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Forecasting Inflation in Times of Stability and Crisis: A Machine Learning Approach

Pronóstico de la inflación en tiempos de estabilidad y crisis: un enfoque con Machine Learning

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Abstract**

The Bolivian economy is undergoing its most severe crisis since the 1980s, marked by a dramatic transition from low and stable inflation to pronounced inflationary pressures. In this context, the development of reliable forecasting tools has become increasingly critical. This study evaluates the predictive performance of several widely used Machine Learning (ML) models under two distinct macroeconomic conditions: periods of relative stability and periods of crisis. The findings reveal that ML models in general outperform traditional econometric approaches across both conditions, with the XGBoost algorithm demonstrating the best performance. Additionally, it was found that incorporating a broader set of macroeconomic indicators enhances forecast accuracy. These results suggest that ML techniques can serve as valuable complements to econometric models in macroeconomic forecasting, particularly in complex environments such as Bolivia's.

Keywords: Machine Learning; inflation; forecasting; crisis.

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** The conclusions, opinions, and viewpoints expressed in this document are the sole responsibility of the author.

Resumen

La economía boliviana atraviesa su crisis más grave desde la década de 1980, marcada por una drástica transición de una inflación baja y estable a presiones inflacionarias pronunciadas. En este contexto, el desarrollo de herramientas de pronóstico fiables se ha vuelto cada vez más crucial. Este estudio evalúa el rendimiento predictivo de varios modelos de Machine Learning (ML) ampliamente utilizados en dos condiciones macroeconómicas distintas: periodos de relativa estabilidad y periodos de crisis. Los resultados revelan que, en general, los modelos de ML superan a los enfoques econométricos tradicionales en ambas condiciones, siendo el algoritmo XGBoost el que demuestra un rendimiento más destacable. Además, se observó que la incorporación de un conjunto más amplio de indicadores macroeconómicos mejora la precisión del pronóstico. Estos resultados sugieren que las técnicas de ML pueden servir como complementos valiosos para los modelos econométricos en el pronóstico macroeconómico, especialmente en entornos complejos como el de Bolivia.

Palabras clave: Machine Learning; inflación; proyecciones; crisis.

Classification/Clasificación JEL: C14, C22, C32, C53, C55, E31, E37.

1. Introduction

Inflation is a critical macroeconomic indicator, not only shows the evolution of prices across goods and services but also serving as a proxy for overall economic health. Reliable forecasts of inflation are therefore essential for policymakers, investors, and the general public. However, producing accurate projections has become increasingly challenging since the impact of the COVID-19 pandemic, as structural changes have triggered inflationary pressures not seen in decades (Liu *et al*., 2024).

However, this situation has not been an impediment for forecasters, as they have been evaluating and incorporating an alternative line of models into their tool base, particularly those rooted in Machine Learning (ML). Unlike conventional econometric models, which often seek to uncover underlying structural relationships, ML models prioritize predictive accuracy and offer notable advantages, including the ability to handle large datasets and capture nonlinear interactions.

Technological advancements have further facilitated the adoption of ML techniques across many disciplines, including economics. The predictive capabilities of these models have been evaluated in different countries with satisfactory results in most cases, even during the volatile pandemic period (*e.g.*, Medeiros *et al.*, 2021; Aras and Lisboa, 2022; Kohlscheen, 2022; Botha *et al.*, 2022; Lenza *et al.*, 2023; Das and Das, 2024; and Liu *et al.*, 2024). While most applications have been carried out in data-rich advanced economies, there is growing interest in extending this methodology to emerging markets, although with mixed empirical outcomes (Garcia *et al.*, 2017; Zahara and Ilmiddaviq, 2020; Rodríguez-Vargas, 2020; Özgür and Akkoç, 2021; Botha *et al.*, 2022; and Ivașcu, 2023).

In the case of Bolivia, the urgency to develop robust forecasting models has grown in light of the current balance of payments crisis, which has triggered inflationary, reaching levels not observed since the early 1990s. This atypical behavior has been driven by various factors, including the emergence of a parallel exchange rate in a context of high monetary liquidity. Traditional econometric models often struggle to process such changes, given the prevalence of structural breaks and unstable dynamics.

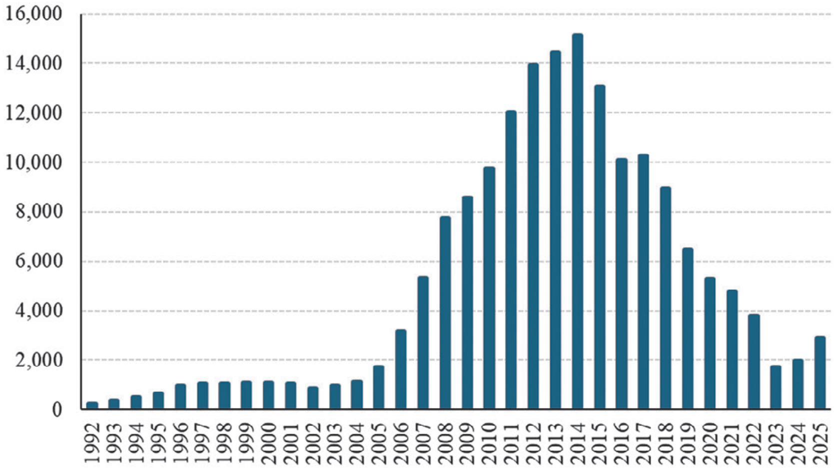
This study seeks to evaluate the predictive performance of several widely used ML models (KNN, Random Forests, XGBoost, and SVR), in comparison with two benchmark econometric models: ARMA (univariate) and VAR (multivariate). The goal is not to identify the definitive forecasting methodology for Bolivia, but rather to take initial steps toward assessing the viability of ML-based approaches within the constraints of a small open economy marked by limited data and high economic instability. The core contribution of this paper lies in evaluating projections under two contrasting macroeconomic conditions: periods of relative stability and episodes of crisis.

The remainder of this paper is organized as follows: Section II provides an overview of Bolivia's current economic context. Subsequently, some of the most important differences between ML models and traditional econometric models are presented, as well as some examples of documents that used these methodologies in inflation projections. Later, the variables used in the study and the selected models are then described. Finally, the main results obtained, and the main conclusions drawn from them are presented.

2. Economic situation in Bolivia

During the 1990s and early 2000s, Bolivia consistently recorded trade deficits, resulting in a low-level of Foreign Reserves. This trend reversed in 2004 when a boom in international commodity prices boosted revenues from gas and mineral exports, giving way to a period of trade surpluses. Public export enterprises, most notably Yacimientos Petrolíferos Fiscales Bolivianos (YPFB), sold their foreign currency earnings to the Central Bank of Bolivia (Banco Central de Bolivia, BCB), leading to an extraordinary accumulation of Foreign Reserves (Figure 1).

Figure 1: Foreign Reserves (in millions of US$ dollars)

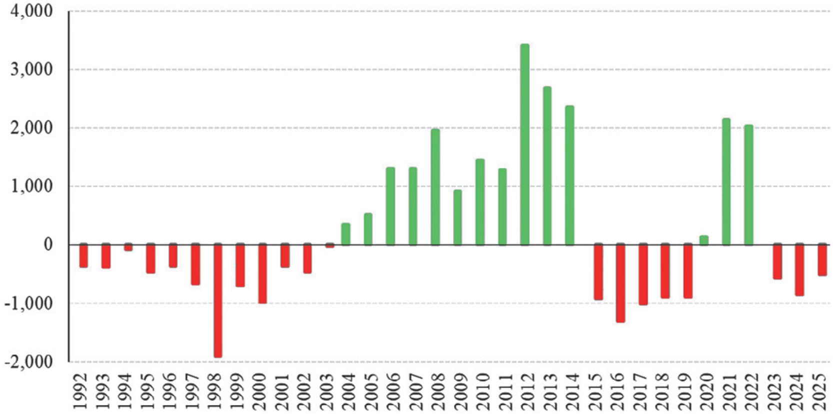


Source: Central Bank of Bolivia.
Note: 2025 data are current up to August.

This era of prosperity ended in 2015, as Bolivia once again entered a cycle of trade deficits (Figure 2). The value and volume of gas and mineral, the main exports, declined due to falling international prices and lower production (lower foreign investment), respectively. While imports continued to rise, both formal and informal[1].

1 Although a trade surplus was recorded between 2020 and 2022, it should be noted that this information does not consider the effects of smuggling.

Figure 2: Balance of trade (in millions of US$ dollars)



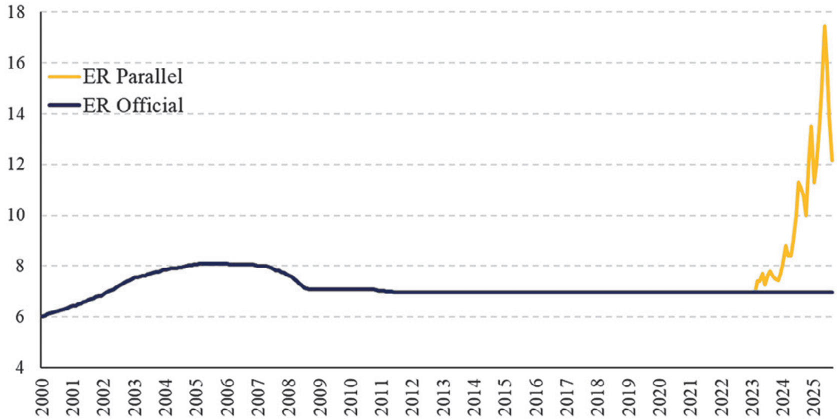
Source: National Institute of Statistics of Bolivia.
Note: 2025 data are current up to July.

In parallel, government policies such as gasoline subsidies have placed significant pressure on public spending. Specially considering that car ownership increased from 443,888 vehicles in 2003 to 2,583,319 in 2024, a surge of 482%, subsidy-related expenditures ballooned. Additionally, the demand for US$ dollars by the population has grown constantly since 2011, particularly during election periods marked by heightened uncertainty. These factors have contributed to a rapid depletion of Foreign Reserves and signal that the Bolivian economy is heading for a severe Balance of Payments Crisis.

One immediate consequence has been intensifying pressure in the exchange rate market due to a shortage of US dollars. Since the mid-1980s, Bolivia had maintained a crawling-peg exchange rate regime, characterized by minor and pre-announced depreciations. Nevertheless, thanks to the accumulation of foreign currency liquidity, the exchange rate appreciated and later stabilized from 2011 onward. This policy decision contributed to anchoring the population's expectations and mitigating the impact of different external shocks.

However, in early 2023, a parallel exchange rate emerged for the first time since 1985. Despite the official exchange rate remaining fixed at Bs. 6.96 since 2011, limited access to foreign currency, banking restrictions, and increasing economic and political uncertainty fueled the growth of the parallel market. According to local news sources, the parallel exchange rate was reported to be up to 2 times higher than the official rate in the last months (Figure 3).

Figure 3: Bolivian Exchange Rate (Bolivians per 1 US$ dollar)

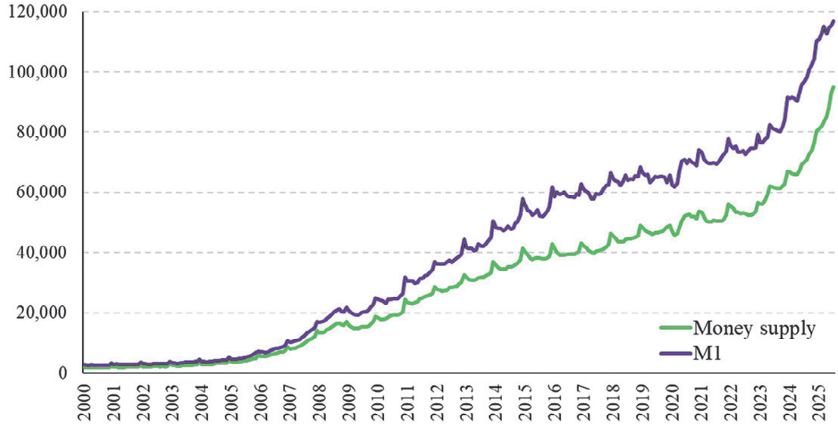


Source: Official Exchange Rate form the Central Bank of Bolivia. The Parallel Exchange rate was built using information reported in different local newspapers since March 2023.

Note: 2025 data are current up to August.

It is important to highlight that the emergence of the parallel exchange rate has taken place within a context of elevated monetary liquidity in the Bolivian economy. Over the past decade, Money supply and Monetary aggregates have exhibited sustained growth. This behavior is largely attributable to the expansionary monetary policy implemented by the Central Bank of Bolivia since late 2014, in response to the end of the favorable external environment and the beginning of economic deceleration. This measure was further intensified since 2020 due to the COVID-19 pandemic and the current economic crisis. Furthermore, fiscal policy has been financed in part through ongoing central bank loans to the government. For example, in 2024 Money supply and the M1 aggregate expanded 20% (Figure 4).

Figure 4: Money supply and Monetary aggregate M1 (in millions of local currency)



Source: Central Bank of Bolivia.

Note: 2025 data are current up to July.

The rise of the parallel exchange rate significantly increased the cost of imported goods and inputs. This triggered broad-based price adjustments in domestic markets, for food (meat and fats and oils), goods (home appliances and personal care items) and essential services (public transportation), generating significant inflationary pressure. After a long period of declining inflation from 2011 onward, inflation accelerated dramatically in mid-2024, reaching levels unseen in over three decades. As of 2025, Bolivia is experiencing inflationary pressures reminiscent of the early 1990s post-hyperinflation period (Figure 5).

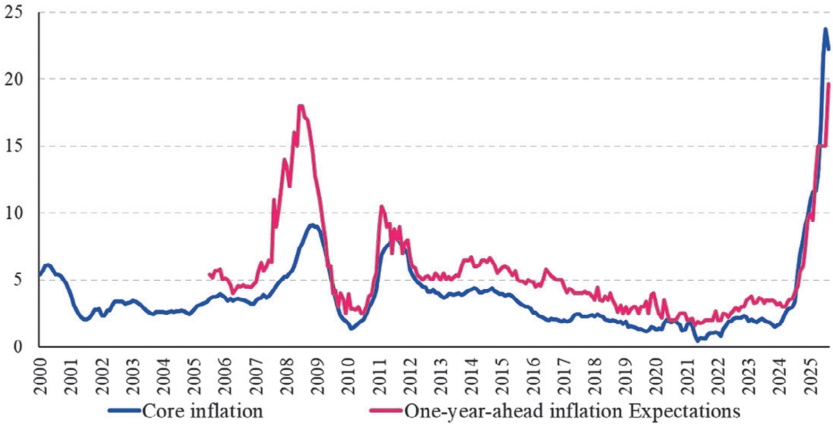
Core inflation and one-year-ahead inflation expectations have also spiked, reflecting the persistent nature of this inflationary trend (Figure 6). Core inflation, a more precise indicator of general and continuous price increases, has reached levels not seen since 1991. Meanwhile, expectations that are one of the main drivers of inflation, and vice versa, are now at levels higher than those observed in 2008. Expectations have risen alongside headline inflation, suggesting the presence of adaptive behavior. This could hinder authorities' ability to control and stabilize inflation.

Figure 5: Bolivian Headline Inflation (year-to-year, in percentage)

Source: National Institute of Statistics of Bolivia.

Note: 2025 data are current up to Aug.

Figure 6: Core Inflation and Expectations (year-to-year, in percentage)

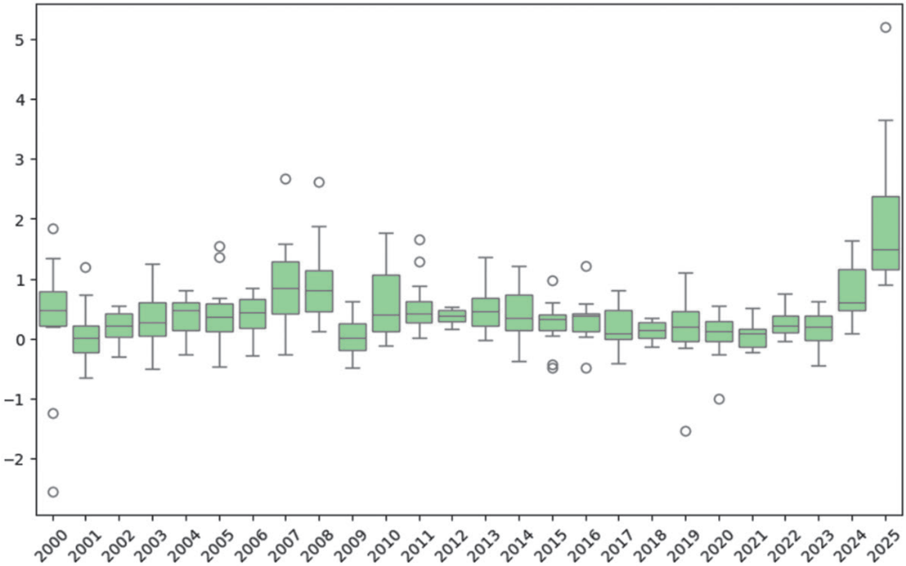


Source: Expectations one year ahead from Central Bank of Bolivia and Core Inflation from Economic Commission for Latin America and the Caribbean (Comisión Económica para América Latina y el Caribe, CEPAL).

Note: 2025 data are current up to Aug.

Therefore, inflation dynamics have shifted markedly since 2024. Inflation throughout the 21st century has been quite moderate; between 2000 and 2023, average monthly inflation remained at 0.33%. Even during the 2007-2008 peak, it only averaged 0.94%. In contrast, between 2024 and Aug 2025, monthly inflation averaged 1.32%, with June 2025 alone recording 5.21%, a scenario not seen since early 1991. Inflation is not only showing higher rates but has become increasingly volatile (Figure 7).

Figure 7: Monthly Inflation Boxplot Grouped by Year (in percentage)



Source: National Institute of Statistics of Bolivia.
Note: 2025 data are current up to Aug.

These developments pose new challenges for policymakers and forecasters. Traditional econometric models rely on historical data from a low-inflation environment. Moreover, long-standing policies, such as an extended fixed exchange rate regime and widespread subsidies, have weakened the historical linkage between inflation and broader economic variables. However, this situation has changed, and Bolivia must face a new economic reality.

3. Econometrics and machine learning

Although econometric approaches have been extensively studied and documented for their ability to forecast inflation and other macroeconomic variables, the same level of coverage for Machine Learning methodologies does not yet exist. This section offers a concise comparison between traditional econometric models and machine learning techniques, considering their respective strengths and limitations. It should be noted that this is not intended to provide an exhaustive formal review of these methods; for an in-depth treatment, readers are encouraged to consult the relevant literature cited throughout this work.

Machine Learning (ML), a concept that has attracted significant attention in recent years, is defined in various ways. However, it is widely regarded as a pioneering branch of artificial intelligence (Masini *et al.,* 2023). One of the earliest definitions was proposed by Samuel (1959), who described ML as a field dedicated to enabling computers to learn from experience, thereby reducing the need for explicit programming. More recently, Rodríguez-Vargas (2020) defined ML as the design and implementation of algorithms that enable systems to enhance their performance on a specific task by learning from new data. According to Hall (2018), ML can also be seen as the art of pattern recognition through a data-driven approach, that usually involves two key elements: a learning method, which uses data to identify optimal patterns among input features, and an algorithm that captures and models the relationship between inputs and outputs.

Some of the key differences between traditional econometric models and machine learning techniques are summarized in the following table. For a more detailed discussion, see the works of Breiman (2001a), Athey and Imbens (2019), Rodríguez-Vargas (2020), Silva and Piazza (2022), and Liu *et al.* (2024).

Traditional Econometrics	Machine Learning
▪ Focuses on identifying the true model that generates the data. ▪ Primarily concerned with fitting data to a pre-specified relationship between input and output variables, often grounded in economic theory. Assumes an underlying stochastic process. ▪ Emphasizes interpretability and causal inference-understanding the effect of one variable on another. ▪ Relies on strong assumptions (linearity, homoscedasticity, and others) that simplify interpretation and testing. ▪ Probability density function is crucial for understanding the distribution of random variables. It describes the likelihood of a continuous random variable taking on specific values.	▪ Emphasizes prediction accuracy and method optimization. ▪ The primary aim is to develop algorithms that predict variable values based on information from other variables. ▪ Prioritizes correlation and predictive power over causal interpretation. ▪ Less reliant on assumptions, flexible in capturing nonlinear, complex patterns without specifying a model structure in advance. ▪ A loss function evaluates how well the predicted values match true outcomes, and model parameters are optimized accordingly.

Traditional Econometrics	Machine Learning
▪ Model validation is often taken for granted, supported mainly by theoretical assumptions. Model selection typically revolves around hypothesis testing under the premise of a true underlying model. Emphasis is placed on desirable estimator properties such as unbiasedness, consistency, and efficiency. ▪ The number of explanatory variables is generally limited based on theoretical relevance. ▪ Evaluates performance using statistical inference tools like p-values, t-tests, and confidence intervals. ▪ Common concepts: Estimation, Regressors or explanatory variables, Coefficients, Data point.	▪ Applies out-of-sample cross-validation to improve generalizability and guard against overfitting ▪ Feature selection follows a data-driven approach, allowing ML models to handle high-dimensional datasets when necessary. ▪ Uses performance metrics such as root mean square error (RMSE), accuracy, precision, recall, and F1 score to evaluate model quality. ▪ Common concepts: training, features, weights, example or instance.

Several authors have highlighted the distinct advantages that ML models offer over traditional econometric approaches. According to Bolhuis and Rayner (2020) and Liu *et al.* (2024), some of these advantages include:

1. Traditional econometric models are constrained by their theoretically definition, the model can only be as good as its specification, regardless of what the data may reveal. In contrast, ML models optimize forecasting performance by automatically identifying functional relationships that best fit the input and output data.
2. ML models can handle a large number of input variables, aided by techniques such as regularization and access to extensive training datasets. This enables the modeling of complex, non-linear relationships that traditional models may struggle to capture.
3. Unlike structural or semi-structural economic models, ML models can be rapidly retrained with updated data, allowing them to adapt more effectively to evolving patterns and structural changes in the data-generating process.
4. ML techniques are specifically designed to learn from historical data without assuming long-term stability in the underlying relationships, minimizing the risk of over-extrapolating from outdated historical patterns.
5. ML encompasses both supervised learning (models are trained on labeled data to predict outcomes) and unsupervised learning (detects latent patterns or clusters in data without predefined labels). This broad toolkit enables ML to tackle a wide array of tasks beyond the reach of conventional econometric techniques.

Despite these strengths, a key criticism of ML approaches is their limited interpretability. Many ML models function as "black boxes", emphasizing predictive accuracy at the expense of explanatory clarity. In that sense, ML models often fall short in revealing the drivers behind their forecasts, an area where traditional econometrics still holds an advantage. Nevertheless, as Varian (2014) argues, the increasing availability of large-scale datasets and the growing complexity of economic relationships justify a broader adoption of ML methods within economics. Although this is true for some cases, in many countries, especially in developing economies, one of the main problems is the lack of availability of a large data set necessary to properly train the models (Ivașcu, 2023).

4. Forecasting inflation

Inflation is one of the most critical economic phenomena and has been extensively studied over time. Its importance is particularly marked for central banks, whose primary mandate in many countries is to maintain price stability. However, it is not sufficient merely to understand inflation behavior, policymakers must also anticipate its future trajectory, given that the effects of monetary policy tend to operate with a significant lag. As a result, a wide array of methodologies has been developed to forecast inflation, ranging from simple rules to sophisticated models[2]. Nonetheless, as emphasized by Greene (2003) and Ivașcu (2023), greater model complexity does not necessarily equate to more accurate forecasts.

Forecasting inflation using traditional econometric techniques presents considerable challenges, particularly in current economic environment. First, the assumption of linearity implies that inflation responds to its determinants in a fixed proportional manner, a premise that is increasingly at odds with theoretical insights and empirical findings, which support the non-linear nature of inflation dynamics (Costain *et al.*, 2022; and Lenza *et al.*, 2023). Second, inflation is influenced by a many potential determinants, making it difficult to model all their interactions comprehensively (Koester *et al.*, 2021). Third, it is essential to identify and include only the most relevant variables, as including irrelevant data can degrade model performance (Silva and Piazza, 2022). Fourth, traditional models often rely on low-frequency data (annual, quarterly, or monthly basis) which limits data availability (Silva and Piazza, 2022). Finally, the

2 Following Faust and Wright (2013) and Ivașcu (2023), there must be over 20 distinct approaches that have been employed in this pursuit.

COVID-19 pandemic brought about structural changes in price dynamics that conventional models were not able to capture (Liu *et al.*, 2024).

In this context, it is not surprising that ML methods have become increasingly popular as a forecasting tool due to its ability to handle large databases, exploit non-linear relationships, and prioritize out-of-sample predictive performance. Moreover, the disruption caused by the pandemic and its consequences has further motivated the adoption of ML methods, as these tools are well-suited to capturing shifts in inflation dynamics. Several studies reported encouraging results considering this period using ML models: Medeiros *et al.* (2021), Aras and Lisboa (2022), Kohlscheen (2022), Botha *et al.* (2022), Lenza *et al.* (2023), Das and Das (2024), and Liu *et al.* (2024).

Although the ML literature in macroeconomic forecasting is still less extensive than its econometric counterpart, there is growing evidence of its potential. For instance, in the case of U.S., Nakamura (2005) demonstrated that Neural Networks (NN) outperformed autoregressive (AR) models in forecasting inflation over one- and two-quarter horizons. Medeiros and Mendes (2016), using the Adaptive LASSO (adaLASSO), showed that this model outperformed standard AR and factor models. Medeiros *et al.* (2021) also found that ML models, with a rich set of covariates, delivered more accurate in terms of forecast inflation over a long period of out-of-sample observations, particularly using the Random Forest (RF).

Using data from 20 advanced economies between 2000 and 2021, Kohlscheen (2022) showed that ML models could reliably predict both headline and core inflation using only a limited set of macroeconomic indicators. Similarly, Liu *et al.* (2022) found that ML techniques outperformed vector autoregressions (VAR) in most of the nine major economies they studied. Lenza *et al.* (2023) concluded that Quantile Regression Forests (QRF) offer a valuable complement to the Eurosystem's inflation forecasting toolbox. In the United Kingdom, Joseph *et al.* (2024) used disaggregated Consumer Price Index (CPI) item data, they found that nonlinear models such as RF and NN capture complex item-level patterns that improve aggregate inflation forecasts.

In emerging and developing countries, there is also a growing use of ML algorithms. Baybuza (2018) found that RF and Boosting models performed at least as well as conventional approaches in forecasting inflation in Russia. Zahara and Ilmiddaviq (2020) applied Long

Short-Term Memory (LSTM) networks using 34 variables for CPI prediction in Indonesia and several optimization algorithms, achieving notable accuracy. Özgür and Akkoç (2021) reported that LASSO and elastic net algorithms outperformed conventional econometric methods in Turkey. Botha *et al*. (2022) highlighted ML's competitive performance during South Africa's COVID-19 lockdown period.

Latin America has not been left behind either. In Brazil, Garcia *et al*. (2017) showed that high-dimensional ML models performed well for real-time inflation forecasting in data-rich environments. Rodríguez-Vargas (2020) found that combining ML models improved inflation forecasts in Costa Rica. Araujo and Gaglianone (2023) evaluated 16 models for Brazil and found that some ML algorithms consistently surpassed traditional econometric techniques.

In Bolivia, literature on the subject is even more limited. Although there are some examples, like Bolivar (2024) who proposed a two-step ML strategy: first training algorithms on monthly data, then applying them to forecast weekly inflation, addressing the challenge of high-frequency economic data scarcity. His findings indicated that ML-based models outperformed traditional methods and survey-based forecasts.

Despite these successes, there are some studies that reported poor performance of ML approaches. Makridakis *et al.* (2018) concluded that traditional statistical methods were more reliable than ML algorithms, criticizing other studies due to their results being supported by few, or even a single, time series, without statistical significance or in the absence of robustness tests. Ivașcu (2023), analyzing Romania's inflation using a range of ML methods, found that simpler models like AR often outperformed ML models, particularly in data-scarce environments. He also highlighted the inconsistency in identifying the best ML approach across different studies. Similarly, Liu *et al.* (2024) found that while LASSO models performed well in Japan, tree-based models fared poorly due to the country's long period of inflation stability (that use for training) and lack of a clear nonlinear relationship.

5. Data

One of the key advantages of ML models lies in their capacity to incorporate a large number of features, in contrast to traditional econometric models, which typically rely on a limited set of relevant variables due to degrees-of-freedom constraints. Following the approach of Rodríguez-Vargas (2020), Araujo and Gaglianone (2023), and Liu *et al.* (2024), this study tried to include a wide array of economic variables with monthly data, with the aim of providing the models with as many information as possible. However, this was not possible by several practical limitations:

1. Not all variables had data coverage as extensive as headline inflation, like inflation expectations,
2. Some potentially relevant indicators, such as Wholesale and Producer Price Indices, Unemployment or Tether for Bolivians (USDT), were published a few years ago,
3. Limited access existed for certain types of data, like public expenditure,
4. Some variables, like investment, lacked monthly data or reliable proxies, and
5. Others, like loans and deposits in the financial system, were affected by structural breaks unrelated to economic dynamics, for example, the closure of Banco Fassil in 2023 temporarily disrupted the recording of this institution's figures until their assets were redistributed across other banks.

Despite these constraints, a deliberate effort was made to select variables reflecting the behavior of the real, monetary, financial, and external sectors of the economy. The selected variables are summarized below:

Table 1
Variables selected

Variable	Category	Source
CPI - Headline inflation	Prices	National Institute of Statistics of Bolivia
Core inflation	Prices	Economic Commission for Latin America and the Caribbean
Bolivia Economic Activity Index - IGAE	Economy	National Institute of Statistics of Bolivia
Imported durable consumer goods	Economy	National Institute of Statistics of Bolivia
Parallel exchange rate	Exchange rate	Constructed using official Central Bank exchange rates and, since March 2023, information reported in different local newspapers.
Real Exchange Rate Index - ITCER	Exchange rate	Central Bank of Bolivia

Variable	Category	Source
Monetary aggregate M1	Money	Central Bank of Bolivia
Reference interest rate - TRe	Financial sector	Central Bank of Bolivia
South America inflation	Exterior	Was constructed based on the inflation rates of the regional countries, except Argentina, Venezuela, and Bolivia, and weighted according to the size of the economy. The data were obtained from the national statistical institutes or central banks of the respective countries.
FAO Food Price Index	Exterior	Food and Agricultural Organization

Source: Own elaboration.

For price dynamics, two alternatives were considered, the Consumer Price Index (CPI) that represent headline inflation and the core inflation. While the CPI captures general price movements and it is the most widely used indicator, core inflation offers a more accurate reflection of persistent price pressures by excluding volatile components.

In the domain of economic activity, the Bolivia Economic Activity Index (IGAE) was selected alongside data on Imported durable consumer goods[3]. To account for external pressures, the FAO International Food Price Index was incorporated, reflecting global commodity trends that. Additionally, inflation rates from neighboring South American countries were considered to capture regional spillover effects and shared vulnerabilities.

Capturing exchange market pressures posed a particular challenge due to Bolivia's dual exchange rate system. There is an official exchange rate determined by the Central Bank and a parallel exchange rate determined by the market. To address this, the parallel exchange rate was constructed using official data up to February 2023, and from March 2023 onward, supplemented with black market rates reported by local newspapers[4]. The Real Exchange Rate Index (ITCER), published by the Central Bank, was also included, despite its reliance on the official nominal rate, as it provides a standardized measure of competitiveness.

3 Durable goods consumption serves as a useful proxy for tracking shifts in aggregate demand, given its sensitivity to consumer expectations and income levels (Caballero, 1991; Gowrisankaran and Rysman, 2012; and McKay and Wieland, 2021). Due to the absence of a national indicator, imported consumer goods were used as a proxy. Measurements were based on weight rather than value to avoid distortions from international price fluctuations.

4 A more detailed explanation can be found in Annex 1.

Regarding monetary conditions, the M1 monetary aggregate was chosen as a proxy for money supply. Given the similar behavior of other aggregates and the monetary base, M1 was considered sufficient to capture liquidity dynamics without redundancy. Finally, to approximate the influence of the financial system, the Reference Interest Rate (TRe) was used. This rate reflects the cost of funds mobilized by financial institutions and serves as a benchmark for lending rates. Other interest rates were excluded due to regulatory distortions that limit their responsiveness to market conditions.

Given data availability, the sample period spans 22 years, from January 2002 to December 2024, yielding a total of 276 monthly observations. In line with standard practices in the ML literature, all features were pre-processed prior to analysis. Specifically, variables were transformed into percentage terms to ensure consistency in scale. Following the methodology of Rodríguez-Vargas (2020) and Liu *et al.* (2024), year-over-year percentage changes were calculated for variables originally expressed in levels[5], except for the TRe, which was already expressed in percentages. This transformation also seeks to make the variables stationary and avoids dealing with seasonality issues. Subsequently, all variables were tested for stationarity using the Phillips-Perron (1988) test[6]. The results indicate that the TRe, core inflation, monetary aggregate M1, and the parallel exchange rate were non-stationary, these variables should not be used in the models.

6. Methodology

A wide range of ML algorithms can be employed to forecast macroeconomic variables such as inflation. The performance of each model, however, is highly dependent on hyperparameter tuning, meaning that even within a single methodological framework, different variants of the same model may yield different results. The aim of this study is not to conduct an exhaustive analysis to identify the optimal forecasting methodology for Bolivia, but rather to take initial steps in assessing the performance of selected ML approaches in the context of a small open economy characterized by limited data availability and ongoing economic instability.

5 The evolution of selected variables is presented in the Annex 2.

6 In the Annex 2, you can find the result from the Phillips–Perron test.

Although advances in computational power have made the implementation of ML algorithms more accessible, the process still incurs costs in terms of model calibration and computational requirements. As noted by Bolhuis and Rayner (2020), some ML algorithms such as RF, Gradient Boosted Trees, and Support Vector Machines (SVM) require minimal parameter tuning and are generally less prone to overfitting. In contrast, models like NN needs large datasets and more complex calibration. Furthermore, methods such as LASSO (Least Absolute Shrinkage and Selection Operator) or Elastic Net can be sensitive to extreme or unexpected changes in predictor variables that were not present during training. This sensitivity makes their performance less reliable in volatile economic contexts, which are common in emerging markets.

Each selected ML model is implemented in both univariate and multivariate forms. In the univariate setting, inflation forecasts are generated using only the lags of the inflation series itself, given the documented inertia in inflation dynamics in emerging economies (Araujo and Gaglianone, 2023). The following lags are included as explanatory variables: 1 lag (1 month ago), 3 lags (1 quarter ago), 6 lags (1 semester ago) and 12 lags (1 year ago). In the multivariate setup, models incorporate the inflation lags as well as additional economic variables and their respective lags (3, 6, and 12 months), resulting in a total of 25 features.

The dataset spans from January 2002 to December 2024 (276 monthly observations) and is divided into a training set (January 2002-December 2023, 264 observations) and a test set (January-December 2024, 12 observations). The year 2024 is particularly relevant due to a notable uptick in inflation during the second half of the year, allowing models to be evaluated under both stable and crisis conditions. Likewise, despite the great advantages that ML models present when making projections, most of the literature has focused on evaluating their predictive capabilities in the short term, commonly considering up to one year as a horizon (Nakamura, 2005; Gabriel *et al.*, 2020; Rodríguez-Vargas, 2020; Ivașcu, 2023; and Liu *et al.*, 2024).

Each modeling approach involves tuning via cross-validation, with hyperparameter configurations selected based on the lowest Root Mean Squared Error (RMSE). Two RMSE values are calculated, one for a 6-month forecast and another for a 12-month forecast. The best-performing ML models are then compared against traditional econometric benchmarks: the ARMA model (univariate) and the VAR model (multivariate).

In addition, two stacked ensemble models were developed to further improve predictive performance. Ensemble stacking combines the forecasts of multiple base learners by training a meta-model that aggregates their predictions, thereby enhancing both accuracy and robustness. In this study, the first ensemble model employs RF as the meta-learner, while the second uses Extreme Gradient Boosting (XGBoost). The base models were configured using the hyperparameters associated with the lowest RMSE in prior tuning rounds. Ensemble models leverage the predictive strengths of individual models while mitigating their weaknesses through model averaging.

Forecasts are generated using a rolling-window framework as in Giacomini and White (2006). With each new data point, the cross-validation window expands while the test window moves forward, allowing the model to incorporate the most recent information and adapt to evolving patterns.

While stationarity is generally desirable, it is not always necessary for all ML methods. Tree-based algorithms, such as RF and Gradient Boosting, can handle dynamic patterns without explicitly assuming stationarity. Nevertheless, non-stationary variables may still impair performance if relationships become unstable over time. Therefore, stationarity remains helpful for both improving accuracy and enhancing interpretability.

Despite concerns over non-stationarity, two additional multivariate models (tree-based algorithms) are estimated, including monetary aggregate M1 and the parallel exchange rate, which are considered crucial for explaining recent inflation dynamics. The M1 aggregate, like the money supply and other aggregates, has shown impressive growth in recent years, driven by expansionary monetary policy since late 2014, which has been boosted in recent years by the current economic crisis.

In the case of the exchange rate, its behavior is even more erratic, since it has been fixed since 2011, helping to anchor expectations and mitigate external shocks. However, the foreign exchange shortage led to the emergence of a black market where a significant high parallel exchange rate was established. Modeling this behavior is a complex challenge, with zero variation for a long period and high volatility in recent months. However, it cannot be ignored, considering that the spike in inflation is largely explained by the rise in imported prices. Therefore, these additional models work with 33 features.

Finally, to strengthen the evaluation of the ML methodologies applied, a complementary analysis was conducted focusing on both model validation and performance assessment. In addition to the RMSE metric used in the main analysis, alternative measures such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were incorporated to provide a more comprehensive comparison of model accuracy. Furthermore, a rolling window validation strategy was implemented, generating sequential forecasts for the years 2022 and 2023, to assess the consistency of the models over time. The results of this extended evaluation are presented in Annex 3.

The following section provides a concise overview of the ML models used in this study. For readers interested in a deeper technical understanding of these methods, the references cited throughout this paper offer further detail.

6.1. Models selected

6.1.1. K-Nearest Neighbours Algorithm (KNN)

The K-Nearest Neighbours (KNN) algorithm is a simple yet powerful method applicable to both classification and regression tasks. In the context of time series forecasting, KNN identifies historical periods like the most recent data and predicts future values by analyzing how the target variable behaved following those comparable instances. Mack (1981) sets out the theoretical basis of KNN regression, while Yakowitz and Karlsson (1987) explored its application in time series forecasting in greater detail.

In this framework, "K" denotes the number of closest historical observations (the nearest neighbours) used for prediction. Selecting an appropriate value for K is essential, as smaller values can result in low bias but high variance (causing an overfitting problem), increasing sensitivity to noise and outliers. In contrast, larger values generally reduce variance but may introduce greater bias by oversmoothing the signal. Cross-validation is commonly employed to determine the optimal K.

KNN operates by constructing a feature vector comprising the target variable and one or more explanatory variables. It then applies a distance metric (Euclidean, Mahalanobis, Manhattan, among others) to identify the K most similar observations. The forecast is then generated by aggregating the outcomes that followed those neighbours, either via a simple average or a distance-weighted approach.

KNN is often described as a "lazy" learning algorithm because it does not build an explicit model during the training phase. Instead, it memorizes the training data and relies on it to make predictions. This simplicity makes it one of the most accessible machine learning techniques, especially when model interpretability is important, since it provides transparent and intuitive results. Additionally, as a non-parametric method, KNN imposes no strict assumptions on the data's underlying distribution, making it flexible enough to adapt to shifting patterns or regime changes in economic data.

Nevertheless, the method is not without its drawbacks. Since KNN calculates distances between the input and all training instances at prediction time, it can be computationally expensive and slow for large datasets. Also, KNN is highly sensitive to the scale of features, those with larger scales can dominate the distance calculation, leading to biased results. Feature normalization or standardization is often necessary. Another limitation is the algorithm's performance in high-dimensional spaces, where increasing the number of features may lead to a reduction in the effectiveness of KNN, a phenomenon commonly known as the curse of dimensionality.

Despite being a simple model, it has been used to make inflation projections, although not in all cases with favorable results. For instance, Rodríguez-Vargas (2020) and Jouilil and Iaousse (2023) found that a univariate KNN model showed strong potential for forecasting inflation in Costa Rica and U.S., respectively. Meanwhile, Khashimova and Buranova (2024) observed that Logistic regression had a higher accuracy rate and better performance metrics over KNN in predicting inflation in Uzbekistan.

6.1.2. Random Forests (RF)

The Random Forest (RF) algorithm, introduced by Breiman (2001b), is a nonparametric ML method designed for both classification and regression tasks. It is based on the principle of bagging (bootstrap aggregation) combining a large set of decision trees, specifically Classification and Regression Trees (CART), to improve predictive performance. Each tree is trained on a bootstrap sample of the original dataset and makes independent predictions, which are aggregated into a final output. For regression tasks, this output is typically the average of all individual tree predictions.

A key strength of RF is the introduction of randomness at two levels: i) each decision tree is trained on a randomly drawn subset of the data (with replacement), and ii) during tree construction, each split is determined using a random subset of predictor variables. This dual-randomization approach reduces the correlation among individual trees and enhances the robustness and generalization of the model. The resulting ensemble typically achieves lower variance compared to a single decision tree, reducing the risk of overfitting. Another advantage of RF is that it provides built-in mechanisms for evaluating the importance of predictors. Feature importance is commonly assessed by measuring the average decrease in impurity (*e.g.*, variance for regression trees) that each variable contributes across all trees in the forest.

Although this method generally requires little parameter tuning, the adjustments on those parameters determine the fitting performance of the final model. There exist several hyperparameters like the number of trees in the ensemble, the maximum depth of each tree, the minimum size of terminal nodes, and the number of predictors randomly selected at each split.

Its ability to generalize well, handle nonlinearity, and quantify variable importance has made it a popular and effective tool in economic forecasting applications. Indeed, it is not surprising that it has been one of the most widely used and most successful models in terms of inflation forecasting: Baybuza (2018), Rodríguez-Vargas (2020), Medeiros *et al.* (2021), Botha *et al.* (2022), Kohlscheen (2022), Araujo and Gaglianone (2023), Lenza et al. (2023), Ivașcu (2023), Masini *et al.* (2023), Joseph *et al.* (2024), Das and Das (2024), Liu *et al.* (2024), among others.

Despite its strengths, the RF algorithm, like any methodology, also has some limitations. It tends to be less interpretable than individual decision trees and may be computationally intensive, particularly with large datasets or extensive tuning.

6.1.3. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is a scalable, efficient, and regularized implementation of the gradient boosting framework, developed by Chen and Guestrin (2016). Boosting methods build an ensemble of weak learners, typically shallow decision trees, trained sequentially, with each new tree aiming to correct residual errors from the previous ensemble.

In contrast to bagging methods like RF, which build trees independently using bootstrap samples, boosting trains trees adaptively. Each iteration focuses on the data points where the model underperforms. Specifically, gradient boosting minimizes a loss function by computing its gradient and fitting a new learner to approximate this gradient. The process is repeated until a predefined number of trees is reached or until convergence.

XGBoost introduces several key improvements over traditional gradient boosting implementations: i) incorporates two types of regularization techniques to control model complexity and reduce overfitting, L1 (Lasso) and L2 (Ridge); ii) implements tree construction using parallel processing, significantly reducing training time; iii) efficiently handles missing data by learning optimal default directions for sparse inputs; and iv) builds trees in a level-wise manner, enhancing computational speed and accuracy.

This algorithm has become as one of the most popular ML techniques in predictive analytics due to its flexibility, accuracy, and speed. It is particularly effective for modeling non-linear relationships in high-dimensional datasets and is well-suited to forecasting tasks involving economic and financial time series. Applications of XGBoost to the forecasting of macroeconomic variables such as inflation can be found in different cases: Baybuza (2018), Rodríguez-Vargas (2020), Momo *et al.* (2021), Botha *et al.* (2022), Araujo and Gaglianone (2023), Ivașcu (2023), Liu *et al.* (2024), among others.

However, as with all boosting methods, XGBoost is not without drawbacks. It tends to be more sensitive to hyperparameter settings and outliers and may overfit when the number of boosting rounds is excessive or when regularization is insufficiently tuned. Despite this, its strong predictive performance and adaptability make it a valuable addition to the suite of ML tools for inflation forecasting.

6.1.4. Support Vector Regression (SVR)

The Support Vector Regression (SVR) is an extension of the Support Vector Machine (SVM) framework, originally developed by Boser *et al.* (1992). This algorithm was modified to address regression problems. SVR combines the principles of margin maximization and kernel-based learning to produce accurate, nonlinear forecasting models.

SVR operates by mapping input data into a high-dimensional feature space using a kernel function and then fitting a linear regression model in that space. It operates with key hyperparameters: i) Epsilon (ε): controls the width of the margin of tolerance around the hyperplane; and ii) Cost parameter (C): balances the trade-off between model complexity and the degree to which deviations beyond ε are tolerated. Choosing appropriate values for these parameters is critical and typically achieved through cross-validation to balance bias and variance effectively.

The goal is to identify a hyperplane that approximates the data within a specified margin of tolerance, denoted by ε. Any data point that falls within this range is considered "close enough" and does not affect the loss function. Meanwhile, points that lie beyond the margin are penalized, these are the deviations that SVR tries to minimize. The optimization procedure minimizes both the norm of the hyperplane (encouraging flatness and generalization) and the penalty for deviations, resulting in a well-posed convex quadratic programming problem.

SVR is particularly well-suited for forecasting in high-dimensional feature spaces, such as those encountered in macroeconomic modeling with numerous indicators. Its strength lies in its capacity to model nonlinear relationships using flexible kernel functions, including linear, polynomial, radial basis function (RBF), and sigmoid kernels, making it adaptable to diverse data structures. The algorithm is also robust to noise and outliers and performs reliably with structured data like time series.

However, it also has some limitations: i) it can be computationally intensive, especially when using nonlinear kernels on large datasets; ii) due to the need to store many support vectors in high-dimensional contexts is memory-demanding; iii) is sensitive to hyperparameters, particularly C and ε, which require careful tuning; iv) choosing the appropriate kernel is critical, as model accuracy depends heavily on its suitability to the problem at hand.

Although less commonly used than other ML methods in the context of inflation forecasting, SVR has been applied in some studies with encouraging results. For instance, Gabriel *et al.* (2020) utilized SVR alongside other ML models to forecast inflation across seven regions in the Philippines. They found that SVR performed particularly well in 12-month ahead dynamic forecasts. Similarly, Momo *et al.* (2021), using data from Bangladesh, reported that SVR, especially with the RBF kernel, exhibited competitive performance compared to models such as RF, AdaBoost, and XGBoost. Meanwhile, Ivașcu (2023) evaluated the predictive capacity of SVR and five other ML algorithms for Romania's inflation. Although SVR did not perform poorly, it was outpaced by other methodologies in terms of forecast accuracy.

6.1.5. Benchmark Econometric models

Autoregressive Moving Average (ARMA): the ARMA model is one of the most widely used statistical tools for time series forecasting. It combines two components-autoregression (AR), which models the relationship between an observation and a number of its own lagged values, and moving average (MA), which incorporates the dependency between an observation and past forecast errors. ARMA models assume that future values are primarily influenced by recent patterns, making them well-suited for variables like inflation, which tend to exhibit persistence over time.

Vector Autoregression (VAR): VAR is a traditional multivariate forecasting method that generalizes the autoregressive model to accommodate multiple interrelated time series. Each variable in the system is modeled as a linear function of its own past values and the past values of all other variables in the system. This structure allows for the dynamic analysis of interactions among macroeconomic variables, providing a flexible framework for capturing feedback effects and temporal dependencies.

7. Empirical results

As part of the hyperparameter tuning process, a wide range of models were estimated for KNN, RF, XGBoost, and SVR, each evaluated under both univariate and multivariate specifications. The final models selected were those that achieved the lowest RMSE within their respective configurations[7].

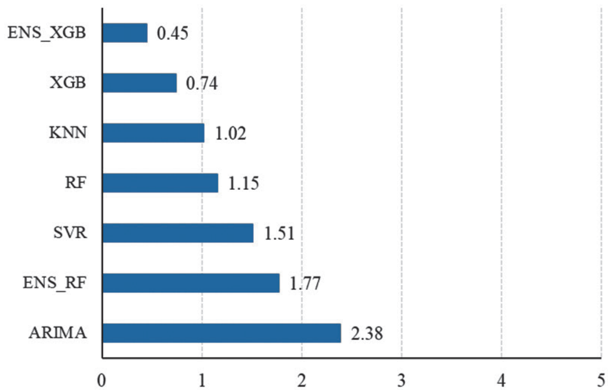
7 A complementary analysis was conducted to enhance the robustness of the ML models, incorporating alternative performance metrics and extended projection periods. These results are presented in Annex 3.

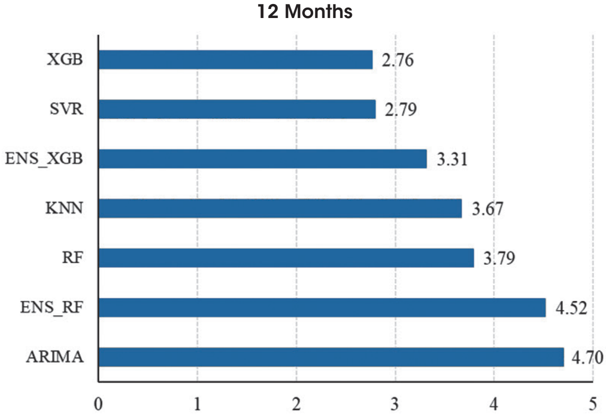
7.1. Univariate models

The results of the univariate models indicate that the ensemble stacking model with XGBoost (ENS_XGB) and the individual XGBoost model (XGB) provide relatively accurate forecasts over a 6-month horizon. In this case, all ML models performed better than the benchmark ARIMA model. However, when extending the forecast horizon to 12 months, performance deteriorates markedly across all models. While the XGB and SVR models offer comparatively better results, overall accuracy is noticeably diminished (Figure 8).

This sharp contrast between both horizons forecasts is not surprising for two main reasons. First, the literature has found that univariate models generally outperform or at least match more sophisticated models only in short-term projections (D'Amato *et al.*, 2018). Because they fail to account for the dynamic interrelationships among macroeconomic variables, univariate approaches are limited in their ability to capture structural shifts in inflation dynamics (Figure 9). Second, the 12-month test period coincides with a phase of rapidly rising inflation. The models, trained primarily on a period of low and stable inflation, are unable to extrapolate dynamics they have not previously encountered.

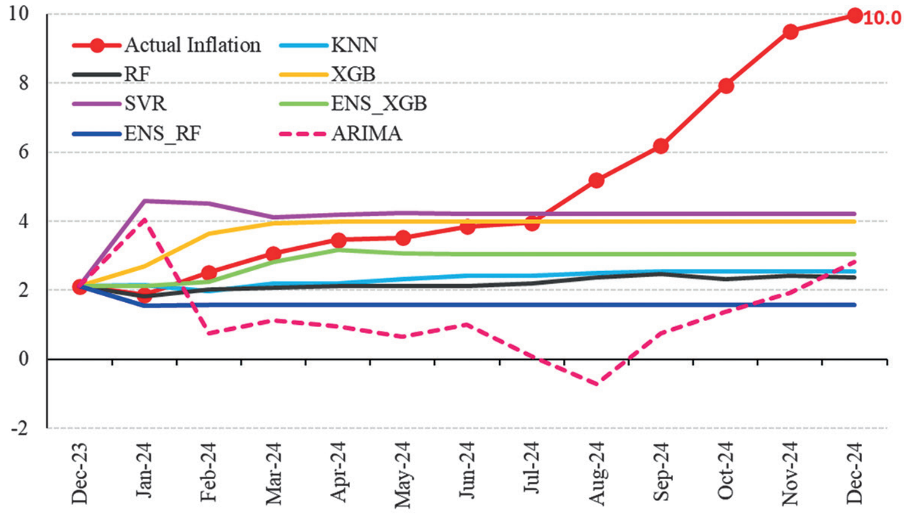
Figure 8: Univariate Models RMSE
6 Months





Source: Own elaboration.

Figure 9: Actual headline inflation and Univariate models inflation forecasts (year-to-year, in percentage)



Source: Own elaboration.

Given the current macroeconomic context, univariate models appear inadequate for forward-looking inflation projections. The data used to train these models largely reflect a long period of price stability that contrasts sharply with present conditions. An out-of-sample forecast exercise was conducted until the end of 2025 using the best-performing univariate

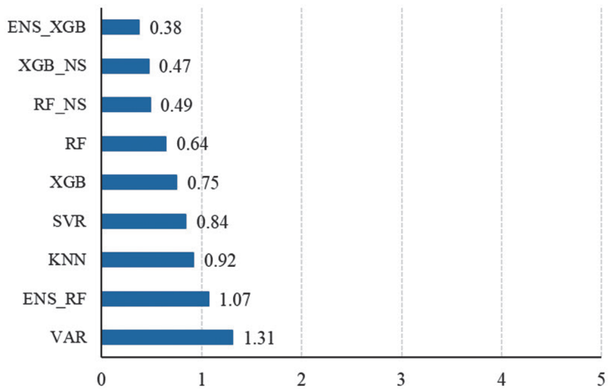
ML models (ENS_XGB and XGB), trained on data from January 2002 through June 2025. The results were unsatisfactory; the models interpreted the recent inflation spike as transitory and projected a rapid decline throughout the remainder of the year.

7.2. Multivariate models

In the case of multivariate models, the results show a notable improvement across both forecast horizons when compared to univariate models, emphasizing the importance of incorporating broader macroeconomic information in inflation projections. Among all models, the benchmark VAR model produced the highest RMSE at both horizons[8]. At the 6-month horizon, the ENS_XGB model delivered the most accurate projections, followed closely by the XGB_NS and RF_NS models (both include the parallel exchange rate and the M1 monetary aggregate[9]). At the 12-month horizon, performance generally declined, although the XGB_NS and XGB models show better results (Figure 10).

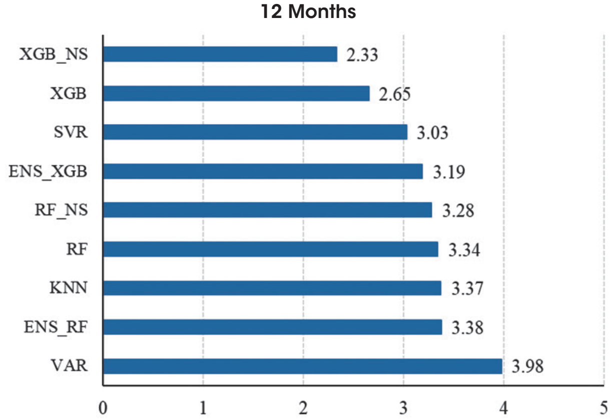
Figure 10: Multivariate Models RMSE

6 Months



8 It is worth noting that the VAR specification was constrained to include only six stationary variables and two lags to preserve model stability and ensure a sufficient degree of fit. Although VAR models are versatile tools for capturing interdependencies, their practical application is often limited by the number of variables they can incorporate.

9 However, since these features were found to be non-stationary, their results should be viewed with caution and not as entirely robust.



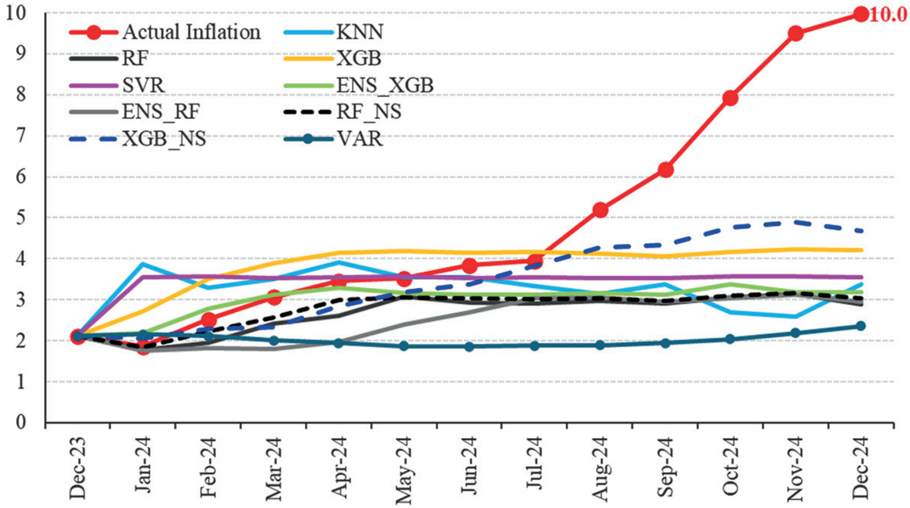
Source: Own elaboration.

Despite the overall improvement in predictive accuracy, multivariate models were also unable to anticipate the inflationary surge observed in 2024. As with univariate models, this limitation is largely attributable to the fact that training was conducted over an extended period of low and stable inflation. Although the inclusion of additional macroeconomic variables, such as the parallel exchange rate and the M1 monetary aggregate, enhanced model responsiveness to some extent, the gains were modest (Figure 11).

This outcome is not entirely unexpected. For many years, inflation in Bolivia has been structurally decoupled from broader economic dynamics due to the implementation of various policy instruments, like fixed exchange rate, subsidies on gasoline and basic food items, price controls, and export restrictions. These interventions have significantly distorted price formation mechanisms and weakened the traditional link between inflation and its traditional drivers.

Variable importance scores from the RF and XGB models offer a quantitative perspective on this disconnection (Table 2). Across all models, the first lag of inflation consistently emerged as the most influential predictor, underscoring the high degree of persistence in Bolivia's inflation dynamics. Other features registered substantially lower importance scores, suggesting that while they may carry some explanatory power, their contribution to the model's predictive capacity is limited.

Figure 11: Actual headline inflation and Multivariate models inflation forecasts (year-to-year, in percentage)



Source: Own elaboration.

The most relevant variables were the FAO International Food Price Index and inflation in South American countries (both external factors), imported durable consumer goods (a proxy for demand-side pressures), and the M1 monetary aggregate (representing money supply). The parallel exchange rate, by contrast, had minimal impact, something that it is not surprising since it has been fixed for so long, which offers little informational value to the models[10].

Nevertheless, under current conditions, multivariate models appear to be the most suitable approach for forecasting inflation. One of the key advantages of ML models lies in their ability to integrate a wide array of indicators, offering the potential for more accurate and adaptive forecasts. Future work should consider expanding the set of explanatory variables to include proxies for black market exchange pressures (like USDT), public spending, the economic effects of social unrest such as blockades or strikes, among others.

An attempt was made to forecast inflation through the end of 2025 using the best multivariate ML models. However, this was not possible for two primary reasons: i) updated data were unavailable for several critical variables (some only have data through 2024); and

10 In Annex 4 you can find the outcomes for 2022 and 2023 predictions.

ii) ML models typically require predefined input values for all explanatory variables over the forecast horizon, a task that is especially complex during periods of heightened uncertainty[11].

Table 2
Main variable importance scores

RF		XGB	
Variable	**Importance**	**Variable**	**Importance**
Inflation Lag1	0.941	Inflation Lag1	0.790
FAO Lag3	0.013	Imp Cons Lag12	0.034
FAO Lag6	0.006	FAO Lag3	0.022
Rest	0.041	Rest	0.154
RF_NS		**XGB_NS**	
Variable	**Importance**	**Variable**	**Importance**
Inflation Lag1	0.935	Inflation Lag1	0.755
FAO Lag3	0.013	FAO Lag3	0.034
Imp Cons Lag12	0.005	M1 Lag6	0.031
M1 Lag3	0.005	Inf SouthAm Lag3	0.022
Rest	0.043	Rest	0.157

Source: Own elaboration.

8. Conclusions

This study aimed to evaluate the predictive capacity of ML models for a small open economy facing limited data availability and experiencing a severe economic crisis. The focus centered on identifying suitable methodologies for forecasting inflation, a variable that had exhibited prolonged stability but surged significantly starting in the second quarter of 2024, reaching levels not observed since the early 1990s.

To this end, several widely adopted ML algorithms were tested in both univariate and multivariate cases. Overall, the multivariate models produced superior short-term forecast performance, especially when compared to traditional econometric benchmarks selected. In particular, the XGBoost and ensemble models built around an XGBoost base learner demonstrated strong predictive accuracy across both modeling frameworks. However, it

11 In such cases, traditional models like VAR offer an advantage, as they jointly forecast all variables in the system, eliminating the need to manually project inputs.

cannot be concluded that this is definitively the best model. Algorithms such as Random Forest may perform better under more stable economic conditions, highlighting the importance of context in model selection. In general, the inclusion of diverse ML approaches is essential, not only to validate and contrast projections, but also to enhance the robustness and credibility of inflation forecasts in uncertain environments.

Incorporating critical variables such as the parallel exchange rate and the M1 monetary aggregate helped narrow the gap between projected and observed inflation rates. However, since these features were found to be non-stationary, the robustness of the results should be interpreted with caution. Even so, their inclusion underscores one of the core strengths of ML approaches: the ability to integrate a broad and flexible set of features to enhance model performance.

While ML models show promising potential for macroeconomic forecasting, they should not be considered as substitutes for econometric models. Rather, they serve as complementary tools. Econometric approaches, such as VAR models, have important advantages in structural interpretation and joint modeling of variables, especially when enhanced through techniques like Bayesian estimation.

It should be noted that this paper does not attempt an exhaustive comparison of ML and econometric methodologies. Instead, it offers preliminary insights into their predictive capabilities under contrasting macroeconomic conditions, periods of stability and crisis. Future research should expand this analysis to include alternative forecasting approaches, and more sophisticated ML and econometric techniques. The quality of projections will ultimately depend on the volume and granularity of available data, feature selection and transformation, and rigorous hyperparameter tuning.

Given Bolivia's growing economic uncertainty, the development of hybrid forecasting frameworks that draw on both ML and econometric insights will be critical. Expanding the pool of explanatory variables to include indicators related to informal exchange markets, public expenditure, and others may further improve inflation forecasts and support more informed decision-making.

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References

1. Aras, S., & Lisboa, P.J. (2022). Explainable inflation forecasts by machine learning models. *Expert Systems with Applications,* 207, 117982. 10.1016/j.eswa.2022.117982.
2. Araujo, G.S., & Gaglianone, W.P. (2023). *Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models.* Working Papers Series N° 561, Central Bank of Brazil, Research Department.
3. Athey, S., & Imbens, G.W. (2019). Machine Learning Methods Economists Should Know About. *Annual Review of Economics,* 11, 685-725.
4. Baybuza, I. (2018). Inflation Forecasting Using Machine Learning Methods. *Russian Journal of Money and Finance,* 77(4), 42-59.
5. Bolhuis, M.A., & Rayner, B. (2020). Deus ex Machina? A Framework for Macro Forecasting with Machine Learning. IMF Working Papers N° 045, International Monetary Fund.
6. Bolivar, O. (2024). Weekly Inflation Forecasting: A Two-Step Machine Learning Methodology. SSRN, https://ssrn.com/abstract=5001681
7. Botha, B., Burger, R., Kotzé, K., Rankin, N., & Steenkamp, D. (2022). Big data forecasting of South African inflation. *Empirical Economics,* 65, 149-188
8. Boser, B.E., Guyon, I.M., & Vapnik, V.N. (1992). A training algorithm for optimal margin classifiers. *Proceedings of the fifth annual workshop on Computational learning theory* (pp. 144-152).
9. Breiman, L. (2001a). Statistical Modeling: The Two Cultures. *Statistical Science,* 16(3), 199-215.
10. ---------- (2001b). Random Forests. *Machine Learning,* 45, 5-32.
11. Caballero, R.J. (1991). *Durable Goods: An Explanation for Their Slow Adjustment.* NBER Working Papers N° 3748, National Bureau of Economic Research, Inc.
12. Chen, T., & Guestrin. C. (2016): *XGBoost: A Scalable Tree Boosting System.* Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco California USA: ACM, 785-94.
13. Costain, J., Nakov, A., & Petit, B. (2022). Flattening of the Phillips Curve with State-Dependent Prices and Wages. *The Economic Journal,* 132(642), 546-581.

14. Das, P.K., & Das, P.K. (2024). Forecasting and analyzing predictors of inflation rate: Using machine learning approach. *Journal of Quantitative Economics*, 22(2), 493-517.

15. D'Amato, L., Garegnani, L., Libonatti, L., Gómez Aguirre, M., & Krysa, A. (2018). *Forecasting Inflation in Argentina: A Comparison of Different Models.* Economic Research Working Papers N° 81.

16. Faust, J., & Wright, J. (2013). Forecasting Inflation. In G. Elliott and A. Timmermann (eds.), *Handbook of Economic Forecasting*, Amsterdam: Elsevier.

17. Gabriel, V., Bautista, D., & Mapa, C. (2020). *Forecasting regional inflation in the Philippines using machine learning techniques: A new approach.* Working Paper N° 10, Bangko Sentral ng Pilipinas.

18. Garcia, M.G.P., Medeiros M.C., & Vasconcelos, G.F.R. (2017). Real-time inflation forecasting with high-dimensional models: The case of Brazil. *International Journal of Forecasting*, 33(3), 679-93.

19. Giacomini, R., & White, H. (2006). Tests of Conditional Predictive Ability. *Econometrica*, 74(6), 1545-78.

20. Gowrisankaran, G., & Rysman, M. (2012). Dynamics of Consumer Demand for New Durable Goods. *Journal of Political Economy*, 120(6), 1173-1219.

21. Greene, W.H. (2003). *Econometric Analysis.* United States: Prentice Hall.

22. Hall, A.S. (2018). Machine Learning Approaches to Macroeconomic Forecasting. *Economic Review*, Federal Reserve Bank of Kansas City, QIV, 63-81.

23. Ivașcu, C., (2023). Can Machine Learning Models Predict Inflation? Proceedings of the International Conference on Business Excellence, *Sciendo*, 17(1), 1748-1756.

24. Joseph, A., Potjagailo, G., Chakraborty, C., & Kapetanios, G. (2024). Forecasting UK inflation bottom up. *International Journal of Forecasting*, 40(4), 1521-1538.

25. Jouilil, Y., & Iaousse, M. (2023). Comparing the Accuracy of Classical and Machine Learning Methods in Time Series Forecasting: A Case Study of USA Inflation. *Statistics, Optimization & Information Computing*, 11(4), 1041-1050. https://doi.org/10.19139/soic-2310-5070-1767

26. Khashimova, N., & Buranova, M. (2024). *Comparative Analysis of Machine Learning Algorithms for Inflation Rate Classification and Economic Trend Forecasting. ICFNDS '23:*

Proceedings of the 7th International Conference on Future Networks and Distributed Systems, 274-282.

27. Koester, G., Lis, E., Nickel, C., Osbat, C., & Smets, F. (2021), *Understanding low inflation in the euro area from 2013 to 2019: cyclical and structural drivers*. Occasional Paper Series, N° 280, ECB.

28. Kohlscheen, E. (2022). *What does machine learning say about the drivers of inflation?* BIS Working Paper N° 980.

29. Lenza, M., Moutachaker, I., & Paredes, J., (2023). Forecasting euro area inflation with machine-learning models. *Research Bulletin N°*112, European Central Bank.

30. Liu, Y., Yang, D., & Zhao Y. (2022): Housing Boom and Headline Inflation: Insights from Machine Learning. IMF Working Papers N° 151, International Monetary Fund.

31. Liu, Y., Pan, R., & Xu, R., (2024). *Mending the Crystal Ball: Enhanced Inflation Forecasts with Machine Learning*. IMF Working Papers N° 206. https://doi.org/10.5089/9798400285387.001

32. Mack, Y.P. (1981). Local properties of k-NN regression estimates'. *SIAM Journal of Algebraic and Discrete Methods*, 2(3), 311-323.

33. Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PLOS ONE, Public Library of Science*, 13(3), 1-26.

34. 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.

35. McKay, A. and Wieland, J.F. (2021). *Lumpy Durable Consumption Demand and the Limited Ammunition of Monetary Policy.* Staff Report 622, Federal Reserve Bank of Minneapolis.

36. Medeiros, M.C., & Mendes, E.F. (2016). ℓ1-regularization of high-dimensional time-series models with non-Gaussian and heteroskedastic errors. *Journal of Econometrics,* 191(1), 255-271.

37. Medeiros, M.C., Vasconcelos, G.F.R., 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.

38. Momo, S., Riajuliislam, M., & Hafiz, R. (2021). Forecasting of Inflation Rate Contingent on Consumer Price Index: Machine Learning Approach. In Intelligent Computing and Innovation on Data Science (pp.137-144). 10.1007/978-981-16-3153-5_17.

39. Nakamura, E. (2005). Inflation Forecasting Using a Neural Network. *Economics Letters,* 86(3), 373-378.

40. Phillips, P., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika,* 75(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

41. Özgür, Ö., & Akkoç, U. (2021). Inflation forecasting in an emerging economy: selecting variables with machine learning algorithms. *International Journal of Emerging Markets,* 17(8), 1889-1908.

42. Rodríguez-Vargas, A. (2020). Forecasting Costa Rican inflation with machine learning methods. *Latin American Journal of Central Banking (previously Monetaria).* 1(1), 1-4.

43. Samuel, A. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development,* 3(3), 210-229.

44. Silva, G., & Piazza, W. (2022). *Machine Learning Methods for Inflation Forecasting in Brazil: new contenders versus classical models*. Working Papers Series 561, Central Bank of Brazil, Research Department.

45. Yakowitz, S., & Karlsson, M. (1987). Nearest neighbour methods for time series, with application to rainfall/runoff prediction. In Macneill, J.B. y Umphrey, G.J. (eds.), *Stochastic Hydrology,* D. Reidel Publishing Co. (pp. 149-160).

46. Varian, H.R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives,* 28(2), 3-28.

47. Zahara, S., & Ilmiddaviq, M.B. (2020). Consumer price index prediction using Long Short Term Memory (LSTM) based cloud computing. *Journal of Physics: Conference Series,* 1456(1), 012022.

Annexes

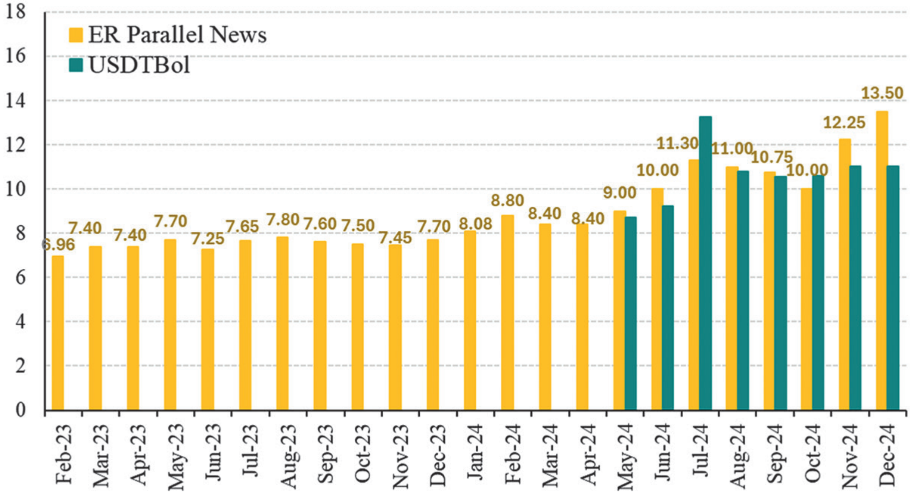
Annex 1

Employing Bolivia's nominal exchange rate presents a considerable challenge due to its evolution over time and the structural shifts it reflects. During the 1990s and early 2000s, it showed a sustained depreciation aimed at preserving the country's trade competitiveness. Between 2005 and 2011, however, the exchange rate appreciated as a policy response to external inflationary pressures, supported by an exceptional accumulation of Foreign Reserves. Since then, the rate has remained fixed, serving as a cornerstone of Bolivia's macroeconomic stability strategy by anchoring the expectations of economic agents. Nevertheless, the recent scarcity of foreign currency has given rise to a black market, where a parallel exchange rate has emerged. This rate became particularly visible beginning in March 2023.

Obtaining reliable data on the parallel exchange rate is complicated due to its informal nature. Initially, local newspapers began publishing estimates based on information gathered from exchange houses and informal traders. As the foreign currency shortage intensified, cryptocurrency platforms gained popularity as alternative channels for quotidian transfers. In particular, Tether (USDT), a stablecoin pegged 1:1 to the U.S. dollar, has recently become the benchmark for the parallel exchange rate. Currently, newspapers regularly report USDT prices as a proxy for the black market rate.

Unfortunately, a sufficiently long time series for USDT prices in Bolivia (USDTBol) was not available for inclusion in this study. Instead, the parallel exchange rate used here was constructed from newspaper-reported values. This indicator exhibits a significant degree of similarity with USDTBol (Figure A1), as evidenced by a cross-correlation coefficient of 0.6. Therefore, while the constructed indicator captures adequately black market exchange rate dynamics, future research should consider using USDTBol as a more robust and transparent alternative.

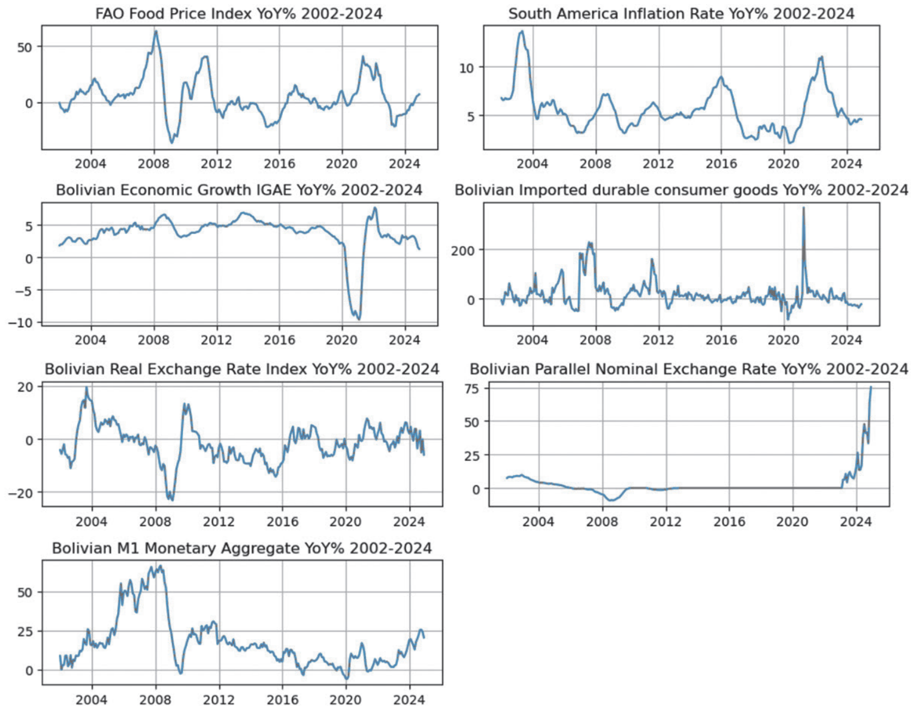
Figure A1: Parallel Bolivian Exchange Rate (Bolivians per 1 US$ dollar)



Source: The Parallel Exchange rate was built using information reported in different local newspapers since March 2023. USDTBol: https://usdtbol.com/

Annex 2

Figure A2: Evolution of selected variables (year-to-year, in percentage)



Source: National Institute of Statistics of South America countries, Central Bank of Bolivia, Food and Agricultural Organization, local news (parallel exchange rate).

Table A1
Phillips-Perron Unit Root test Results

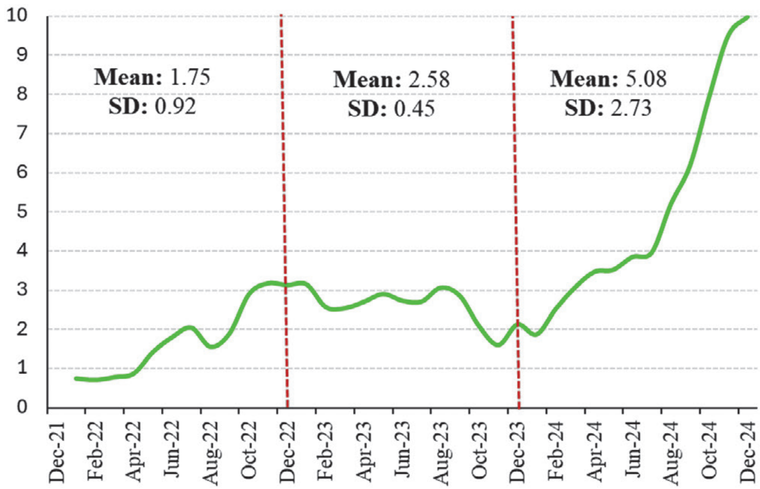
Variable	P-value
Headline inflation	0.0620
Core inflation	0.1652
Economic Growth IGAE	0.0163
Imported durable consumer goods	0.0000
Parallel exchange rate	1.0000
ITCER	0.0047
M1	0.2971
TRe	0.2461
South America inflation	0.0362
FAO Food Price Index	0.0067

Source: Own elaboration.

Annex 3

To evaluate the temporal consistency of the ML models performance, projections were generated for the years 2022, 2023, and 2024. While these periods correspond to the most recent years, each is characterized by distinct macroeconomic contexts (Figure A3). In 2022, inflation started from a relatively low level, and began to rise, although without representing a macroeconomic risk. In 2023, was marked by greater price stability and reduced volatility. In contrast, in 2024 inflation experienced a sharp and erratic rebound, exhibiting dynamics not observed in nearly three decades. This diversity of contexts provides a meaningful framework for assessing the robustness and adaptability of the models across varying economic environments.

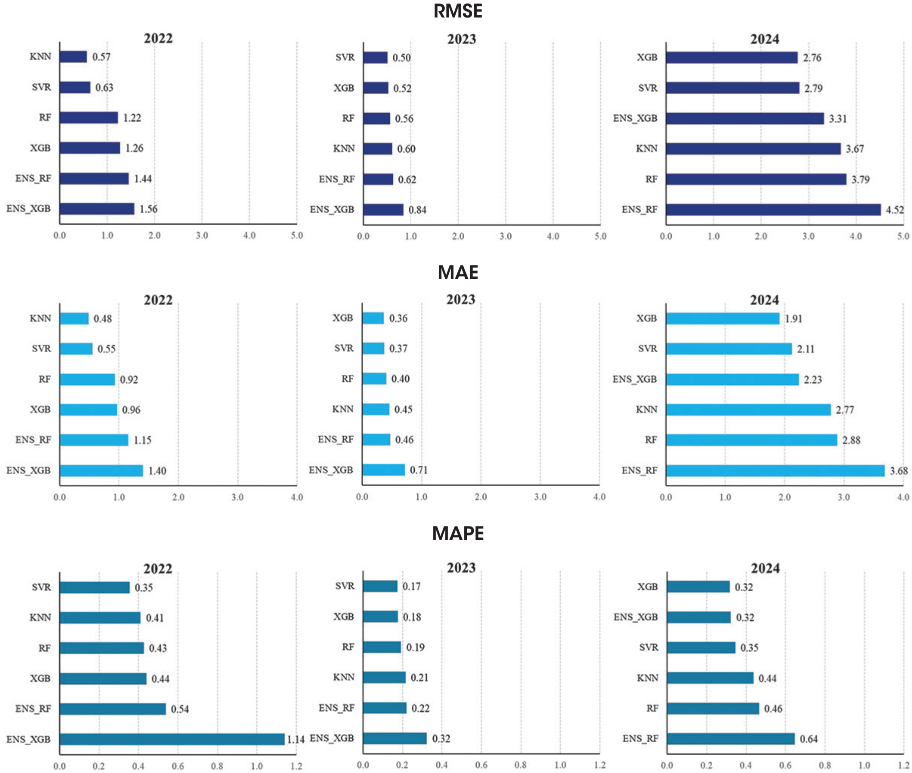
Figure A3: Bolivian Headline Inflation between 2022 and 2024 (year-to-year, in percentage)



Source: National Institute of Statistics of Bolivia.

In the case of univariate models, the XGB and SVR methodologies consistently demonstrate superior performance across the different testing periods, as evidenced by their lower RMSE, MAE, and MAPE values (Figure A4). These models produce particularly accurate projections for 2022 and 2023, years in which inflation exhibited relatively stable and controlled dynamics. This suggests that univariate models may be well-suited for short-term forecasting, especially under conditions of macroeconomic stability.

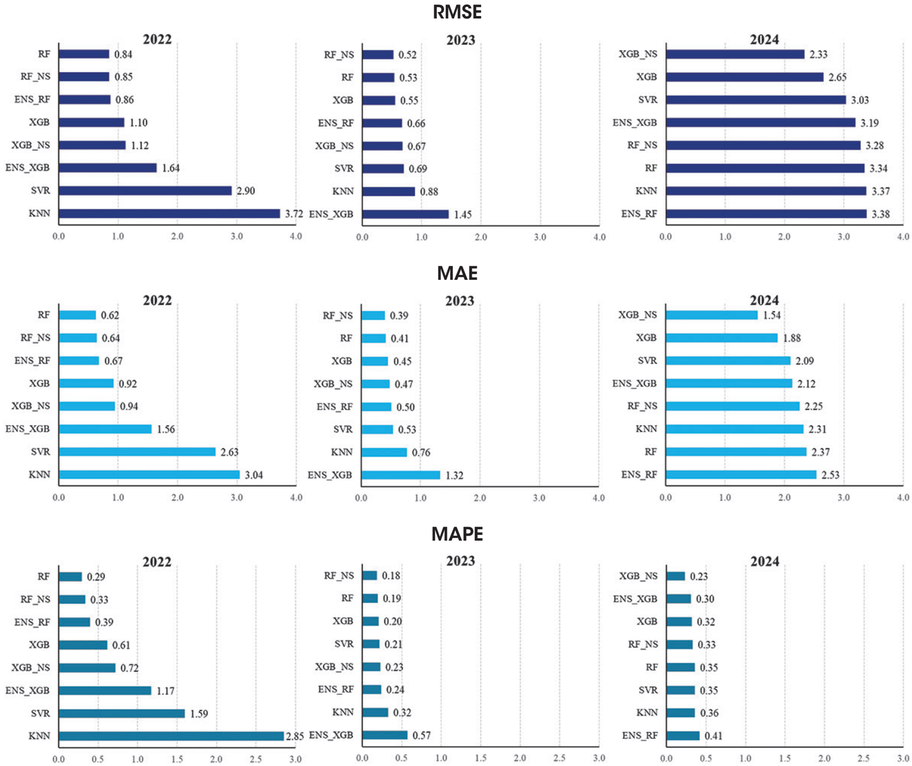
Figure A4: Univariate models evaluation



Source: Own elaboration.

Multivariate models, on the other hand, generally outperform their univariate counterparts across all evaluation metrics and projection periods (Figure A5). This reinforces the importance of incorporating relevant macroeconomic variables to enhance predictive accuracy. Their improved performance in 2022 and 2023 further supports their applicability in macroeconomic forecasting, particularly when the underlying economic environment is well-behaved. However, when examining individual model performance, results are more heterogeneous. No single methodology consistently dominates across all periods. Overall, XGB tends to produce the most reliable outcomes, while KNN exhibits the poorest performance.

Figure A5: Multivariate models evaluation



Source: Own elaboration.

A separate analysis should be done for the Random Forest (RF) methodology. RF performs exceptionally well in both univariate and multivariate configurations during 2022 and 2023, but its accuracy deteriorates significantly in 2024. Despite its widespread use and strong track record in various studies (*e.g.*, Medeiros *et al.*, 2021; Araujo and Gaglianone, 2023; and Botha *et al.*, 2023), its limitations become apparent under more volatile conditions. As Liu *et al.* (2024) note, nonlinear models like RF tend to reduce bias but at the cost of increased variance. This trade-off can lead to overfitting, limiting the model's ability to generalize to unseen data. Indeed, Liu *et al.* (2024) found that RF performed poorly in Japan because inflation was very stable in most of the training dataset, failing to adapt effectively to a subsequent period of higher inflation. A similar dynamic may explain its underperformance in Bolivia's 2024 inflationary rebound.

Annex 4

Table A2
Main variable importance scores per year

Random Forest (RF)					
2022		2023		2024	
Variable	Importance	Variable	Importance	Variable	Importance
Inflation Lag1	0.94	Inflation Lag1	0.941	Inflation Lag1	0.941
FAO Lag3	0.015	FAO Lag3	0.013	FAO Lag3	0.013
Imp Cons Lag12	0.006	FAO Lag6	0.006	FAO Lag6	0.006
Rest	0.039	Rest	0.041	Rest	0.041
XGBoost (XGB)					
2022		2023		2024	
Variable	Importance	Variable	Importance	Variable	Importance
Inflation Lag1	0.802	Inflation Lag1	0.853	Inflation Lag1	0.79
Inf SouthAm Lag3	0.031	FAO Lag3	0.033	Imp Cons Lag12	0.034
Imp Cons Lag12	0.026	Inf SouthAm Lag3	0.018	FAO Lag3	0.022
Rest	0.141	Rest	0.096	Rest	0.154
Random Forest with Non Stationary Variables (RF_NS)					
2022		2023		2024	
Variable	Importance	Variable	Importance	Variable	Importance
Inflation Lag1	0.934	Inflation Lag1	0.933	Inflation Lag1	0.935
FAO Lag3	0.012	FAO Lag3	0.01	FAO Lag3	0.013
M1 Lag3	0.006	M1 Lag6	0.006	Imp Cons Lag12	0.005
M1	0.005	FAO Lag6	0.006	M1 Lag3	0.005
Rest	0.044	Rest	0.046	Rest	0.043
XGBoost with Non Stationary Variables (XGB_NS)					
2022		2023		2024	
Variable	Importance	Variable	Importance	Variable	Importance
Inflation Lag1	0.755	Inflation Lag1	0.773	Inflation Lag1	0.755
M1 Lag3	0.034	M1 Lag6	0.045	FAO Lag3	0.034
M1 Lag6	0.029	FAO Lag3	0.037	M1 Lag6	0.031
Inf SouthAm Lag3	0.029	M1 Lag3	0.02	Inf SouthAm Lag3	0.022
Rest	0.153	Rest	0.125	Rest	0.157

Source: Own elaboration.