Universitá degli studi di Milano

Advanced Macroeconomics
M.Sc. Data Science & Economics

Inflation and interest rate forecast, Colombia 2022

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Introduction

The last couple of years have been a test for the world economy and its diverse economic systems, and Colombia is not an exception. With a real GDP growth of 6.8% and an inflation rate of 5.6% in 2021, the Colombian economy is facing the challenge of cement their recovery while controlling inflation around the 3% target set by its Central Bank.

In this sense, the scope of this project is to answer the question: *Which will be the inflation and the nominal interest rate for Colombia in 2022?*. To answer it, I estimated several models and forecasted quarterly inflation for 2022, then, estimated the Taylor Rule coefficients for Colombia for the 2010 - 2021 period and used them to compute the nominal interest rate according to the forecasted inflation. Of the six estimated models for inflation, one endogenizes the nominal interest rate, showing the reaction of inflation to the interest rate set by the Central Bank.

Data and Methodology

I used four quarterly data series, ranging from 2010:1 to 2021:4: log of real GDP (2015 prices) in COP, quarterly average of the annual inflation, inflation target for the sample period and monetary policy intervention rate. The data was gathered from the websites of the DANE (Colombia's official statistics bureau) and Banco de la República.

Inflation forecast

The first part of the project is to forecast inflation. For this purpose, the models can be divided into two groups: univariate models (1 to 4) and multivariate models (5 and 6), The examined models are:

1. Random Walk model: a benchmark model used as a baseline for comparison, also called the naive forecast, where $\pi_{t+h} = \pi_{t-1} + \epsilon_t$
2. ARMA(1,1): a model that sets inflation equal to its past realisation plus its past error, weighted by some coefficients: $\pi_t = \phi_1 \pi_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t$. This model is used based on (Nikolsko-Rzhevskyy, 2011), who used it as often this is the best performing time series model to describe inflation.
3. SARIMA(2,1,0)(2,0,0)(4): a model that takes into account the fact that the sample series is I(1) according to an ADF test performed on the data. The AR and MA order were chosen based on ACF and PACF analysis of the sample, as well as the seasonal AR components. Inflation was not seasonally adjusted on the initial data series.

$$\Delta\pi_t = \alpha + \phi_1 \Delta\pi_{t-1} + \phi_2 \Delta\pi_{t-2} + \Phi_1 z_1 + \Phi_2 z_2 + \epsilon_t,$$

   where z_1, z_2 are the AR seasonal components.

4. SARIMA(2,0,0)(2,0,0)(4): similar to model no. 3, but without taking first differences on the inflation series. The motivation to include this model was to test the built-in function that R has to automatically estimate ARIMA models. The function auto.arima selects from a set of tested models the one with the lowest AIC criterion. In this case:

$$\pi_t = \alpha + \phi_1\pi_{t-1} + \phi_2\pi_{t-2} + \Phi_1 z_1 + \Phi_2 z_2 + \epsilon_t,$$

5. VAR(2) (inflation, GDP gap): the first estimated VAR, inspired in the Aggregate Supply curve of the AS-AD model. The endogenous variables are inflation and GDP gap. Main goal is to determine how much the GDP gap can affect an inflation forecast. Although some Information Criterion suggested higher lags, at two lags serial error autocorrelation disappeared, suggesting a parsimonious way to model inflation (Ouliaris et al., 2016). Seasonally controls were included as well. Our model for inflation is then:

$$\pi_t = \alpha + \beta_1\pi_{t-1} + \gamma_1 GDPgap_{t-1} + \beta_2\pi_{t-2} + \gamma_2 GDPgap_{t-2} + \Phi_1 z_1 + \Phi_2 z_2 + \Phi_3 z_3 + \epsilon_t,$$

where z_1, z_2 and z_3 are the seasonal components.

6. VAR(2) (inflation, GDP gap, interest rate): the second VAR and last estimated model is an extension of model number no.5. Here, I added the nominal interest rate set by the Central Bank in order to endogenize it and measure its effect on the inflation forecast:

$$\pi_t = \alpha + \beta_1\pi_{t-1} + \gamma_1 GDPgap_{t-1} + \delta_1 Nominalr_{t-1} + \beta_2\pi_{t-2} + \gamma_2 GDPgap_{t-2} + \delta_2 Nominalr_{t-2} + \Phi_1 z_1 + \Phi_2 z_2 + \Phi_3 z_3 + \epsilon_t,$$

where z_1, z_2 and z_3 are the seasonal components.

Taylor Rule and interest rate estimation

A forward looking Taylor rule to estimate the policy interest rate can be written as (Nikolsko-Rzhevskyy, 2011):

$$i_t^* = R^* + E\pi_{t+h} + \delta(\pi_{t+h} - \pi^*) + \gamma\hat{y}_t$$

Where i_t is the policy nominal interest rate, R^* is the equilibrium level of the real interest rate, Eπ_{t+h} is the expected year-over-year inflation rate, $(\pi_{t+h} - \pi^*)$ is the inflation gap and $\hat{y}$ is the output gap. Just as (Nikolsko-Rzhevskyy, 2011) did, R* and π^* were treated as constants, therefore simplifying the equation to be estimated:

$$i_t^* = R^* + \delta E\pi_{t+h} + \gamma\hat{y}_t$$

It is important to note that these coefficients were estimated using the realized past inflation (a backward looking Taylor Rule) instead of inflation expectations made t periods before. Using OLS, the estimated Taylor Rule for the sample period is then (s.e. in brackets):

$$i_t^* = \underset{(0.393)}{1.86} + \underset{(0.101)}{0.65}\, E\pi_{t+h} + \underset{(0.024)}{0.012}\hat{y}_t \ (1)$$

The coefficients for the equilibrium interest rate R^* and expected inflation $\mathrm{E}\pi_{t+h}$ were highly significant at 99% confidence level, while the coefficient for the output gap was not significant at all.

Results

Here are displayed the results of each forecast and the corresponding nominal interest rate that the Central Bank would set according to (1). Recall that for model number 6, each quarterly forecast was fed with the last interest rate estimation based on (1).

Table 1: Inflation rate forecasts 2022:1 - 2022:4

Model	2022:1	2022:2	2022:3	2022:4
1. Random Walk	5.16	5.16	5.16	5.16
2. ARMA(1,1)	5.47	5.13	4.86	4.64
3. SARIMA (2,0,0)(2,0,0)(4)	5.60	5.44	5.24	5.04
4. SARIMA (2,1,0)(2,0,0)(4)	5.63	5.45	5.14	4.78
5. VAR(2) (π_t, $\hat{y}_t$)	5.46	5.45	5.20	4.86
6. VAR(2) (π_t, $\hat{y}_t$, i_t)	6.16	6.31	5.99	5.54
GDP gap	(6.50)	(2.88)	0.07	7.94

Table 2: Nominal interest rate 2022:1 - 2022:4

Model	2022:1	2022:2	2022:3	2022:4
1. Random Walk	5.15	5.19	5.23	5.33
2. ARMA(1,1)	5.35	5.18	5.04	4.99
3. SARIMA (2,0,0)(2,0,0)(4)	5.44	5.38	5.29	5.25
4. SARIMA (2,1,0)(2,0,0)(4)	5.46	5.38	5.22	5.08
5. VAR(2) (π_t, $\hat{y}_t$)	5.35	5.38	5.26	5.13
6. VAR(2) (π_t, $\hat{y}_t$, i_t)	5.80	5.95	5.78	5.58
GDP gap	(6.50)	(2.88)	0.07	7.94

It is clear that model no.6 is the one showing a greater persistence of past values of inflation. Also, we can see that the Taylor Rule only sets an interest higher than inflation for 2022:4, nevertheless pushing down the inflation rate in the previous three periods.

At the light of the sample data and the estimated models, we can conclude that although the Banco de la República will increase -and mantain- nominal interest rates around 5%, it won't push down inflation anywhere close the 3% target in 2022. Maybe a more aggressive monetary policy would achieve it, but it is unlikely to happen as Central Banks tend to smooth changes in the interest rate (Clarida et al., 2000).

Bibliography

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