Weekly Inflation Forecasting: A Two-Step Machine Learning Methodology

Osmar Bolivar*

October 2024

Abstract

This paper presents a novel two-step machine learning methodology tailored for forecasting weekly inflation rates in developing countries, with a specific focus on Bolivia. Addressing the challenge of high-frequency economic data scarcity, this methodology innovatively trains and validates machine learning algorithms on monthly inflation data and subsequently applies these models to generate weekly predictions, assuming a similar distribution of data across different time frequencies. The final forecast model significantly outperforms existing machine learning approaches, traditional econometric models, and survey-based methods in terms of predictive accuracy. It demonstrates marked effectiveness during periods of significant economic disruptions, precisely capturing the week-to-week fluctuations in inflation trends. This study not only fills a crucial gap in the economic forecasting literature but also enhances the toolkit available to policymakers for timely and informed economic decision-making in resource-constrained settings.

Keywords: Inflation Forecasting; Machine Learning; Economic Policy; Developing Countries; Data Scarcity

JEL Codes: C53; E31; C22

*This working paper is a preliminary version intended for feedback prior to submission to a formal journal. It has not undergone peer review and is posted on SSRN solely for early dissemination and improvement. The author's views and perspectives expressed herein are personal and may not reflect the positions of affiliated institutions. E-mail: `osmar.economics@gmail.com`

1 Introduction

In developing countries, limited access to high-frequency economic data significantly hampers effective policymaking, particularly in critical areas like inflation monitoring (Ghysels & Marcellino, 2018). Unlike developed economies, where daily or weekly economic indicators are abundant and pivotal to decision-making, in developing regions, these data are often scarce or of low quality.

This scarcity impedes the ability of policymakers to respond promptly to economic shifts, necessitating the development of methodologies that leverage lower-frequency data —typically monthly or quarterly— to forecast high-frequency economic variables. Inflation forecasting is especially crucial as it directly influences monetary policy and economic planning (Bernanke & Woodford, 1997).

Historically, econometric models like autoregressive integrated moving average, structural vector autoregressive, state-space, and dynamic stochastic general equilibrium models have been staples in inflation prediction (Faust & Wright, 2013; Stock & Watson, 1999). These models are valued for their interpretability, which is essential for policy formulation. However, they often fall short in capturing the complex interactions within inflation dynamics due to their linear frameworks and assumptions about data distributions.

Recent innovations have focused on forecasting high-frequency economic variables like inflation. Notably, the use of mixed data sampling (MIDAS) models and bridge equations has advanced. MIDAS models enable the integration of variables sampled at different frequencies within a single regression framework, enhancing the prediction of economic indicators using high-frequency predictors (Clements & Galvão, 2008; Ghysels, Sinko, & Valkanov, 2007). Bridge models, similarly, link lower-frequency economic outcomes with high-frequency predictors, offering practical solutions in data-sparse environments (Baffigi, Golinelli, & Parigi, 2004; Barhoumi, Darné, Ferrara, & Pluyaud, 2012).

Conversely, the introduction of machine learning has revolutionized economic analysis by enabling the modeling of non-linear dynamics prevalent in economic data. These techniques often surpass traditional models by accommodating complex and non-linear relationships without predefined model specifications (Goulet Coulombe, Leroux, Stevanovic, & Surprenant, 2022; Masini, Medeiros, & Mendes, 2023; Varian, 2014). Machine learning models, including Random Forests, shrinkage methods like lasso and elastic net, and neural networks, have shown promise in inflation forecasting (Baybuza, 2018; Joseph, Potjagailo, Chakraborty, & Kapetanios, 2024; Medeiros, Vasconcelos, Veiga, & Zilberman, 2021; Moshiri & Cameron, 2000; Teräsvirta, Van Dijk, & Medeiros, 2005; Ülke, Sahin, & Subasi, 2018).

The success of these models often depends on the richness of the dataset and the economic context, with non-linear models being particularly useful in emerging economies (Mahajan & Srinivasan, 2020). Even in atypical events like the COVID-19 pandemic or periods of heightened volatility and uncertainty, machine learning models have proved superior to benchmark econometric models in forecasting the undulations of inflation rates (Aras & Lisboa, 2022; Das & Das, 2024). Overall, the integration of machine learning into inflation forecasting represents a significant advancement in economic prediction methodologies.

This paper introduces a novel methodology tailored for developing economies with limited high-frequency data. By employing a two-step machine learning approach, this study first trains and validates algorithms on monthly inflation data, then applies these models to predict weekly inflation. The premise for applying monthly-trained algorithms to weekly predictions rests on the construction of both monthly and weekly variables as averages of daily observations, ensuring that the expected weekly value closely approximates the expected monthly value, assuming uniform data distribution across frequencies. This approach not only addresses data scarcity but also leverages advanced analytics to provide accurate high-frequency forecasts, thereby enhancing the decision-making capabilities in economic policy and planning.

The effectiveness of this methodology is demonstrated using data from Bolivia, representing typical challenges faced by many developing economies. This case study validates the proposed approach and its applicability in real-world settings, contributing to the discourse on improving economic forecasting in developing and emerging markets.

2 Methodology

2.1 Two-Step Methodology for Weekly Forecasting

This study introduces a two-step methodology for weekly forecasting, leveraging machine learning algorithms initially trained on monthly data, which are then applied to weekly data to facilitate higher frequency forecasting.

Consider a dataset $\mathcal{D}$ encompassing daily, weekly, and monthly observations. The target variable Y and features X are derived from the averages of high-frequency data, executing the methodology in two sequential steps:

Step 1: Monthly Inflation Forecasting

The process begins by aggregating high-frequency data into monthly averages, aligning with the frequency of the target variable. Denote $x_{i,t}^d$ as the daily observations of feature i on day t. The aggregated feature $x_{i,m}$ for month m is thus:

$$x_{i,m} = \frac{1}{N_m} \sum_{t \in M} x_{i,t}^d, \tag{1}$$

where N_m represents the number of days in month m, and M is the set of all days within that month. The target variable Y_m is calculated in a similar manner.

Subsequently, a machine learning algorithm is trained on the aggregated dataset $\mathcal{D}_m = \{(X_m, Y_m)\}$, with X_m comprising all features aggregated for month m.

Step 2: Applying Monthly-Validated Algorithms for Weekly Prediction

For weekly target variable prediction, the algorithm trained on monthly data is utilized, adjusting inputs by calculating weekly averages of daily data in a comparable aggregation process:

$$x_{i,w} = \frac{1}{N_w} \sum_{t \in W} x_{i,t}^d, \tag{2}$$

where $x_{i,w}$ signifies the weekly average of feature i, N_w the number of days in week w, and W the set of all days within that week.

The presumption for applying monthly-trained algorithms to weekly predictions rests on the linearity of expectations and averages across frequencies. As both monthly and weekly variables are averages of daily observations, the expected weekly variable value closely approximates the expected monthly variable value, assuming similar data distribution across the period. This strategy ensures the algorithm captures data patterns applicable across varying time scales:

$$\mathbb{E}[Y_w] \approx \mathbb{E}[Y_m], \text{ given } \mathbb{E}[x_{i,w}] \approx \mathbb{E}[x_{i,m}], \tag{3}$$

where $\mathbb{E}[Y_w]$ and $\mathbb{E}[Y_m]$ represent the expected values of the weekly and monthly target variables, respectively.

2.2 Justification for the Proposed Methodology

Assume daily data $\{x_t^d\}_{t=1}^T$ for a specific feature over T days within a month, with x_t^d as the observation on day t. The monthly average $\bar{x}^m$ is:

$$\bar{x}^m = \frac{1}{T}\sum_{t=1}^{T} x_t^d. \tag{4}$$

Similarly, the weekly average $\bar{x}_j^w$ for the j-th week, containing N_j days, is:

$$\bar{x}_j^w = \frac{1}{N_j}\sum_{t\in W_j} x_t^d, \tag{5}$$

with W_j denoting the days within the j-th week.

Linking weekly to monthly averages, the expected value of the target variable $\mathbb{E}[Y_m]$ correlates to the monthly average $\bar{x}^m$, while $\mathbb{E}[Y_{w_j}]$ aligns with the weekly average $\bar{x}_j^w$.

Upon aggregating daily data to weekly and monthly averages, it follows that:

$$\mathbb{E}[\bar{x}^m] = \frac{1}{T}\sum_{t=1}^{T} \mathbb{E}[x_t^d] = \mathbb{E}[x_t^d], \tag{6}$$

presuming daily data distribution consistency throughout the month. Likewise, for the weekly average:

$$\mathbb{E}[\bar{x}_j^w] = \frac{1}{N_j}\sum_{t\in W_j} \mathbb{E}[x_t^d] = \mathbb{E}[x_t^d]. \tag{7}$$

Given the identical distribution assumption of daily data within the month, the expected values of weekly and monthly averages converge, affirming:

$$\mathbb{E}[Y_{w_j}] \approx \mathbb{E}[Y_m], \tag{8}$$

provided the target variable directly correlates with the daily data averages. This rationale underpins the application of monthly-trained models for weekly outcome predictions, maintaining target variable expected values across aggregation levels under consistent data distribution.

2.3 Target Variable

Employing a two-step methodology, this research endeavors to forecast weekly inflation, with a focus on developing economies characterized by limited access to high-frequency data. Bolivia is selected as a case study, illustrating a scenario where monthly inflation statistics represent the most detailed publicly available data. The absence of high-frequency financial and stock market data, commonly accessible in more developed economies, poses a unique challenge for predicting inflation.

In Bolivia, inflation is measured as the percentage change in the Consumer Price Index (CPI), an established metric that encapsulates price variations for a representative basket of goods and services, reflecting household expenditure patterns. Compiled by the National Institute of Statistics of Bolivia, this index is derived from comprehensive price data collected throughout the month across a wide geographical span, covering major demographic and economic centers (INE, 2016).

The CPI is identified as the target variable (Y_m), attributed to its substantial correlation with the selected features, thereby exceeding the correlation observed with direct inflation rate measurements. This pronounced correlation enhances the forecasting capabilities of the machine learning algorithms deployed for predicting weekly inflation rates. CPI's correlation with the chosen features is available in Appendix A.

While the study primarily aims to generate monthly and weekly inflation estimates, the conversion of CPI forecasts into predicted inflation rates allows for an exhaustive performance evaluation of the forecasting model. This is accomplished by comparing the predicted inflation rates against the results yielded by existing models documented in the literature.

The CPI data facilitates the step 1 of the two-step methodology for weekly forecasting, encompassing the training and validation of algorithms for monthly inflation forecasting, with the time-series spanning from January 2011 to December 2023.

2.4 Features

This subsection is dedicated to outlining the assembly of a diverse dataset, poised for the two-step methodology aimed at forecasting weekly inflation. The dataset is segmented into five groups: wholesale prices, Google Trends data, financial variables, commodity prices, and lags. This categorization enables a holistic analysis that melds global economic insights with localized market conditions and the intricate dynamics of inflation.

The data compilation process is designed to facilitate the construction of time-series across daily, weekly, and monthly intervals, potentially serving as features within the forecasting methodology:

- **Wholesale Prices:** The dataset incorporates wholesale price data, sourced from Bolivia's Agro-Environmental and Productive Observatory (OAP), as a pivotal component. This data offers preliminary insights into market supply and demand dynamics, serving as an early indicator of potential inflationary trends (Cushing & McGarvey, 1990). A detailed dataset is compiled, which includes monthly ($x_{i,m}^{\mathrm{WS}}$) and weekly ($x_{i,w}^{\mathrm{WS}}$) averages derived from daily observations ($x_{i,t}^{d,\mathrm{WS}}$) across a variety of products (meats, tubers, fruits, vegetables, and agro-industry).[1]

- **Google Trends Data:** Incorporating Google Trends data augments the forecasting model with an innovative layer of analytics, capturing shifts in consumer sentiment towards economic indicators and commodities (Bulut, 2018; Eugster & Uhl, 2024; Simionescu, 2022). For the study period, weekly ($x_{i,w}^{\mathrm{GT}}$) and monthly ($x_{i,m}^{\mathrm{GT}}$) time

[1]Superscript "WS" stands for the subset of features corresponding to wholesale prices. Likewise, superscripts "GT", "FIN" and "COM" stand for the feature subsets google trends data, financial variables and commodity prices, respectively.

series are compiled. A specialized transformation is applied to weekly data ($x_{i,w}^{\text{GT-ADJ}}$) to ensure alignment with monthly aggregates:

$$x_{i,w}^{\text{GT-ADJ}} = x_{i,w}^{\text{GT}} \times \frac{x_{i,m}^{\text{GT}}}{\frac{1}{W_m}\sum_{w\in M^{\text{w}}} x_{i,w}^{\text{GT}}} \tag{9}$$

- **Financial Variables:** In the context of Bolivia's developing economy, the absence of a well-established stock market narrows the field of suitable high-frequency financial indicators correlating with aggregate price movements. After an exhaustive review, two financial variables emerged as potential predictors: the Housing Development Unit (UFV) and the USD/BOB exchange rate from Google Finance (GF). The UFV, a daily index calculated based on inflation and published by the Central Bank of Bolivia, serves as a benchmark for financial transactions, contracts, and legal acts in national currency, ensuring value preservation relative to domestic price evolution. Conversely, the exchange rate influences the cost of imported goods and services, thereby affecting the overall inflation rate. Despite Bolivia's crowding-peg exchange rate regime maintaining a fixed rate since November 2011, the USD/BOB exchange rate from GF, calculated from publicly available data reflecting the mid-market rate, spot rate, or interbank rate, offers more variability and is deemed more suitable for forecasting purposes.

  Furthermore, the LIBOR rate, despite not being a domestic financial variable, is included due to its demonstrated positive and significant correlation with Bolivia's CPI. Monthly ($x_{i,m}^{\text{FIN}}$) and weekly ($x_{i,w}^{\text{FIN}}$) averages are derived from daily values ($x_{i,t}^{d,\text{FIN}}$), offering a detailed perspective on the financial dimensions influencing inflation (Huybens & Smith, 1999).

- **Commodity Prices:** Global economic influences on domestic inflation are traced through commodity prices, incorporating a broad array of goods from oil and metals to agricultural products (Altansukh, Becker, Bratsiotis, & Osborn, 2017). Monthly ($x_{i,m}^{\text{COM}}$) and weekly ($x_{i,w}^{\text{COM}}$) series are generated from daily data ($x_{i,t}^{d,\text{COM}}$), allowing the model to account for external shocks and supply chain dynamics.

- **Lags:** To capture the inherent seasonality and persistence within inflation trends, lags of the CPI variable —specifically 1, 2, 3, 6, 9, and 12 months— are included as potential predictors (Bolivar, 2024). This inclusion enhances the model's ability to predict inflationary trends accurately.

Following the compilation of over 500 high-frequency potential predictors (broader description of these variables in Appendix B), a correlation analysis is conducted to filter variables based on their relationship with the CPI, adhering to a threshold for positive correlation greater than 0.5. This rigorous selection criteria narrows down the feature matrix X to a total of 86 variables (detailed in Appendix A), optimized for the forecasting model.

The two-step methodology for weekly forecasting encompasses both monthly (X_m) and weekly (X_w) sets of features, with the monthly set spanning January 2011 to December 2023 for Step 1, and the weekly set covering from the first week of January 2019 to the last week of December 2023 for Step 2. The distinction in start dates accommodates the availability of daily and weekly data for the selected features, ensuring the robustness of the forecasting model.

2.5 Training, Validation, and Test Sets

The step 1 of the methodology leverages the monthly-frequency feature matrix X_m and the target variable Y_m as inputs, denoted as $\mathcal{D}_m = \{(X_m, Y_m)\}$.[2] This dataset forms the basis for training and validating machine learning algorithms with the express goal of accurately forecasting monthly inflation rates. To this end, $\mathcal{D}_m$ is partitioned such that 80% (comprising 124 observations) is designated for training, and the remaining 20% (32 observations) for validation.

This subdivision strategy, opting for a random assignment of observations to training and validation sets over a temporally contiguous split, is informed by the dataset's feature composition and the strategic inclusion of CPI lags. With the majority of features being contemporaneous and supplemented by CPI lags, which reveal historical inflation trends, it ensures that the predictive models are trained and validated against a broad spectrum of inflationary dynamics encapsulating the whole analysis period. This randomization approach affords a robust validation mechanism, evaluating the model's efficacy across various economic conditions and temporal phases, thereby avoiding the potential limitations of a validation confined to a specific, possibly atypical, timeframe.

Proceeding to step 2 of the methodology, the algorithms, having been trained and validated on the monthly data ($\mathcal{D}_m$), are subsequently applied to a weekly-frequency feature matrix (X_w).[3] This effectively positions X_w as the test set for generating weekly forecasts of the target variable Y_w.

It is imperative to highlight that prior to analysis, both $\mathcal{D}_m$ and X_w are subjected to z-score normalization to ensure uniformity across variables and to minimize any potential biases. Specifically, for any given variable j within the $\mathcal{D}_m$ matrix, normalization is conducted as follows:

$$\tilde{x}_{j,m} = \frac{x_{j,m} - \mu_j}{\sigma_j} \tag{10}$$

where μ_j and σ_j denote the mean and standard deviation, respectively, of variable j across the training set within $\mathcal{D}_m$. This normalization procedure is consistently applied to variables in X_w, maintaining methodological integrity and comparability across the datasets.

2.6 Machine Learning Algorithms

This subsection provides an overview of the machine learning algorithms selected to achieve the research objectives, focusing on their prevalent use in time series prediction. The selection includes algorithms capable of modeling both linear and non-linear relationships, thus ensuring a robust approach to understanding the complexities of CPI forecasting.

Hyperparameter tuning is crucial for optimizing the performance of these algorithms. It involves selecting appropriate values for various hyperparameters that control the behavior of each algorithm. The tuning process is conducted using a 5-fold cross-validation (5F-CV) technique to ensure that the models generalize well on unseen data.

The following outlines detail the algorithms used and their respective hyperparameter tuning processes:

[2] $\mathcal{D}_m$ is a 156×87 matrix.
[3] X_w is a 312×86 matrix.

1. **Ridge Regression** employs an L2 penalty to prevent overfitting by minimizing the magnitude of the coefficients (Hoerl & Kennard, 1970). The hyperparameter space for Ridge regression, H^{Ridge}, includes the regularization parameter λ, and binary options *positive* and *intercept*. These are optimized using a 5F-CV as follows:

$$H_{\text{opt}}^{\text{Ridge}} = \underset{H^{\text{Ridge}}}{\text{argmin}}\ \text{MSE}(H^{\text{Ridge}}),$$

where λ is explored within a logarithmically spaced range from 10^{-1} to 10^2. Both *positive* and *intercept* are assessed for states $[\text{True}, \text{False}]$.

2. **Lasso Regression** utilizes an L1 penalty to enhance sparsity among the coefficients (Tibshirani, 1996). The hyperparameter space, H^{Lasso}, similarly includes λ, *positive*, and *intercept*. These parameters are optimized through:

$$H_{\text{opt}}^{\text{Lasso}} = \underset{H^{\text{Lasso}}}{\text{argmin}}\ \text{MSE}(H^{\text{Lasso}}),$$

exploring λ in the same range as Ridge, with additional evaluations for *positive* and *intercept*.

3. **ElasticNet** combines the features of Ridge and Lasso, using both L1 and L2 penalties (Zou & Hastie, 2005). Its hyperparameter space H^{EN} includes λ, α (the ratio of L1 to L2 regularization), *positive*, and *intercept*. Tuning is achieved through:

$$H_{\text{opt}}^{\text{EN}} = \underset{H^{\text{EN}}}{\text{argmin}}\ \text{MSE}(H^{\text{EN}}),$$

with λ and α tuned across ranges from logarithmically spaced 10^{-1} to 10^2 and 0.01 to 0.99, respectively.

4. **AdaBoost Regressor** integrates multiple weak learners, optimizing for noise and complexity (Freund & Schapire, 1997). The hyperparameters H^{ADA} include the learning rate α, the number of estimators T, and the maximum depth of decision trees d, optimized through:

$$H_{\text{opt}}^{\text{ADA}} = \underset{H^{\text{ADA}}}{\text{argmin}}\ \text{MSE}(H^{\text{ADA}}),$$

where α spans logarithmic values from 10^{-2} to $10^{0.5}$, T ranges from 50 to 200, and d from 1 to 10, ensuring a balanced approach to model complexity and performance.

5. **Gradient Boosting Regressor** corrects residuals in a step-by-step manner using weak learners (Friedman, 2001). Its configuration H^{GBR} includes the learning rate γ, number of estimators T, and tree depth d, tuned as follows:

$$H_{\text{opt}}^{\text{GBR}} = \underset{H^{\text{GBR}}}{\text{argmin}}\ \text{MSE}(H^{\text{GBR}}),$$

evaluating γ over 10^{-2} to $10^{0.5}$, T from 100 to 300, and d from 3 to 9, each ensuring the model adapts well to the underlying data patterns.

6. **Random Forest Regression** uses an ensemble of trees to predict outcomes, effectively handling complex, non-linear interactions (Breiman, 2001). Hyperparameters

H^{RF} include T, d, and the minimum samples required to split a node mss, optimized through:

$$H^{\mathrm{RF}}_{\mathrm{opt}} = \underset{H^{\mathrm{RF}}}{\mathrm{argmin}}\ \mathrm{MSE}(H^{\mathrm{RF}}),$$

where T is assessed from 100 to 300, d from 3 to 9, and mss from 2 to 20, each range carefully chosen to enhance model accuracy without overfitting.

7. **Extra Trees Regressor**: Employs extremely randomized trees to improve prediction stability and accuracy, particularly by adding randomness to the model construction (Geurts, Ernst, & Wehenkel, 2006). Hyperparameter tuning H^{ET} focuses on T, d, mss, and whether to bootstrap samples, with:

$$H^{\mathrm{ET}}_{\mathrm{opt}} = \underset{H^{\mathrm{ET}}}{\mathrm{argmin}}\ \mathrm{MSE}(H^{\mathrm{ET}}),$$

exploring T from 100 to 300, d from 3 to 9, and mss from 2 to 20, alongside the binary decision on bootstrapping, ensuring robustness across different data scenarios.

2.7 Aggregated Metrics for Forecasting

In addition to the forecasts generated by the seven trained and validated algorithms, aggregated forecast metrics are constructed following a methodology akin to that described by Bolivar (2024). This approach capitalizes on the heterogeneity and variability of individual predictions to enhance overall forecasting performance. The procedure is delineated as follows:

- Forecasts of the target variable, initially normalized to z-scores ($\hat{\tilde{y}}_i$; $i = 1, \ldots, 7$), are transformed back to their original units to represent predicted CPI values ($\hat{y}_i$; $i = 1, \ldots, 7$).
- Aggregation of individual forecasts is performed to compute several statistics:
  - The arithmetic mean of all individual predictions, denoted as $\hat{y}_{\mathrm{AM}}$.
  - The weighted arithmetic mean of all individual predictions, denoted as $\hat{y}_{\mathrm{WAM}}$, where weights are assigned based on the inverse of the mean squared errors (MSE) of each algorithm.
  - The weighted arithmetic mean considering only the three best-performing algorithms, denoted as $\hat{y}_{\mathrm{WAM\text{-}BEST}}$, with weights similarly based on the inverse of the MSE.
  - The weighted geometric mean of all individual predictions, denoted as $\hat{y}_{\mathrm{WGM}}$, applying weights as the inverse of the MSE.
  - The weighted geometric mean considering only the three best-performing algorithms, denoted as $\hat{y}_{\mathrm{WGM\text{-}BEST}}$, with weights again based on the inverse of the MSE.
- Utilizing the metrics constructed in the preceding step, the predicted year-over-year (y-o-y) inflation rates are computed as $\hat{\pi}_{\mathrm{AM}}$, $\hat{\pi}_{\mathrm{WAM}}$, $\hat{\pi}_{\mathrm{WAM\text{-}BEST}}$, $\hat{\pi}_{\mathrm{WGM}}$, and $\hat{\pi}_{\mathrm{WGM\text{-}BEST}}$.[4] These aggregated forecasts serve as the primary predictive outputs.

[4] Predicted y-o-y inflation rates are also computed for each of the individual predictions from the seven algorithms.

Additionally, to provide a range of certainty in inflation forecasts, a forecast interval is established. The upper and lower limits of this interval are determined by the maximum ($\hat{\pi}_{\text{max}}$) and minimum ($\hat{\pi}_{\text{min}}$) values of the forecasts from the three best-performing algorithms.

These analyses and transformations apply to the CPI predictions on both a monthly (Y_m) and weekly (Y_w) basis, allowing for flexibility and adaptability in forecast granularity.

3 Forecasting Monthly Inflation

3.1 Baseline Model

The initial step of the methodology centers on the training and validation of machine learning algorithms aimed at forecasting inflation with monthly frequency. Seven distinct algorithms to predict the Consumer Price Index (CPI) levels in Bolivia are evaluated, each subjected to a 5-fold cross-validation to ensure robustness and validity of the forecast models.

The effectiveness of these algorithms was assessed using several key statistical metrics: mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). Notably, except for the Extra Trees algorithm, a significant improvement in performance was observed for all models following hyperparameter tuning. This enhancement highlights the critical role of optimal parameter selection in maximizing forecasting accuracy. The specifics of these metrics and the hyperparameters selected after tuning are detailed in Appendix C.

Subsequent to the validation phase, aggregation techniques outlined in subsection 2.7 were applied. These techniques consolidate individual forecasts into aggregated forecast metrics, which are then used to compute predicted y-o-y inflation rates.

Table 1: Forecast Evaluation by Aggregated Forecast Metrics and Algorithms

Forecast	Full Sample			Train Set			Validation Set		
	MSE	MAE	R^2	MSE	MAE	R^2	MSE	MAE	R^2
$\hat{\pi}_{\text{WAM-BEST}}{}^{\dagger}$	0.031	0.126	0.995	0.022	0.109	0.997	0.063	0.194	0.983
$\hat{\pi}_{\text{WGM-BEST}}{}^{\dagger}$	0.031	0.126	0.995	0.022	0.109	0.997	0.063	0.194	0.983
$\hat{\pi}_{\text{WGM}}$	0.027	0.119	0.996	0.018	0.100	0.997	0.064	0.194	0.983
$\hat{\pi}_{\text{WAM}}$	0.027	0.119	0.996	0.018	0.100	0.997	0.064	0.194	0.983
ET	0.018	0.076	0.997	0.003	0.041	1.000	0.077	0.211	0.979
$\hat{\pi}_{\text{AM}}$	0.068	0.206	0.989	0.063	0.199	0.991	0.089	0.233	0.976
Ridge	0.131	0.274	0.980	0.137	0.276	0.981	0.106	0.268	0.971
RF	0.068	0.174	0.989	0.054	0.142	0.992	0.124	0.296	0.966
GBR	0.029	0.091	0.995	0.003	0.041	1.000	0.132	0.285	0.964
ADA	0.068	0.166	0.989	0.025	0.113	0.997	0.238	0.373	0.936
ENET	0.309	0.420	0.952	0.315	0.423	0.955	0.285	0.407	0.923
Lasso	1.612	1.003	0.751	1.650	1.010	0.767	1.466	0.975	0.603

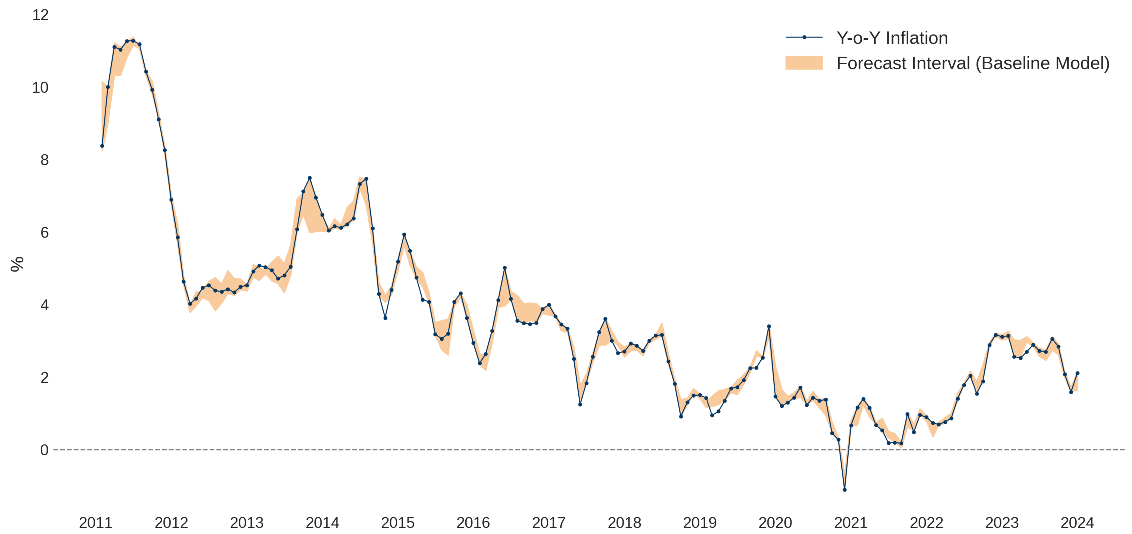
Note: The forecast evaluation is computed with observed and predicted values in y-o-y inflation rates. WAM and WGM stand for Weighted Arithmetic Mean and Weighted Geometric Mean, respectively.
(†) The three best-performing algorithms are Extra Trees, Ridge, and Random Forest.

Table 1 presents the forecast performance of both individual algorithms and aggregated metrics over the monthly y-o-y inflation forecast. Intriguingly, the Extra Trees Regressor (ET) emerged as the most accurate individual algorithm, closely followed by the Ridge and Random Forest (RF) algorithms. This result underscores the utility of both linear and non-linear models in inflation forecasting contexts.

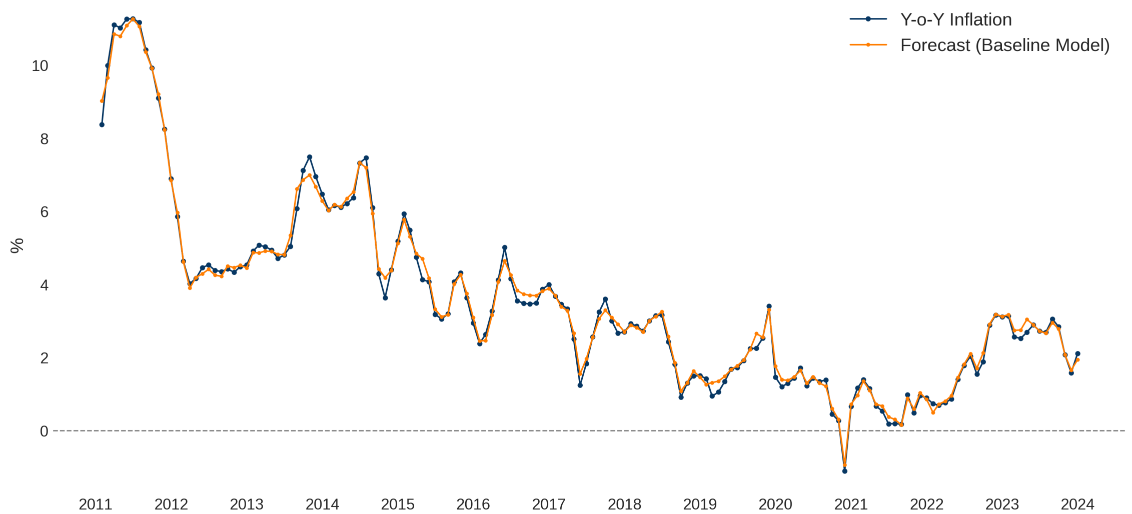
Consistent with established literature on ensemble methods (Breiman, 1996; Dietterich, 2000; Wolpert, 1992), aggregated forecast metrics notably enhance prediction accuracy. The weighted arithmetic and geometric means that incorporate only the three best-performing algorithms (ET, Ridge, and RF) particularly stand out, achieving the lowest MSE and MAE values and the highest R^2 across the validation dataset. Consequently, the weighted arithmetic mean of these top algorithms, denoted $\hat{\pi}_{\text{WAM-BEST}}$, is designated as the baseline model for forecasting monthly-frequency inflation, validating its efficacy in achieving the most reliable inflation predictions.

Figure 1: Forecast Interval and Baseline Forecast Y-o-Y Inflation Rate

(a) Forecast Interval



(b) Baseline Forecast



(a): The upper and lower limits of the forecast interval are determined by the maximum ($\hat{\pi}_{\max}$) and minimum ($\hat{\pi}_{\min}$) values of the forecasts generated by the three best-performing algorithms.
(b): The forecast of the y-o-y inflation rate is the weighted arithmetic mean of the three best-performing algorithms ($\hat{\pi}_{\text{WAM-BEST}}$).

Prior to presenting the results obtained from the baseline model for predicted inflation, it is illustrative to examine a preliminary example of how machine learning algorithms perform. Figure 1-(a) delineates the forecast interval for the entire analysis period. This interval is defined by the minimum and maximum values predicted by the three best-performing algorithms —ET, Ridge and RF. The graphical representation effectively captures the fluctuations in the observed y-o-y inflation rate. Notably, during certain months, the forecast interval significantly narrows and closely aligns with the actual observed values, demonstrating the precision and adaptability of the employed forecasting models.

Figure 1-(b) displays the weighted arithmetic mean of the three best-performing algorithms, denoted as $\hat{\pi}_{\text{WAM-BEST}}$, overlaid with the observed y-o-y inflation rate. Within the Bolivian context, while all selected features in the baseline model are contemporaneously available, official inflation data is typically published with an average one-month delay, rendering $\hat{\pi}_{\text{WAM-BEST}}$ a conditional one-month-ahead forecast.

The alignment of the baseline-model forecast with the observed y-o-y inflation rate is accurate across the entire analysis period. Notably, this period witnessed significant fluctuations in inflation within Bolivia: rates soared to double digits between 2011 and 2015, subsequently plummeting to below 1% —markedly in November 2020 when inflation hit -1.1%. Post mid-2022, inflation rates stabilized around an average of 2.5%. These dynamics are effectively captured by the baseline forecast, underscoring its adaptability and precision.

Quantitatively, the baseline model achieves an MSE of 0.063, an MAE of 0.194, and an R^2 of 0.983, for the validation set. Another dimension of evaluating the predictive strength of the baseline model involves comparing its forecast evaluation indicators with those from parallel studies in the literature that also forecast one-period-ahead inflation. Unfortunately, most inflation forecasting studies provide relative MSEs rather than absolute values, complicating direct comparisons. However, some studies using machine learning techniques furnish MSE or MAE absolute values, enabling a comparison with the baseline model's performance.

For example, Moshiri and Cameron (2000) used Neural Networks (NN) to forecast Canada's inflation rates, achieving MSEs between 0.25 and 0.36, and MAEs between 0.3 and 0.4. Küçükefe (2018) reported a lowest MSE of 0.58 for short-term inflation forecasts in Turkey using machine learning algorithms. Although it was for a 3-month-ahead inflation forecast, Ülke et al. (2018) attained a low MSE of 0.15 with a k-nearest neighbor (KNN) model in the USA. When forecasting India's inflation, Pratap and Sengupta (2019) reported MSEs between 0.17 and 0.55 using various algorithms including NN and RF. Rodríguez-Vargas (2020) used RF, extreme gradient boosting (EGB), and long short-term memory networks (LSTM) to forecast Costa Rica's inflation, arriving at a lowest MSE of 0.10. Araujo and Gaglianone (2023) reported MSEs from 0.07 to 0.085 in Brazil using a mix of machine learning and econometric models. Almosova and Andresen (2023) reached a MSE of 0.107 and a MAE of 0.236 using LSTM models for forecasting US CPI inflation. Finally, Cárdenas-Cárdenas, Cristiano-Botia, and Martínez-Cortés (2023) reported MSEs ranging from 0.02 to 0.06 during the pre-pandemic period (2016-2020) and from 0.11 to 0.13 in the post-pandemic period (2020-2022)

The performance of the baseline model in forecasting Bolivia's inflation is noteworthy, ranking among the top in terms of the lowest MSE and MAE when compared across the above spectrum of studies. Indeed, this model, along with the model described by Cárdenas-Cárdenas et al. (2023), represents the best-performing approaches in the context of inflation forecasting reviewed in this analysis.

Although the baseline model has demonstrated robust predictive capability, a subsequent subsection (3.2) will introduce a final model designed to further optimize the prediction of y-o-y inflation rates for Bolivia. This model adjusts by excluding certain features to achieve even better forecasting performance.

3.2 Feature Importance

Table 2 presents the relative importance assigned by the seven (evaluated) machine learning algorithms to various groups and individual features in forecasting Bolivia's CPI.[5] Importance scores are aggregated through the weighted arithmetic mean (WAM), where weights are defined inversely proportional to the algorithms' MSE.

Table 2: Feature Importance

Group or Feature	Ridge	Lasso	ENET	ADA	GBR	RF	ET	WAM
LAGS	59.2	100.0	35.0	31.6	60.8	52.0	36.8	47.9
CPI (lag 1)	15.9	100.0	7.4	7.0	24.4	12.3	9.2	14.5
CPI (lag 6)	10.3	0.0	6.8	6.5	13.0	8.6	9.8	9.5
CPI (lag 2)	13.0	0.0	7.2	5.4	10.4	14.0	5.5	9.2
CPI (lag 12)	9.5	0.0	6.5	8.4	7.4	7.5	7.6	7.8
CPI (lag 3)	10.5	0.0	7.0	4.3	5.7	9.6	4.7	6.9
WS	25.1	0.0	51.2	59.0	22.3	33.5	53.9	39.2
Flour (10)	0.6	0.0	0.0	2.4	10.0	8.4	6.1	5.1
Corn II (4)	0.0	0.0	0.0	4.1	4.6	6.1	6.8	4.1
Milk (9)	1.7	0.0	1.6	2.1	0.0	0.3	4.6	2.0
Milk (1)	0.0	0.0	0.8	4.5	1.0	1.2	3.9	2.0
Milk (8)	0.0	0.0	1.7	3.8	0.0	0.3	4.5	1.8
FIN	11.2	0.0	9.0	7.1	16.6	13.7	9.1	11.2
UFV	10.5	0.0	6.8	6.1	16.3	12.8	8.7	10.5
LIBOR	0.6	0.0	0.9	0.9	0.3	0.4	0.4	0.5
USD/BOB	0.1	0.0	1.2	0.1	0.0	0.4	0.0	0.2
GT†	3.9	0.0	4.8	2.2	0.2	0.7	0.0	1.5
Precio - Tema	2.2	0.0	2.9	0.0	0.0	0.3	0.0	0.7
dinero	0.9	0.0	0.8	0.0	0.0	0.3	0.0	0.3
la inflación	0.6	0.0	0.8	0.0	0.0	0.0	0.0	0.2
Interés - Tema	0.0	0.0	0.0	1.1	0.2	0.0	0.0	0.1
Dinero - Tema	0.0	0.0	0.3	1.0	0.0	0.0	0.0	0.1
COM	0.6	0.0	0.0	0.1	0.0	0.1	0.1	0.2
Zinc	0.6	0.0	0.0	0.1	0.0	0.1	0.1	0.2

(WP) wholesale prices; (GT) google trends data; (FIN) financial variables; (COM) commodity prices. (1) Bolivia; (4) City of El Alto.; (8) City of Oruro; (9) City of Potosí; (10) City of Tarija. (II) stands for a second type of product.
(†) Google Trends' variables are named as their original Spanish search.
Note: WAM stands for the weighted arithmetic mean of individual-algorithm importance.

The CPI lag values, particularly the most recent month (lag 1), prominently influence most models, with Ridge and GBR assigning high importance. This underscores the predictive significance of recent inflation trends, reflecting the persistence typically observed in economic time series.

[5] While the complete dataset comprises 86 features, Table 2 selectively presents only the most significant individual features to enhance clarity and focus in visualization.

Variability in the importance of wholesale prices (WS) across algorithms highlights their sensitivity to supply-side dynamics. Notably, ADA and Elastic Net prioritize this group, suggesting an acute responsiveness to early inflationary signals manifest in commodity price fluctuations.

Within the financial variables (FIN) group, the Housing Development Unit (UFV) stands out in models like GBR and RF, indicating its efficacy in capturing domestic price evolution —recall UFV is indexed to price evolution.

Conversely, data from google trends (GT) generally receive modest attention, except in Elastic Net and ADA. This implies that while online search trends provide some economic insights, their predictive utility for inflation is indirect and less immediate compared to conventional economic measures.

Among commodities, zinc's price exhibits minimal impact across all models, suggesting that global commodity price fluctuations might exert a limited or delayed influence on Bolivia's inflation, possibly due to government interventions in food markets which stabilize local prices against external shocks.

The diverse importance scores across models underscore the complex interplay of economic variables in inflation dynamics. Notably, LAGS and WS emerge as critical feature groups, affirming that both past inflation data and current market conditions are pivotal for forecasting Bolivia's inflation. This analysis confirms the utility of machine learning in enhancing economic forecasts by integrating and quantitatively assessing diverse data sources.

While the preceding analysis underscores the significance of individual features, Table 3 elucidates the relative MSE, MAE, and R^2 values across various model-feature combinations. This comparative approach uses the baseline model ($\hat{\pi}(1) = \hat{\pi}_{\text{WAM-BEST}}$), which incorporates all 86 features, as a reference. The relative metrics are defined as follows: $\text{Rel-MSE}_{\text{Comparison}} = \frac{\text{MSE}_{\text{Comparison}}}{\text{MSE}_{\text{Baseline}}}$, similarly calculated for MAE and R^2. This standardization facilitates a coherent assessment across different sets of features.

The analysis reveals that removing commodity prices (No COM) markedly improves forecasting accuracy, especially when utilizing the weighted arithmetic mean of the three best-performing algorithms. This combination not only outperforms the baseline with 20% lower MSE, 13% lower MAE, and a 0.4% higher R^2, but it also underscores the importance of feature selection in refining model efficacy. While commodity prices may provide certain economic insights, their exclusion minimizes noise and curtails overfitting, thereby enhancing predictive accuracy for Bolivia's inflation dynamics.

Conversely, no significant enhancement in predictive power is observed when feature sets are restricted to combinations such as lags with wholesale prices (Lags + WS), lags with Google Trends data (Lags + GT), or lags with financial variables (Lags + FIN). This outcome suggests that while these elements individually contribute to the comprehension of inflationary pressures, their solitary impacts do not substantially surpass the baseline model's performance.

Interestingly, the exclusion of Google Trends data (No GT), while retaining other features, results in modest improvements in forecasting capabilities compared to the baseline. This indicates that while Google Trends data can offer some economic insights, it might also introduce redundancy or noise, which, when eliminated, slightly boosts model efficiency.

The exemplary performance of the "No COM" configuration emphasizes the critical role of feature selection in economic forecasting. This finding highlights that not all data should be indiscriminately utilized in modeling efforts. Effective selection can significantly elevate a model's performance by focusing on the most informative predictors and eliminating those that might detract from the model's accuracy and operational efficiency.

Table 3: Relative Forecast Evaluation by Sets of Features

Model-feature	Metric	$\hat{\pi}(1)$	$\hat{\pi}(2)$	$\hat{\pi}(3)$	$\hat{\pi}(4)$	ET	$\hat{\pi}(5)$	Ridge	RF	GBR	ADA	Enet	Lasso
All variables	MSE	1.000	1.000	1.001	1.002	1.214	1.399	1.671	1.953	2.087	3.743	4.487	23.100
	MAE	1.000	1.000	0.997	0.998	1.087	1.199	1.378	1.524	1.465	1.916	2.095	5.018
	R^2	1.000	1.000	1.000	1.000	0.996	0.993	0.988	0.983	0.981	0.952	0.939	0.614
No WS	MSE	1.012	1.009	0.976	0.976	0.967	2.138	2.440	1.422	2.813	3.466	11.327	23.100
	MAE	1.008	1.006	1.002	1.003	0.949	1.447	1.606	1.206	1.714	1.833	3.186	5.018
	R^2	1.000	1.000	1.000	1.000	1.001	0.980	0.975	0.993	0.968	0.957	0.820	0.614
No GT	MSE	0.912	0.912	0.974	0.974	0.871	1.625	1.981	2.258	1.838	3.411	5.008	23.100
	MAE	0.921	0.921	0.942	0.942	0.912	1.314	1.449	1.619	1.381	1.809	2.259	5.018
	R^2	1.002	1.002	1.000	1.000	1.002	0.989	0.983	0.978	0.985	0.958	0.930	0.614
No FIN	MSE	1.017	1.017	1.000	1.000	1.237	1.353	1.653	1.859	2.265	3.490	5.129	23.100
	MAE	0.966	0.966	0.998	0.998	1.061	1.185	1.379	1.449	1.675	1.878	2.289	5.018
	R^2	1.000	1.000	1.000	1.000	0.996	0.994	0.989	0.985	0.978	0.956	0.928	0.614
No COM	MSE	0.799	0.799	0.884	0.890	1.132	1.426	1.733	2.056	1.626	3.321	4.489	23.100
	MAE	0.867	0.867	0.968	0.971	0.974	1.228	1.428	1.542	1.359	1.749	2.098	5.018
	R^2	1.004	1.004	1.002	1.002	0.998	0.993	0.987	0.982	0.989	0.959	0.939	0.614
Lags + WS	MSE	1.228	1.229	1.340	1.344	1.632	1.811	1.994	2.451	2.596	3.706	5.702	23.100
	MAE	1.027	1.029	1.098	1.100	1.146	1.326	1.412	1.627	1.584	1.926	2.494	5.018
	R^2	0.996	0.996	0.994	0.994	0.989	0.986	0.983	0.975	0.972	0.953	0.918	0.614
Lags + GT	MSE	1.140	1.140	1.156	1.157	1.609	2.032	1.627	1.794	2.681	3.527	10.881	23.100
	MAE	1.084	1.084	1.116	1.117	1.285	1.492	1.281	1.325	1.633	1.894	3.132	5.018
	R^2	0.998	0.998	0.997	0.997	0.989	0.982	0.989	0.986	0.971	0.956	0.827	0.614
Lags + FIN	MSE	1.222	1.217	1.132	1.132	1.333	2.215	2.319	1.499	1.960	3.458	10.537	23.100
	MAE	1.108	1.105	1.096	1.096	1.140	1.450	1.587	1.201	1.350	1.820	3.111	5.018
	R^2	0.996	0.996	0.998	0.998	0.994	0.979	0.977	0.991	0.983	0.957	0.833	0.614

Note: $\hat{\pi}(1) = \hat{\pi}_{\text{WAM-BEST}}$; $\hat{\pi}(2) = \hat{\pi}_{\text{WGM-BEST}}$; $\hat{\pi}(3) = \hat{\pi}_{\text{WGM}}$; $\hat{\pi}(4) = \hat{\pi}_{\text{WAM}}$; $\hat{\pi}(5) = \hat{\pi}_{\text{AM}}$. **No WS:** Set without wholesale prices. **No GT:** Set without google trends data. **No FIN:** Set without financial variables. **No COM:** Set without commodity prices. **Lags + WS:** Set with lags and wholesale prices. **Lags + GT:** Set with lags and google trends data. **Lags + FIN:** Set with lags and financial variables. Shaded cells are the best model-feature combination.

Following the feature importance analysis, the final forecast model has been established. It employs the weighted arithmetic mean of the three best-performing algorithms, which have been trained and validated on a feature set that excludes commodity prices. This model configuration is utilized for predicting weekly inflation rates (as detailed in section 4) and further analyzed in subsection 3.3. Detailed performance metrics for this model, including absolute MSE, MAE, and R^2, along with visual representations of the predicted versus actual inflation rates, are available in Appendix D.

3.3 Comparison with Other Forecast Methods

This subsection delves into a comparative analysis of the final forecast model —defined as the weighted arithmetic mean of the three best-performing algorithms, excluding commodity prices from the feature set. This model has demonstrated substantial accuracy in monthly inflation forecasting, positioning it favorably against other machine learning-based studies.

I further assess the robustness of the final model by comparing its predictive performance with traditional econometric approaches and survey-based forecasts specifically tailored for the Bolivian context. The alternatives evaluated include:

- **SARIMA:** A benchmark in inflation forecasting, the Seasonal Autoregressive Integrated Moving Average model, is tailored to capture complex seasonal patterns using historical y-o-y inflation data. Various SARIMA configurations are tested to generate one-month-ahead forecasts, each model trained up to the penultimate month preceding the forecast month for observations in the validation set.[6]

- **Stepwise Least Squares (SLS):** This method employs a systematic approach to refine predictive models by adding or removing variables iteratively, aiming to minimize residuals. Two versions are tested: one employing forward selection and the other using backward elimination, both using the complete dataset from January 2011 to December 2023. The key here is to balance relevance and simplicity, avoiding overfitting while utilizing all 86 features developed in this study. It's important to note that SLS models provide in-sample predictions, thus presenting a higher benchmark for the final forecast model to surpass.

- **Central Bank's Survey:** Studies suggest that judgmental forecasts from economic surveys can sometimes surpass model-driven predictions (Faust & Wright, 2013). I compare the final forecast model against the Economic Expectations Survey's (EES) inflation predictions conducted by the Central Bank of Bolivia, which aligns with international methodologies and targets a broad spectrum of economic analysts.[7]

Table 4 presents both absolute and relative MSE, MAE, and R^2 values, providing a comprehensive view of how the final model measures against each compared method.

Table 4: Forecast Evaluation by Methods

Method	MSE	MAE	R^2	Rel-MSE	Rel-MAE	Rel-R^2
Final Forecast Model†	0.051	0.168	0.986	1.000	1.000	1.000
Stepwise Least Squares (Backward)	0.083	0.215	0.987	1.628	1.276	1.001
Stepwise Least Squares (Forward)	0.085	0.215	0.987	1.668	1.276	1.001
SARIMA	0.102	0.255	0.973	2.002	1.512	0.986
Central Bank's Survey	0.237	0.340	0.867	4.679	2.019	0.879

(†) The weighted arithmetic mean of the three best-performing algorithms, trained and validated on feature set without commodity prices.

The final forecast model significantly outperforms traditional econometric approaches such as SARIMA and Stepwise Least Squares, as well as the judgmental forecasts from the Central Bank's Economic Expectations Survey.

Despite its designed efficacy for handling seasonal patterns, SARIMA exhibits considerably higher MSE and MAE values —100% and 51% higher relative to the final model, respectively. This highlights its lesser predictive accuracy compared to the machine learning-based approach of the final model.

Both backward and forward selection methods of SLS, although they are in-sample predictions, show increased MSE and MAE values —63% to 67% and 28% higher, respectively. This indicates that while SLS is effective for feature selection, it falls short in accuracy when compared to the machine learning techniques employed in the final model.

[6] For instance, to predict October 2011's inflation (first observation in the validation set), data from January 1990 to September 2011 are used.

[7] The survey is designed to capture diverse expert opinions, ensuring representativeness and heterogeneity among respondents.

The survey-based forecasts, while insightful for capturing expert sentiment, demonstrate the highest MSE and the lowest R^2. This underscores the advantage of data-driven analytical models over subjective judgmental methods in forecasting accuracy.

These results confirm the superiority of the machine learning approach in the final forecast model, not only in terms of accuracy but also as a dependable tool for policymakers and economic analysts focusing on the dynamics in Bolivia. By omitting less predictive or noise-inducing features like commodity prices, the final model sharpens its forecasting precision, outstripping more traditional and subjective forecasting methods.

4 Forecasting Weekly Inflation

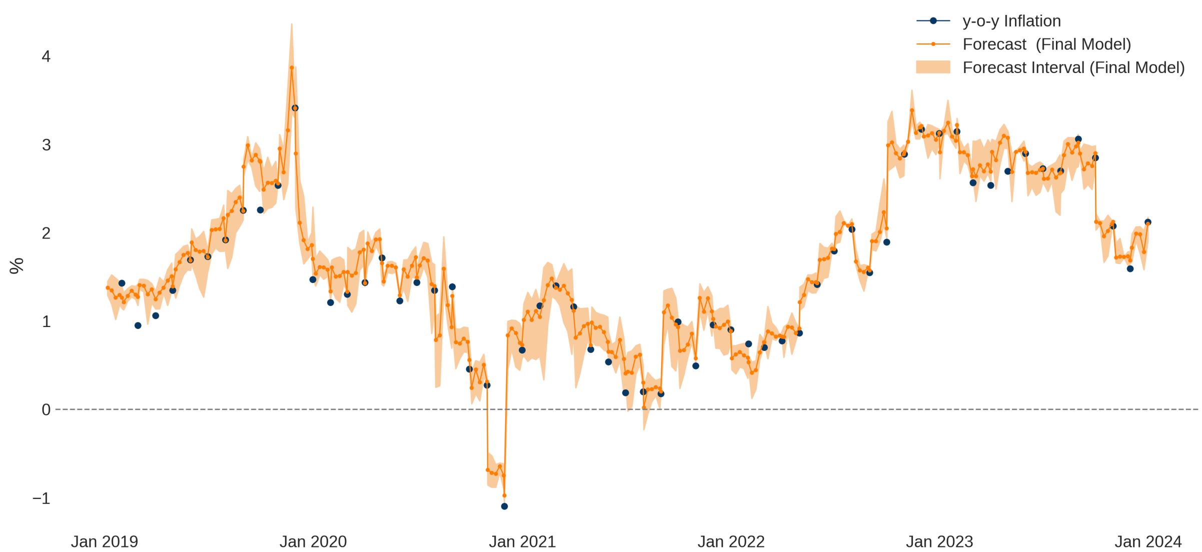
4.1 Weekly Inflation Time-Series

The initial phase of the two-step methodology for forecasting weekly inflation has established the final forecast model as the weighted arithmetic mean of the three best-performing algorithms, trained and validated on a feature set excluding commodity prices. This subsection introduces the application of this model to weekly inflation forecasting.

Unlike the analysis period for monthly forecasts, the weekly forecasting spans from the first week of 2019 to the last week of 2023. This timeframe was selected based on the availability of data and to serve the illustrative purpose of providing weekly inflation estimates for the past five years.

During the selected period, weekly forecasts (see Figure 2) consistently align with the broader trends and cyclical movements observed in monthly inflation reports. However, notable within-month variations are captured, highlighting potential early signals of inflationary shifts, which are critical for responsive economic policymaking.

Figure 2: Observed Y-o-Y Inflation Rate and Weekly Forecast



Note: This figure includes both weekly estimates and predicted end-of-month values. The forecast is the weighted arithmetic mean of the three best-performing algorithms, trained and validated on feature set without commodity prices.

Given the predictive setup of the methodology, this model enables up to one-month-ahead inflation forecasts. Such timely predictions are essential for policymakers and analysts to identify early inflationary tendencies and adapt their economic strategies proactively. For instance, an unexpected weekly rise in inflation could lead policymakers to consider immediate measures to mitigate inflationary pressures before they are confirmed by subsequent monthly data.

The advantages of weekly over monthly inflation forecasts are manifold:

- **Timeliness:** Weekly data provides more immediate insights, crucial for quick responses to economic changes.
- **Detail:** Capturing within-month fluctuations exposes transient economic shocks that monthly averages may obscure.
- **Predictive Accuracy:** A nuanced understanding of inflation dynamics enhances the efficacy of economic decision-making processes.

Overall, the transition to weekly forecasting harnesses the enhanced capabilities of this study's methodology, providing detailed and proactive insights into Bolivia's inflationary trends. This supports more timely and informed policy interventions.

Additionally, recall that the validity of applying algorithms trained on monthly data for weekly inflation forecasts hinges on the assumption that data distributions remain consistent across these time frequencies. To empirically support this premise, the two-sample Smirnov test is employed (Berger & Zhou, 2014). This test compares the distributions between observed and forecasted monthly y-o-y inflation, as well as between weekly predicted inflation and observed monthly inflation. The results suggest that the distributions of both monthly and weekly predicted inflation rates are statistically indistinguishable from the observed monthly y-o-y inflation data, evidenced by p-values of 0.9994 and 0.3967, respectively. These values do not support rejecting the null hypothesis that asserts the distributions are identical, thereby underpinning the methodological soundness of using monthly-trained models to forecast weekly inflation.[8]

Furthermore, the following subsection presents additional analysis supporting the accuracy of weekly predictions in capturing within-month events in Bolivia that significantly impact inflationary changes.

4.2 Weekly Forecast and Special Events

The absence of official weekly inflation data in Bolivia highlights the crucial role of predictive models for analyzing short-term economic fluctuations. Figure 3-(a) illustrates the trajectory of predicted weekly inflation during November 2019, a period marked by considerable political and social unrest.

In this month, predicted inflation is estimated to have escalated sharply from the second week, reaching a peak of 3.9% in the fourth week. The month ended with a y-o-y inflation rate of 3.4%, which represents an increase of 0.9 percentage points from October. This period of political crisis, triggered by mass protests and culminating in the resignation of the President on November 10, likely led to considerable economic uncertainty. Such conditions typically cause rapid price adjustments as markets react to potential risks and disruptions in the supply chain (Gholipour, 2019).

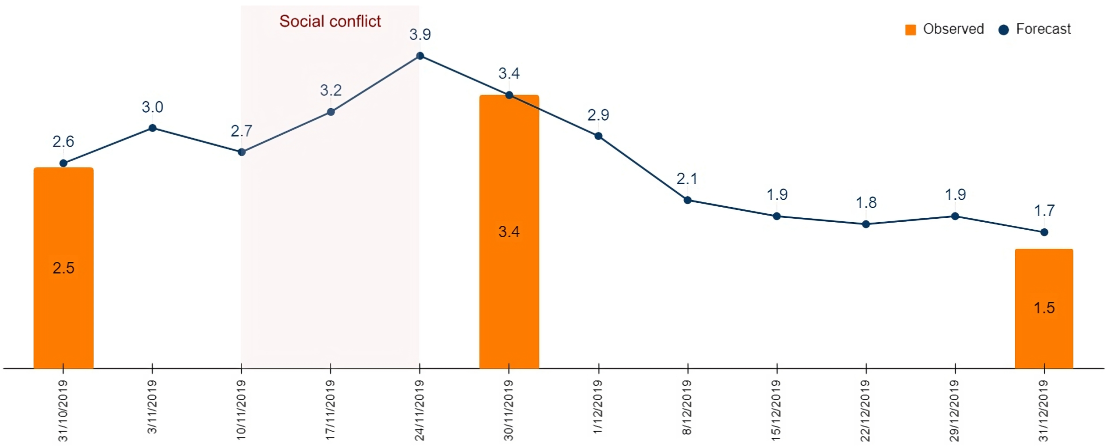
The appointment of an interim President later in the month appeared to restore some political stability, reflected by a gradual decrease in inflation rates. This transition phase

[8]For comparative purposes, the analysis encompasses monthly and weekly time-series data spanning from 2019 to 2023.

is pivotal for economic recovery, often facilitating the restoration of consumer and investor confidence and stabilizing prices. Consequently, the weekly forecasts not only emphasize the inflationary impact of political upheaval but also illustrate the potential for swift economic normalization post-crisis.

Figure 3: Weekly Forecast Y-o-Y Inflation Rate, for Selected Periods

(a) October to December 2019



(b) September to December 2022

Furthermore, beginning in early October 2022, Bolivia contended with severe droughts, primarily impacting the agricultural sector.[9] This environmental challenge was compounded by socio-economic disruptions, particularly due to a prolonged civil strike in the Santa Cruz region, which lasted 36 consecutive days, causing extensive economic shutdowns and supply chain disruptions throughout the country.

As depicted in Figure 3-(b), the final forecasting model effectively captured these dynamics, with predicted weekly inflation rates reflecting the initial impacts of the drought from the beginning of October. The influence of these climatic conditions on prices was noticeable and was further exacerbated by the peak effects of social conflicts, particularly in the second week of November. These events, as predicted, not only heightened inflation in the short term but also suggested prolonged impacts on aggregated prices.

[9] In response to the drought, the Bolivian government launched the "Plurinational Plan for Immediate Response to Drought" in November 2022, to mitigate the impact of La Niña phenomenon. This climatic event significantly affected over 2,000 communities and 100,000 families across Bolivia.

This capability of the model to reflect immediate and sustained economic changes underscores its value for policymakers and analysts, providing them with a nuanced understanding of inflation dynamics under crisis conditions.

5 Concluding Remarks

This study has introduced a two-step machine learning methodology designed for forecasting weekly inflation rates in developing countries, with a detailed application to the Bolivian context. By leveraging machine learning and monthly aggregated data to produce high-frequency weekly forecasts, this approach addresses the pervasive issue of data scarcity common in emerging markets. This methodology not only fills a void in the economic forecasting literature but also augments the capabilities of policymakers by providing more granular and accurate inflation forecasts.

Throughout the research, a robust final forecast model was established by selecting an optimal set of features and employing the weighted means of the three best-performing machine learning algorithms. This model exhibited superior performance compared to those reported in the existing literature, effectively surpassing traditional econometric approaches and survey-based forecasting methods. Its effectiveness was particularly notable during periods characterized by significant economic disruptions, where it precisely traced inflationary trends and their weekly progressions.

Moreover, the study's findings highlight the critical importance of feature selection in enhancing the predictive accuracy of inflation models. By carefully curating relevant features and excluding less informative ones, the final model was able to reduce noise and prevent overfitting, thereby improving its forecasting precision. This refined approach is instrumental for accurately assessing the economic impacts of sudden events, such as political instability and environmental challenges, which can swiftly alter inflation dynamics.

In conclusion, the deployment of this novel forecasting methodology contributes to the academic field and offers practical tools for economic decision-making in Bolivia and potentially other similar settings. Future research could further this approach by expanding it to other nations facing similar economic and data constraints, potentially incorporating real-time data updates and integrating more predictive indicators to enhance the accuracy and utility of the forecasts.

References

Almosova, A., & Andresen, N. (2023). Nonlinear inflation forecasting with recurrent neural networks. *Journal of Forecasting*, *42*(2), 240–259.

Altansukh, G., Becker, R., Bratsiotis, G., & Osborn, D. R. (2017). What is the globalisation of inflation? *Journal of Economic Dynamics and Control*, *74*, 1–27.

Aras, S., & Lisboa, P. J. (2022). Explainable inflation forecasts by machine learning models. *Expert systems with applications*, *207*, 117982.

Araujo, G. S., & Gaglianone, W. P. (2023). Machine learning methods for inflation forecasting in brazil: New contenders versus classical models. *Latin American Journal of Central Banking*, *4*(2), 100087.

Baffigi, A., Golinelli, R., & Parigi, G. (2004). Bridge models to forecast the euro area gdp. *International Journal of forecasting*, *20*(3), 447–460.

Barhoumi, K., Darné, O., Ferrara, L., & Pluyaud, B. (2012). Monthly gdp forecasting using bridge models: Application for the french economy. *Bulletin of Economic Research*, *64*, s53–s70.

Baybuza, I. (2018). Inflation forecasting using machine learning methods. *Russian Journal of Money and Finance*, *77*(4), 42–59.

Berger, V. W., & Zhou, Y. (2014). Kolmogorov–smirnov test: Overview. *Wiley statsref: Statistics reference online*.

Bernanke, B. S., & Woodford, M. (1997). Inflation forecasts and monetary policy. *Journal of Money, Credit and Banking*, *29*(4), 653.

Bolivar, O. (2024). Gdp nowcasting: A machine learning and remote sensing data-based approach for bolivia. *Latin American Journal of Central Banking*, *5*(3), 100126.

Breiman, L. (1996). Bagging predictors. *Machine learning*, *24*, 123–140.

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5–32.

Bulut, L. (2018). Google trends and the forecasting performance of exchange rate models. *Journal of Forecasting*, *37*(3), 303–315.

Cárdenas-Cárdenas, J. A., Cristiano-Botia, D. J., & Martínez-Cortés, N. (2023). Colombian inflation forecast using long short-term memory approach. *Borradores de Economía; No. 1241*.

Clements, M. P., & Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the united states. *Journal of Business & Economic Statistics*, *26*(4), 546–554.

Cushing, M. J., & McGarvey, M. G. (1990). Feedback between wholesale and consumer price inflation: A reexamination of the evidence. *Southern Economic Journal*, 1059–1072.

Das, P. K., & Das, P. K. (2024). Forecasting and analyzing predictors of inflation rate: Using machine learning approach. *Journal of Quantitative Economics*, 1–25.

Dietterich, T. G. (2000). Ensemble methods in machine learning. In *International workshop on multiple classifier systems* (pp. 1–15).

Eugster, P., & Uhl, M. W. (2024). Forecasting inflation using sentiment. *Economics Letters*, 111575.

Faust, J., & Wright, J. H. (2013). Forecasting inflation. In *Handbook of economic forecasting* (Vol. 2, pp. 2–56). Elsevier.

Freund, Y., & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, *55*(1), 119–139.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of statistics*, 1189–1232.

Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. *Machine learning*, *63*, 3–42.

Gholipour, H. F. (2019). The effects of economic policy and political uncertainties on economic activities. *Research in International Business and Finance*, *48*, 210–218.

Ghysels, E., & Marcellino, M. (2018). *Applied economic forecasting using time series methods*. Oxford University Press.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). Midas regressions: Further results and new directions. *Econometric Reviews*, *26*(1), 53–90.

Goulet Coulombe, P., Leroux, M., Stevanovic, D., & Surprenant, S. (2022). How is machine learning useful for macroeconomic forecasting? *Journal of Applied Econometrics*, *37*(5), 920–964.

Hoerl, A. E., & Kennard, R. W. (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, *12*(1), 55–67.

Huybens, E., & Smith, B. D. (1999). Inflation, financial markets and long-run real activity. *Journal of monetary economics*, *43*(2), 283–315.

INE. (2016). *Índice de precios al consumidor: Documento metodológico* (Tech. Rep.). Instituto Nacional de Estadística.

Joseph, A., Potjagailo, G., Chakraborty, C., & Kapetanios, G. (2024). Forecasting uk inflation bottom up. *International Journal of Forecasting*.

Küçükefe, B. (2018). Forecasting inflation using summary statistics of survey expectations: A machine-learning approach. *Ekonomi-tek*, *7*(1), 1–16.

Mahajan, K., & Srinivasan, A. (2020). *Inflation forecasting in emerging markets: A machine learning approach.* Centre for Advanced Financial Research and Learnin.

Masini, R. P., Medeiros, M. C., & Mendes, E. F. (2023). Machine learning advances for time series forecasting. *Journal of economic surveys*, *37*(1), 76–111.

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

Moshiri, S., & Cameron, N. (2000). Neural network versus econometric models in forecasting inflation. *Journal of forecasting*, *19*(3), 201–217.

Pratap, B., & Sengupta, S. (2019). *Macroeconomic forecasting in india: Does machine learning hold the key to better forecasts?* Reserve Bank of India.

Rodríguez-Vargas, A. (2020). Forecasting costa rican inflation with machine learning methods. *Latin American Journal of Central Banking*, *1*(1-4), 100012.

Simionescu, M. (2022). Econometrics of sentiments-sentometrics and machine learning: the improvement of inflation predictions in romania using sentiment analysis. *Technological Forecasting and Social Change*, *182*, 121867.

Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. *Journal of monetary economics*, *44*(2), 293–335.

Teräsvirta, T., Van Dijk, D., & Medeiros, M. C. (2005). Linear models, smooth transition autoregressions, and neural networks for forecasting macroeconomic time series: A re-examination. *International Journal of Forecasting*, *21*(4), 755–774.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288.

Ülke, V., Sahin, A., & Subasi, A. (2018). A comparison of time series and machine learning models for inflation forecasting: empirical evidence from the usa. *Neural*

Computing and Applications, *30*, 1519–1527.
Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of economic perspectives*, *28*(2), 3–28.
Wolpert, D. H. (1992). Stacked generalization. *Neural networks*, *5*(2), 241–259.
Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the royal statistical society: series B (statistical methodology)*, *67*(2), 301–320.

A Correlation: CPI and Selected Features

Feature	Corr.	P-value	Source	Feature	Corr.	P-value	Source
CPI (lag 1)	0.999	0.0000	Lag	Banana (10)	0.655	0.0000	WP
CPI (lag 2)	0.999	0.0000	Lag	Flour (10)	0.654	0.0000	WP
CPI (lag 3)	0.998	0.0000	Lag	Banana (4)	0.654	0.0000	WP
UFV	0.998	0.0000	FIN	Milk II (2)	0.652	0.0000	WP
CPI (lag 6)	0.997	0.0000	Lag	la inflación	0.652	0.0000	GT
CPI (lag 9)	0.996	0.0000	Lag	Sorghum (1)	0.646	0.0000	WP
CPI (lag 12)	0.995	0.0000	Lag	Inflación	0.636	0.0000	GT
Milk (3)	0.916	0.0000	WP	Beef (8)	0.631	0.0000	WP
Milk (2)	0.915	0.0000	WP	Flour (9)	0.631	0.0000	WP
Milk (8)	0.903	0.0000	WP	Sorghum (2)	0.625	0.0000	WP
Milk (1)	0.880	0.0000	WP	USD/BOB	0.625	0.0000	FIN
Paprika (10)	0.878	0.0000	WP	Grapefruit (9)	0.620	0.0000	WP
Milk (5)	0.877	0.0000	WP	Beef (5)	0.619	0.0000	WP
Rice (4)	0.870	0.0000	WP	Bean (10)	0.616	0.0000	WP
Beef (2)	0.855	0.0000	WP	Corn (4)	0.613	0.0000	WP
Beef (3)	0.851	0.0000	WP	Rice II (12)	0.613	0.0000	WP
Milk (9)	0.850	0.0000	WP	Zinc	0.605	0.0000	COM
Milk (7)	0.850	0.0000	WP	Inflación - Tema	0.605	0.0000	GT
Squash (10)	0.836	0.0000	WP	Apple (8)	0.599	0.0000	WP
Milk (6)	0.818	0.0000	WP	Flour II (4)	0.594	0.0000	WP
Banana (12)	0.810	0.0000	WP	Banana (10)	0.586	0.0000	WP
Banana (4)	0.803	0.0000	WP	Beef (6)	0.585	0.0000	WP
Pineapple (4)	0.800	0.0000	WP	Milk II (3)	0.585	0.0000	WP
Precio - Tema	0.799	0.0000	GT	Greenbean (10)	0.582	0.0000	WP
Beef (1)	0.798	0.0000	WP	LIBOR	0.580	0.0000	FIN
Corn (12)	0.791	0.0000	WP	Banana (5)	0.577	0.0000	WP
Milk (8)	0.788	0.0000	WP	Peas (10)	0.574	0.0000	WP
Interés - Tema	0.785	0.0000	GT	Apple (1)	0.565	0.0000	WP
Milk II (9)	0.778	0.0000	WP	Grapefruit (6)	0.562	0.0000	WP
Corn II (4)	0.775	0.0000	WP	Pineapple (8)	0.555	0.0000	WP
Papaya (10)	0.772	0.0000	WP	que es inflación	0.552	0.0000	GT
Milk (4)	0.755	0.0000	WP	Wheat (1)	0.545	0.0000	WP
Wheat (5)	0.750	0.0000	WP	Redpepper (9)	0.544	0.0000	WP
Apple (5)	0.736	0.0000	WP	Peas (4)	0.541	0.0000	WP
dinero	0.734	0.0000	GT	Potato (4)	0.532	0.0000	WP
Dinero - Tema	0.731	0.0000	GT	Banana (7)	0.526	0.0000	WP
Beef (7)	0.716	0.0000	WP	Lemon (6)	0.523	0.0000	WP
Sorghum (3)	0.693	0.0000	WP	Rice II (8)	0.514	0.0000	WP
Onion II (9)	0.688	0.0000	WP	Banana (3)	0.510	0.0000	WP
Rice (4)	0.677	0.0000	WP	Quinoa (4)	0.509	0.0000	WP
Banana (1)	0.676	0.0000	WP	Salario - Tema	0.504	0.0000	GT
Redpepper (10)	0.671	0.0000	WP	Oil (12)	0.503	0.0000	WP
Política - Tema	0.656	0.0000	GT	Beef (10)	0.501	0.0000	WP

(WP) wholesale price; (GT) google trends; (FIN) financial; (COM) commodity price. (1) Bolivia; (2) Department of La Paz; (3) City of La Paz; (4) City of El Alto.; (5) City of Santa Cruz; (6) City of Cochabamba; (7) City of Sucre; (8) City of Oruro; (9) City of Potosí; (10) City of Tarija; (11) City of Trinidad; (12) City of Cobija. (II) second type of product.

B Potential predictors of inflation

Group	Variables	Source
Wholesale prices	**Products:** apple, banana, bean, beef, carrot, cassava, chicken, chili, corn, flour, grapefruit, greenbean, lard, lemon, milk, noodle, oil, onion, orange, potato, papaya, paprika, peas, pineapple, quinoa, redpepper, rice, sorghum, soy, squash, sugar, tomato, watermelon, and wheat. They are collected by cities: La Paz, El Alto, Santa Cruz, Cochabamba, Sucre, Oruro, Potosí, Tarija, Trinidad, Cobija; and aggregated at a national level.	Agro-Environmental and Productive Observatory
Google Trends†	**Bolivia's searches related to inflation and prices:** Bien económico - Tema; Contabilidad - Campo de estudio; Coste - Tema; Cuenta - Tema; Deflación - Tema; Deflactor - Tema; Demanda - Economía; Desempleo - Tema; Dinero - Tema; Economía - Campo de estudio; Economía - Ciencia económica; Gasto - Tema; Hiperinflación - Tema; Inflación; Inflación - Tema; Instituto Nacional de Estadística - Agencia de gobierno; Interés - Tema; Macroeconomía - Campo de estudio; Mercado - Tema; Política - Tema; Política monetaria - Tema; Precio - Tema; Producto interno bruto - Tema; Producto interno bruto real - Tema; Salario - Tema; Tasa - Matemáticas; ajuste por inflación y tenencia de bienes; canasta familiar; causas de la inflación; como se calcula el ipc; cpi; deflactor; deflactor del pib; demanda; desempleo; dinero; economia; el ipc; indice de precios del consumidor; indice precios al consumidor; ine; ine bolivia; ine ipc; inflacion; inflacion en bolivia; inflación argentina; inflación bolivia; inflación económica; inflación en bolivia; inflación monetaria; ipc; ipc bolivia; ipc que es; la inflacion; la inflación; pib; pib bolivia; precios al consumidor; que es el ipc; que es inflacion; que es inflación; que es la inflacion; que es la inflación; que es pib; que es una inflación; qué es inflación; qué es la inflación; tasa de inflación; tasa de inflación - Tema; tipo de inflación; Índice de precios al consumidor - Tema; índice de precios - Tema.	Google Trends
Financial	Housing Development Unit. USD/BOB exchange rate. London Interbank Offered Rate (LIBOR).	Central Bank of Bolivia Google Finance Bloomberg
Commodity prices	WTI oil, natural gas, gold, silver, zinc, tin, soybean, soybean meal, soybean oil, lead, and copper.	Bloomberg, FRED, Trading Economics

(†) Google Trends' variables are named as their original Spanish search.

C Fine-Tuned Hyperparameters

The statistics below are calculated for the validation set.

Table C.1: Forecast Evaluation Indicators and Fine-Tuned Hyperparameters

Algorithm	Without tuning			After tuning (5-fold cross-validation)			
	MSE	MAE	R^2	MSE	MAE	R^2	hyperparameters
Ridge	0.0014	0.0308	0.9984	0.0008	0.0246	0.9990	$\lambda = 0.11327$ $positive$ =True $intercept$ =False
Lasso	0.9523	0.8455	0.0030	0.0099	0.0850	0.9895	$\lambda = 0.1$ $positive$ =True $intercept$ =False
ENET	0.2878	0.4602	0.6968	0.0022	0.0361	0.9977	$\lambda = 0.11327$ $\alpha = 0.1$ $positive$ =True $intercept$ =False
ADA	0.0037	0.0469	0.9961	0.0015	0.0308	0.9983	$d = 5$ $\alpha = 1.23548$ $T = 115$
GBR	0.0014	0.0291	0.9984	0.0009	0.0242	0.9990	$\gamma = 7$ $T = 135$
RF	0.0012	0.0277	0.9987	0.0009	0.0257	0.9990	$mss = 2$ $T = 265$
ET	0.0005	0.0177	0.9994	0.0005	0.0177	0.9994	default values

Note 1: The target variable is the z-score normalized CPI.
Note 2: The scikit-learn library was employed. Certain hyperparameters are not included in the table above, because, during the fine-tuning process, it was determined that the default values in the scikit-learn functions were the most suitable, hence, these default values have been omitted from the table.

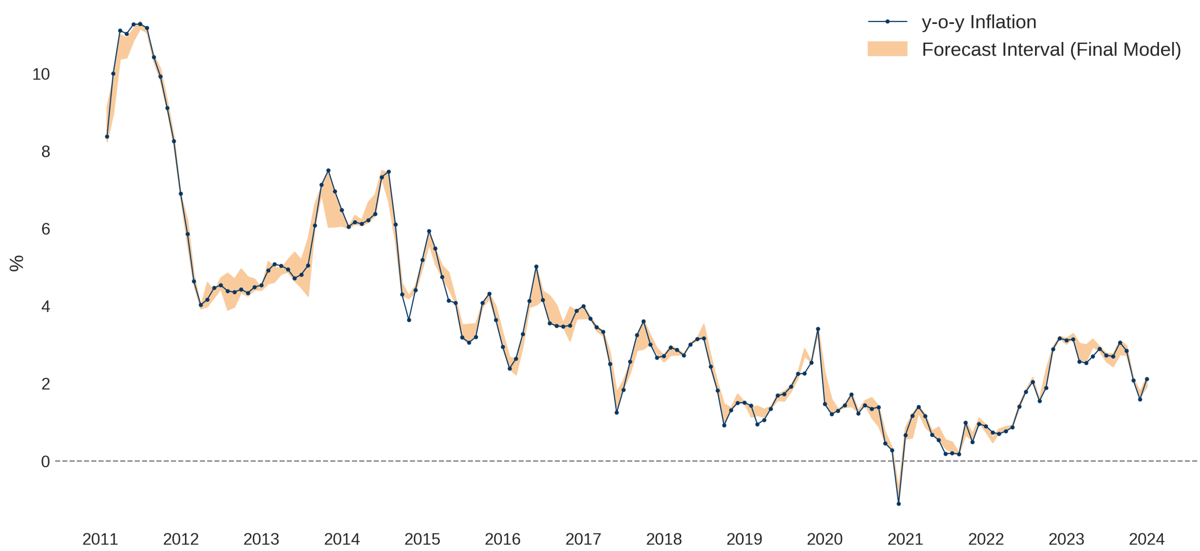
D Monthly Inflation Forecast for Feature Set without Commodity Prices

Table D.1: Forecast Evaluation by Aggregated Forecast Metrics and Algorithms

Forecast	Full Sample			Train Set			Validation Set		
	MSE	MAE	R^2	MSE	MAE	R^2	MSE	MAE	R^2
$\hat{\pi}_{\text{WAM-BEST}}{}^{\dagger}$	0.019	0.097	0.997	0.011	0.079	0.998	0.051	0.168	0.986
$\hat{\pi}_{\text{WGM-BEST}}{}^{\dagger}$	0.019	0.097	0.997	0.011	0.079	0.998	0.051	0.168	0.986
$\hat{\pi}_{\text{WGM}}$	0.024	0.114	0.996	0.015	0.095	0.998	0.056	0.188	0.985
$\hat{\pi}_{\text{WAM}}$	0.024	0.114	0.996	0.016	0.095	0.998	0.056	0.189	0.985
ET	0.017	0.071	0.997	0.003	0.041	1.000	0.072	0.189	0.981
$\hat{\pi}_{\text{AM}}$	0.070	0.208	0.989	0.065	0.200	0.991	0.091	0.239	0.976
GBR	0.023	0.087	0.996	0.003	0.042	1.000	0.103	0.264	0.972
Ridge	0.132	0.278	0.980	0.137	0.278	0.981	0.110	0.278	0.970
RF	0.075	0.179	0.988	0.061	0.148	0.991	0.131	0.300	0.965
ADA	0.058	0.150	0.991	0.019	0.101	0.997	0.211	0.340	0.943
ENET	0.310	0.421	0.952	0.316	0.424	0.955	0.285	0.408	0.923
Lasso	1.612	1.003	0.751	1.650	1.010	0.767	1.466	0.975	0.603

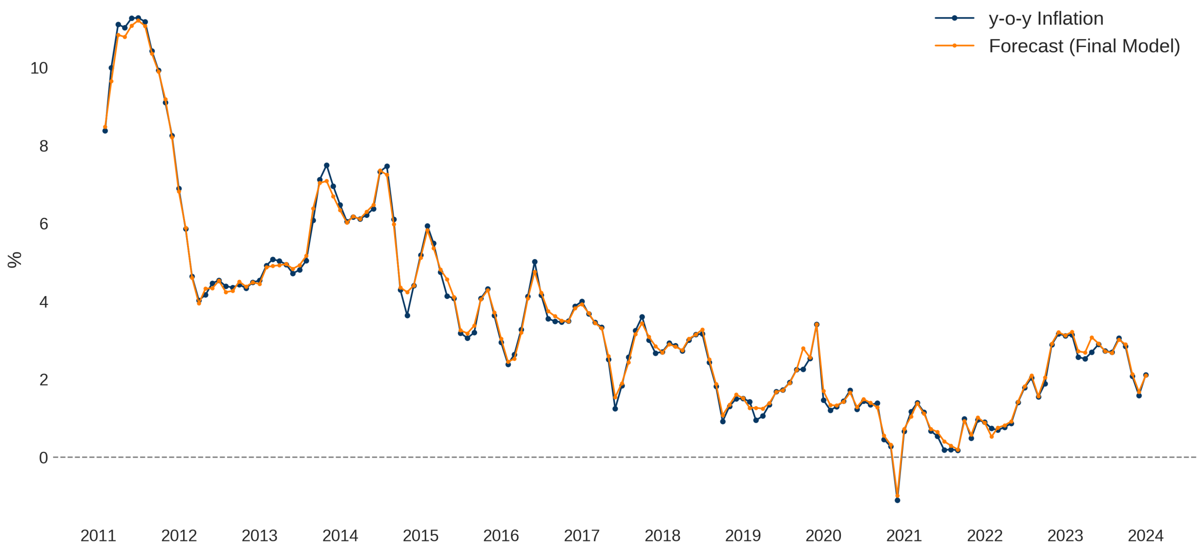
Note: The forecast evaluation is computed with observed and predicted values in y-o-y inflation rates. WAM and WGM stand for Weighted Arithmetic Mean and Weighted Geometric Mean, respectively.
(†) The three best-performing algorithms are Extra Trees Regressor, Gradient Boosting Regressor, and Ridge.

Figure D.1: Observed Y-o-Y Inflation Rate and Forecast Interval



Note: The upper and lower limits of the forecast interval are determined by the maximum ($\hat{\pi}_{\text{max}}$) and minimum ($\hat{\pi}_{\text{min}}$) values of the forecasts generated by the three best-performing algorithms.

Figure D.2: Observed Y-o-Y Inflation Rate and Forecast



Note: The forecast of the y-o-y inflation rate is the weighted arithmetic mean of the three best-performing algorithms ($\hat{\pi}_{\text{WAM-BEST}}$).