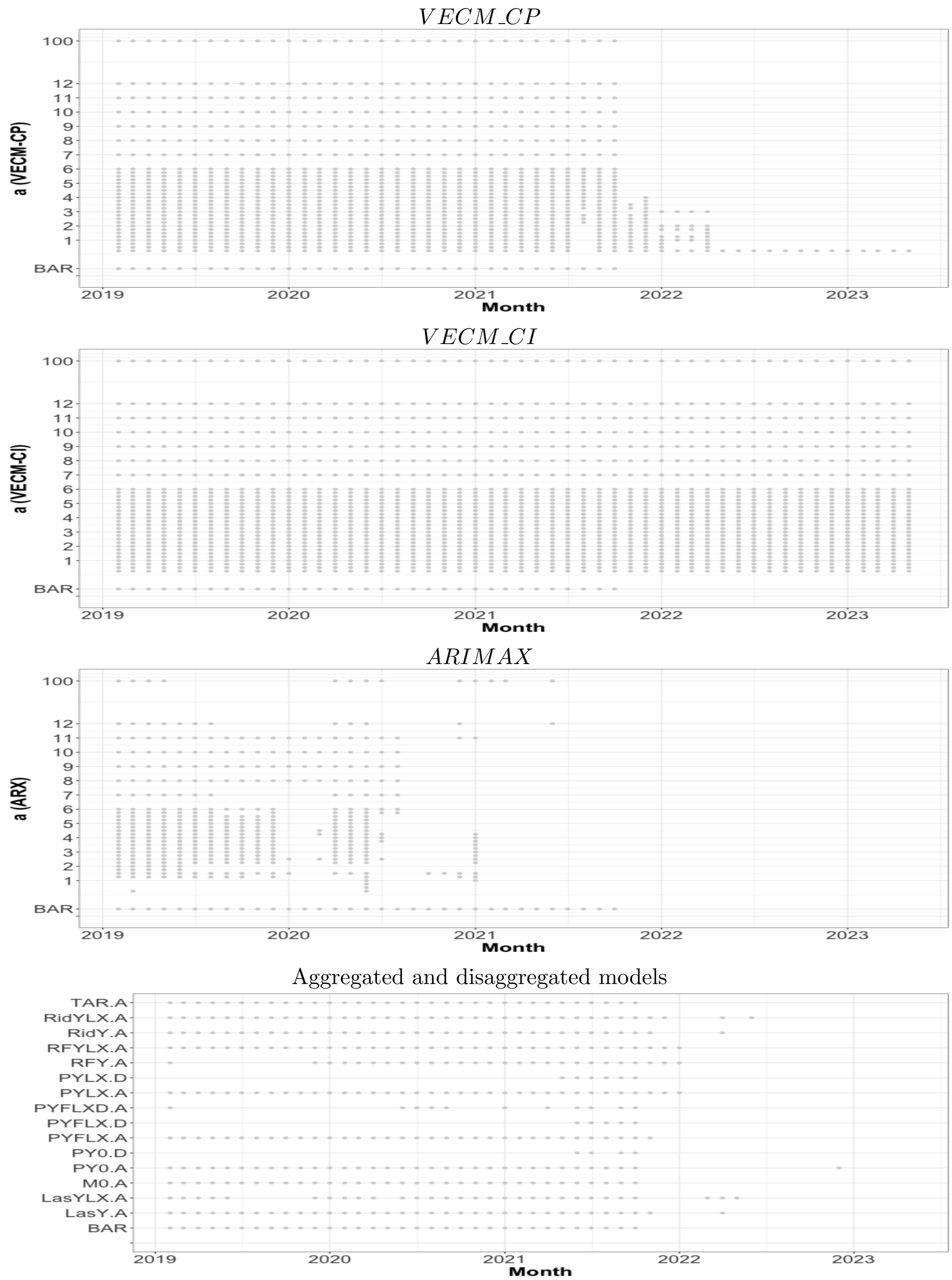


Figure 7: **CO Results Headline inflation (Historical performance for Horizon 1) using S2**. Subset of the better forecasters through time (gray dots).

References

Cryer, J. and Chan, K. (2008) *Time Series Analysis, with Applications in R.* Springer-Verlag.

Diebold, F. X. and Mariano, R. S. (1995) Comparing predictive accuracy. *Journal of Business & Economic Statistics*, **13**, 253–263. URL: `https://www.tandfonline.com/doi/abs/10.1080/07350015.1995.10524599`.

Eeckhout, J. (2023) Instantaneous inflation. *Available at SSRN 4554153.*

Lütkepohl, H. (1987) *Forecasting aggregated vector VARMA processes.* Springer-Verlag.

Martínez-Rivera, W., Caicedo, G. E. and Tique, J. (2013) Exploring the relationship between the cpi and the ppi: The colombian case. *International Journal of Business and Management*, **8**, 142.

Martínez-Rivera, W., González-Molano, E. R. and Caicedo-García, E. (2025) Forecasting inflation from disaggregated data. *Applied Stochastic Models in Business and Industry*, **41:e70023**.

Martínez-Rivera, W., Nieto, F. H. and Poncela, P. (2016) Choosing a dynamic common factor as a coincident index. *Statistics & Probability Letters*, **109**, 89–98.

Tsay, R. S. (2013) *Multivariate time series analysis: with R and financial applications.* John Wiley & Sons.

6 Appendix

Proof of property 1 for instantaneous inflation:

From equation (5), if $a = 0$ we have that

$$\kappa(\tau, 0) = \frac{M}{\sum_{\tau=0}^{M-1} 1} = \frac{M}{M} = 1. \tag{11}$$

Proof of property 2 for instantaneous inflation:

First, we check for $\tau = 0$, thus

$$\begin{aligned}
\kappa(0, \infty) &= \lim_{a\to\infty} \frac{M^a M}{M^a + (M-1)^a + \cdots + 1} \\
&= M \lim_{a\to\infty} \frac{M^a}{M^a + (M-1)^a + \cdots + 1}, \qquad \text{(dividing by } M^a\text{)} \\
&= M \lim_{a\to\infty} \frac{1}{1 + \left(\frac{M-1}{M}\right)^a + \left(\frac{M-2}{M}\right)^a + \cdots + \left(\frac{1}{M}\right)^a} \\
&= M \frac{\lim_{a\to\infty} 1}{\lim_{a\to\infty} \left[1 + \left(\frac{M-1}{M}\right)^a + \cdots \left(\frac{1}{M}\right)^a\right]} \\
&= M.
\end{aligned}$$

Second, for any $0 < \tau \leq M - 1$,

$$K(\tau, \infty) = \lim_{a\to\infty} \frac{(M-\tau)^a M}{M^a + (M-1)^a + \cdots + 1}$$

for example, for $\tau = 1$

$$K(1,\infty) = \lim_{a\to\infty} \frac{(M-1)^a M}{M^a + (M-1)^a + \cdots + 1}$$
$$= M \lim_{a\to\infty} \frac{\left(\frac{M-1}{M}\right)^a}{1 + \left(\frac{M-1}{M}\right)^a + \cdots + \left(\frac{1}{M}\right)^a} = M\frac{0}{1} = 0.$$

Thus, we conclude for any $1 < \tau \leq M-1$.

	Headline						Core					
	US		UK		CO		US		UK		CO	
a	I0	I1	I0	I1	I0	I1	I0	I1	I0	I1	I0	I1
0.25	73	0	71	2	73	0	73	0	73	0	73	0
0.50	73	0	71	2	73	0	73	0	73	0	73	0
0.75	73	0	71	2	73	0	73	0	73	0	73	0
1.00	73	0	71	2	73	0	73	0	73	0	73	0
1.25	73	0	71	2	73	0	73	0	73	0	73	0
1.50	73	0	71	2	73	0	73	0	73	0	73	0
1.75	73	0	71	2	73	0	73	0	73	0	73	0
2.00	73	0	71	2	73	0	73	0	73	0	73	0
2.25	73	0	71	2	73	0	73	0	73	0	73	0
2.50	73	0	71	2	73	0	73	0	73	0	73	0
2.75	73	0	71	2	73	0	73	0	73	0	73	0
3.00	73	0	71	2	73	0	73	0	73	0	73	0
3.25	73	0	71	2	73	0	73	0	73	0	73	0
3.50	73	0	71	2	73	0	73	0	73	0	73	0
3.75	73	0	71	2	73	0	73	0	73	0	73	0
4.00	73	0	71	2	73	0	73	0	73	0	73	0
4.25	73	0	71	2	73	0	73	0	73	0	73	0
4.50	73	0	71	2	73	0	73	0	73	0	73	0
4.75	73	0	71	2	73	0	73	0	73	0	73	0
5.00	73	0	71	2	73	0	73	0	73	0	73	0
5.25	73	0	71	2	73	0	73	0	73	0	73	0
5.50	73	0	71	2	73	0	73	0	73	0	73	0
5.75	73	0	71	2	73	0	73	0	73	0	73	0
6.00	73	0	71	2	73	0	73	0	73	0	73	0
7.00	73	0	71	2	73	0	73	0	73	0	73	0
8.00	73	0	71	2	73	0	73	0	73	0	73	0
9.00	73	0	71	2	73	0	73	0	73	0	73	0
10.00	73	0	71	2	73	0	73	0	73	0	73	0
11.00	73	0	71	2	73	0	73	0	73	0	73	0
12.00	73	0	71	2	73	0	73	0	73	0	73	0
100.00	73	0	71	2	73	0	73	0	73	0	73	0

Table 3: **Unit root test:** Stationarity conditions for case S1. I0 means the number of times i_t^y and $i_t^\kappa(a)$ do not need differentiation, and I1 means the number of times they need to be differentiated once to get stationarity. These results are performed for the expanding window approach from January 2018 to December 2023.

a	Opt Lag CP					Horizon (%)				
	-5	-4	-3	-2	-1	1	3	6	9	12
0.25	0	0	0	0	73	100	100	100	100	100
0.5	0	0	0	0	73	49	67	100	100	100
0.75	0	0	0	0	73	51	66	100	100	100
1	0	0	0	73	0	48	67	100	100	100
1.25	0	0	0	73	0	46	66	100	100	100
1.5	0	0	0	73	0	46	64	100	100	100
1.75	0	0	0	73	0	41	62	100	100	100
2	0	0	1	72	0	41	62	100	100	100
2.25	0	0	73	0	0	41	49	100	100	100
2.5	0	0	73	0	0	41	46	100	100	100
2.75	0	0	39	34	0	41	59	100	100	100
3	0	0	39	34	0	41	59	100	100	100
3.25	0	0	39	34	0	43	59	100	100	100
3.5	0	0	73	0	0	43	46	100	100	100
3.75	0	0	73	0	0	46	46	100	100	100
4	0	0	71	2	0	46	46	100	100	100
4.25	0	0	3	70	0	49	62	100	100	100
4.5	0	0	3	70	0	52	64	100	100	100
4.75	0	0	3	70	0	54	64	100	100	100
5	0	0	45	28	0	49	61	100	100	100
5.25	0	0	2	68	3	61	69	100	100	100
5.5	0	0	2	68	3	64	69	100	100	100
5.75	0	0	0	34	39	90	69	100	100	100
6	0	0	0	34	39	90	69	100	100	100
7	26	26	21	0	0	48	48	100	100	100
8	0	0	52	20	1	87	59	100	100	100
9	0	42	28	3	0	46	46	100	100	100
10	0	43	27	3	0	46	46	100	100	100
11	26	14	1	2	30	62	49	100	100	100
12	26	14	1	3	29	64	49	100	100	100
100	38	3	3	1	28	64	46	100	100	100
BAR						100	39	38	56	66

Table 4: **CO results Core inflation.** Note: Same description as in Table 2

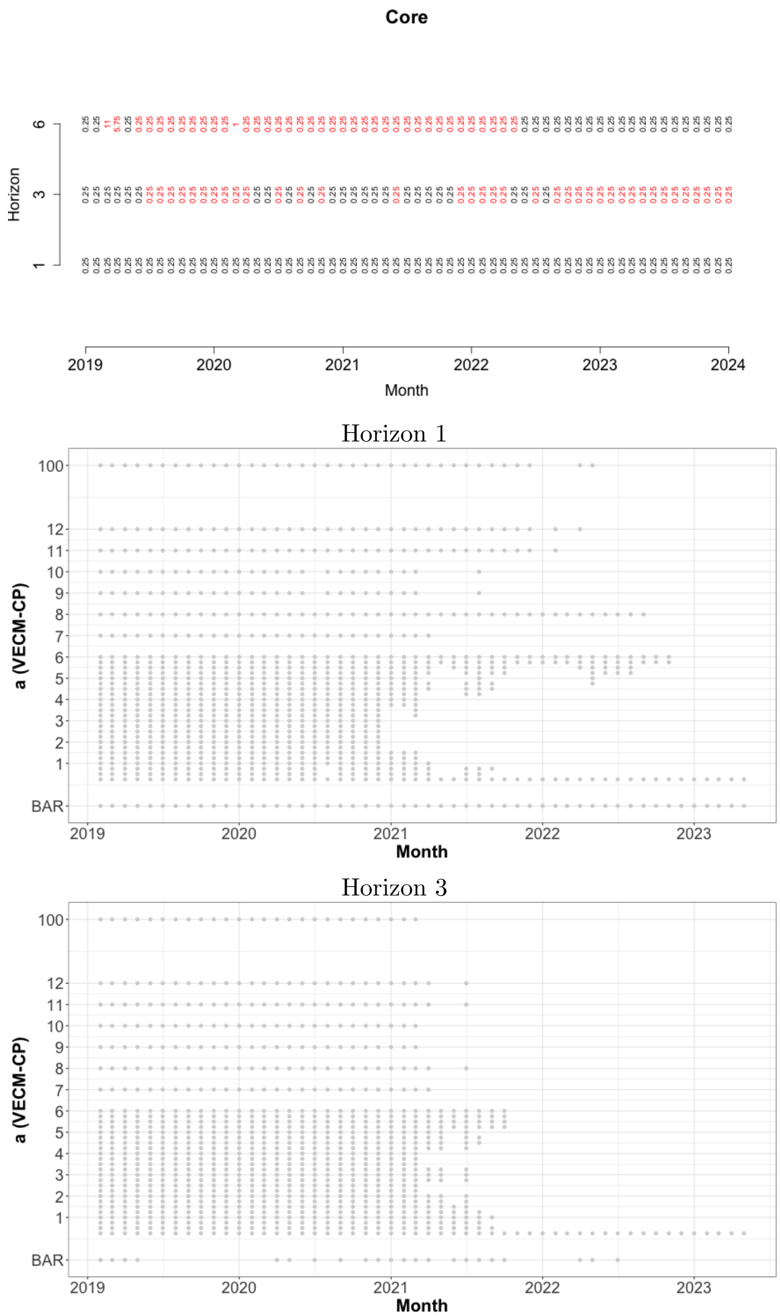


Figure 8: **CO Results Core inflation, Top panel**. Note: Same description as in Figure 3. Historical performance of the better subset models (middle and bottom panels). Note: Same description as in Figure 4

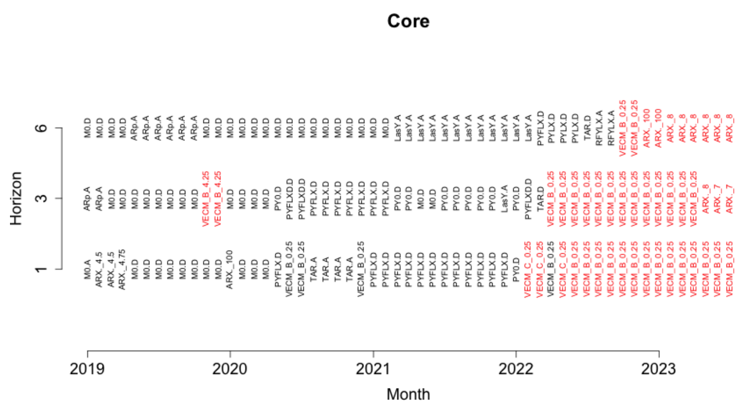


Figure 9: **CO Results Core inflation. Best forecaster comparison using S2**. Note: Same description as in Figure 6

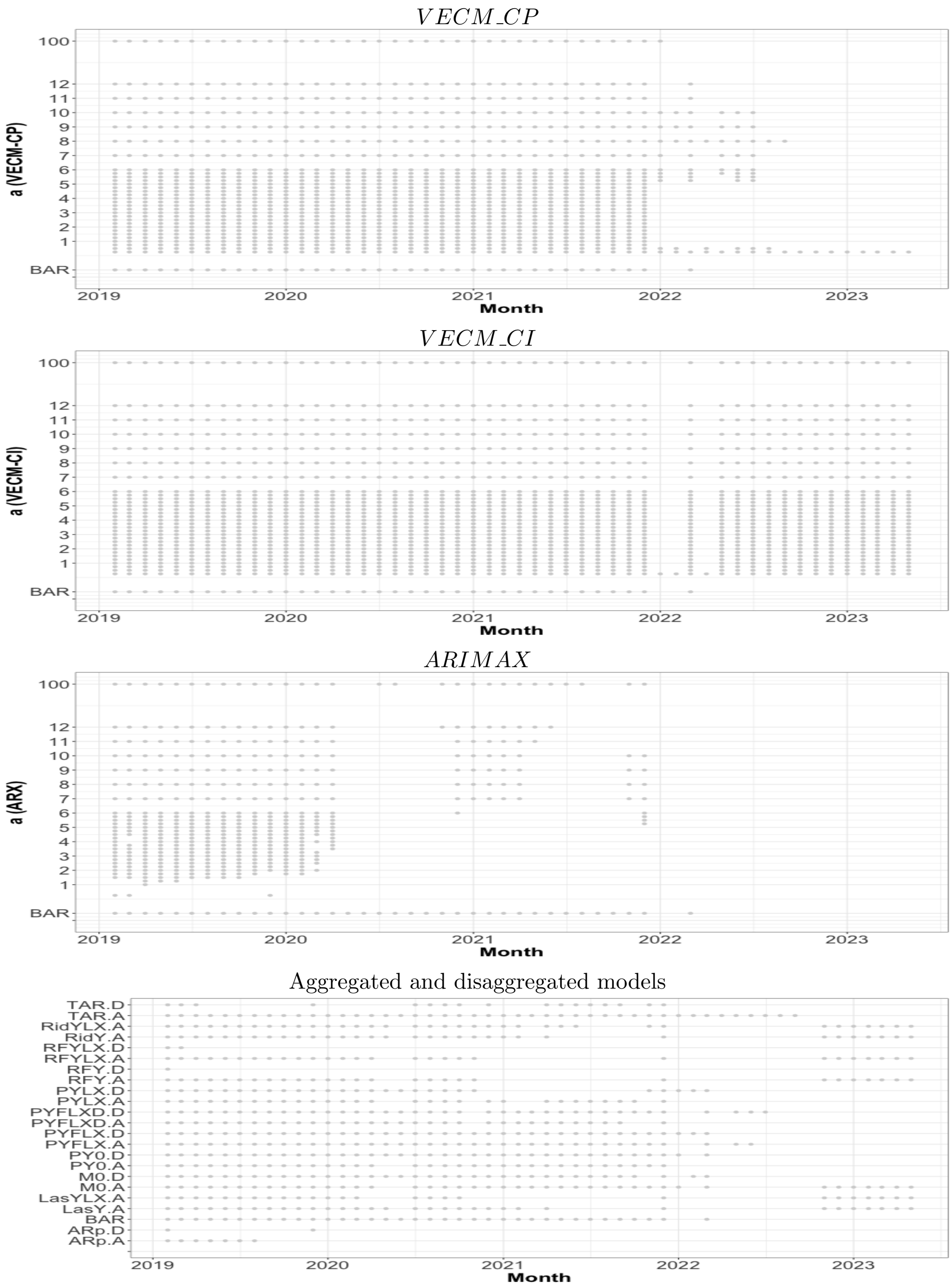


Figure 10: **CO Results Core inflation (Historical performance for Horizon 1) using S2**. Note same description as in Figure 7.

a	Opt Lag CP				Horizon (%)				
	-4	-3	-2	-1	1	3	6	9	12
0.25	0	0	0	73	100	100	98	100	98
0.5	0	0	0	73	75	82	98	100	98
0.75	0	0	0	73	77	79	98	100	98
1	0	0	0	73	80	80	100	100	98
1.25	0	0	0	73	80	80	100	100	98
1.5	0	0	73	0	100	100	95	100	100
1.75	0	0	73	0	77	98	95	100	100
2	0	30	43	0	80	95	95	95	98
2.25	0	73	0	0	87	100	95	95	97
2.5	0	73	0	0	85	100	97	97	97
2.75	0	73	0	0	85	98	97	97	98
3	0	31	42	0	87	87	98	98	97
3.25	0	0	60	13	89	62	100	100	98
3.5	0	0	73	0	77	75	100	98	100
3.75	0	0	73	0	77	74	100	98	100
4	0	0	73	0	77	72	100	100	100
4.25	0	30	43	0	85	84	100	100	98
4.5	0	0	73	0	75	70	100	100	100
4.75	0	73	0	0	85	84	100	100	98
5	0	73	0	0	85	84	100	100	98
5.25	0	69	4	0	85	84	100	100	98
5.5	0	7	66	0	87	77	100	100	98
5.75	0	0	73	0	75	67	100	100	100
6	0	0	73	0	75	67	100	100	100
7	0	0	73	0	77	66	100	100	100
8	0	0	73	0	77	64	100	100	100
9	19	54	0	0	87	85	100	100	98
10	0	73	0	0	85	80	100	100	98
11	0	73	0	0	85	80	100	100	98
12	0	23	50	0	89	82	100	100	97
100	0	45	28	0	85	82	100	100	98
BAR					67	52	95	100	100

Table 5: **US results Headline inflation.** Note: Same description as in Table 2

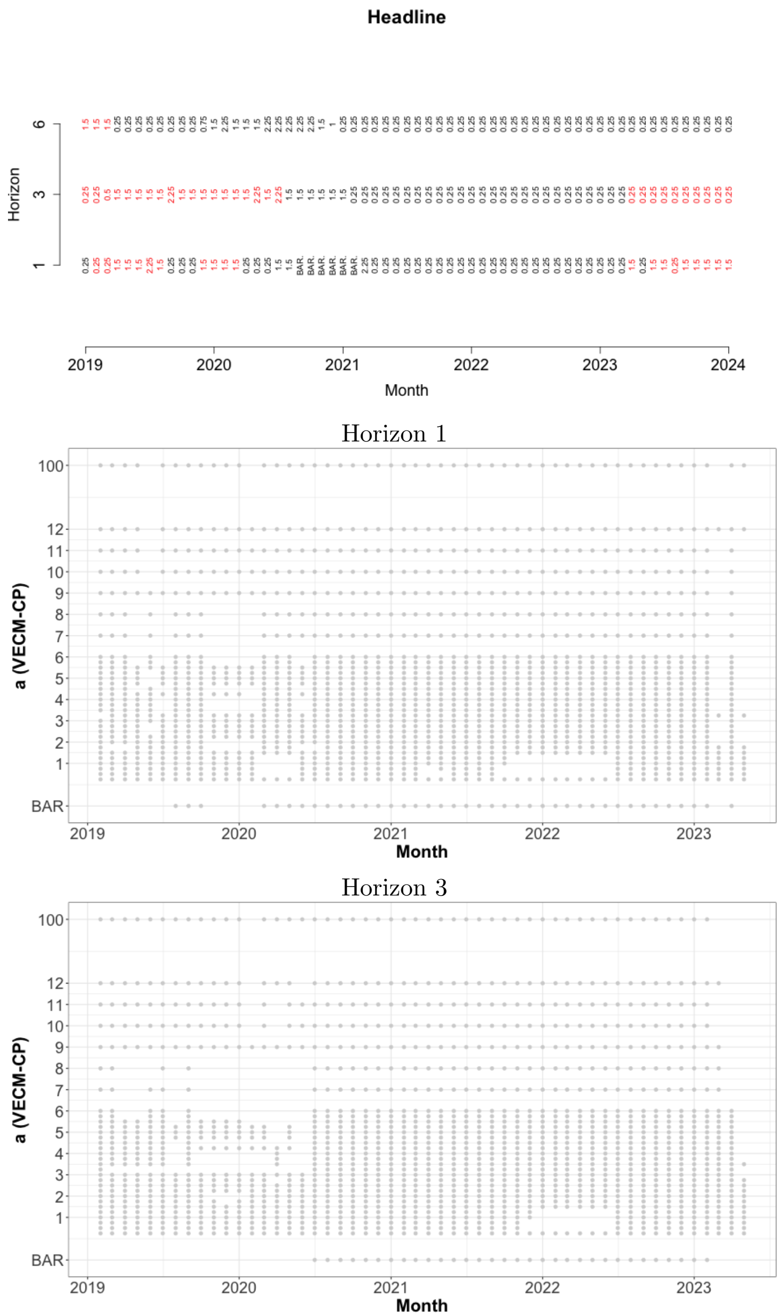


Figure 11: **US Results headline inflation, Top panel**. Note: Same description as in Figure 3. Historical performance of the better subset models (middle and bottom panels). Note: Same description as in Figure 4

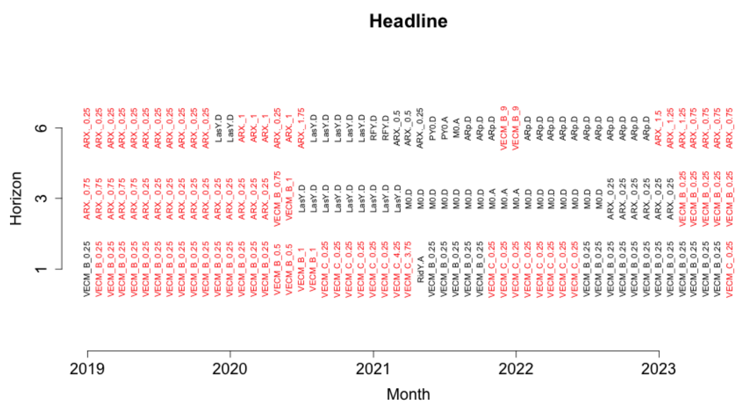


Figure 12: **US Results Headline inflation. Best forecaster comparison using S2**. Note: Same description as in Figure 6

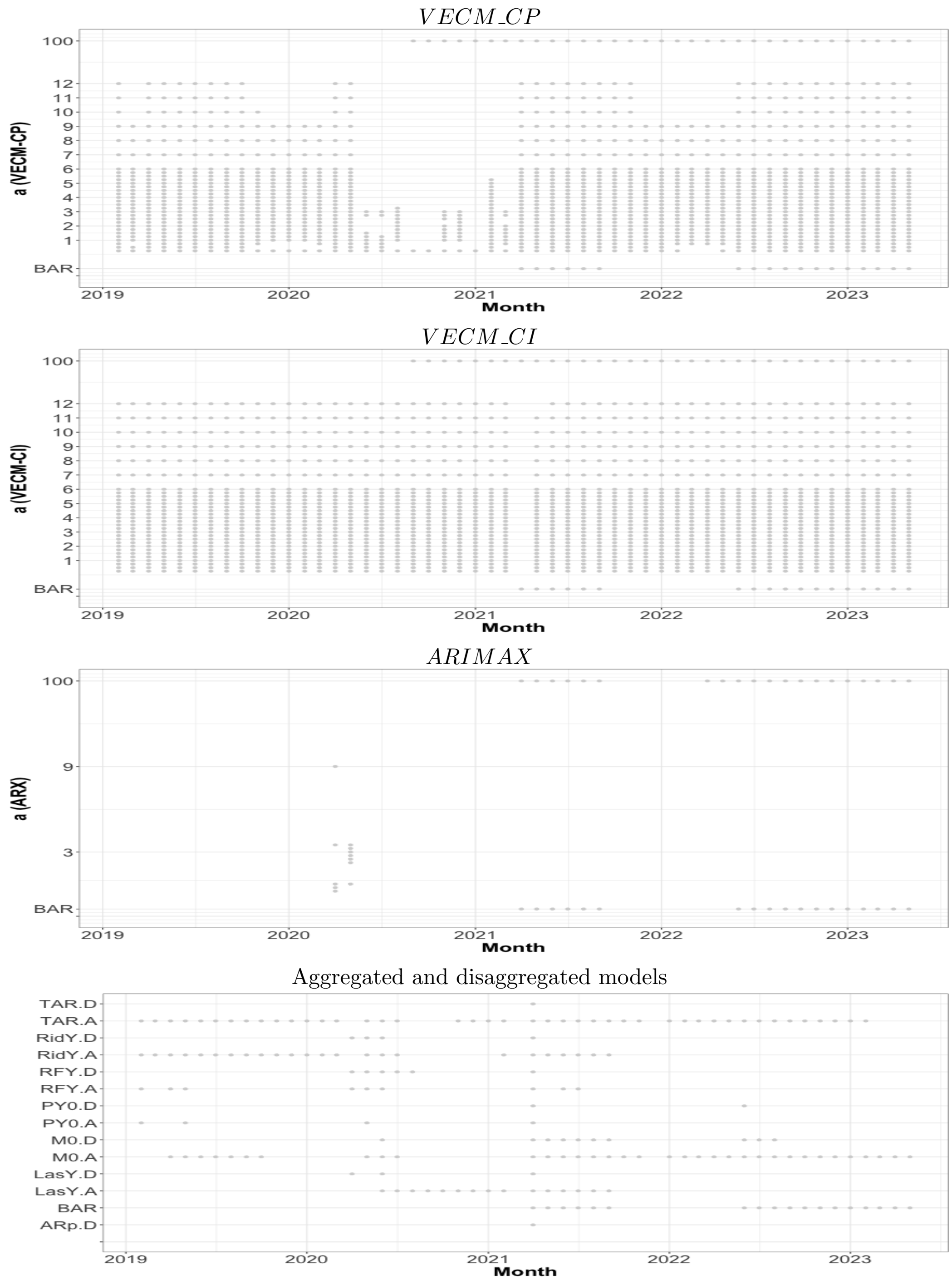


Figure 13: **US Results Headline inflation (Historical performance for Horizon 1) using S2**. Note same description as in Figure 7.

a	Opt Lag CP				Horizon (%)				
	-4	-3	-2	-1	1	3	6	9	12
0.25	0	4	69	0	100	90	100	97	98
0.5	0	0	73	0	66	90	100	97	100
0.75	24	49	0	0	100	82	80	87	95
1	73	0	0	0	100	84	82	92	98
1.25	21	52	0	0	95	87	75	87	95
1.5	17	56	0	0	87	90	77	87	92
1.75	25	48	0	0	87	95	89	80	90
2	0	53	20	0	75	84	100	100	100
2.25	0	53	20	0	75	79	100	100	100
2.5	53	20	0	0	84	95	100	93	98
2.75	53	20	0	0	82	95	100	93	100
3	53	20	0	0	80	89	100	93	100
3.25	53	20	0	0	80	82	100	93	100
3.5	0	53	20	0	77	74	100	100	100
3.75	0	49	24	0	75	72	100	100	100
4	0	49	24	0	75	70	100	100	100
4.25	0	49	24	0	75	70	100	100	100
4.5	0	0	49	24	66	61	100	100	100
4.75	0	0	0	73	69	66	87	100	100
5	0	0	0	73	69	66	85	100	100
5.25	0	0	0	73	69	66	85	100	100
5.5	0	0	0	73	69	66	85	100	100
5.75	0	0	0	73	69	66	85	100	100
6	0	0	60	13	70	62	87	100	100
7	0	0	60	13	70	62	85	100	100
8	0	0	0	73	69	66	84	100	100
9	0	0	0	73	69	66	84	100	100
10	0	0	0	73	69	66	84	100	100
11	0	0	0	73	69	66	84	100	100
12	0	0	0	73	69	66	84	100	100
100	0	0	0	73	74	66	84	100	100
BAR					89	90	97	100	100

Table 6: **UK results Headline inflation.** Note: Same description as in Table 2

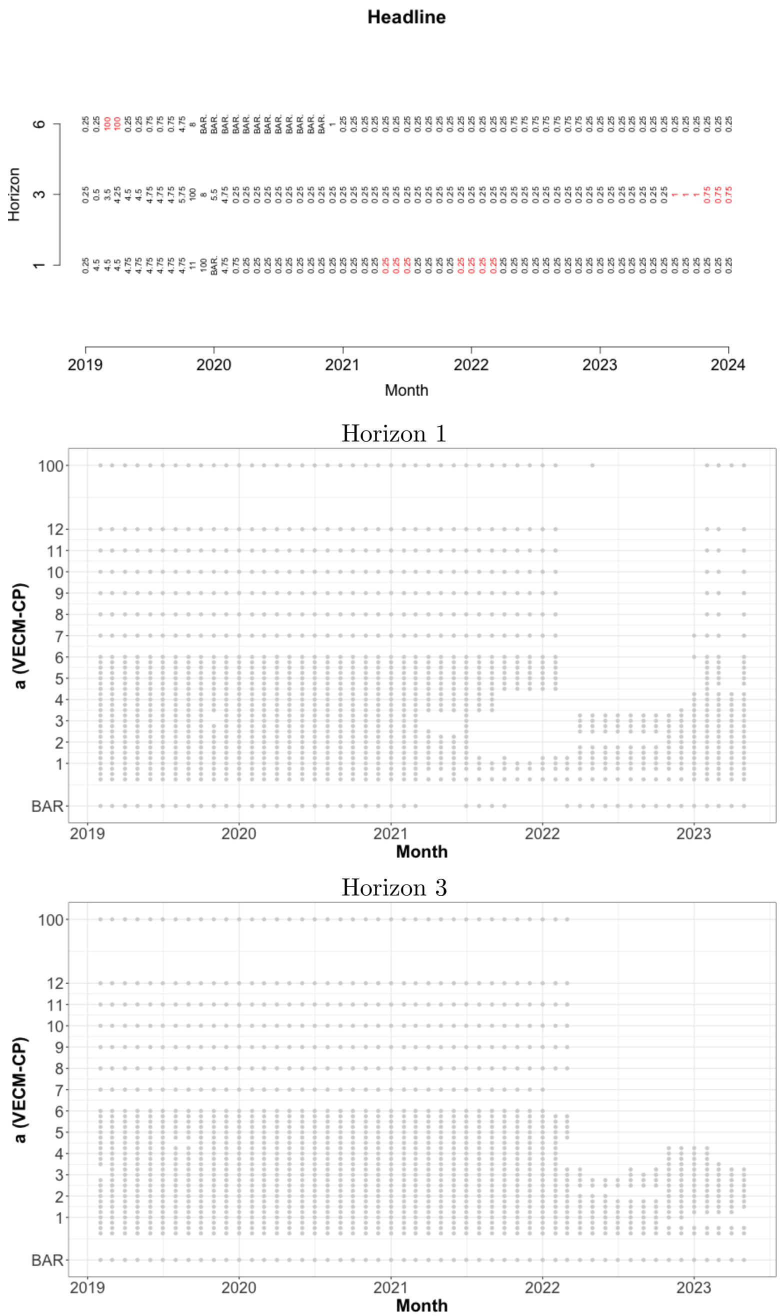


Figure 14: **UK Results headline inflation, Top panel**. Note: Same description as in Figure 3. Historical performance of the better subset models (middle and bottom panels). Note: Same description as in Figure 4

Figure 15: **UK Results Headline inflation. Best forecaster comparison using S2**. Note: Same description as in Figure 6

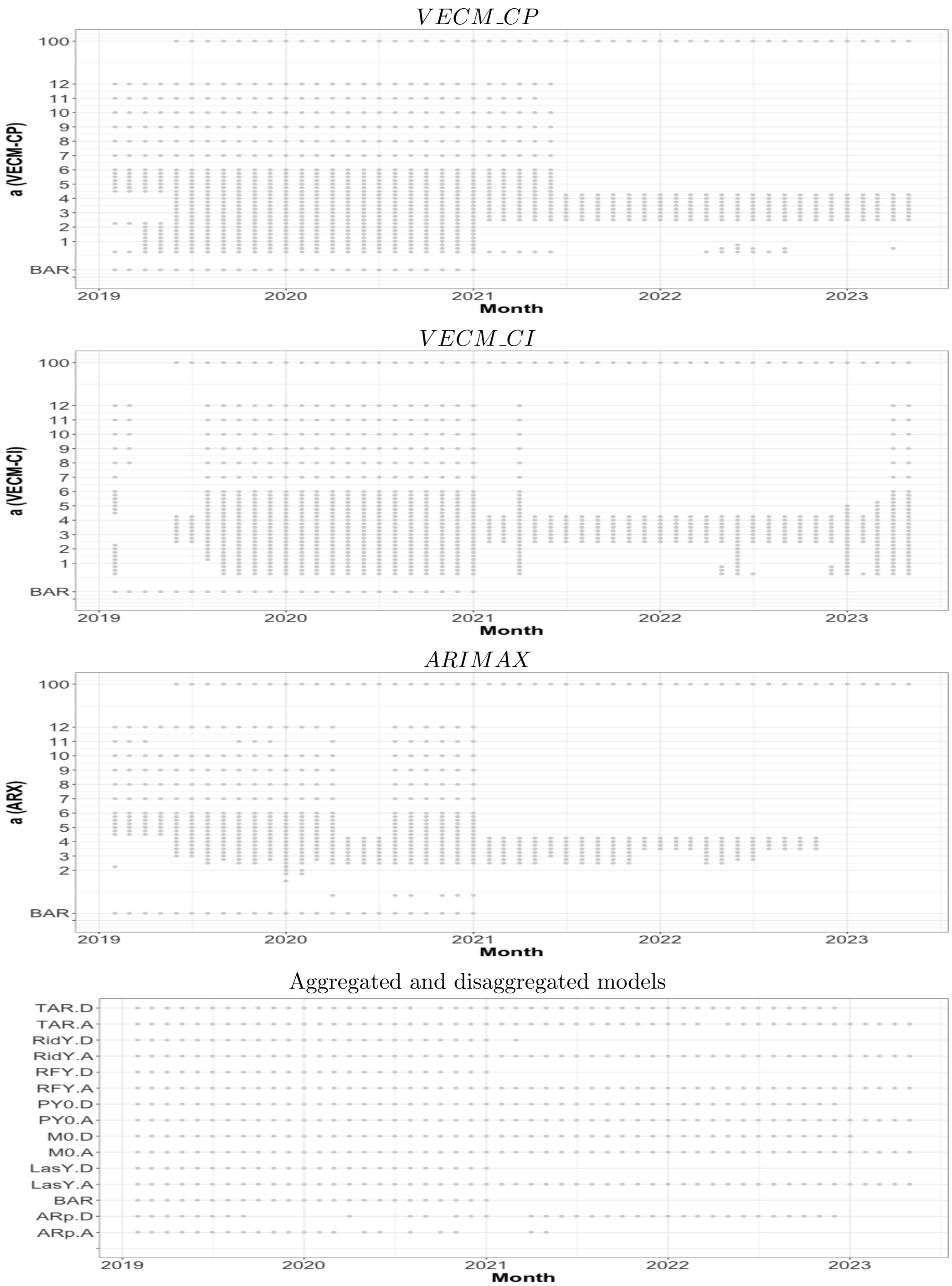


Figure 16: **UK Results Headline inflation (Historical performance for Horizon 1) using S2**. Note same description as in Figure 7.