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Forecasting Inflation in Nicaragua: Comparative Evidence from Machine Learning and Traditional Econometrics

Carlos Martínez Rivera[1], Jesllyn Torres Bone[2]
[1]Universidad Nacional de Ingeniería UNI; carlos.martinez11me@std.uni.edu.ni; https://orcid.org/0000-0003-1031-256
[2]Universidad Nacional de Ingeniería UNI; jesllyn.torres91me@std.uni.edu.ni; https://orcid.org/0000-0003-1031-2561

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Abstract

The application of Machine Learning (ML) techniques in econometric analysis has expanded considerably in recent years, deepening the discussion on how to forecast key macroeconomic variables such as inflation. In the case of Nicaragua, there is currently no evidence that ML methods have been integrated into inflation forecasting frameworks, despite the variable's central role in monetary policy. This study evaluates the predictive performance of Traditional Econometric (TE) and ML models in forecasting inflation in Nicaragua over the 2006–2024 period. A dataset comprising 20 explanatory variables was constructed, and six models were trained: Multiple Linear regression (LM), ARIMAX, and VAR (TE), together with Elastic Net, Random Forest (RF), and XGBoost; (ML). The results indicate no statistically significant differences in predictive accuracy between both approaches in the short and long term. However, ML models identified meaningful relationships with oil and import prices that were not captured by traditional techniques.

1. Introduction

Inflation is a central variable in central banks' monetary planning, where expected values reflected in their forecasts constitute the main input for decision-making (Svensson, 1997). Because the world is in constant change, generating reliable forecasts remains a continuous challenge for economic policymakers and economic agents alike (Araujo & Gaglianone, 2020).

There is currently a wide range of models for forecasting inflation dynamics, and economists generally choose among four alternatives (Ang, Bekaert, & Wei, 2007): (i) atheoretical statistical methods (e.g., ARIMA variants); (ii) methods grounded in economic fundamentals (e.g., the Phillips curve); (iii) asset-pricing methods (e.g., the interest rate yield curve); and (iv) survey-based methods (e.g., surveys of professionals and consumers to measure expectations).

However, alongside this variety of inflation-forecasting methodologies, an ongoing debate without consensus persists, becoming more complex when considering the growing advantages offered by Machine Learning (ML, hereafter) methods in macroeconomic applications—such as the identification of nonlinear relationships, greater adaptability to large volumes of data, and a pattern-based exploratory approach (Varian, 2014; Araujo & Gaglianone, 2020).

In Nicaragua, existing studies on inflation forecasting propose methodologies based on Traditional Econometrics (TE, hereafter), as shown in Bello (2009) and Castillo-Maldonado & Ortiz-Cardona (2017). Consequently, there is no evidence that ML models are currently used for this purpose. This situation places Nicaragua at a disadvantage relative to regional peers that already apply ML methods, as documented in studies such as Rodríguez-Vargas (2020), Mejía & Ramírez (2022) and Barrios et al. (2021).

In light of emerging trends in the use of machine learning techniques for forecasting economic time series, this study seeks to contribute to the empirical discussion on how to improve the accuracy of inflation estimation. To this end, a comparative analysis is conducted of the performance of two groups of models: those belonging to Traditional Econometrics (TE) and those based on Machine Learning (ML).

Grounded in economic theory and exploratory statistical techniques, a set of 20 explanatory variables was constructed for the period 2006:1–2024:12, on which six predictive models were trained and evaluated: LM, ARIMAX, and VAR from the TE group; and Elastic Net, RF, and XGBoost from the ML group. Model accuracy was assessed using performance metrics and hypothesis tests, with the aim of providing empirical evidence on the relevance of incorporating ML methods into current inflation-forecasting methodologies.

The results show that there are no significant differences in accuracy between ML and TE models, with neither consistently outperforming the other across different forecasting horizons. In a context of limited data, it is expected that ML models may not fully exploit their capacity to capture nonlinear relationships; nevertheless, they succeeded in identifying relevant links between inflation, oil prices, and imports that TE models did not detect. In conclusion, the incorporation of ML models can complement forecasts generated by traditional approaches by enabling better detection of complex relationships and greater adaptability to structural changes. The remainder of the document is organized as follows. After this introduction, Section 2 presents the review of the literature related to the research topic. Section 3 describes the methodological aspects and the data used in the study. Section 4 presents the empirical results and their discussion. Finally, Section 5 concludes.

2. Review of the literature

Inflation is a key macroeconomic indicator due to its impact on economic stability, households' purchasing power, and the design of monetary policy. Its accurate measurement and forecasting are therefore essential for both public authorities and private agents. The literature has addressed this phenomenon through diverse approaches, ranging from Traditional Econometric (TE) models such as the Phillips curve, autoregressive (AR) models, and random walks, to more recent Machine Learning (ML) techniques such as Random Forests, boosting methods, and artificial neural networks.

Although conventional methods have been widely used, their effectiveness has been questioned—particularly regarding the relationship between inflation and unemployment (Atkeson & Ohanian, 2001).

In this context, ML has emerged as a complementary tool by enabling the processing of large volumes of data and the capture of nonlinear relationships, thereby improving predictive performance in emerging economies characterized by volatile inflation and dependence on external shocks (Medeiros et al., 2018; Kohlscheen, 2021; Forte, 2024). Models such as XGBoost and Random Forest have enhanced the accuracy of inflation projections and provided more robust inputs for policy formulation and strategic decision-making in environments of high uncertainty (Namadankh, 2022; Quiguiri, 2023).

2.1 Theorical Determinants of Inflation

The analysis of the determinants of inflation has a long tradition in economic theory. Initially, the seminal work of Phillips (1958) established an inverse relationship between inflation and unemployment, suggesting the existence of a trade-off for policymakers. However, the experience of stagflation in the 1970s called this relationship into question, prompting the incorporation of expectations as a central factor (Friedman, 1968; Muth, 1961). Subsequently, the hybrid Phillips curve developed by Galí & Gertler (1999) consolidated the notion that inflation is determined not only by deviations of output from its potential (the output gap), but also, to a significant extent, by future expectations.

2.1.1 Macroeconomic Factors (Monetary, Supply-Side, and Expectations)

The debate extends to specific transmission mechanisms. The classical monetarist perspective, summarized byFriedman (1968), holds that inflation is essentially, and in the long run, a monetary phenomenon: a growth in the money supply that exceeds output growth inevitably leads to a general increase in prices. This process is transmitted through two main channels: an increase in aggregate demand caused by greater money availability, and the influence of expectations and central bank credibility, where a credible nominal anchor contains inflationary pressures (Galí & Gertler, 1999).

International empirical evidence reinforces the importance of liquidity and monetary aggregates as explanatory and predictive variables. Frain (2003), using a multi-country dataset from the International Monetary Fund (IMF), demonstrated a strong and consistent correlation between the growth rates of monetary aggregates M0, M1, and M2, and long-term average inflation, robust even after removing countries with hyperinflation. The author emphasized that excess money exerts inflationary pressures when not accompanied by a proportional increase in output, highlighting that liquidity control is essential for macroeconomic stability and is a key component in forecasting models and monetary policy formulation.

In contrast, supply shocks—especially those related to energy and food prices—affect inflation through production costs and the prices of tradable goods and inputs (Dornbusch, Fischer, & Startz, 2009). An adverse supply disturbance has an immediate impact on the economy by shifting the aggregate supply curve upward, resulting in a higher overall price level along with a reduction in economic output. Increases in the prices of crucial inputs, such as energy and food, raise firms' production costs, forcing them to raise prices to maintain profit margins. This price increase generates indirect effects, including upward pressure on wages and consequent price rises in other tradable goods and productive sectors, embedding inflation within the economy's cost structure.

Finally, expectations constitute a central channel in inflation dynamics: they determine prices and wages, and the degree to which they are anchored defines inflation persistence (Friedman, 1968; Muth, 1961; Galí & Gertler, 1999). The literature on inflation targeting underscores their relevance for monetary policy design. Key transmission mechanisms include: *(i) the determination of wages and prices, where agents anticipate inflation and adjust their decisions accordingly; and (ii) anchoring, as credible central banks reduce the response of prices and wages to transitory shocks.*

Empirical evidence, such as that of Kohlscheen (2021) and Pizzarro Levi (2021) in Argentina and other contexts, reinforces the importance of this factor in high-inflation environments.

2.1.2 Inflation Factors and Dynamics in Open Economies: The Case of Nicaragua

Within the framework of open economies, the exchange rate plays a crucial role as a transmitter of international price variations to domestic inflation. This relationship is grounded in pass-through theory, which postulates that a depreciation of the national currency directly increases the prices of imported goods. This increase, in turn, is reflected in the Consumer Price Index (CPI), depending on the pricing structure and dynamics—a phenomenon extensively documented in the economic literature, as noted by Goldberg & Knetter (1996).

Mendieta (2017) quantified the pass-through from international commodity price shocks. Using a Bayesian Vector Autoregressive (BVAR) model, the study demonstrated that domestic inflation is highly sensitive to these external shocks. The pass-through of food prices was particularly high, reaching 16.1% over 12 months and 28.4% over 24 months. Oil prices also showed significant, though smaller, pass-through effects of 6.4% over one year. These findings reaffirm the role of imported commodity volatility as a key external determinant.

Monetary policy in Nicaragua, anchored to the exchange rate, has also been studied. Mendieta (2019) analyzed inflation persistence in the country using distributed lag and Markov regime-switching models. The study also assessed the costs of inflation for firms and households, employing the Real Exchange Rate (RER) decomposition for external competitiveness and a general equilibrium model with compensating variation simulations for households. The analysis concluded that households experience greater welfare when inflation is below 7 percent.

As a future research direction and policy recommendation, Mendieta (2019) suggests the need to evaluate a transition toward a more active monetary policy framework, such as inflation targeting, to more effectively anchor medium- and long-term expectations. This regime shift, as suggested by the author, establishes an economic policy framework that underscores the relevance of this research, since expected inflation values reflected in forecasts are the primary input for decision-making under such schemes (Svensson, 1997, as cited in Mendieta, 2019).

Regarding supply shocks, Bello (2013) examines the nonlinear relationship between oil prices and inflation in Nicaragua, using a Smooth Transition Autoregressive (STAR) model on monthly data from 1994:01 to 2011:05. The main conclusion is that the impact of oil shocks is significantly higher under a high-inflation regime than under a low-inflation regime, attributing this asymmetry to greater inflationary uncertainty. This evidence leads the author to highlight the need to strengthen analytical tools for predicting inflation, emphasizing that improving forecast accuracy requires moving beyond traditional models.

2.2 Models Applied to Inflation Forecasting

The literature on inflation forecasting begins with Stock & Watson (1999), who showed that the linear version of the Phillips curve outperformed univariate models in the United States. However, Atkeson & Ohanian (2001) challenged these findings by documenting the "flattening" of the Phillips curve: between 1985 and 2000, changes in unemployment exhibited little relationship with inflation, and naïve models based on past inflation outperformed the Phillips curve in terms of accuracy, as measured by RMSE.

Since then, approaches have been divided between TE based on theoretical relationships, and ML, which extracts patterns directly from the data (Quiguiri, 2023). In this regard, Varian (2014) argues that the growth of datasets and the increasing complexity of economic relationships render methods designed for small samples insufficient, thereby motivating the application of ML in economic research.

In line with this perspective, several studies have proposed using ML instead of TE to generate more accurate inflation forecasts, taking advantage of large datasets and the ability to model nonlinear relationships. Medeiros et al (2018) showed for the United States that incorporating a large number of explanatory variables systematically improves forecast accuracy, with the Random Forest (RF) algorithm achieving the best performance, delivering gains of up to 30% in Mean Squared Error (MSE) relative to benchmark models.

This superiority has been validated across multiple geographies and economic regimes. Araujo & Gaglianone (2020), examining the case of Brazil, found that ML algorithms—particularly RF—outperform traditional models by substantially reducing forecast bias without increasing variance. This robustness extends across different economic regimes: Heeren (2021) compared the performance of ML and TE in a developed economy (the United States) and an emerging one (Mexico), finding that in both contexts ML delivered more accurate results than TE. The best-performing model was RF, while LSTM performed even worse than the random walk (RW).

Beyond accuracy, ML also provides value in uncovering relationships. Kohlscheen (2021) analyzed 20 advanced economies using RF, not only validating its predictive power but also revealing nonlinear empirical relationships, such as the relevance of inflation expectations. This highlights the usefulness of ML for discovering complex relationships between inflation and its explanatory variables. Regarding forecast horizons, Narmandakh (2022), in the case of Mongolia, concluded that ML algorithms—especially XGBoost—excel in medium-term forecasts (two to three quarters ahead), although he emphasized that model combinations yield superior results.

Finally, the inclusion of a broad set of variables remains crucial. Liu, Pan & Xu (2024) showed that adding a large set of variables improves the accuracy of ML models by capturing nonlinear relationships. For Japan, the LASSO model emerged as the most accurate, highlighting the importance of household expectations, inbound tourism, the exchange rate, and the potential output gap in inflation dynamics.

In the case of Nicaragua, studies are more recent and more limited in scope, but they reveal relevant insights into the complexity of local inflation dynamics. Bello (2013), using a STAR model, examined the nonlinear relationship between oil prices and inflation in Nicaragua, finding that this relationship depends on the inflation regime: when inflation is high, the impact of oil prices is greater than in periods of stability. This result provided evidence of the existence of nonlinear and complex relationships between inflation and its determinants.

Regarding the mitigation of price pressures, Treminio (2021) evaluated the effectiveness of reducing the crawling peg rate to contain inflationary pressures in Nicaragua. The study found that this relationship may be conditioned by the output gap and external pressures from international oil and food prices, showing that inflation and the crawling peg rate can move in opposite directions under certain conditions.

From a methodological perspective, Castillo-Maldonado y Ortiz-Cardona (2017) developed the NICA algorithm, a forecast combination scheme that assigns weights across different time horizons based on the historical performance of models within a rolling estimation window. The system draws on five traditional models and explanatory variables such as U.S. inflation, the exchange rate, real supply, and bank credit.

3. Methodological Aspects

Inflation forecasting requires models capable of capturing both traditional linear patterns and the nonlinear complexities of the economy (Kohlscheen, 2021). In this regard, TE models remain a fundamental tool for analyzing well-established structural relationships, while ML methods offer a complementary approach that can process large volumes of data and detect more complex patterns.

3.1 Models

The study compares the predictive accuracy of six models (three based on TE and three based on ML) using the following general forecasting framework:

$$\pi_{t+h} = F(X_t) + \varepsilon_{t+h} \quad (1)$$

Where π_{t+h} denotes inflation in month,

$t+h$, X_t is an n- dimensional vector of covariates- (including lags of inflation and a broad set of predictors), and $F(X_t)$ represents the objective function (of a model or set of models) estimated using a data window of size *T*. Inflation is forecast one to six months ahead *(h ∈ {1,2,…,6})*. Cross-validation is used to select the model with the best performance, employing monthly data starting in January 2006.

3.1.1 Traditional Econometric (TE) Models

These models are selected due to their widespread use and their ability to capture structural relationships and dynamics in time series.

Multiple Linear Regression (LM): Ordinary Least Squares (OLS)

This constitutes the foundation of the LM approach, which estimates the model parameters by minimizing the sum of squared residuals (Woolridge, 2010). It is employed due to its simplicity.

Functional form:

$$\pi_t = \beta_0 + \sum_{i=1}^{k} \beta_i X_{it} + \varepsilon_t \quad (2)$$

Where:

π_t :inflation in period (dependent variable).

X_{it}:explanatory variables.

β_0: intercept or constant of the model.

β_i: coefficients quantifying the effect of each variable.

ε_t : error term.

Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX)

An extension of the ARIMA model that incorporates exogenous variables. It allows capturing trend dynamics, seasonal patterns, and the influence of other economic factors, and it is widely used for inflation forecasting (Martinez et al., 2017).

Functional form:

$$\phi(L)(1-L)^d \pi_t = \theta(L)\varepsilon_t + \sum_{i=1}^{k} \beta_i X_{i,t} \quad (3)$$

Where:

- π_t : inflation in period *t*.
- L: lag operator.
- d: degree of differencing to achieve stationarity.
- $\phi(L) and\ \theta(L)$: polynomials of autoregressive and moving average lags, respectively.
- $X_{i,t}$: exogenous variables influencing inflation.
- ε_t: error term.
- β_i: coefficients quantifying the effect of each variable.

Vector Autoregressive (VAR)

A multivariate tool that characterizes and analyzes the simultaneous interactions among a set of variables, where each endogenous variable is explained by its own lags and the lags of the other variables in the system. Its main advantage is that it avoids the identification problem of the structural model by being estimated in its reduced form (Novales, 2017).

However, VAR models require the estimation of a large number of parameters, which can be a limitation when working with small samples (Rodó, 2019).

Functional form:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \quad (4)$$

Where:

- Y_t: vector of endogenous variables.
- Y_{t-j}: vector of lags of the endogenous

variables up to lag .

- A_i: matrices of lag coefficients.
- ε_t: vector of errors.

3.1.2 Machine Learning (ML) Models

ML is selected for its ability to capture complex nonlinear relationships, handle high-dimensional data, and improve forecast accuracy compared to traditional benchmarks (Medeiros et al., 2018). This flexibility has led to the increasing use of ML techniques in macroeconomic analysis, providing more adaptive and precise tools for studying phenomena such as inflation.

Random Forest (RF)

An ensemble model that builds multiple regression trees in parallel, combining their predictions. Its robustness stems from the incorporation of randomness (bagging and random selection of predictors) to reduce variance and improve the model's generalization ability (Quiguiri, 2023).

In economic applications, Random Forest has proven effective for inflation forecasting. Kohlscheen (2021) compared the performance of traditional regression techniques with ML methods across a broad set of advanced economies. The analysis confirmed the usefulness of this ML technique in explaining inflation patterns, achieving a 28% reduction in Root Mean Squared Error (RMSE) compared to AR(1) and an 8% reduction relative to OLS. Additionally, the study highlighted that inflation expectations and past inflation are the most relevant predictors for the model's performance.

Functional form:

$$\widehat{\pi}_t = \frac{1}{N}\sum_{i=1}^{N} T_i\left(X_t\right) \quad (5)$$

Where:

- π_t: inflation forecast for period.
- X_t: vector of explanatory variables.
- T_i: decision trees trained on random samples and subsets of variables.
- N: total number of trees in the forest.

Elastic Net Regression

A regularization technique that simultaneously combines λ_1 (LASSO) and λ_2 (Ridge) penalties. It is particularly useful when working with a large set of correlated variables, as it performs automatic predictor selection and improves model stability in the presence of multicollinearity (Baladram, 2024; Medeiros et al., 2018).

Functional form:

$$\pi_t = \beta_0 + \sum_{i=1}^{k} \beta_i X_{i,t} + \lambda_1 \sum_{i=1}^{k} |\beta_i| + \lambda_2 \sum_{i=1}^{k} \beta_i^2 \quad (6)$$

Where:

- π_t: in period (dependent variable).
- $X_{i,t}$: explanatory variables.
- β_0: intercept or constant of the model.
- β_i: coefficient of variable .
- λ_1: Lasso (L1) regularization parameter,

promoting variable selection.

- λ_2: Ridge (L2) regularization parameter, reducing the magnitude of coefficients to prevent overfitting.

Extreme Gradient Boosting (XGBoost)

A powerful algorithm based on iterative decision trees. Its main advantage lies in its ability to improve accuracy, efficiency, and scalability compared to other traditional boosting methods. It is effective for inflation forecasting by capturing complex and nonlinear relationships (Namadankh, 2022).

Each decision tree within the XGBoost model is defined by two key elements:

−**Structure q:** Represents the configuration of the tree, i.e., how the data is split at each node.

−**Weights ω:** Values assigned to the leaves of the tree, which determine the final predictions.

The algorithm minimizes a loss function that includes regularization terms to control model complexity and prevent overfitting.

Functional form:

$$\widehat{\pi}_t = \sum_{m=1}^{M} f_m\left(X_t\right), \quad f_m \in \textit{decision trees} \quad (7)$$

Where:

- f_m: inflation forecast for period t.
- $\widehat{\pi}$: vector of features or explanatory variables at t.
- X_t: the m-th decision tree modeling the residuals of the previous ensemble.
- M: total number of trees in the boosting sequence.

3.2 Dataset

The dataset consists of 228 monthly observations covering the period from January 2006 to December 2024. The included macroeconomic variables are drawn from sources such as the Central Bank of Nicaragua (BCN), Nicaraguan Social Security Institute (INSS), National Institute of Development Information (INIDE), Secretariat of the Central American Monetary Council (SECMCA), Food and Agriculture Organization of the United Nations (FAO), Central Bank of Mexico (BANXICO), and Federal Reserve Economic Data (FRED), ensuring access to extensive and detailed time series on inflation and its determinants. Below is a description of the considered macroeconomic variables (see table 1).

Following studies that analyze the transmission of international prices to domestic inflation (FMI, 2018; Choudhri & Hakura, 2001), the external inflation variable was constructed as a weighted average of the month-to-month inflation of the eight main countries of origin for Nicaragua's imports: the United States, China, Mexico, El Salvador, Guatemala, Honduras, Costa Rica, and Panama. Each country was assigned a weight proportional to its share of total imports, aiming to more accurately account for the effect of international prices on domestic inflation.

Table 1: Classification of Variables and Data Sources.

Classification	Variable	Abbreviation	Sources
Inflation (target)	Inflation	cpi	SECMCA
Economic Activity	Monthly Economic Activity Index	imae_orig	SECMCA
Monetary and Exchange Rate	Crawling Exchange Rate	slippage_exchange_rate	SECMCA
Sector Externo	M1 Monetary Aggregate	m1	BCN
	Total Credit (Millions of USD)	total_loans_usd	SECMCA
	WTI Crude Oil Price	oil_price_index	FRED
	Global Food Price Index	food_price_index	FAO
	Global Supply Chain Pressure Index	gscpi	SECMCA
	Remittance Inflows	remittances	SECMCA
	Import Price Index	mpi	BCN
	Export Price Index	xpi	BCN
	Terms of Trade Index	tti	BCN
	External Inflation	ext_inflation	FRED / SECMCA / BANXICO

Note: The abbreviations presented in this table correspond to the nomenclature used in the estimation of each model.

Source: Authors' estimates.

Although these studies do not directly present this methodology, they provide the conceptual basis supporting it: the IMF (2018) emphasizes that the transmission of international price shocks to domestic prices depends on the degree of trade openness and the import structure, while Choudhri & Hakura (2001) show that the sensitivity of local inflation to external prices varies according to each country's structural characteristics. From this perspective, weighting the inflation of trading partners according to their relative share in imports allows for a more realistic capture of the differential effect that each country has on domestic inflation, aligning with the rationale of the aforementioned studies.

3.3 Model Performance Evaluation Metrics

The study aims to conduct a comparative analysis between estimates from TE and ML models, evaluating their predictive performance using metrics that quantify accuracy and fit to observed data, as in Medeiros et al. (2018), Araujo & Gaglianone (2020) and Heeren (2021). Among the accuracy metrics considered are (see table 2).

3.3.1 Calculation of Cumulative Inflation

Cumulative inflation was calculated from the monthly inflation rate using a compound accumulation formula through an iterative approach, which allows for accurately reflecting the cumulative effect of monthly price changes over time.

Table 2: Performance Evaluation Metrics

Indicator	Abbreviation	Calculation Method	Dimension	Scale / Values	Considerations
Mean Absolute Error (Error Absoluto Medio)	MAE	$\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2$	Estimation errors	$(0, \infty)$	Measures the average magnitude of the errors in the same units as the data, regardless of direction.
Root Mean Square Error	RMSE	$\sqrt{\frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{n}}$	Estimation errors	$(0, \infty)$	Used as a training heuristic. The square root mitigates the scale of squared residuals and penalizes large errors.
Mean Absolute Percentage Error	MAPE	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_i - \hat{y}_i\rvert}{y_i}\cdot 100\%$	Estimation errors	$(0, \infty)$	Facilitates accuracy comparison across datasets with heterogeneous scales
Bias	BIAS	$E\left(\hat{\theta}\right) - \theta$	Estimation bias	$(-\infty, \infty)$	Determines error directionality (overestimation vs. underestimation) to identify systematic model bias.
Coefficient of Determination	R^2	$1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2}$	Model fitting	$[0,1]$	Measures the proportion of variance explained by the model. Coefficients close to 1 signify a robust fit.
Theil's U Statistic	Theil_U	$\frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - f_t\right)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n} y_t^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n} f_t^2}}$	Time series comparison	$(0, \infty)$	Assesses relative predictive precision. Values converging to 0 denote higher forecasting accuracy.

Note: For the application of Theil's U, a naïve or simplistic model was estimated, assuming that inflation in period is equal to that in.

Source: Authors' estimates.

Let i_{t+k} be the decimal inflation rate in month t+k. The realized cumulative inflation between month t(start) and t+n (n months later) is calculated as:

$$\text{cumulativeinflation}_{t+n} = \prod_{k=}^{n}(1 + i_{t+k}) - 1 \quad (8)$$

The iterative forecasting method was chosen over the direct method for projecting cumulative inflation at horizons of 3, 6, 9, 12, and 18 months. The rationale for this choice is based on several arguments: (i) The iterative method maintains temporal coherence and model parsimony by deriving long-horizon forecasts from a single short-term model; (ii) It preserves statistical efficiency in contexts with limited sample size; (iii) It is particularly compatible with ML approaches, as these do not require specific hyperparameter tuning to estimate each forecast horizon (Marcellino, Stock, & Watson, 2006; Makridakis, Spiliotis, & Assimakopoulos, 2018)

For the purposes of this study, short-term horizons are considered 1–6 months, medium-term 7–12 months, and long-term over 12 months, as suggested by Makridakis, Spiliotis & Assimakopoulos (2018). The cumulative inflation estimates were calculated for the following horizons: (i) 3 months, (ii) 6 months, (iii) 9 months, (iv) 12 months, and (v) 18 months.

3.4 Statistical Test Diebold-Mariano

The Diebold-Mariano (DM) test compares the predictive accuracy of two forecasting models. It is widely used to assess whether the differences in prediction errors between two models are statistically significant (Diebold, 2012; Camacho & Checo, 2018).

Let be the loss differential between two models, where is a loss function. The DM test requires only that the loss differential be covariance stationary. That is, the DM assumptions are:

$$Assumptions\ DM = \begin{cases} E(d_{12t}) = \mu, \forall t \\ cov(d_{12t}, d_{12(t-\tau)}) = \gamma(\tau), \forall t \\ 0 < var(d_{12t}) = \sigma^2 < \infty \end{cases} \quad (9)$$

$Let d_{12t} = L(e_{1t}) - L(e_{2t})$ be the loss differential between two models, where $L(.)$ is a loss function. The DM test requires only that the loss differential be covariance stationary. That is, the DM assumptions are:

The key null hypothesis of equal predictive accuracy (i.e., equal expected loss) is $E(d_{12t}) = 0$.Under the maintained DM assumption:

$$DM_{12} = \frac{\bar{d}_{12}}{\hat{\sigma}_{\bar{d}_{12}}} \rightarrow N\left(0,1\right), \quad (10)$$

where $\bar{d}_{12} = \sum_{t=1}^{T} d_{12t}$ is the sample mean of the loss differential, and $\hat{\sigma}_{\bar{d}_{12}}$ is a consistent estimate of the standard deviation of $\bar{d}_{12}$.

4. Results

4.1 Properties of the series

Using the Augmented Dickey–Fuller (ADF) test, the presence of unit roots was confirmed in the variables when expressed in levels.

Therefore, to ensure stationarity, the series were transformed using logarithmic differences and first differences, depending on the nature of each variable.

This procedure guarantees stability in the estimations, particularly those generated from traditional econometric models (Heeren, 2021; Singh & Bhoi, 2022; Camacho & Checo, 2018; Mejía & Ramírez, 2022).

Table 3: Stationarity of the Series

Variable	P-Value (levels)	Transformation	P-Value (transformed)	Stationarity conclusion
CPI	0.9066	Logarithmic differences	Below 0.0100	Significant at 5%
slippage_exchange_rate	0.9888	First differences	Below 0.0100	Significant at 5%
oil_price_wti	0.2756	Logarithmic differences	Below 0.0100	Significant at 5%
food_price_index	0.1001	Logarithmic differences	Below 0.0100	Significant at 5%
imae_orig	0.4418	Logarithmic differences	Below 0.0100	Significant at 5%
gscpi	0.3946	First differences	Below 0.0100	Significant at 5%
total_loans_usd	0.2494	Logarithmic differences	0.0641	Significant at 10%
xpi	0.9612	Logarithmic differences	Below 0.0100	Significant at 5%
mpi	0.3474	Logarithmic differences	Below 0.0100	Significant at 5%
tti	0.5691	Logarithmic differences	Below 0.0100	Significant at 5%
remittances	0.9900	Logarithmic differences	Below 0.0100	Significant at 5%
m1	0.9900	Logarithmic differences	Below 0.0100	Significant at 5%
ext_inflation	Below 0.0100	None	Below 0.0100	Significant at 5%

Note: The null hypothesis indicates that the series contains a unit root. The statistical tests included an intercept and a linear trend.

Source: Authors' estimates.

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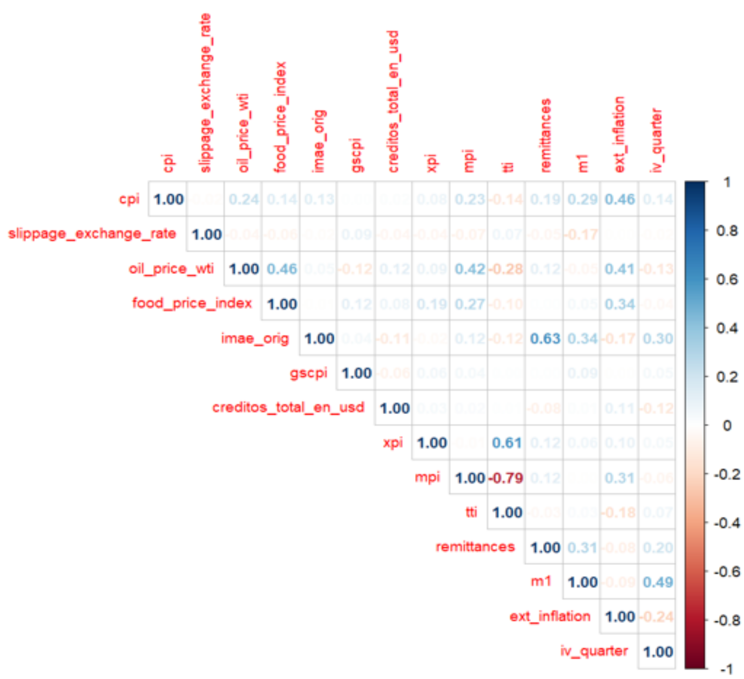
4.2 Exploratory Analysis

In the first row of the correlation matrix (Figure No. 1), the main associations identified in the exploratory analysis are presented. External inflation (0.48) and the monetary aggregate M1 (0.29) stand out for exhibiting a moderate positive linear relationship with domestic inflation.

This finding is consistent with the economic literature, as inflation in Nicaragua's main trading partners, as well as the level of liquidity in the economy, may exert upward pressure on domestic inflation dynamics. Mendieta (2017), argues that external inflation is one of the medium-term determinants of inflation in Nicaragua. Similarly, Frain (2003) documents strong positive correlations between monetary aggregates (such as M1) and inflation, even in low-inflation environments.

According to Mendieta (2017), inflation in Nicaragua is a phenomenon that is highly sensitive to external factors, such as international food prices and oil prices. Contrary to expectations, a weak positive correlation is observed between domestic inflation and changes in the price of WTI crude oil, as well as with the international food price index. Although this result appears unusual, it is necessary to consider the possible existence

Figure 1: Correlation Plot of the Variable Set



Note: The values represent the correlation coefficients between the variables corresponding to each cell intersection.

Source: Authors' estimates.

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of non-linear relationships between inflation and both variables, which could generate low correlation coefficients, as evidenced by Bello (2013), in the case of inflation and oil prices. With respect to the remaining variables of interest, inflation exhibits weak linear relationships; therefore, these variables are not expected to play a significant role in model variable selection unless non-linear patterns are identified, a feature that is characteristic of machine learning models. The fact that correlations among the explanatory variables are generally weak represents an advantage, as it suggests low levels of multicollinearity and the absence of potentially redundant variables (Gujarati & Porter, 2010). However, an exception is observed among the terms of trade index (TTI), import prices (MPI), and export prices (XPI), where a strong and economically expected correlation is present . This result suggests that including all three variables within the same model could lead to severe multicollinearity.

The autocorrelation (ACF) and partial autocorrelation (PACF) functions of monthly inflation suggest the presence of an AR(1) process in the series (Figure A5). This result aligns with Araujo & Gaglianone (2020) who indicate that developing and emerging countries typically exhibit a certain degree of inflation persistence, as evidenced in the case of Brazil. Therefore, it was necessary to include a one-period lag of monthly inflation in the dataset.

Additionally, the cross-correlation plots identified significant intertemporal relationships between inflation and some explanatory variables, leading to the inclusion of the following variables in the training sample (Figure A6).

- Food Price Index: 1-month lag
- External Inflation: 1-month lag
- Monetary Aggregate M1: 12-month lag

Similarly, a binary variable was added for observations corresponding to the fourth quarter of each year to capture the expected seasonality during these periods, as observed in the monthplot (Figure A4).

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4.3 Model Training and Variable Selection

For the traditional econometric models, an automatic variable selection procedure based on the Akaike Information Criterion (AIC) was implemented, with the aim of identifying the combination of regressors that offered the best balance between explanatory power and parsimony in the linear regression models. In contrast, machine learning models incorporate internal variable selection mechanisms, the nature of which depends on the structure of each algorithm (Varian, 2014). For the latter group of models, it was necessary to apply a normalization process to the variables based on the mean and standard deviation calculated in the training sample; these parameters were subsequently used to normalize the observations in the test set.

In the multiple linear regression (LM) model, the variables suggested by the selection algorithm were used; however, two variables—**oil_price_wti** and **m1_lag12**—were excluded because they were not significant at the 5% level and their inclusion reduced the statistical significance of the remaining regressors. These variables were also omitted in the other traditional econometric models.

For the ARIMAX model, the variable **cpi_lag1** was not included to avoid potential distortions in the automatic selection of autoregressive (AR) and moving average (MA) components. The procedure resulted in the specification of an ARIMA (0,0,1) model with three exogenous variables: (i) subprime crisis, (ii) remittances, and (iii) external inflation.

In the VAR model, the optimal number of lags was determined to be 1. Monthly inflation and the monthly change in M1 were classified as endogenous variables, while the same exogenous variables used in the ARIMAX model were included. The characteristic roots obtained (0.268 and 0.044) fell within the unit circle, confirming the stability of the estimated system.

For the Elastic Net model, the optimal penalty parameter (λ) was 0.0016, and the mixing parameter (α) was 0.1, implying a weighting of 90% Ridge penalty and 10% Lasso penalty. This procedure led to the automatic selection of 12 variables from a total of 19 initially considered. The estimated coefficients highlighted greater sensitivity to external inflation and one-period lagged domestic inflation, which together explained 54.7% of the variability.

In the Random Forest and XGBoost models, all available variables were included, although only those that collectively explained at least 80% of inflation variability were highlighted. Both models underwent hyperparameter tuning. For Random Forest, the optimal mtry value was 8, while for the XGBoost model, the optimal parameters were: (i) nrounds = 500, (ii) max_depth = 3, (iii) eta = 0.1, (iv) gamma = 0, (v) colsample_bytree = 0.8, (vi) min_child_weight = 1, and (vii) subsample = 0.6.

Table 4: Explanatory variables selected for each model.

Group	Selected predictor variables	Models					
		LM	ARIMAX	VAR	ELASTIC NET	RANDOM FOREST (82.0%)	XGBOOST (80.9%)
Monetary and/or exchange rate	slippage_exchange_rate						
	m1	✓	✓	✓	✓	✓	✓
	total_loans_usd						
International context	oil_price_wti				✓	✓	✓
	food_price_index						✓
	gscpi						✓
	xpi				✓		✓
	mpi				✓	✓	✓
	tti						
	remittances	✓	✓	✓	✓		
	ext_inflation	✓	✓	✓	✓	✓	✓
Production	imae_orig						
Dummy variables	subprime_crisis	✓	✓	✓	✓		
	iv_quarter	✓			✓		
	months					✓	
Lags	cpi_lag1	✓		✓	✓	✓	✓
	food_price_index_lag1				✓		
	ext_inflation_lag1				✓	✓	✓
	m1_lag1			✓			
	m1_lag12				✓	✓	✓

Note: The table shows the explanatory variables selected by each model from the total set of variables.

Source: Authors' estimates.

4.4 Model Performance Evaluation

4.4.1 Performance Metrics

The model with the best fit on the testing sample was Random Forest. This finding aligns with Kohlscheen (2021), Heeren (2021), Araujo y Gaglianone (2020) y Medeiros et al (2018), who also identified this model as one of the most powerful due to its predictive ability for forecasting inflation.

Random Forest exhibited the lowest MAE and RMSE, indicating that the model successfully captures the underlying trend of monthly inflation. It also achieved the highest goodness-of-fit according to the R^2 coefficient, showing that it best explains the variability of the series. Additionally, it presented the lowest Theil's U coefficient, supporting the idea that Random Forest outperforms a naive model that assumes next month's inflation equals the previous month's.

Elastic Net ranked second in terms of MAE and RMSE but first according to MAPE. It is the model with the lowest BIAS (closest to zero) and the second-best performance in R^2 and Theil's U metrics. Both models belong to the Machine Learning group and outperform the traditional

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econometric models LM, ARIMAX, and VAR. Among the traditional models, LM stands out across all available metrics. Confidence intervals were constructed for the ET models using standard deviations at a 95% level, whereas ML models required bootstrapping techniques to capture the 2.5% and 97.5% percentiles of the iterations.

This resulted in confidence intervals of very different widths, with ET models showing wider ranges. To standardize the estimates, the average interval size across all models was divided by 2 and then added and subtracted from each model's point forecast as a measure to mitigate differences in interval calculation and ensure comparability (Makridakis, Spiliotis, & Assimakopoulos, 2018). The resulting value was 0.745%, producing projections with a confidence level of 83.7% .

Although Random Forest demonstrated the best performance, it is necessary to verify whether the differences in model accuracy are statistically significant. For this purpose, the Diebold-Mariano tests were applied.

4.4.2 Diebold-Mariano Tests

The results of the tests indicate a general tie among the performance of all models, as none of the tests rejected the null hypothesis at the 5% significance level. According to the estimates, it can only be stated that Random Forest is statistically better than ARIMAX, VAR, and XGBoost at a 10% significance level.

Therefore, in the short term, there is no clear winner among the models. Although Random Forest shows the best evaluation metrics, it could be matched by the LM or Elastic Net models, since the differences in performance are not statistically significant.

Table 5: Model performance metrics on the testing sample.

Models	MAE	RMSE	MAPE	BIAS	R2	Theil_U
LM	0.0044	0.0053	136.74	-0.0001	0.1312	0.8015
ARIMAX	0.0045	0.0054	142.53	0.0000	0.1101	0.8124
VAR	0.0046	0.0057	137.19	-0.0003	0.1004	0.8555
ElasticNet	0.0040	0.0051	123.29	0.0000	0.1417	0.7699
RandomFores	0.0040	0.0050	127.92	-0.0003	0.1925	0.7488
XGBoost	0.0047	0.0060	138.06	-0.0008	0.1324	0.9097

Note: Lower values of MAE, RMSE, MAPE, BIAS, and Theil-U indicate higher accuracy; higher R^2 values reflect better fit.

Source: Authors' estimates.

Table 6: Diebold-Mariano Test p-values

	LM	ARIMAX	VAR	ELASTIC NET	RANDOM FOREST	XGBOOST
LM	1	0.6978	0.2955	0.2477	0.1392	0.2626
ARIMAX		1	0.2236	0.1208	0.0875	0.3055
VAR			1	0.1091	0.0579	0.5114
ELASTIC_NET				1	0.5369	0.1970
RANDOM_FOREST					1	0.0891
XGBOOST						1

Note: The null hypothesis suggests that the forecasts are not statistically different. If the null hypothesis is rejected, the performance of one model is significantly better or worse than the other. If it is not rejected, the models are tied.

Source: Authors' estimates.

4.4.3 Forecasts Across Different Time Horizons

The results reveal clear distinctions starting from the three-month horizon and a significant reordering of forecasts based on MAE performance. However, there is no consistent dominance of one type of model over another across all forecast horizons.

Short-term (1 to 6 months): The Elastic Net and Linear Model (LM) models exhibit the best fit, with an average forecast error of 0.70% at 3 months and 0.94% at 6 months. Initially, they are tied with the Random Forest and ARIMAX models, but by the six-month horizon, both outperform these models with a statistically significant difference at the 5% level (p-value = 0.0435). In this horizon, there remains a tie between ET and ML models.

1. Medium-term (7 to 12 months): The LM model emerges as the best performer at the 9- and 12-month horizons, showing significant differences compared to the second-best models. Contrary to expectations, the average error decreases at the 12-month horizon, a pattern observed across all models. In this evaluation period, ET models take the lead in terms of accuracy. The maximum average error reached 0.98% for the LM model in the medium term, compared to 0.93% in 6 months, indicating only a slight increase.
2. Long-term (over 12 months): At the 18-month forecast horizon, the average error rises across all models, resulting once again in a statistical tie in model ranking, with the LM and XGBoost models leading. This is the first time XGBoost has appeared among the top-performing models. The average error increases to 1.26% for LM, which has remained the model with the lowest error since the 6-month horizon.

These findings differ from Medeiros et al. (2018), Singh & Bhoi (2022) y Namadankh

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(2022), who report consistently superior performance of ML models compared to ET models across all forecast horizons. They also contrast with Makridakis, Spiliotis & Assimakopoulos (2018) who found that ET models outperformed ML models in both the short and long term.

Conversely, the strong short-term performance of the Elastic Net aligns with Liu, Pan & Xu (2024) who reported similar results with the Lasso model (a special case of Elastic Net) in Japan. Likewise, the consistent tie in predictive accuracy across models aligns with Iftikhar et al. (2025) who found no significant differences in model performance under the Diebold-Mariano test in their inflation forecasts Overall, the results demonstrate that ET models maintain relevance and utility across different forecast horizons, while ML models offer greater flexibility, which can be advantageous in highly dynamic scenarios (Alomani, Kayid, & Abdel-Aal, 2025).

Table 7: Model Performance Across Different Time Horizons.

Order	Model	3-month horizon	
		MAE	DM Test
1	ElasticNet	0.0068	0.8509
2	LM	0.0070	0.4295
3	RandomForest	0.0073	0.0789
4	ARIMAX	0.0080	0.0164
5	VAR	0.0091	0.9622
6	XGBOOST	0.0091	
	Average MAE of TE models	0.0080	
	Average MAE of ML models	0.0077	
		0.0250	

		Order	Model	6-month horizon	
				MAE	DM Test
ET	6	1	LM	0.0093	0.2979
ML	6	2	ElasticNet	0.0094	0.0435
ML	6	3	RandomForest	0.0103	0.2878
ET	6	4	ARIMAX	0.0108	0.2234
ML	6	5	XGBOOST	0.0128	0.5994
ET	6	6	VAR	0.0130	
			Average MAE of TE models	0.0111	
			Average MAE of ML models	0.0108	
				0.0300	

Order	Model	9-month horizon	
		MAE	DM Test
1	LM	0.0098	0.0304
2	ElasticNet	0.0108	0.5806
3	RandomForest	0.0108	0.0404
4	ARIMAX	0.0124	0.6022
5	XGBOOST	0.0130	0.8130
6	VAR	0.0133	
	Average MAE of TE models	0.0118	
	Average MAE of ML models	0.0115	
		0.0300	

Order	Model	12-month horizon	
		MAE	DM Test
1	LM	0.0078	0.0286
2	VAR	0.0090	0.0303
3	RandomForest	0.0107	0.7998
4	ElasticNet	0.0108	0.0592
5	ARIMAX	0.0114	0.8144
6	XGBOOST	0.0115	
	Average MAE of TE models	0.0094	
	Average MAE of ML models	0.0110	
		0.0300	

Order	Model	18-month horizon	
		MAE	DM Test
1	LM	0.0126	0.2368
2	XGBOOST	0.0136	0.2644
3	VAR	0.0144	0.8978
4	RandomForest	0.0159	0.5199
5	ElasticNet	0.0167	0.1439
6	ARIMAX	0.0181	
	Average MAE of TE models	0.0150	
	Average MAE of ML models	0.0154	
		0.0300	

Note: The "DM Test" column shows the p-value of the Diebold-Mariano test between each forecast and the immediately next-ranked model. For example, in the 3-month forecast, the DM test does not reject the null hypothesis between the LM and Elastic Net models, with a probability of 85.09%.

Source: Authors' estimates.

5. Conclusions

The possibility of incorporating machine learning (ML) models into inflation forecasting methodologies in Nicaragua was analyzed, aiming to capture complex relationships that traditional econometric (ET) models fail to adequately reflect. Currently, there is no evidence of ML models being used for this purpose in the country, despite the importance of inflation in the strategic planning of the Central Bank. To evaluate this possibility, forecasts were generated using six statistical models—three ET and three ML—with the goal of determining whether ML approaches improve the accuracy of estimates compared to traditional methods.

The evaluation of forecast performance shows that there are no statistically significant differences between ET and ML models, both in the short and long term. Diebold-Mariano tests suggest a generalized tie between the two groups, with LM and Elastic Net models tending to show better fit, although without consistent superiority over the others. This finding is supported by the verification of assumptions in parametric models and the adequate optimization of parameters in ML models, lending statistical robustness to the results.

In the variable selection process, ML models identified significant relationships between inflation and both oil prices and import prices, whereas ET models considered these effects negligible, to the point of excluding them from their estimations. This finding aligns with Bello (2013), who documented a nonlinear relationship between Nicaraguan inflation and oil prices.

Although there is no clear dominance of one group of models over the other, the evidence suggests that combining traditional techniques with machine learning can enrich current forecasting methodologies. As Forte (2024), points out, the incorporation of ML models represents a methodology that is easier to implement, requires less preprocessing of variables, allows greater flexibility regarding assumption compliance, and enhances the capacity to identify nonlinear patterns.

The absence of statistically significant differences between ML and ET models could be attributed to the limited size of the datasets available in Nicaragua. The literature notes that ML methods require large volumes of data to fully exploit their ability to model nonlinear relationships (James et al., 2021). In contexts with more limited information, traditional parametric approaches, such as the LM model, tend to provide more stable and parsimonious estimates (Coulumbe et al., 2019). Applied studies on inflation forecasting in advanced economies indicate that the advantages of ML mainly emerge in environments with abundant predictors and extensive observations (Medeiros et al., 2019).

Looking ahead, the research agenda and discussion on inflation estimation methodologies remain extensive. First, the analysis could be expanded by including other

ET models, such as the vector error correction (VEC) model, and additional ML approaches, such as neural networks or deep learning. It is also essential to develop robust methodologies for estimating expected values of explanatory variables used in multivariate inflation models. Furthermore, dummy variables such as splines could be included in the training dataset to capture hidden trends, or Fourier series could be employed to track complex seasonality. Another aspect to consider is the application of robustness checks during the training stage using sophisticated sampling techniques, such as cross-validation.

6. References

Alomani, G., Kayid, M., & Abdel-Aal, M. (2025). Global inflation forecasting and Uncertainty Assessment: Comparing ARIMA with advanced machine learning. *Journal of Radiation Research and Applied Sciences*,18, (2)

Ang, A., Bekaert, G., & Wei, M. (2007). Do macro variables, asset markets, or surveys forecast inflation better? *Journal of Monetary Economics 54,* 1163-1212.

Araujo, G., & Gaglianone, W. (2020). *Machine learning methods for inflation forecasting in Brazil: new contenders versus classical models.* Banco Central do Brasil (BCB).

Atkeson, A., & Ohanian, L. (2001). Are Phillips Curves Useful for Forecasting Inflation? Federal Reserve Bank of Minneapolis. *Quaterly Review 25*, (1) 12-11.

Baladram, S. (2024). *Lasso and Elastic Net Regressions, Explained: A Visual Guide with Code Examples. towards data science*.

Barrios, J. J., Escobar, J., Leslie, J., Martin, L., & Peña, W. (2021). *Nowcasting para predecir actividad económica en tiempo real: los casos de Belice y El Salvador [Nowcasting to predict economic activity in real time: The cases of Belize and El Salvador]*. Publications Inter-American Devolpment Bank (IDB).

Bello, O. (2009). *Combinación de Pronósticos de Inflación de Nicaragua [Combination of inflation forecasts for Nicaragua].* (Working Paper No. DT-011). Central Bank of Nicaragua (CBN).

Bello, O. (2013). *Relación no lineal entre el precio del petróleo e inflación en Nicaragua [Non-linear relationship between oil price and inflation in Nicaragua].* (Working Paper No. DT-029). Central Bank of Nicaragua (CBN).

Breiman, L. (2001). Random Forests. Kluwer Academic Publishers. *Machine Learning Vol.* 45, 5-32.

Camacho, F., & Checo, A. (2018). *Evolución del poder predictivo de los modelos de inflación: Teoría versus Desempeño [Evolution of the predictive power of inflation models: Theory vs. performance].* (Working Paper No. DT 2018-01). Central Bank of the Dominican Republic.

Castillo-Maldonado, C., & Ortiz-Cardona, E. (2017). *The nicaraguan inflation combination assessment (Nica): A forecast combination system through an efficient forecast path.* (Working Paper No. DT-060) Central Bank of Nicaragua (CBN).

Choudhri, E. U., & Hakura, D. S. (2001). *Exchange Rate Pass-Through to Domestic Prices: Does the Inflationary Enviroment Matter? International Monetary Fund (IMF).*

Coulombe, P., Leroux, M., Stevanovic, D., & Surprenant, S. (2019). *How is Machine Learning Useful for Macroeconomic Forecasting?* Université du Québec à

Montréal.

De Grauwe, P., & Polan, M. (2001). *DP2841 Is Inflation Always and Everywhere a Monetary Phenomenon? CEPR Press,* Paris & London.: CEPR Discussion Paper No. 2841.

Diebold, F. (2012). *Comparing predictive accuracy, twenty years later: a personal perspective on the use and abuse of diebold-mariano tests.* National Bureu of Economic Research.

Dornbusch, R., Fischer, S., & Startz, R. (2009). *Macroeconomía.* DF, México: The MacGraw-Hill.

FMI. (2018*). Challenges to Steady Growth. International Monetary Fund.*

Forte, F. D. (2024). *Pronóstico de inflación de corto plazo en Argentina con modelos Random Forest*. Argentina: BBVA Research.

Frain, J. (2003). *Inflation and Money Growth: Evidence form a Multi-Country Data-Set.* Central Bank and Financial Services Authority of Ireland.

Friedman, M. (1968). The role of monetary policy. *The American Economic Review* 58 (1) 1-17.

Galí, J., & Gertler, M. (1999). Inflation dynamics: A structural econometric analysis. *Journal of Monetary Economics,* 195-222.

Goldberg, P. K., & Knetter, M. M. (1996). *Good prices and exchange rates: what have we learned?* National Bureau of Economic Research.

Gujarati, D., & Porter, D. (2010). *Basic Econometrics.* McGraw-Hill.

Hamilton, J. D. (2000). *Inflación óptima en Nicaragua [Optimal inflation in Nicaragua].* National Bureau of Economic Research.

Heeren, S. (2021). *Forecasting Inflation using Machine Learning for an Emerging Economy. Rotterdam, Países Bajos:* Erasmus University of Rotterdam.

Iftikhar, H., Khan, F., Canas, P., Atiah, A., & Allohibi, J. (2025). *Forecasting of Inflation Based on Univariate and Multivariate Time Series Models: An Empirical Application. Mathematics.*

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An Introduction to Statistical Learning with Applications* in R. Springer.

Johnson, R. A., & Wichern, D. W. (2007). Applied multivariate statistical analysis (6th ed.). . Pearson.

Kohlscheen, E. (2021). *What does machine learning say about the drivers of inflation?* Basilea, Suiza: BIS Working Paper no. 980.

Kutner, M. J., Nachtsheim, C. J., Neter, J., & Li, W. (2005). A*pplied Linear Statical Models.* McGraw-Hill.

Liu, Y., Pan, R., & Xu, R. (2024). *Mending the Crystal Ball: Enhanced Inflation Forecasts with Machine Learning.* Japón: IMF Working Paper.

Ljung, G. M., & Box, G. E. (1978). *On a Measure of Lack of Fit in Time Series Models.* Biometrika.

Lopez, F., & Zea, J. F. (2021). *Análisis de Anomalías con R. RPubs by studio.*

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). *Statistical and Machine Learning forecasting methods: Concerns and ways forward.* PLoS ONE.

Marcellino, M., Stock, J., & Watson, M. (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics, 135. 499-526* https://doi.org/10.1016/j.jeconom.2005.07.020

Martinez Orozco, M. A., Guzman Aguilar, D. S., Pérez Ramírez, F. O., & Marí Rodrígues, N. J. (2017). ARIMAX-EGARCH quantitative model for prediction of the

Colombian exchange rate (COP/USD). *Revista Espacios*.

McDonald, B. (2002). A Teaching Note on Cook's Distance - A Guideline. *Research Letters in the Information and Mathematical Sciences. 3.*

Medeiros, M., Veiga, Á., Vasconcelos, G., & Zilberman, E. (2018). *Forecasting inflation in a Data-Rich Environment: The Benefits of Machine Learning Methods*. Brasil: Pontifical Catholic University of Rio de Janeiro.

Mejía, M., & Ramírez, N. (2022). *Precisión del pronóstico de la inflación subyacente en el contexto del Covid-19. [Accuracy of core inflation forecasting in the context of Covid-19].* (Working Paper No. DT 2022-03) Central Bank of the Dominican Republic.

Mendieta, W. (2017). *Un análisis de sensibilidad macroeconómica para Nicaragua: Un enfoque Bayesiano [A macroeconomic sensitivity analysis for Nicaragua: A Bayesian approach].* (Working Paper No. DT-53) Central Bank of Nicaragua (CBN).

Mendieta, W. (2019). *Inflación óptima en Nicaragua* [Optimal inflation in Nicaragua]. Central Bank of Nicaragua (CBN).

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica.* https://doi.org/10.2307/1909635.

Namadankh, B. (2022). I*nflation forecasting with ML methods: A case of Mongolia.* t: Universidad de Tokyo.

Noble, J. (n.d.). *¿Qué es la autocorrelación? [What is autocorrelation?*]. Retrieved from IBM. https://www.ibm.com/es-es/think/topics/autocorrelation

Novales, A. (2017). *Modelos vectoriales regresivos [Vector regressive models].* Madrid: Complutense University of Madrid.

Perez Lopez, C. (2011). *Econometría Avanzada: Técnicas y herramientas [Advanced econometrics: Techniques and tools].* Madrid, España: IBERGACETA PUBLICACIONES, S.L.

Phillips, W. (1958). The Relationship between Unemployment and the Rate of Change of Money Wages in the United Kingdom 1861-1957. *Economica, 25* (100), 283-299.

Pizarro Levi, E. G. (2021). *Determinantes de la inflación: un análisis del caso argentino a través del Filtro de Kalman 2004 - 2020 [Determinants of inflation: An analysis of the Argentine case through the Kalman Filter].* Central Bank of the Republic of Argentina.

Quiguiri, C. (2023). *Contrastando el Machine Learning y la Econometría en series temporales.* Quito: Escuela Politécnica Nacional.

Rodó, P. (2019, July 31). *Economipedia. Retrieved from Modelo VAR:* https://economipedia.com/definiciones/modelo-var.html

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

Singh, N., & Bhoi, B. (2022). Inflation Forecasting in India: Are Machine Learning Techniques Useful? *Reserve Bank of India Occasional Papers, 43,* (2).

Stock, J., & Watson, M. (1999). Forecasting Inflation. *Journal of Monetary Economics 44,* 293-335.

Svensson, L. (1997). Inflation forecast targetting: Implementing and monitoring inflation targets. *European Economic Review 41*, 1111-1146.

Treminio, J. (2021). *Reducciones del deslizamiento cambiario y la inflación doméstica en Nicaragua* [Reductions in the exchange rate crawl and domestic inflation in Nicaragua]. (Working Paper No. DT-080) Central Bank of Nicaragua (CBN).

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

Woolridge, J. (2010). *Introducción a la econometría: Un enfoque moderno.* México, D.F.: Cengage Learning, Inc.

Appendices

Table A1: Literature Review: Comparative Performance of ML and ET in Inflation Forecasting

Year	Author	Abstract	Conclusions	Country
2018	Medeiros et al. (2018)	High-dimensional study (>100 variables) evaluating whether ML systematically improves inflation forecast-ing accuracy relative to tradi-tional models.	ML systematically improved accu-racy. Random Forest was the best performer, achieving the highest reduction in MSE. Its superiority is due to robust variable selection and capturing non-linear relationships.	USA
2020	Araujo y Gaglianone (2020)	Evaluates the use of ML algorithms to project inflation in an emerging economy with high volatility, comparing its performance across different time horizons.	The superiority of ML is corroborated, with Random Forest as the dominant model. It achieves a considerable reduction in prediction bias while keeping variance under control.	Brasil (Emerging Economy)
2021	Heeren (2021)	Replicates and expands the study by Medeiros et al. by adding BART and LSTM models, comparing ML performance against Econometric Techniques (ET).	ML methods showed more precise results than ET. Random Forest was the best predictive model. LSTM performed poorly, suggesting not all ML techniques are suitable for macroeconomic time series.	USA and Mexico
2021	Kohlscheen (2021)	Analyzed 20 advanced economies using RF, validating its predictive capacity and revealing non-linear empirical relationships (e.g., relevance of inflationary expectations).	ML demonstrated good predictive performance. ML RMSE systematically outperformed econometric benchmarks (28% reduction vs AR(1)). Highlights the role of inflation expectations.	20 Advanced Countries
2022	Narmandakh (2022)	Compares 4 ML algorithms with 2 ET models in recursive out-of-sample forecasts, focused on a small economy with frequent external shocks and limited data.	ML models dominate inflation forecasts in the medium term. XGBoost showed the best overall performance. ML is a superior alternative for short and medium-term forecasting.	Mongolia (Emerging Economy)
2024	Liu, Pan y Xu (2024)	Evaluates if the addition of a large number of variables and ML methods could improve forecast accuracy, especially in the post-pandemic context.	Two ML models outperformed ET. The LASSO model was the most accurate. Highlights the importance of variable selection (household expectations, tourism, exchange rates) in periods of uncertainty.	Japan (Post-Pandemic)

Note: Summary of key empirical findings contrasting the predictive superiority of ML models over ET in inflation forecasting across various economies.

Source: Authors' estimates.

Table A2: Comparative Review of Empirical Literature on Inflation Forecasting in Nicaragua

Year	Author	Abstract	Conclusions
2013	Bello (2013)	This study investigates the existence of a non-linear relationship between oil price fluctuations and inflation in Nicaragua. It utilizes the STAR Model, which allows the impact of oil to change smoothly depending on the "regime" of domestic inflation.	The impact of oil on inflation depends on the inflation state. In a low-inflation regime, the impact is nearly 2.5 times lower than in a high-inflation regime. It suggests prioritizing anchoring expectations during high-inflation periods.
2017	Castillo-Maldonado y Ortiz-Cardona (2017)	The paper proposes the NICA algorithm to generate accurate forecasts for Nicaraguan inflation. NICA combines forecasts from a family of base models (ARMA, VAR, VEC, OLS, SWLS) using a dynamic weighting system and an endogenous trimming process.	The NICA algorithm proved to be consistently superior to simpler forecast combination methods. It is strongly recommended that this tool be adopted by the Central Bank of Nicaragua to strengthen its forecasting capacity.
2021	Treminio (2021)	This study evaluates the effectiveness of the crawling peg reduction policy (applied in 1993, 1999, 2004, and 2019) to contain domestic inflation. It uses an impact evaluation regression model controlling for exogenous factors like the output gap and oil prices.	The crawling peg reduction policy is highly effective: reductions prior to 2019 decreased inflation by 0.78 percentage points for every one-point drop in the crawl. The 2019 reduction was projected to lower year-on-year inflation by 2 percentage points.

Note: Summary of key empirical findings in Nicaragua contrasting the predictive superiority of ML models over ET in inflation forecasting.

Source: Authors' estimates.

Table A3: Optimal Values of Regularization Parameters for ML Models

Parameter	Model	Description	Interpretation
λ = 0.0016	Elastic Net	Penalty parameter that regulates the magnitude of coefficients. Small values indicate mild penalization.	"A very low λ was obtained, implying the model retains most relevant variables, barely shrinking coefficient magnitudes. "
α = 0.1	Elastic Net	Combines ridge (L2) and lasso (L1) penalties. α=0.1 implies 90% ridge and 10% lasso.	"The model favored retaining correlated variables (ridge effect), reducing only some of lesser importance (lasso effect). "
mtry = 8	Random Forest	Number of variables randomly considered at each split.	"With 8 predictors per split, the model balances diversity among trees and predictive power, favoring key variable capture in inflation. "

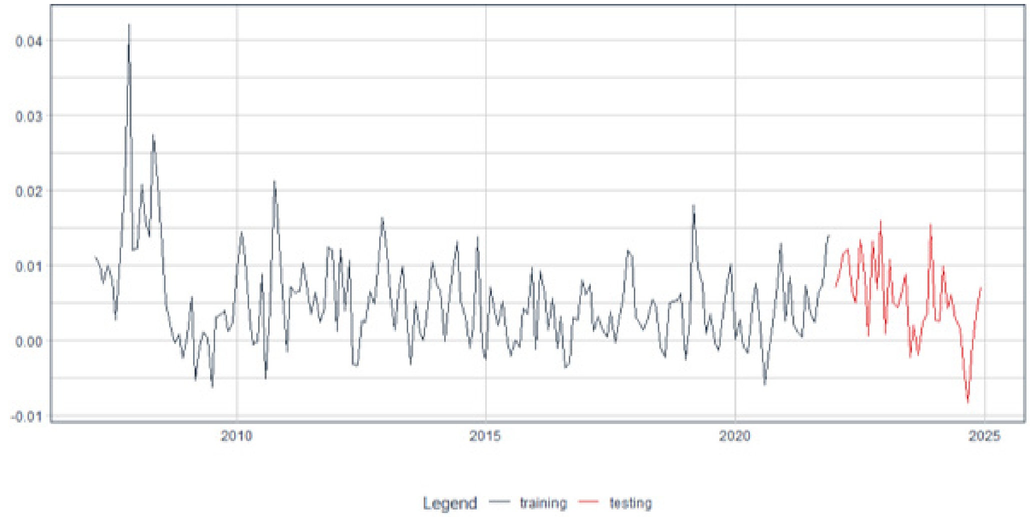
nrounds = 500	XGBoost	Number of iterations (trees) in the boosting process.	"The model trained 500 trees, allowing it to capture complex patterns while controlling overfitting with η=0.1 and subsample=0.6. "
max_depth = 3	XGBoost	Maximum depth of each tree.	"Shallow trees limit complexity and help generalization, avoiding overfitting in noisy macroeconomic series. "
eta = 0.1	XGBoost	Learning rate.	"Gradual, conservative learning allows the model to adjust stably over 500 iterations. "
gamma = 0	XGBoost	Minimum loss reduction required to split a node.	"With gamma=0, the model allows splits whenever they improve the loss function, increasing split flexibility. "
colsample_bytree = 0.8	XGBoost	Proportion of variables used in each tree.	"Each tree trained with 80% of predictors, introducing randomness that reduces correlation among trees and improves robustness. "
min_child_weight = 1	XGBoost	Minimum sum of instance weight needed in a child.	"Low value allows splits even with few observations, increasing fine-tuning ability to the data. "
subsample = 0.6	XGBoost	Proportion of observations used in each iteration.	"Each tree trained with 60% of the sample, reducing overfitting risk and improving generalization.

Note: The optimal values were estimated using the Grid Search method.

Source: Authors' estimates.

https://doi.org/10.62407/cvpevd47

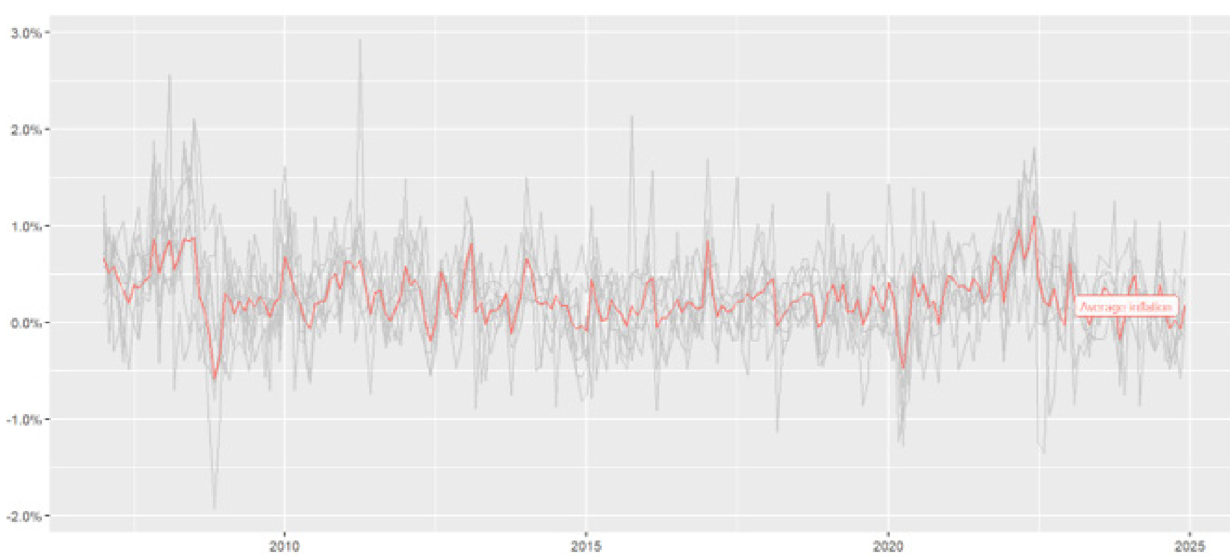
Figure A1: Monthly Inflation (2006-2024) - Training and Testing series



Note: Partition of the inflation data into training and testing sets.

Source: Authors' estimates.

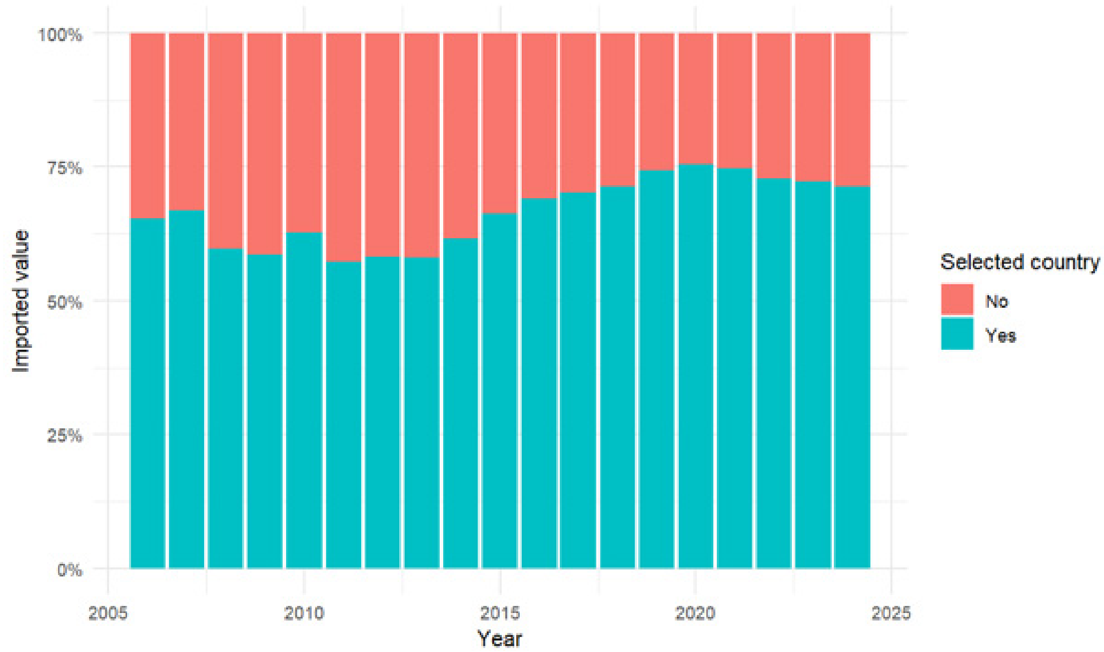
Figure A2: External Monthly Inflation



Note: Weighted average monthly inflation of the eight main trading partners based on the origin of imports.

Source: Authors' estimates.

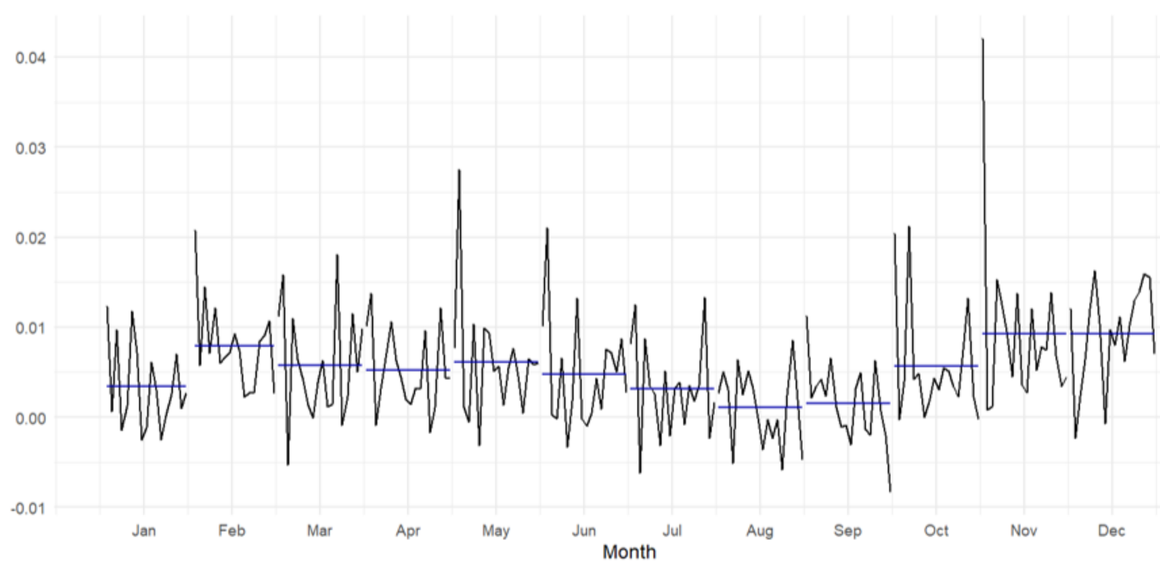
Figure A3: Share of the eight main importing countries in total imports.



Note: The top 8 countries account for approximately 75% of the value of imports over the last five years.

Source: Authors' estimates.

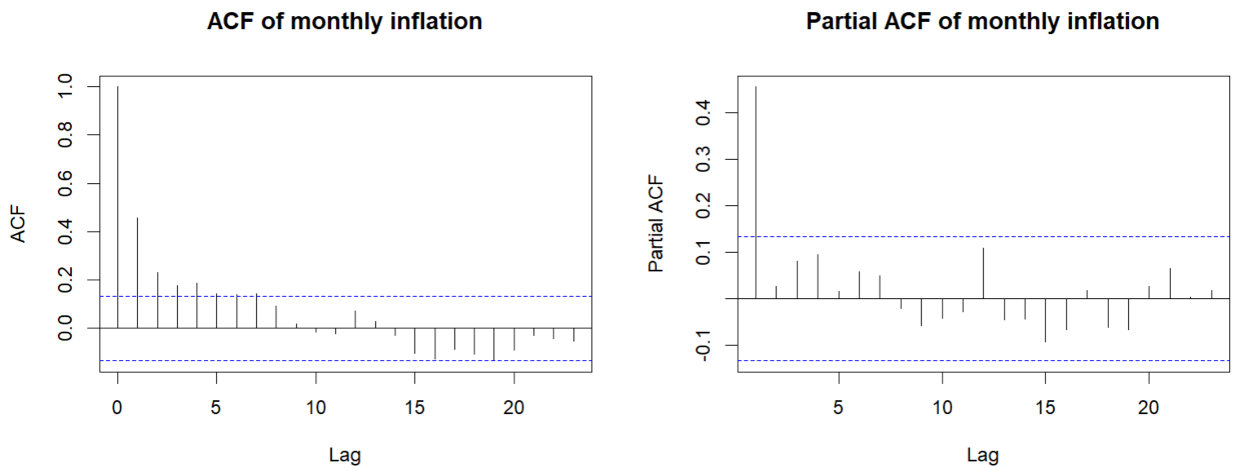
Figure A4: Monthplot of Monthly Inflation



Note: The horizontal blue lines represent the average monthly inflation across all years for each month.

Source: Authors' estimates.

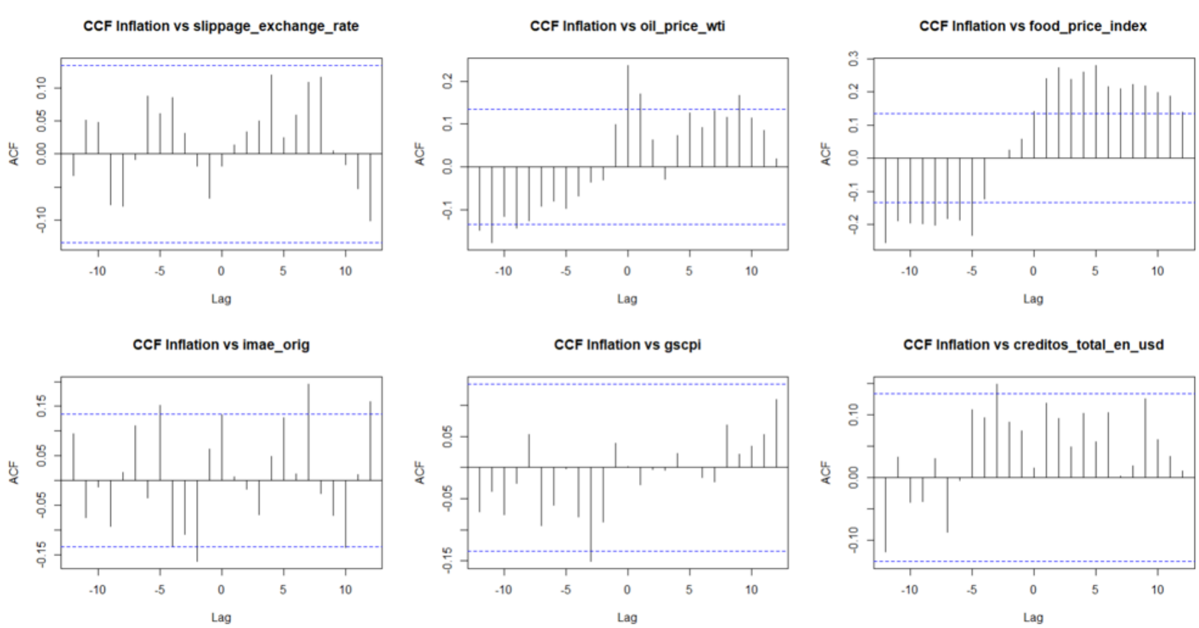
Figure A5: Autocorrelation of monthly inflation



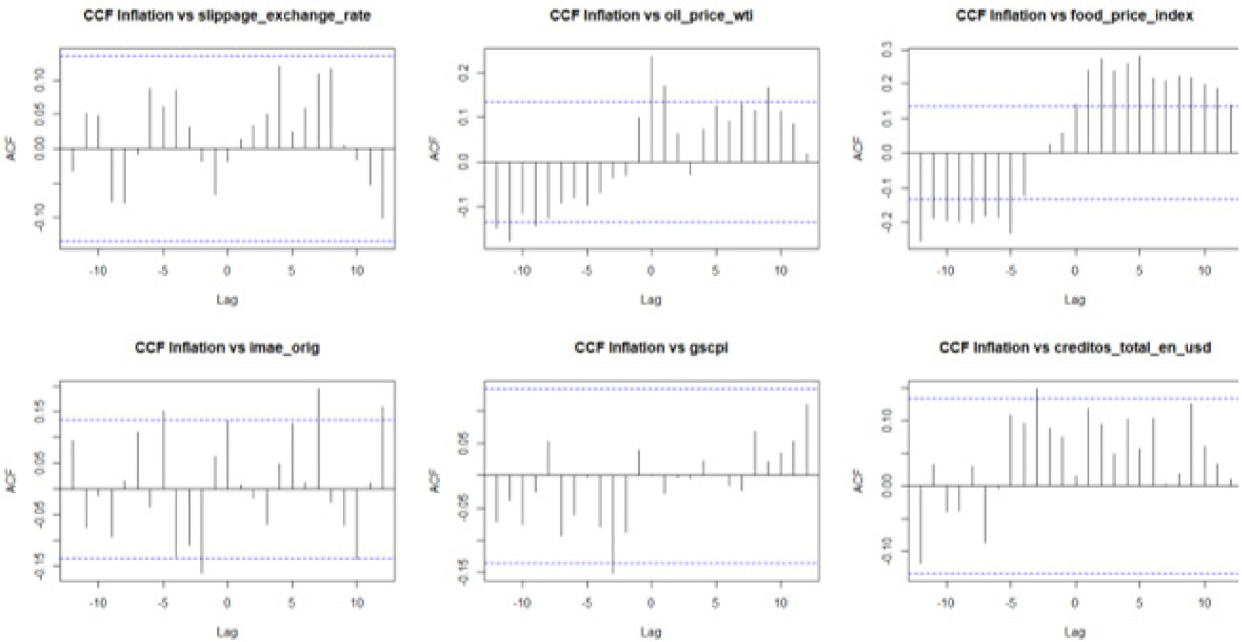
Note: Monthly inflation follows an AR(1) process, indicating significant temporal dependence, where the current value linearly depends on the previous month's value plus a white noise error term. This suggests the presence of short-term inflation persistence or inertia.

Source: Authors' estimates.

Figure A6: Cross-correlations



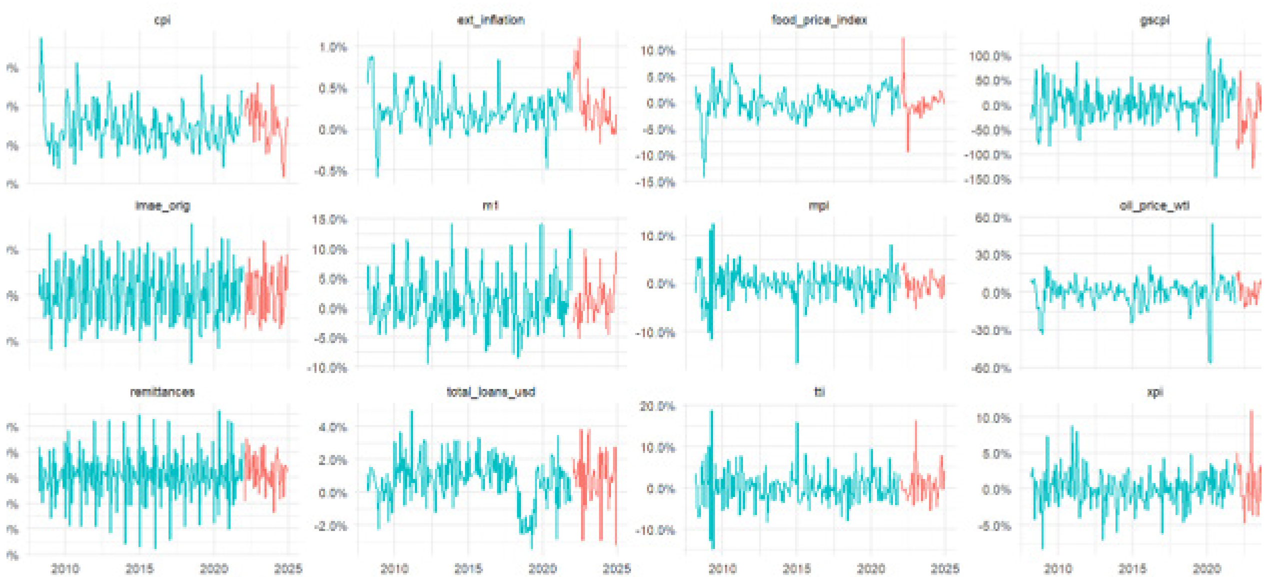
https://doi.org/10.62407/cvpevd47



Note: Cross-correlations were calculated to evaluate the dynamic relationship between the series, considering different lags and leads. High values indicate temporal dependence between the variables.

Source: Authors' estimates.

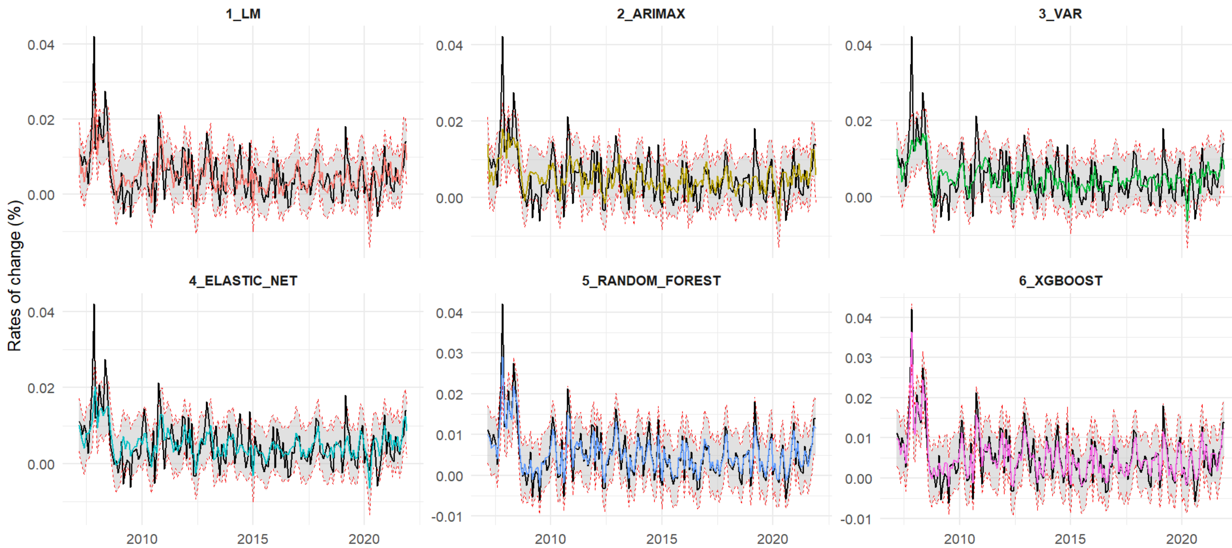
Figure A7: Time series of the variable set



Note: The confidence intervals were standardized using the average size of the intervals originally constructed through parametric estimates (ET models) and bootstrapping (ML models).

Source: Authors' estimates.

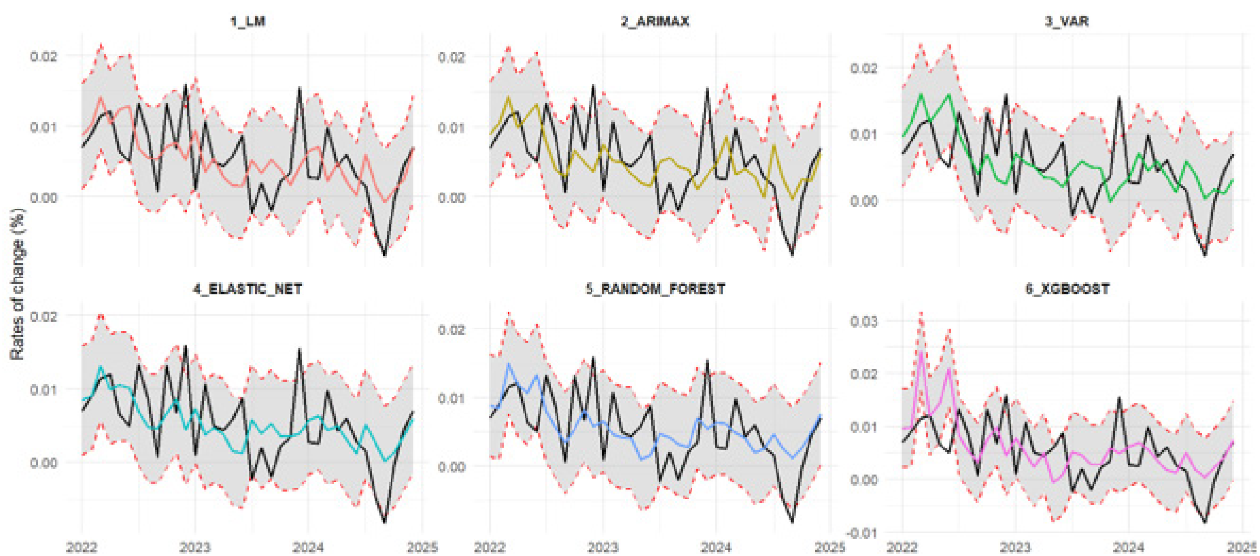
Figure A8: In-sample forecasts of Nicaragua's monthly inflation



Note: The confidence intervals were standardized using the average size of the intervals originally constructed through parametric estimates (ET models) and bootstrapping (ML models).

Source: Authors' estimates.

Figure A9: Out-of-sample forecasts of Nicaragua's monthly inflation

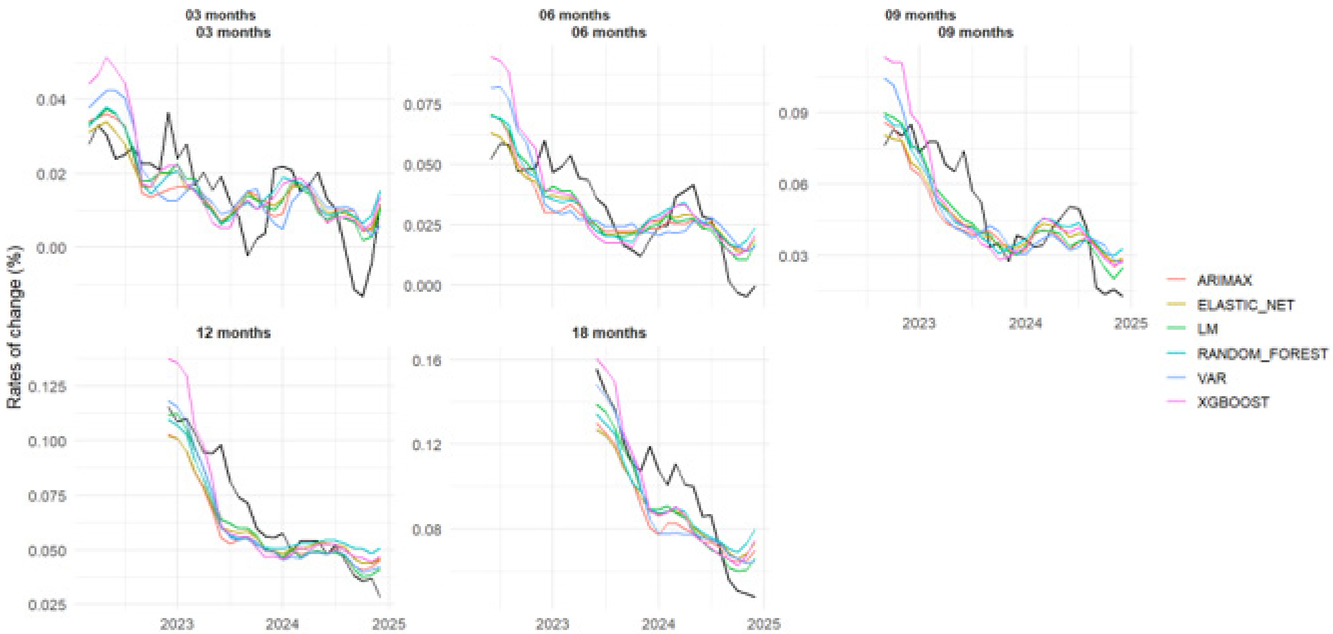


Note: The confidence intervals were standardized using the average size of the intervals originally constructed through parametric estimates (ET models) and bootstrapping (ML models).

Source: Authors' estimates.

https://doi.org/10.62407/cvpevd47

Figure A10: Out-of-sample forecasts at Different Time Horizons



Source: Authors' estimates.

Table A4: Model Performance Metrics Across Different Time Horizons.

3-month horizon

Models	MAE	RMSE	MAPE	BIAS	R2
LM	0.0070	0.0085	130.47	-0.0002	0.4974
ARIMAX	0.0080	0.0098	153.30	0.0002	0.3514
VAR	0.0091	0.0111	165.03	-0.0010	0.2969
ElasticNet	0.0068	0.0086	141.83	0.0001	0.4845
RandomFore	0.0073	0.0089	145.80	-0.0009	0.4551
XGBoost	0.0091	0.0111	139.77	-0.0025	0.4148

6-month horizon

Models	MAE	RMSE	MAPE	BIAS	R2
LM	0.0093	0.0107	259.71	0.0007	0.6736
ARIMAX	0.0108	0.0131	312.92	0.0018	0.5192
VAR	0.0130	0.0152	275.52	- 0.0006	0.4503
ElasticNet	0.0094	0.0113	291.81	0.0013	0.6565
RandomFore	0.0103	0.0124	345.03	- 0.0002	0.5635
XGBoost	0.0128	0.0161	306.09	- 0.0030	0.5262

9-month horizon

Models	MAE	RMSE	MAPE	BIAS	R2
LM	0.0098	0.0116	25.00	0.0034	0.7565
ARIMAX	0.0124	0.0150	32.38	0.0056	0.6182
VAR	0.0133	0.0159	35.02	0.0027	0.5610
ElasticNet	0.0108	0.0132	30.03	0.0041	0.7174
RandomFore	0.0108	0.0134	31.74	0.0023	0.6562
XGBoost	0.0130	0.0162	32.08	-0.0007	0.6251

12-month horizon

Models	MAE	RMSE	MAPE	BIAS	R2
LM	0.0078	0.0107	11.74	0.0057	0.8773
ARIMAX	0.0114	0.0151	16.59	0.0087	0.8025
VAR	0.0090	0.0123	13.90	0.0059	0.8252
ElasticNet	0.0108	0.0137	16.33	0.0065	0.8321
RandomFore	0.0107	0.0139	18.20	0.0043	0.7489
XGBoost	0.0115	0.0147	17.70	0.0011	0.7533

18-month horizon

Models	MAE	RMSE	MAPE	BIAS	R2
LM	0.0126	0.0146	14.18	0.0079	0.8656
ARIMAX	0.0181	0.0199	19.72	0.0115	0.7838
VAR	0.0144	0.0178	16.87	0.0073	0.7310
ElasticNet	0.0167	0.0181	19.05	0.0087	0.8506
RandomFore	0.0159	0.0175	19.41	0.0061	0.7955
XGBoost	0.0136	0.0158	16.47	0.0026	0.7629

Note: Lower values of MAE, RMSE, MAPE, and BIAS indicate higher accuracy; higher R^2 values reflect better fit.

Source: Authors' estimates.