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External vs. domestic factors to forecast the inflation in dollarized economy

Paul Carrillo-Maldonado
Centro de Investigaciones Económicas y Empresariales, Universidad de las Américas, Quito, Ecuador

Jeniffer Rubio
Centro de Investigaciones Económicas y Empresariales, Universidad de las Américas, Quito, Ecuador

Susana Herrero-Olarte
Centro de Investigaciones Económicas y Empresariales, Universidad de las Américas, Quito, Ecuador

Abstract

In this paper we evaluate the influence of external and domestic factors for forecasting inflation in a small, open and dollarized economy. We estimate different econometric models for time series to identify the precision to forecast the inflation of Ecuadorian economy. We also implemented least square, quantile regression and stochastic volatility proposals to compare the same specification. The results show that models that include external factors are more accurate in the short term, while in the medium term, it is explained more by internal factors. Quantile regression is practical because it captures the determinants of inflation at different levels.

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Contact: Paul Carrillo-Maldonado - paul.carrillo.maldonado@udla.edu.ec, Jeniffer Rubio - jeniffernathaly.rubio@udla.edu.ec, Susana Herrero-Olarte - susana.herrero@udla.edu.ec.
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1. Introduction

Analyzing inflation in a small, open economy is essential, as such economies participate in international trade but have limited capacity to influence global prices. It must therefore accept global market prices and conditions (Zhang and Dai, 2020). This makes it more vulnerable to external shocks, such as fluctuations in international commodity prices, imported inflation, the monetary and trade policies of major trading partners, and exchange rate movements (Nagy and Tengely, 2018; Szafranek et al., 2024).

Specifically, variations in international prices, such as those of food, oil, and other goods, have increased the costs of goods imported into the country, generating inflationary pressures in countries that are highly dependent on imports of these products (Lora et al., 2011; Kia, 2006), which has also affected the increase in the costs of intermediate goods used in production, resulting in imported inflation (Nagy and Tengely, 2018). Factors such as supply chain disruptions, volatility in commodity prices, specific disruptions in energy prices, especially during the COVID-19 pandemic, and geopolitical conflicts have contributed to inflation (Szafranek et al., 2024). Thus, external inflationary shocks can be quickly transmitted to the domestic market.

On the other hand, inflation in an economy also depends on internal factors, such as monetary and fiscal policy, aggregate demand, inflation expectations, and the labor market, among others (Mohanty and Klau, 2001). Monetary policy controls inflation through interest rates and the money supply, while expansionary fiscal policy can increase aggregate demand, which raises prices if production is insufficient (Nagy and Tengely, 2018). Demand-driven inflation arises when purchasing power exceeds productive capacity. Inflation expectations are also key; if economic agents expect future price increases, they will adjust their prices and wages preventively, which will increase inflation. On the other hand, in labor markets, wage increases lead to higher production costs and final prices, which generate inflation (Bojaj and Djurovic, 2020). The most influential internal factors in Latin American inflation are inflation expectations and the wage cost component (Trajtenberg et al., 2016; de la Torre et al., 2020).

In this context, inflation in a small, open economy reflects external factors that, although not directly controlled by the local economy, significantly affect domestic prices. In addition, internal factors affecting inflation depend mainly on the country's economic policies and conditions (Szafranek et al., 2024). In small economies, inflation is primarily explained by external shocks, whereas in larger economies it is driven by internal factors (Nagy and Tengely, 2018). However, their influence will depend on the economy being analyzed (Cepni and Clements, 2024). In the case of small, open economies that are dollarized, such as Ecuador, where the country does not have its own currency, there are limitations in responding to inflationary shocks, as they cannot use traditional monetary policy tools, such as adjusting interest rates or issuing money, nor do they have control over their exchange rate, as economies with their own currency do (Edwards, 2001; Anderson, 2016; Quispe-Agnoli and Whisler, 2006).

Therefore, correctly understanding the external and internal factors that influence inflation in a dollarized economy is essential for more accurate inflation projections, thereby enabling the formulation of preventive policies that anticipate and mitigate inflationary shocks and maintain price stability (Ascari et al., 2023; Mandalinci, 2017). Especially in a small, open economy, it allows for the design of appropriate policies related to competitiveness, investment, and the well-being of the population (Taylor, 2019). Unpredictable inflation can discourage domestic and foreign investment and limit capital flows, which are vital to the growth of these economies (Faria and Carneiro, 2001).

This research seeks to provide empirical evidence comparing the accuracy of inflation forecasts explained by external and internal factors in a small, open, dollarized economy, using Ecuador's dollarization since 2000 as a case study. This measure was adopted to stabilize the economy after a financial crisis characterized by hyperinflation (Quispe-Agnoli and Whisler, 2006). To our knowledge, no previous study of this type of economy has carried out this exercise for inflation forecasts. The existing literature has mainly focused on analyzing the internal and external factors that influence global inflation (Kia, 2006). However, few studies have accounted for these factors when forecasting inflation. Therefore, this study contributes to this field. The data, methodology, results, and conclusions are presented below.

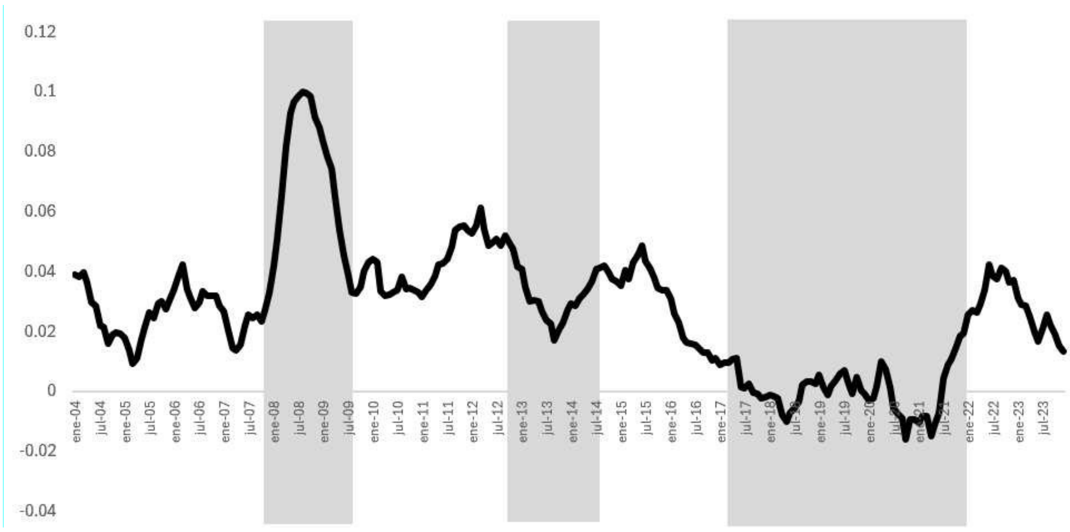
2. Data

Monthly data from the National Institute of Statistics and Census were used. As a training set for model estimation from 2004 to 2021, and as a test set to evaluate the model's predictive power and validate its out-of-sample performance from 2022 to 2023. The primary variable of interest is the annual inflation rate, derived as the year-on-year logarithmic change in the Consumer Price Index (CPI):

$$\pi_t = 100 * \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

The inflation time series analyzed (Figure 1) shows episodes of volatility, with both inflationary and deflationary periods observed throughout the study period. These fluctuations are influenced by variations in external and internal factors over different years.

Figure 1. Annual variation in the inflation rate



In this framework, π_t represents the annual inflation rate in period t, while P_t corresponds to the price index for the same period. Several internal and external factors are incorporated to explain inflationary dynamics in Ecuador. From an internal perspective, the short-term economic activity index (IDEAC) is included, which is an indicator of production; the monetary aggregate (M2), which measures the liquidity available (money supply) for consumption and investment; and the real exchange rate (RER), which measures external competitiveness to analyze the influence of international price variations on domestic inflationary pressures. From an external perspective, it includes the prices of essential commodities such as crude oil (WTI), coffee, and gold. In addition, the global index of real economic activity in industrial product markets captures the influence of global financial cycles on international prices (Kilian, 2019). The data were seasonally adjusted to eliminate periodic fluctuations unrelated to the underlying economic cycle, so logarithmic transformations and differences were applied to represent real economic trends better.

3. Methodology

According to the methodology proposed by Faust and Wright (2013), the model is estimated by direct projection as follows:

$$\pi_{t+h} = \beta x_t + \varepsilon_{t+h} \tag{2}$$

Where h denotes the available forecast horizon after the sample, while x_t represents the vector of predictive variables for inflation, following Stock and Watson (2007) and Faust and Wright (2013), the models were estimated for inflation forecasts using frequentist and Bayesian techniques.

- A random walk model:

$$\pi_{t+h} = \pi_t + \varepsilon_{t+h} \tag{3}$$

- An autoregressive (AR) model. Where p represents the number of lags, α is a constant term, delta δ_i are the coefficients associated with each lag of inflation, and ε_{t+h} is the error term:

$$\pi_{t+h} = \alpha + \sum_{i=1}^{p} \delta_i \pi_{t+h-i} + \varepsilon_{t+h} \tag{4}$$

- A moving average (MA) model posits that future inflation is a function of past errors. Where q represents the number of optimal lags selected, φ_j are the coefficients associated with the error term lags. The lag structure (q) is determined using information criteria such as Akaike (AIC).

$$\pi_{t+h} = \alpha + \sum_{i=1}^{q} \varphi_j \varepsilon_{t+h-j} + \varepsilon_{t+h} \tag{5}$$

At a later stage, structural econometric models are incorporated to analyze the relationship between inflationary pressures and their explanatory factors. Two models are distinguished: those that explain inflation projections with internal factors and those that present external factors.

- The autoregressive model. Where the vector of all variables (π_t, x_t) is represented by w_t, the constant α is also included, as are the coefficients of the variables in question, represented contemporaneously by θ. The vector of coefficients of the lag i of the variables is represented by δ, while p is the number of optimal lags, which can vary for each variable. Finally, the error term is represented by ε_{t+h}.

$$\pi_{t+h} = \alpha + \theta x_t + \sum_{i=1}^{p} \delta_i w_{t-i} + \varepsilon_{t+h} \tag{6}$$

- Quantile regression captures asymmetries in the determinants of inflation by estimating coefficients across the distribution, unlike conventional methods. Where $Q_\tau(\pi_{t+h})$ represents the quantile τ of the inflation distribution, while the coefficients α_τ, θ_τ, and $\delta_{i\tau}$ are the estimates for quantile τ. The term $\varepsilon_{\tau,t+h}$ denotes the error term h of horizon in quantile τ.

$$Q_\tau(\pi_{t+h}) = \alpha_\tau + \theta_\tau x_t + \sum_{i=1}^{p} \delta_{i\tau} w_{t-i} + \varepsilon_{\tau,t+h} \tag{7}$$

- Quantile regression is particularly valuable for forecasting inflation, as it captures asymmetries in the distribution of the dependent variable, unlike traditional models that focus solely on the conditional mean. Estimating relationships among quantiles allows analysis of extreme inflation outcomes and provides more robust estimates in the presence of outliers. In addition, quantile regression is well-suited for assessing forecast uncertainty and making inferences about the entire predictive distribution. This approach can reveal predictive relationships between inflation and explanatory variables that standard least squares regression may not detect, making it a powerful tool for economic forecasting (Koenker, R. (2005); Korobilis, D. (2017).

- A stochastic volatility (SV) model to capture dynamic variations in inflation uncertainty. Where μ_t is the conditional mean of inflation during the specified period, σ_t is the conditional standard deviation of inflation, which measures volatility in the period.

$$\pi_{t+h} = \mu_t + \sigma_t \, \varepsilon_{t+h} \tag{8}$$

- The model assumes that the conditional variance of inflation follows a stochastic process, where n_t captures the stochastic shock on the variance.

$$ln(\sigma_t^2) = ln(\sigma_{t-1}^2) + n_t, \qquad n_t \sim N(0, \lambda^2). \tag{9}$$

Finally, the root mean square error of prediction (RMSFE) is used to evaluate the accuracy of the projected results by comparing observed values with those predicted at different time horizons. Where h represents the number of horizons to be forecast, while π_{t+i} denotes the inflation rate observed in period $t + i$. Similarly, $\hat{\pi}_{t+i}$ means the inflation forecast for period $t + i$. This measure allows us to quantify the magnitude of the root mean square error of the forecast made by each of the models.

$$\text{RMSFE} = \sqrt[2]{\frac{1}{h}\sum_{i=1}^{h}(\pi_{t+i} - \hat{\pi}_{t+i})^2} \tag{10}$$

Additionally, the RMSFE of each model was normalized relative to a benchmark model (the random walk model), setting the benchmark RMSFE equal to 1. This comparison is presented as the relative RMSFE:

$$RMSFE_{relative_i} = \frac{RMSFE_i}{RMSFE_{baseline}} \tag{11}$$

Where $RMSFE_i$ corresponds to the prediction error of the alternative model, and $RMSFE_{baseline}$ is the error of the baseline model. Values less than 1 indicate that the alternative model outperforms the baseline model in predictive accuracy. This relative metric facilitates direct comparison between the models and the baseline.

4. Results

The results for the accuracy (RMSFE and relative RMSFE) of the inflation projections across different time horizons (1 month, 1 year, and 2 years) and under different methodological approaches are presented below (Table I).

Table I. Performance Evaluation of Inflation Projection Models

	Specifications	**RMSFE**			**Relative RMSFE**		
		First month	**First-year**	**Second year**	**First month**	**First-year**	**Second year**
1)	Random Walk (Baseline)	0.3476	0.2347	0.2764	1	1	1
1)	AR AIC	0.2891	0.2282	0.2766	0.8317	0.9723	10.008
2)	MA AIC	0.348	0.2968	0.2555	10.009	12.647	0.9244
3)	Internal Factors (IF)	0.2922	0.2292	0.2455	0.8405	0.9768	0.8883
4)	External Factors (EF)	0.3212	0.2399	0.3112	0.9239	10.224	11.261
5)	Quantile Regression (IF)	0.3514	0.2749	**0.1828**	10.109	11.713	**0.6613**
6)	Quantile Regression (EF)	**0.2251**	**0.2186**	0.2401	**0.6476**	**0.9315**	0.8688
7)	IF with SV	0.3519	0.2824	**0.1889**	10.122	12.035	**0.6835**
8)	EF with SV	0.3887	0.2369	0.227	11.183	10.095	0.8214

Note: The random walk model is used as a reference for comparison; therefore, its relative RMSFE is 1 for all horizons. Those with the lowest relative RMSFE values are the models that achieve the highest accuracy relative to the reference model and are highlighted in the table.

The results reveal distinct patterns in the accuracy of inflation forecasts over different time horizons, reflecting the strengths and limitations of each model. In the short term (the first month and the first year), the quantile regression model with external factors (Specification 6) performs best, compared to the base model (Specification 1). This highlights the immediate and significant influence of global economic conditions and international price fluctuations on inflation in small, open economies. Domestic factors, mainly when modeled using quantile regressions (Specification 5), gain predictive superiority in the second year. This suggests that domestic determinants play a more significant role in the long run, indicating that domestic economic policies and structural conditions cumulatively affect inflation.

Quantile regressions for internal and external factors show strong performance across all horizons, underscoring their usefulness for capturing the heterogeneous dynamics of inflation under different economic conditions. The use of quantile regression to forecast inflation in Ecuador is particularly relevant given the country's inflation dynamics during 2004-2023. Throughout this period, there have been episodes of high inflation, reaching 10%, as well as prolonged deflation, including consecutive negative inflation rates. This nonlinear behavior, with pronounced upward and downward fluctuations, reflects an inflationary pattern influenced by multiple sources of uncertainty and by both internal and external shocks. In this context, quantile regression emerges as a methodologically appropriate tool, especially for small, open, and dollarized economies such as Ecuador's. It allows modeling the complete conditional distribution of inflation, capturing not only the central trend but also the risks associated with the distribution's extremes. This feature is particularly valuable for anticipating episodes of high inflation or deflation, as it provides more robust data for designing economic policies in volatile environments. Furthermore, its robustness to outliers and its flexibility in handling nonlinear relationships make it a superior alternative to traditional approaches that focus solely on the conditional mean.

Complementarily, although quantile regression shows the best overall performance, in the long term (two years), incorporating stochastic volatility also improves the predictive capacity of models based on internal factors (Specification 7) relative to the base model (Specification 1). This suggests that considering time-varying uncertainty can be a valuable approach to improving inflation forecasts in volatile economic environments.

5. Conclusions

Inflation is determined by external and internal factors, whose influence varies across economies (Szafranek et al., 2024). Taking these factors into account in inflation forecasts is essential for achieving more robust analyses. The objective is to evaluate the performance of inflation forecasts, differentiating between models explained by external factors and those described by internal factors, using various forecasting methodologies for a small, open, dollarized economy. The main results show that inflation forecasts that account for external factors are more accurate in the short- and medium-term. In the long term (two years), internal factors provide more accurate predictions. The performance of quantile regression for inflation forecasting exercises is noteworthy. These tools enable more precise inflation forecasting and an understanding of its dynamics in relation to internal and external determinants. This will allow policymakers to anticipate and respond to risks, especially by focusing on mitigating external vulnerability, particularly in small, open economies.

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