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Data-Driven Decision Support for Central Bank Operations: Machine Learning and Structural Break Analysis for Inflation Forecasting — A Bolivian Case Study (1980–2026)

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Abstract

Central banks in emerging economies routinely face a hard problem: how to forecast inflation when the underlying regime is shifting under their feet. Recurrent policy shocks, currency stress, and administered-price interventions make the parameters of any single model unstable, and the operational cost of getting the forecast wrong is high. This paper proposes an integrated, data-driven decision-support framework that combines three complementary techniques—structural break detection, Lasso regularization for feature selection, and ARIMAX modeling with identifiable policy dummies—to forecast monthly inflation in Bolivia. Using a monthly dataset that spans March 1980 to May 2026 (555 observations), we apply the Bai–Perron, CUSUM/CUSUMSQ, and Chow tests to identify structural regime changes; a Lasso model with time-based cross-validation to distill the most informative predictors from a candidate pool of 27 variables; and an ARIMAX(1,0,1) model with two policy dummies—one for the fuel subsidy period and one for the fixed-exchange-rate regime—to quantify how much specific policy interventions contribute to inflation dynamics. The results confirm that the 1985–1986 post-hyperinflation stabilization is the dominant structural break in the series (Bai–Perron BIC-selected break; Chow $F = 212.5$), while the August 2004 introduction of the fuel subsidy emerges as a statistically significant break in its own right (Chow $F = 23.8$, $p < 0.0001$), which empirically justifies modeling it explicitly. The Lasso singles out a monetary differential factor and international reserves as the most robust linear predictors, and the ARIMAX finds that the fuel subsidy period is associated with an additional 0.28 percentage points of monthly inflation ($p = 0.023$). It also delivers, to our knowledge, the first quantitative estimate of the parallel-market exchange-rate pass-through for Bolivia: 1.32 percentage points per boliviano of depreciation ($p = 0.009$). Together, these outputs provide a reproducible and interpretable pipeline that monetary authorities can use to track inflation drivers when regimes shift.

Keywords

Inflation forecasting; Structural breaks; Lasso regularization; ARIMAX; Central bank decision support.

1. Introduction

Producing timely and accurate inflation forecasts is a core operational task for any central bank. In economies exposed to recurrent policy shocks, currency stress, and administered-price interventions, however, the task goes beyond point forecasting. Analysts also need to identify which structural regime the economy is currently in, and to trace observed inflation back to the specific policy or macroeconomic drivers that are producing it (Bok et al. 2018; Cipollone, 2024). Traditional linear econometric models—ARIMA, ARIMAX, and vector autoregressions—assume parameters that remain stable over the estimation window. That assumption tends to fail precisely in the economies where these models are needed most: those with hyperinflation episodes, long-lived subsidy periods, and abrupt liberalizations. Machine learning methods have emerged as a natural complement, since they can accommodate high-dimensional predictor sets and non-linear relationships (Mullainathan and Spiess, 2017; Medeiros et al., 2021; Goulet Coulombe et al., 2022). Yet most of the machine learning literature on inflation forecasting has been built around advanced

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economies with stable regimes, and its deployment as an operational decision-support tool in structurally unstable emerging economies remains largely unexplored.

Bolivia offers a natural case study for this problem. Within a single sample, its monthly inflation series contains the most severe hyperinflation episode in South American history (peaking at 182.8% monthly in February 1985), a forty-year post-stabilization regime, a twenty-one-year fuel subsidy period (August 2004 to November 2025), a fourteen-year fixed-exchange-rate regime (November 2011 to November 2025), and an extraordinary policy transition beginning in 2025 with the elimination of the fuel subsidy (Supreme Decree 5503, November 2025) and the liberalization of the exchange rate (December 2025). These events span virtually every category of shock that an emerging-economy central bank might have to monitor: hyperinflation stabilization, administered-price reform, currency crisis, and monetary regime change (Aliaga and Terrazas 2025; Aliaga Lordemann and Bhattacharyya 2026).

This paper develops and applies a data-driven decision-support framework that combines three complementary techniques: (i) structural break detection to identify regime changes endogenously, (ii) Lasso regularization to select the most informative predictors from a broad candidate set, and (iii) ARIMAX modeling with identifiable policy dummies to quantify the marginal contribution of specific interventions. Rather than relying on a single model, the framework is designed to answer three operational questions at once—questions that are of interest to any monetary authority operating in a structurally unstable environment: when did the regime change, which variables matter, and how much do specific policies contribute to observed inflation. The analytical products it generates could serve as a technical input for an emerging-market central bank aiming to monitor the drivers of inflation and take informed policy decisions under regime shifts.

1.1 Objectives

The research pursues four specific objectives. First, to identify statistically significant structural breaks in the monthly inflation series of Bolivia between March 1980 and December 2024, using the Bai–Perron, CUSUM/CUSUMSQ, and Chow tests. Second, to select the most parsimonious and predictive set of macroeconomic variables through Lasso regularization applied to a candidate pool of 27 predictors. Third, to estimate an ARIMAX(1,0,1) model with policy dummies for the fuel subsidy and the fixed-exchange-rate regime, and to quantify the marginal effect of each policy on monthly inflation. Fourth, to integrate the three approaches into a reproducible decision-support pipeline that a monetary authority can use to attribute observed inflation to structural, macroeconomic, and policy factors.

2. Literature Review

The literature relevant to this research draws on four bodies of work: structural break testing, regularized regression for macroeconomic forecasting, ARIMAX modeling, and the more recent wave of machine learning applications to inflation forecasting in emerging economies.

Structural break testing rests on a well-established foundation. Chow (1960) introduced the classical test for a single known break point, and Bai and Perron (1998) generalized it to allow for multiple unknown breaks selected through information criteria. The CUSUM and CUSUM-of-squares tests, complementary tools for detecting parameter instability, have been used extensively in monetary policy applications. Perron (2006) offers a comprehensive review of structural break inference and its role in macroeconomic forecasting. In emerging economies, structural breaks are frequently tied to policy interventions, currency crises, and regime shifts, which makes their detection a prerequisite for meaningful parameter estimation rather than a purely diagnostic step.

The Lasso, introduced by Tibshirani (1996) and extended in Hastie et al. (2015), has become a standard tool for variable selection in high-dimensional settings. Within macroeconomic forecasting, Bai and Ng (2008) showed that targeted predictors selected through regularization can outperform factor-augmented models on standard benchmarks. Medeiros et al. (2021) demonstrated that machine learning methods, including Lasso and Random Forest, outperform traditional econometric models for U.S. inflation forecasting in a data-rich environment. Goulet Coulombe et al. (2022) provided a broad benchmarking exercise across machine learning methods for macroeconomic forecasting and found consistent gains from regularization and non-linear methods. Araujo and Gaglianone (2023) applied a suite of machine learning methods to Brazilian inflation forecasting, with results that reinforce the value of regularized methods in Latin American contexts.

ARIMAX models, following the Box and Jenkins (1976) tradition, remain the workhorse of applied inflation forecasting, thanks to their interpretability and their ability to accommodate exogenous covariates. Hamilton (1994) provides the standard reference. Central bank applications of ARIMAX with policy dummies are common; recent

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examples in Latin America include Cáceres (2016) for Bolivia and Banco Central de Bolivia (2019) for GDP forecasting with dynamic factor models. The tension between the interpretability of ARIMAX and the predictive power of machine learning has motivated hybrid approaches that try to combine both perspectives (Masini et al. 2023). Machine learning applications for Bolivia are still emerging. Bolivar (2024) developed a machine learning nowcasting framework for the Bolivian GDP index using remote-sensing data, reducing the publication lag from six to two months. Bolivar (2025) extended this line of work to high-frequency inflation forecasting using a two-step Ridge–Lasso pipeline, showing that daily and weekly inflation predictions can be statistically indistinguishable from monthly official releases. Ramos (2023) applied logistic regression, random forests, and XGBoost to recession prediction for Bolivia, identifying industrial electricity consumption, monetary aggregates, and fiscal indicators as leading predictors. Aliaga and Terrazas (2025) and Aliaga Lordemann and Bhattacharyya (2026) examined the macroeconomic implications of the Bolivian fuel-subsidy elimination, providing the policy context for the present study.

Fuel subsidies and oil price shocks have received substantial attention in the macroeconomic literature. Hamilton (1983, 2003) documented the systematic association between oil price shocks and recessions in the United States, while Blanchard and Galí (2007) examined how this macroeconomic response has changed over time. Kilian (2009) disentangled demand-side from supply-side shocks. Coady et al. (2017, 2019) quantified the global scale of fuel subsidies and their fiscal implications, estimating them at more than 6% of world GDP once environmental externalities are included. Coady et al. (2006) provided an early comparative analysis of fuel subsidies in Bolivia, Ghana, Jordan, Mali, and Sri Lanka. Bhattacharyya (2024) developed a transmission model for fuel-importing economies that is directly relevant to Bolivia's situation.

In sum, the literature offers separate methodological toolkits—structural break tests, Lasso, ARIMAX, machine learning—and separate empirical studies for Bolivia (Bolivar 2024, 2025; Ramos 2023; Aliaga and Terrazas 2025). What is missing is an integrated framework that combines these tools as a coherent decision-support system for central bank operations, applied to a case in which structural breaks, policy dummies, and predictor selection all interact within the same forecasting exercise. This paper aims to fill that gap.

3. Methods

The framework proceeds in three sequential steps: (i) structural break detection to characterize regime changes in the inflation series; (ii) Lasso feature selection to identify the most robust linear predictors from a broad candidate set; and (iii) ARIMAX estimation with identifiable policy dummies to quantify the marginal contribution of specific policies. Each step yields both a stand-alone diagnostic and an input for the next stage. All analyses are performed in Python 3.12, using statsmodels for structural breaks and ARIMAX and scikit-learn for Lasso, which ensures full reproducibility.

3.1 Structural Break Detection

Three complementary tests are applied to the monthly inflation series (denoted π_t): the Bai–Perron test with BIC-based selection of the number of breaks; the CUSUM and CUSUM-of-squares tests, which visualize the cumulative instability of parameters; and the Chow test, applied to six policy-relevant candidate dates—the post-hyperinflation stabilization (August 1985), the Bai–Perron optimum (February 1986), the introduction of the fuel subsidy (August 2004), the failed subsidy withdrawal (December 2010), the fixed-exchange-rate regime (November 2011), and the terminal currency shortage (September 2023). The Chow test statistic is defined as

$$F = [(RSS_r - RSS_1 - RSS_2) / k] / [(RSS_1 + RSS_2) / (n - 2k)]$$

where RSS_r is the restricted residual sum of squares, RSS_1 and RSS_2 are the subsample residual sums of squares, k is the number of parameters, and n is the total sample size. Triangulating across the three tests provides robust evidence of regime changes.

3.2 Lasso Regularization for Feature Selection

The Lasso (Tibshirani 1996) solves the regularized least-squares problem

$$\beta_{Lasso} = \text{argmin}_\beta \{ (1/2n) \Sigma_i (y_i - x_i'\beta)^2 + \lambda \Sigma_j |\beta_j| \}$$

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where the L1 penalty $\lambda \geq 0$ controls the sparsity of the coefficient vector. As λ increases, more coefficients are shrunk to exactly zero, providing embedded variable selection. In this paper, the Lasso is applied to a candidate pool of 27 monthly predictors that cover monetary aggregates, exchange rates, international reserves, and activity indicators.

A key design decision concerns the temporal window over which the Lasso is fitted. The Lasso is evaluated from April 2008 onward because this is the point in time from which records are simultaneously available for all 27 candidate variables in the high-frequency block—weekly monetary aggregates, regional exchange-rate series, activity indicators, and international commodity prices, among others. Before 2008, many of these variables were not published at monthly frequency for the Bolivian case or simply did not exist, which would make it impossible to use them jointly in a variable-selection model. The methodological strategy of the study is therefore sequential: first, the variables with the greatest predictive weight are identified through Lasso on the broad candidate set of the recent period (2008–2024); then, once the economically most relevant variables that also have extended historical records have been selected, the analysis reaches further back to March 1980—the earliest date for which continuous monthly data are available for the key macroeconomic variables that enter the ARIMAX (inflation, international reserves, parallel-market exchange rate, diesel price, and the traditional monetary block). This strategy combines the best of both horizons: the informational richness of the contemporary period for variable selection, and the historical depth of the extended period for estimating structural coefficients with identifiable policy dummies.

To respect the temporal structure of the data, we use a time-based split of the sample: cross-validation on the April 2008 to December 2021 window (165 observations) to select λ, an external validation set from January 2022 to December 2024 (36 observations) to confirm the chosen λ, and a test set from January 2025 to May 2026 (17 observations) to evaluate out-of-sample performance. This split preserves the causal ordering of the data and prevents information leakage from the future. Predictors are standardized using training-only statistics, and the monetary block is compressed via PCA into two orthogonal factors (PC1, PC2) fitted on the training window.

One methodologically important limitation of this step is that policy dummies defined after 2021—specifically, a high-inflation dummy starting in September 2023 and a fuel-shock dummy starting in December 2025—cannot be identified within this temporal split, because they are constant at zero over the entire cross-validation window on which the Lasso is fitted. This limitation is intrinsic to the regularization approach: a variable with zero variance in the fitting sample cannot receive a non-zero coefficient. The dummies are therefore retained conceptually for later stages of the framework, where they can be identified.

3.3 ARIMAX with Policy Dummies

To identify the effects of the fuel subsidy and the fixed-exchange-rate regime, we estimate an ARIMAX(1,0,1) model over the extended sample from February 1986 to December 2024 (466 observations). This window excludes the hyperinflation period, in line with the Bai–Perron result, but retains enough pre- and post-subsidy observations for identification. The model specification is

$$\pi_t = c + \varphi\, \pi_{\{t-1\}} + \theta\, \varepsilon_{\{t-1\}} + \gamma' X_t + \varepsilon_t$$

where π_t is monthly inflation and X_t is a vector of exogenous covariates that includes the fuel subsidy dummy ($D_{subsidio}$ = 1 for August 2004 to November 2025), the fixed-exchange-rate dummy (D_{TC_fijo} = 1 for November 2011 to November 2025), the first difference of international reserves (d_{rin}), the first difference of the parallel-market exchange rate (d_{tcpar}), the lagged first difference of the diesel price (d_{diesel_lag1}), the second principal component of the monetary block ($PC2_{mon}$), and the one-month lag of inflation ($infl_{lag1}$). The ARIMAX order (p=1, d=0, q=1) is selected through a grid search over $p \in \{0,\ldots,4\}$ and $q \in \{0,\ldots,4\}$, using BIC as the selection criterion. Estimation is by maximum likelihood, and standard errors are computed under the standard Gaussian assumption.

The dummies are constructed so as to be fully identifiable over the estimation window: $D_{subsidio}$ has 245 months in state 1 and 221 months in state 0 within February 1986 to December 2024; D_{TC_fijo} has 158 months in state 1 and 308 months in state 0. This identifiability is what allows the ARIMAX to succeed where the Lasso cannot: the dummies are variables with meaningful variance in the fitting sample.

4. Data Collection

The dataset consists of 555 monthly observations spanning March 1980 to May 2026 for Bolivia. The dependent variable is monthly inflation, expressed as a percentage and computed as $\pi_t = (IPC_t / IPC_{\{t-1\}} - 1) \times 100$, where IPC_t

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is the official Consumer Price Index published by the Instituto Nacional de Estadística (INE). The predictor set includes five macroeconomic series: (i) international reserves in millions of U.S. dollars (RIN), published by the Central Bank of Bolivia; (ii) the monetary base, deposits, and credit series that form the monetary block; (iii) the parallel-market exchange rate in bolivianos per U.S. dollar; and (iv) the domestic diesel price in bolivianos per liter. Where appropriate, the series are transformed into first differences (d_{rin}, d_{tcpar}, d_{diesel}) to ensure stationarity, which is verified using the Augmented Dickey–Fuller test (Dickey and Fuller 1979).

A methodological challenge is that the diesel price was frozen at roughly 3.72 bolivianos per liter throughout the twenty-one-year subsidy period (August 2004 to November 2025), and no records exist for the January 1980 to July 1985 interval. The pre-1985 gap is filled through backward imputation, using the first available value (0.13 bolivianos in August 1985), and the constancy during the subsidy period is retained as observed data. Only 18 unique values of the diesel price exist across the 555 observations, which limits the identification of its coefficient but does not prevent estimation, because the extended sample still includes nineteen pre-subsidy years of genuine price variation.

The monetary block is compressed through principal component analysis to avoid multicollinearity. The PCA is fitted exclusively on the February 1986 to December 2024 estimation window, using log first differences (approximate growth rates) of the monetary base, deposits, and credit; the first two components together explain 85.9% of the total variance (PC1 = 54.7%, PC2 = 31.2%). Only PC2, which captures the monetary differential between deposits and credit, enters the models as an explanatory variable, because it is the component with the strongest inflation signal identified by both the Lasso and the ARIMAX.

5. Results and Discussion

5.1 Numerical Results

Table 1 reports the Chow test results for the six policy-relevant candidate dates. The dominant break in the series is the 1986 post-hyperinflation stabilization ($F = 212.5$, $p < 0.0001$), consistent with the Bai–Perron result. Three other events are also statistically significant: the introduction of the fuel subsidy in August 2004 ($F = 23.8$, $p < 0.0001$), the failed subsidy withdrawal of December 2010 ($F = 13.6$, $p = 0.0003$), and the fixed-exchange-rate regime of November 2011 ($F = 12.6$, $p = 0.0004$). The September 2023 currency crisis is not significant when the full 1980–2024 sample is used ($F = 1.0$, $p = 0.31$), because the 1984–1985 hyperinflation dominates the total variance of the series.

Table 1. Chow test results for six candidate structural break dates in Bolivian inflation (1980–2024)

Candidate date	F-statistic	p-value	Conclusion
Bai–Perron: Feb-1986	212.46	< 0.0001	Highly significant
Stabilization: Aug-1985	159.71	< 0.0001	Highly significant
Fuel subsidy: Aug-2004	23.83	< 0.0001	Significant
Gasolinazo: Dec-2010	13.57	0.0003	Significant
Fixed FX regime: Nov-2011	12.55	0.0004	Significant
Currency crisis: Sep-2023	1.03	0.3117	Not significant

The Lasso identifies three predictors as active at the optimal penalty $\lambda = 0.070$ (Table 2). $PC2_{monetario}$, which represents the differential between deposit growth and credit growth, enters with a coefficient of −0.053, indicating that increases in the credit-over-deposits differential are associated with lower inflation. International reserves (rin_{mmusd}) enter with a coefficient of +0.030, suggesting a moderate positive association. The Argentine peso exchange rate against the U.S. dollar (tc_{ars_usd}) enters with a small but non-negligible positive coefficient. Only three of the 27 candidate variables receive non-zero coefficients, which indicates that the linear signal in monthly inflation is highly concentrated in a few variables.

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Table 2. Lasso coefficients at the optimal λ (three active variables out of 27 candidates)

Variable	Coefficient	Economic interpretation
$PC2_{monetario}$	−0.0526	Deposits vs. credit differential (monetary imbalance)
rin_{mmusd}	+0.0301	Change in international reserves (external buffer)
tc_{ars_usd}	+0.0006	Argentine peso exchange rate (regional spillover)

The appearance of the Argentine peso exchange rate (tc_{ars_usd}) as an active Lasso predictor, even with a small coefficient, has a robust economic rationale that warrants a closer look. Bolivia shares a land border of more than 900 kilometers with Argentina, and this border constitutes a zone of intense formal and informal commercial activity, with pairs of twin cities such as La Quiaca–Villazón and Salvador Mazza–Yacuiba effectively operating as integrated local markets. When the Argentine peso depreciates against the dollar during Argentina's recurrent bouts of inflation and currency stress, at least three transmission channels toward Bolivian inflation become active. First, a commercial arbitrage channel: relative prices on the two sides of the border shift, and Bolivian traders stock up on goods in northern Argentina, generating excess demand that pushes up prices in the border region. This phenomenon has been documented by Aliaga and Terrazas (2025) for the Bolivian case and is consistent with the general pattern of persistent smuggling to and from Argentina described by the U.S. Department of State (2025). Second, a monetary channel of store-of-value substitution: during the more severe Argentine crises, the boliviano has functioned as a safe-haven currency for residents of northern Argentina, generating additional pressure on the Bolivian foreign exchange market and transmitting volatility to the parallel-market exchange rate. Third, an expectations-contagion channel: Bolivian agents adjust their inflation expectations in response to Argentine inflation dynamics, given the commercial and geographic ties between the two economies. The positive coefficient estimated by the Lasso is therefore consistent with the theory of regional spillovers in neighboring economies with asymmetric commercial integration. Its modest magnitude reflects the fact that these channels operate on specific subregions of the country rather than on the national economy as a whole.

The ARIMAX(1,0,1) estimation results are reported in Table 3. Three coefficients are statistically significant at conventional levels. The fuel subsidy dummy $D_{subsidio}$ has a coefficient of +0.281 ($p = 0.023$), which implies that the subsidy period is associated with an additional 0.28 percentage points of monthly inflation on average, after controlling for the autoregressive structure and the remaining covariates. The parallel-market exchange rate coefficient d_{tcpar} is +1.318 ($p = 0.009$). This provides, to our knowledge, the first quantitative estimate of the parallel-market pass-through for Bolivia: each boliviano of parallel-market depreciation adds 1.32 percentage points to monthly inflation. The lagged inflation coefficient is +0.166 ($p < 0.001$), consistent with modest but statistically significant inflation persistence. The coefficients for D_{TC_fijo}, d_{rin}, d_{diesel_lag1}, and $PC2_{mon}$ are not significant at conventional levels.

Table 3. ARIMAX (1,0,1) coefficient estimates for February 1986 to December 2024

Variable	Coefficient	p-value
$D_{subsidio}$ (fuel subsidy dummy)	+0.2809	0.023 *
D_{TC_fijo} (fixed-exchange-rate dummy)	−0.0788	0.622
d_{rin} (change in reserves)	+0.0005	0.145
d_{tcpar} (change in parallel FX)	+1.3179	0.009 **
d_{diesel_lag1} (lagged diesel change)	+0.3719	0.480
$PC2_{mon}$ (monetary factor)	−0.0115	0.880
$infl_{lag1}$ (lagged inflation)	+0.1661	< 0.001 ***
AR(1)	+0.9908	< 0.001 ***
MA(1)	−0.9999	0.275

*Note: *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.*

The finding of a positive and statistically significant coefficient on $D_{subsidio}$ (+0.28 pp of additional monthly inflation) deserves an extended discussion, because it seems to contradict the immediate theoretical intuition of a subsidy. A

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direct subsidy on the price of fuel should, in principle, contain inflation by keeping a critical input to production and transport artificially low. Over the past two decades, however, the macroeconomic literature has consistently documented that in emerging economies with limited fiscal capacity, the direct containment effect can be dominated by larger indirect effects operating through three main channels.

The first channel is the fiscal cost of the subsidy and its monetary financing. Coady et al. (2019) estimate that explicit subsidies to fossil fuels globally reached USD 4.7 trillion in 2015 (6.3% of world GDP), and in economies whose tax revenues cannot absorb this cost, the subsidy ends up being financed through monetary emission by the central bank—generating inflationary pressures that exceed the direct containment effect. For Bolivia, the fiscal cost of the fuel subsidy has been estimated at more than USD 2 billion per year in recent years (Aliaga and Terrazas 2025; Aliaga Lordemann and Bhattacharyya 2026), with over 80% financed through BCB emission. The Economics Observatory (2026) diagnosis of Bolivia states this explicitly: the monetary financing of the fiscal deficit driven by the subsidy is the main engine of the recent Bolivian inflationary episode.

The second channel is the depletion of international reserves and its transmission to the parallel-market exchange rate. Bolivia imports roughly 86% of its diesel and more than 50% of its gasoline (U.S. Department of State 2025), which means that sustaining the subsidy requires foreign currency to pay international prices for imports that are then sold domestically at a frozen price. When reserves fall to critical levels, as happened in Bolivia from 2023 onward, the resulting scarcity of foreign currency puts pressure on the parallel-market exchange rate, whose pass-through to inflation is substantial (1.32 pp per boliviano of depreciation, according to our estimate). This indirect channel—subsidy → reserve depletion → parallel-market depreciation → inflation—turns the subsidy into an inflationary force in its own right.

The third channel is smuggling and artificial scarcity. The price gap between Bolivia and its neighbors (Peru, Brazil, Argentina, Chile) has generated persistent incentives to smuggle fuel, estimated at around USD 600 million per year (Aliaga and Terrazas 2025), which reduces the domestic supply and pushes up the prices of transport-dependent goods. Comparative international evidence reinforces this pattern. In Nigeria, the IMF documented that fuel subsidies reached an unsustainable fiscal cost prior to their removal in June 2023; their elimination, together with the end of monetary financing of the fiscal deficit, allowed annual inflation to fall from 31% in 2024 to 23.7% in April 2025 (IMF 2025). In Ecuador, fuel subsidies have been systematically associated with chronic fiscal deficits that eroded macroeconomic stability before the partial reforms of 2020–2024. In Iran, the 2011 subsidy reform came with sizable inflationary shocks, precisely because of the monetary effects accumulated during years of prior subsidy financing (Coady et al. 2015). Del Granado, Coady, and Gillingham (2012) systematized this evidence for twenty developing countries, showing that fuel subsidies with monetary financing tend to generate more inflation than they prevent, especially when the fiscal cost exceeds 1% of GDP on a sustained basis. The Bolivian case fits this international pattern: the estimated positive effect of $D_{subsidio}$ does not deny the direct containment effect on the diesel price, but rather reflects that the indirect effects—monetary financing, reserve depletion, and smuggling—quantitatively dominated the direct effect over the twenty-one years the subsidy was in force.

5.2 Graphical Results

Figure 1 displays the Bai–Perron regime segmentation of the monthly inflation series. The BIC-selected single-break model identifies February 1986 as the optimal break point, separating a pre-1986 regime with a monthly inflation mean of 19.28% and a standard deviation of 28.06 from a post-1986 regime with a mean of 0.59% and a standard deviation of 0.90. Figure 2 shows the CUSUM and CUSUM-of-squares tests, both of which cross the 95% confidence bands dramatically during the 1984–1985 hyperinflation, confirming the dominance of this regime shift. Figure 3 shows the F-statistics of the Chow tests across the six candidate dates, providing a visual summary of the relative magnitude of each break.

Figure 4 displays the Lasso coefficient path as a function of the log-penalty. $PC2_{monetario}$ is the first variable to activate as λ decreases, followed by rin_{mmusd}, and then tc_{ars_usd} at very low penalty. Figure 5 shows the cross-validation and external validation R^2 curves used to select the optimal λ. Figure 6 shows the ARIMAX residual diagnostics: the residuals appear centered at zero, but the Ljung–Box test detects statistically significant residual autocorrelation at lags 12 and 24 ($p = 0.025$ and $p = 0.013$, respectively), indicating that a seasonal component is not fully captured by the ARIMAX(1,0,1) specification. Figure 7 shows the observed and predicted monthly inflation over the full sample, with the 2025–2026 out-of-sample period marked separately.

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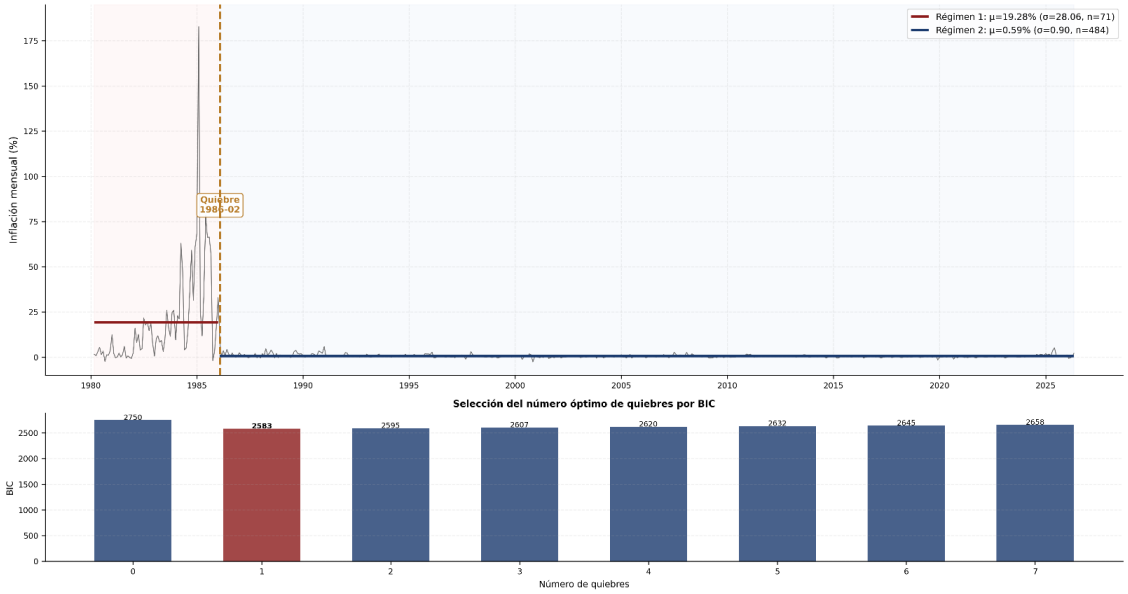


Figure 1. Bai–Perron regime segmentation of Bolivian monthly inflation (1980–2026)

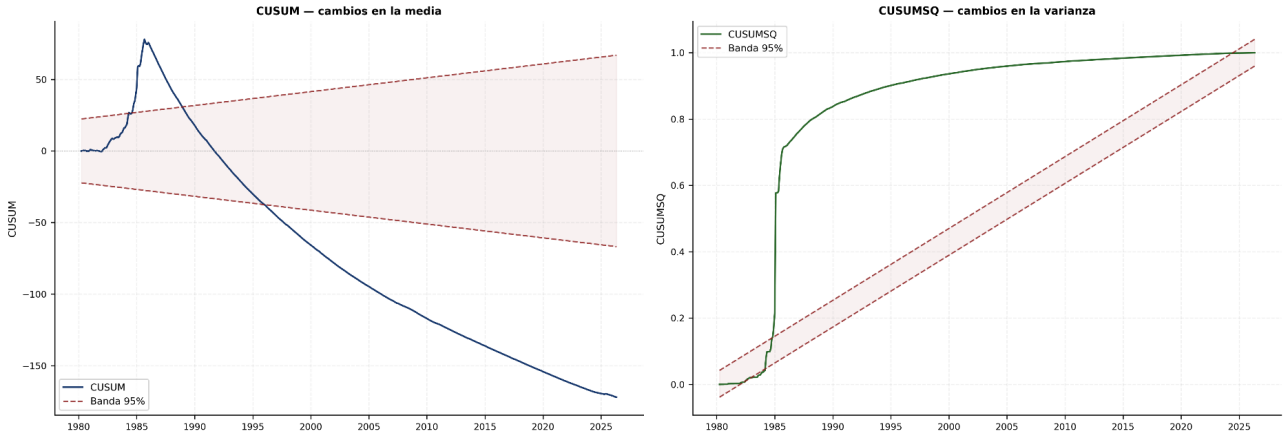


Figure 2. CUSUM and CUSUM-of-squares tests with 95% confidence bands

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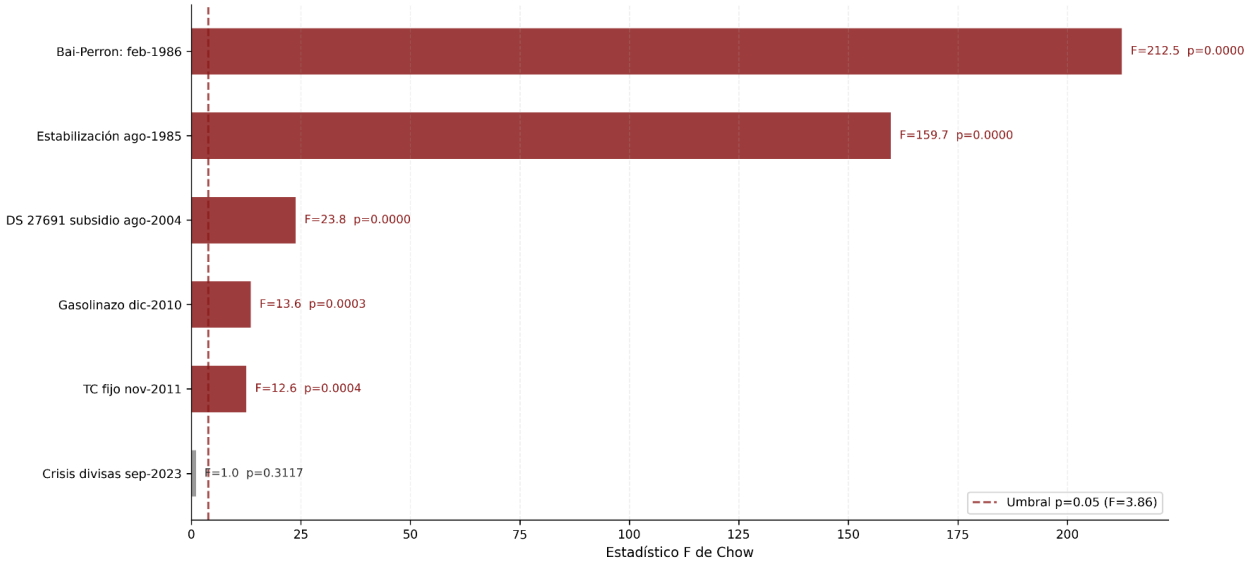


Figure 3. Chow test F-statistics for six policy-relevant candidate break dates

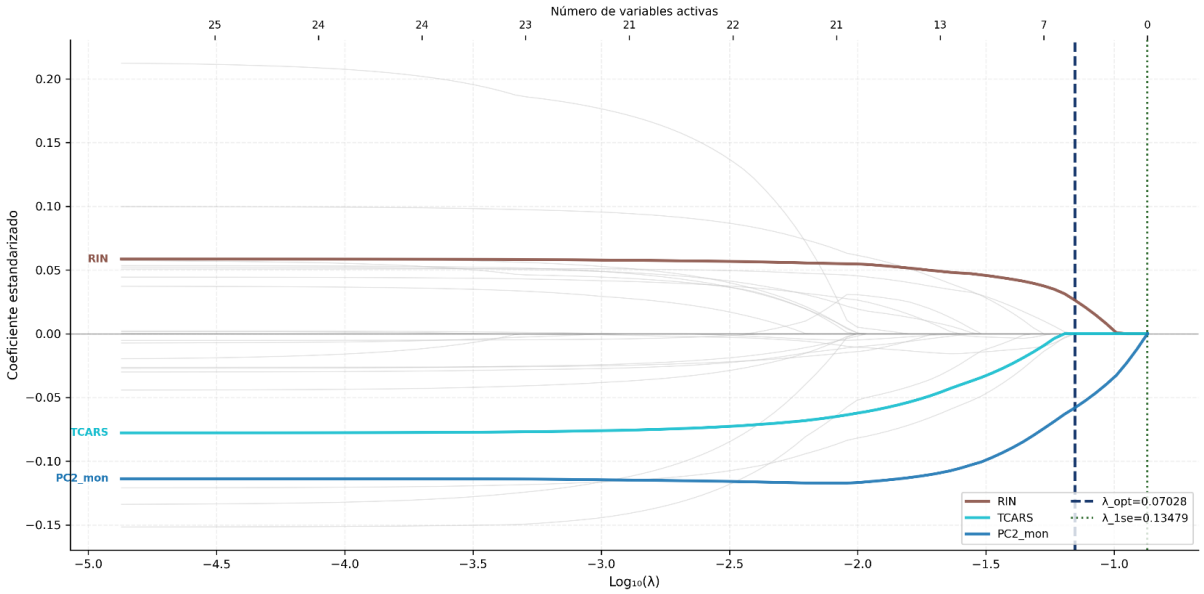


Figure 4. Lasso coefficient path as a function of log-penalty

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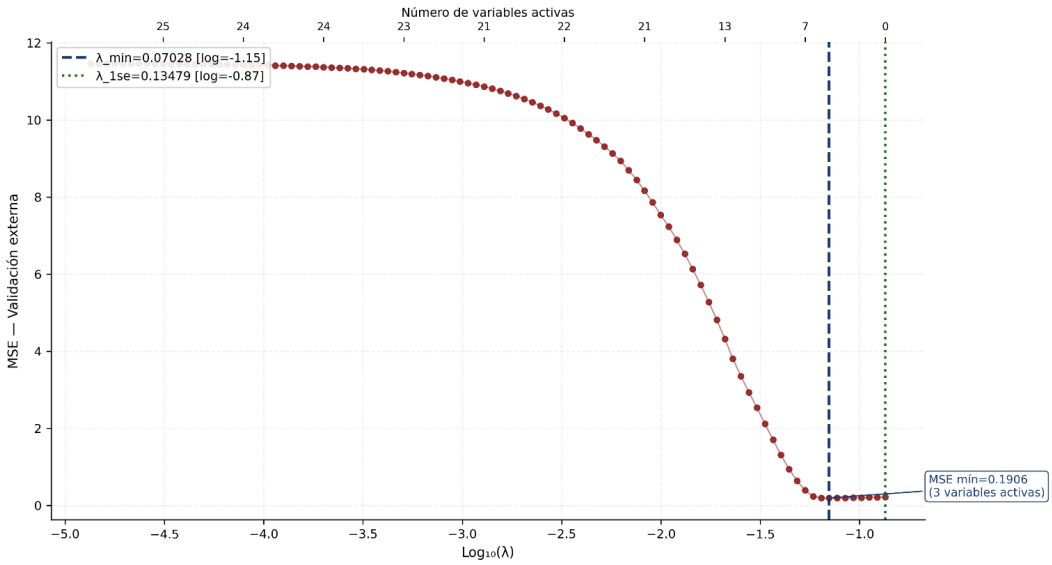


Figure 5. Cross-validation and external validation R^2 for Lasso penalty selection

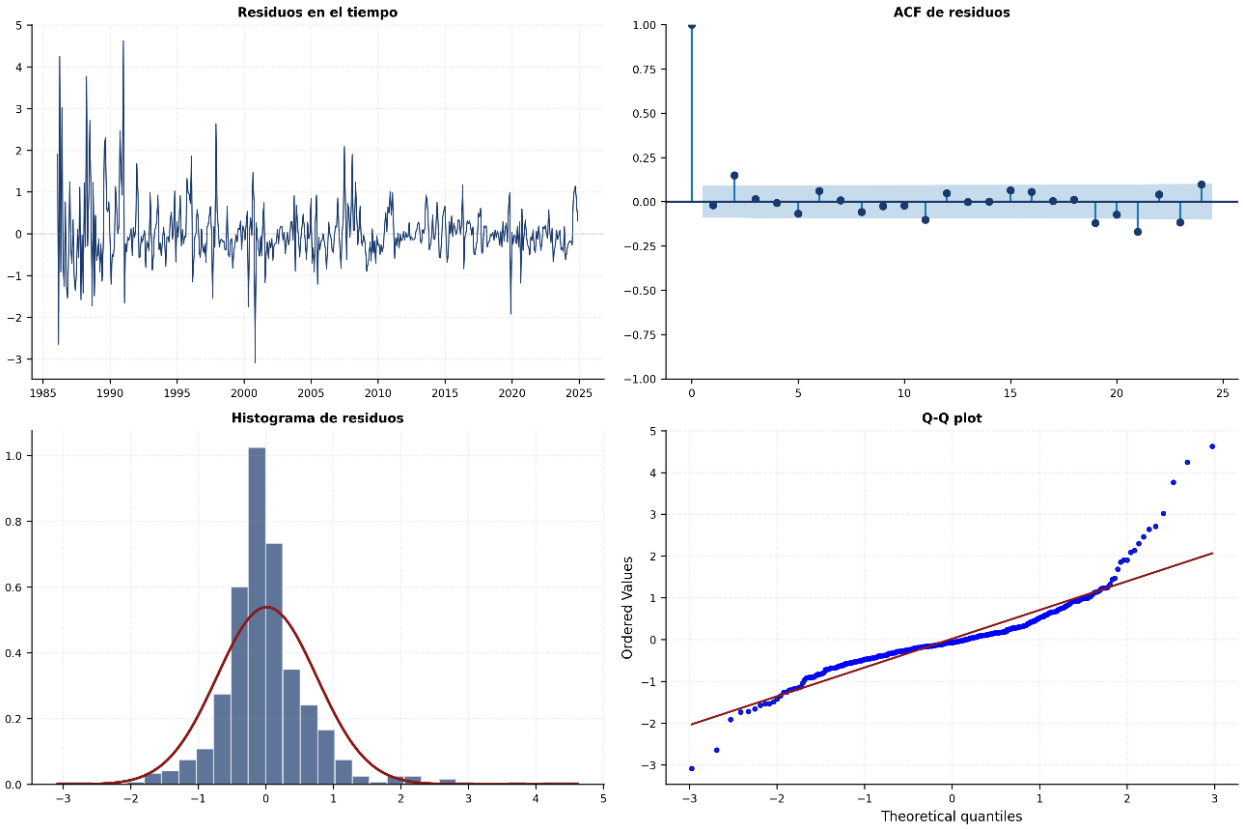


Figure 6. ARIMAX (1,0,1) residual diagnostics with the Ljung–Box test

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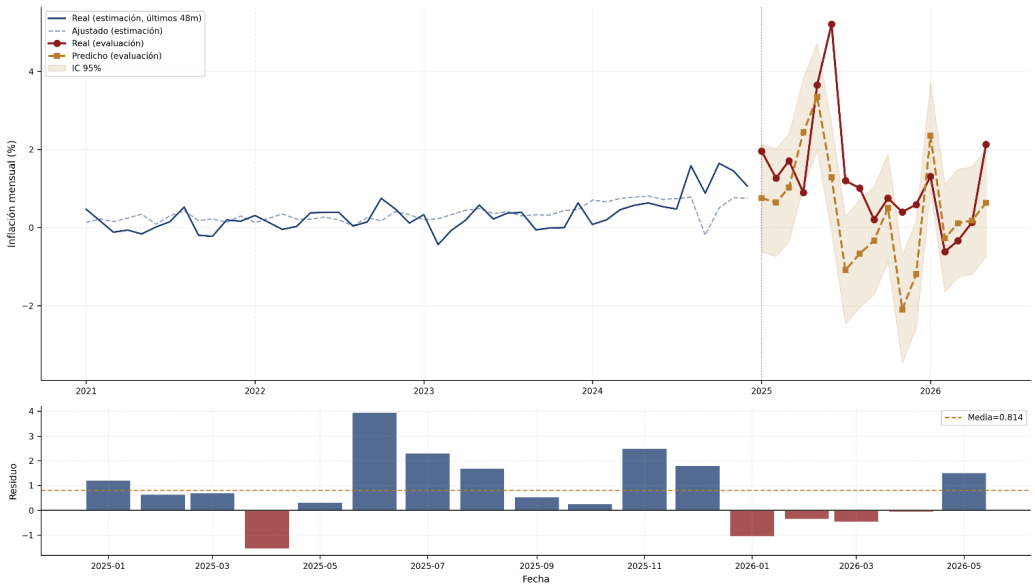


Figure 7. Observed and ARIMAX-predicted monthly inflation (1986–2026)

5.3 Proposed Improvements

The framework can be strengthened along three directions that build directly on the residual diagnostics of Section 5.1. First, the residual autocorrelation detected by the Ljung–Box test at lags 12 and 24 suggests that a SARIMAX specification with a seasonal component could improve the residual behavior of the ARIMAX without altering the interpretation of the coefficients. Second, the sign reversal of the $D_{subsidio}$ coefficient across specifications—positive in the ARIMAX but negative when the monetary and exchange-rate covariates are removed—suggests that the fuel subsidy effect operates through indirect channels (monetary financing, reserve depletion) that the current specification does not decompose. Adding an interaction term between $D_{subsidio}$ and the parallel-market exchange rate would allow separating the direct price-containment effect from the indirect currency-stress channel. Third, the identifiability limitation of the Lasso for post-2021 dummies could be addressed by adopting a rolling-window cross-validation scheme in place of the fixed temporal split, at the cost of a smaller estimation window per fold.

5.4 Validation

The out-of-sample performance of both models is evaluated on the January 2025 to May 2026 window, which contains 17 monthly observations covering the elimination of the fuel subsidy and the exchange-rate liberalization. The Lasso achieves a test-set root mean squared error (RMSE) of 1.578 percentage points, a mean absolute error (MAE) of 1.083 percentage points, and a test-set R^2 of −0.288. The ARIMAX achieves a test-set RMSE of 1.564 percentage points, an MAE of 1.217 percentage points, and a test-set R^2 of −0.266. Both models exhibit negative out-of-sample R^2 values, which indicates that neither outperforms the sample mean as a predictor of the extraordinary 2025–2026 period. This is not evidence of model failure per se, but rather of the intrinsic limits of linear forecasting under unprecedented policy shocks: neither model has been trained on the joint occurrence of subsidy elimination and exchange-rate liberalization, and both are forced to extrapolate outside their training distribution.

The interpretation of the ARIMAX coefficients, however, remains valid and useful for decision support. The identification of $D_{subsidio}$ as statistically significant provides monetary authorities with an evidence-based estimate of the marginal contribution of the subsidy period to observed inflation. The estimated pass-through of 1.32 percentage points per boliviano of parallel-market depreciation provides an actionable elasticity for scenario analysis under alternative exchange-rate assumptions. These outputs are the primary deliverables of the framework as a decision-support tool, regardless of point-forecast accuracy.

6. Conclusion

This paper developed and applied an integrated data-driven decision-support framework for central bank operations that combines structural break detection, Lasso feature selection, and ARIMAX modeling with policy dummies.

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Applied to the Bolivian monthly inflation series over the extended sample from March 1980 to May 2026, the framework yields four main findings that address the objectives set out in Section 1.1. First, the Bai–Perron and Chow tests confirm the 1985–1986 post-hyperinflation stabilization as the dominant structural break of the series ($F = 212.5$, $p < 0.0001$), and they identify the August 2004 introduction of the fuel subsidy as a statistically significant break in its own right ($F = 23.8$, $p < 0.0001$), providing empirical justification for modeling the subsidy period explicitly. Second, the Lasso identifies the monetary differential factor ($PC2_{monetario}$) and international reserves as the most robust linear predictors of monthly inflation out of a candidate pool of 27 variables. Third, the ARIMAX(1,0,1) estimates that the fuel subsidy period adds 0.28 percentage points of monthly inflation on average ($p = 0.023$)—an effect that comparative international evidence (Coady et al. 2019; Del Granado et al. 2012) attributes to the dominance of indirect channels of monetary financing and reserve depletion over the direct price-containment effect—and quantifies the parallel-market exchange-rate pass-through at 1.32 percentage points per boliviano of depreciation ($p = 0.009$). Fourth, the integrated pipeline is fully reproducible and provides monetary authorities with a coherent set of diagnostics: when did the regime change, which variables matter, and how much does each policy contribute to observed inflation.

The framework has three important limitations that motivate future work. The Lasso cannot identify policy dummies defined outside the fitting window, a limitation intrinsic to regularized methods with fixed temporal splits. The ARIMAX residuals exhibit residual seasonal autocorrelation that a SARIMAX specification would address. Neither model, being linear, can anticipate the interaction of multiple simultaneous policy shocks such as those of 2025–2026, which explains their negative out-of-sample R^2. A companion paper by the same author extends the framework with vector autoregression (VAR) and Long Short-Term Memory (LSTM) neural network models, which are specifically designed to capture the non-linear and joint dynamics of macroeconomic shocks, and provides comparative benchmarking and policy simulations under alternative shock scenarios.

The unique contribution of this research is not a new algorithm but the integrated deployment of well-established techniques as a decision-support system tailored to the operational needs of a monetary authority in a structurally unstable emerging economy. For central banks facing similar contexts—emerging economies with policy dummies, currency crises, and administered-price interventions—the framework provides a reproducible template that separates the tasks of regime identification, predictor selection, and policy attribution into a coherent, sequential pipeline.

References

Akaike, H., A new look at the statistical model identification, *IEEE Transactions on Automatic Control*, vol. 19, no. 6, pp. 716–723, 1974.

Aliaga, J. and Terrazas, R., Macroeconomic impact of the elimination of the fuel subsidy in Bolivia: Analysis of abrupt and gradual reforms, *INESAD Development Working Paper Series*, no. 6/2025, Instituto de Estudios Avanzados en Desarrollo, 2025.

Aliaga Lordemann, J. and Bhattacharyya, A. C., Coyuntura analysis: Oil price, fuel subsidy and macroeconomic vulnerability in Bolivia, *INESAD Development Working Paper Series*, no. 2/2026, Instituto de Estudios Avanzados en Desarrollo, 2026.

Araujo, G. S. and Gaglianone, W. P., Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models, *Latin American Journal of Central Banking*, vol. 4, no. 1, pp. 100087, 2023.

Bai, J. and Ng, S., Forecasting economic time series using targeted predictors, *Journal of Econometrics*, vol. 146, no. 2, pp. 304–317, 2008.

Bai, J. and Perron, P., Estimating and testing linear models with multiple structural changes, *Econometrica*, vol. 66, no. 1, pp. 47–78, 1998.

Banco Central de Bolivia, Pronósticos del PIB mediante modelos de factores dinámicos, *Revista de Análisis del Banco Central de Bolivia*, vol. 31, 2019.

Bhattacharyya, A. C., A transmission model for fuel-importing economies, Technical report, Energy Inclusion, 2024.

Blanchard, O. and Galí, J., The macroeconomic effects of oil price shocks: Why are the 2000s so different from the 1970s?, in J. Galí and M. Gertler (Eds.), *International Dimensions of Monetary Policy*, pp. 373–421, University of Chicago Press, 2007.

Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M. and Tambalotti, A., Macroeconomic nowcasting and forecasting with big data, *Annual Review of Economics*, vol. 10, pp. 615–643, 2018.

Bolivar, O., GDP nowcasting: A machine learning and remote sensing data-based approach for Bolivia, *Latin American Journal of Central Banking*, vol. 5, no. 3, pp. 100126, 2024.

Bolivar, O., High-frequency inflation forecasting: A two-step machine learning methodology, *Latin American Journal of Central Banking*, vol. 7, pp. 100172, 2025.

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Box, G. E. P. and Jenkins, G. M., *Time Series Analysis: Forecasting and Control*, revised edition, Holden-Day, San Francisco, 1976.

Cáceres, R., Pronósticos del IGAE mediante modelos econométricos y redes neuronales artificiales, Working Paper, Banco Central de Bolivia, 2016.

Chow, G. C., Tests of equality between sets of coefficients in two linear regressions, *Econometrica*, vol. 28, no. 3, pp. 591–605, 1960.

Cipollone, P., Artificial intelligence: A central bank's view, Speech at the European Central Bank, July 4, 2024. Available: https://www.ecb.europa.eu/press/key/date/2024/html/ecb.sp240704_1.en.html, Accessed on January 15, 2026.

Coady, D., El-Said, M., Gillingham, R., Kpodar, K., Medas, P. and Newhouse, D., The magnitude and distribution of fuel subsidies: Evidence from Bolivia, Ghana, Jordan, Mali, and Sri Lanka, IMF Working Paper No. 06/247, International Monetary Fund, 2006.

Coady, D., Parry, I. W. H., Sears, L. and Shang, B., How large are global energy subsidies?, IMF Working Paper No. 15/105, International Monetary Fund, 2015.

Coady, D., Parry, I., Sears, L. and Shang, B., How large are global fossil fuel subsidies?, *World Development*, vol. 91, pp. 11–27, 2017.

Coady, D., Parry, I. W. H., Le, N.-P. and Shang, B., Global fossil fuel subsidies remain large: An update based on country-level estimates, IMF Working Paper No. 19/89, International Monetary Fund, 2019.

Del Granado, F. J. A., Coady, D. and Gillingham, R., The unequal benefits of fuel subsidies: A review of evidence for developing countries, *World Development*, vol. 40, no. 11, pp. 2234–2248, 2012.

Dickey, D. A. and Fuller, W. A., Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association*, vol. 74, no. 366, pp. 427–431, 1979.

Diebold, F. X. and Mariano, R. S., Comparing predictive accuracy, *Journal of Business & Economic Statistics*, vol. 13, no. 3, pp. 253–263, 1995.

Economics Observatory, From crisis to stability: What next for Bolivia's economy?, January 2026. Available: https://www.economicsobservatory.com/from-crisis-to-stability-what-next-for-bolivias-economy, Accessed on February 20, 2026.

Goulet Coulombe, P., Leroux, M., Stevanovic, D. and Surprenant, S., How is machine learning useful for macroeconomic forecasting?, *Journal of Applied Econometrics*, vol. 37, no. 5, pp. 920–964, 2022.

Hamilton, J. D., Oil and the macroeconomy since World War II, *Journal of Political Economy*, vol. 91, no. 2, pp. 228–248, 1983.

Hamilton, J. D., *Time Series Analysis*, Princeton University Press, Princeton, NJ, 1994.

Hamilton, J. D., What is an oil shock?, *Journal of Econometrics*, vol. 113, no. 2, pp. 363–398, 2003.

Hastie, T., Tibshirani, R. and Wainwright, M., *Statistical Learning with Sparsity: The LASSO and Generalizations*, CRC Press, Boca Raton, FL, 2015.

International Monetary Fund, IMF staff completes 2025 Article IV mission with Nigeria, Press Release No. 25/231, July 1, 2025. Available: https://www.imf.org/en/news/articles/2025/07/01/pr-25231-nigeria-imf-staff-completes-2025-article-iv-mission, Accessed on February 20, 2026.

Kilian, L., Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, *American Economic Review*, vol. 99, no. 3, pp. 1053–1069, 2009.

Masini, R. P., Medeiros, M. C. and Mendes, E. F., Machine learning advances for time series forecasting, *Journal of Economic Surveys*, vol. 37, no. 1, pp. 76–111, 2023.

Medeiros, M. C., Vasconcelos, G. F., Veiga, Á. and Zilberman, E., Forecasting inflation in a data-rich environment: The benefits of machine learning methods, *Journal of Business & Economic Statistics*, vol. 39, no. 1, pp. 98–119, 2021.

Mullainathan, S. and Spiess, J., Machine learning: An applied econometric approach, *Journal of Economic Perspectives*, vol. 31, no. 2, pp. 87–106, 2017.

Perron, P., Dealing with structural breaks, in T. C. Mills and K. Patterson (Eds.), *Palgrave Handbook of Econometrics*, vol. 1, pp. 278–352, Palgrave Macmillan, 2006.

Ramos, J., Prediction of economic recessions in Bolivia using machine learning methods, Working Paper, Universidad Privada Boliviana, 2023.

Tibshirani, R., Regression shrinkage and selection via the Lasso, *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.

U.S. Department of State, 2025 Investment Climate Statements: Bolivia, U.S. Department of State, 2025. Available: https://www.state.gov/reports/2025-investment-climate-statements/bolivia, Accessed on February 20, 2026.

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Biography

Ginamaria García Garcés is an Industrial Engineer with master's degrees in Integrated Management Systems and Business Administration (MBA). She currently serves as Director of the Industrial Engineering Program at Universidad Católica Boliviana, Cochabamba Campus. She has more than two decades of teaching experience at several universities in Cochabamba, specializing in Exact Sciences, Operations Research, Simulation, and Optimization. Throughout her academic career, she has contributed to curriculum development, academic management, and the promotion of applied research in Industrial Engineering and data-driven decision-making. She previously served as National Academic Vice Rector at Universidad Privada Abierta Latinoamericana (UPAL), where she led academic and institutional improvement initiatives. She was also awarded a doctoral scholarship in Mathematics at the University of Cádiz, Spain, strengthening her academic and research background. Currently, she is a doctoral candidate in the Doctorate in Business Sciences program, with research interests focused on optimization, analytics, operational improvement, and higher education management.

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