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A Comparison of Different Models

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Non-Technical Summary

Research Question

Forecasts of Inflation are a key input in monetary policy decisions. In this context, we propose a set of time series and causal models to forecast inflation in the short run. Different channels of monetary policy transmission are implicitly tested since we include at least two variations of each type of model, depending on which variables are included.

Contribution

We implement standard vector autoregressions, Bayesian vector autoregressions and time-varying parameter vector autoregressions, in addition to Phillips curves, to generate forecasts of monthly inflation. The predictive capacity of these models is contrasted to a Random Walk benchmark, for every horizon (one- to six-months-ahead).

Results

The results indicate that no model dominates the others at all horizons. The forecasting performance of the Random Walk and the rest of the models is not statistically different at very short horizons (one- to two-step-ahead). As we forecast further into the future (three- to six-step-ahead), univariate and multivariate models outperform the benchmark in predictive capacity.

Forecasting Inflation in Argentina: A Comparison of Different Models

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Abstract

In general, central banks are concerned with keeping the inflation rate stable while also sustaining output close to an efficient level. Under "inflation targeting", forecasts of the evolution of the general price level are an essential input for policy decisions and these are usually released in quarterly "Inflation Reports". The costs and benefits of transparency in monetary policy are widely debated, but the need for a central bank to incorporate forecasts of future inflation is broadly agreed. In short, forecasting inflation is of foremost importance to households, businesses, and policymakers. In 2016, the Central Bank of Argentina began announcing and inflation targeting scheme. In this context, providing the authorities with good estimates of relevant macroeconomic variables turns out to be crucial to make the pertinent corrections to reach the desired policy goals. This paper develops a group of models to forecast inflation in Argentina and conducts a comparison of their predictive ability at different horizons. Our variety of models includes: (i) univariate time series models, (ii) VARs, Bayesian VARs and Time-Varying Parameter VARs, and (iii) conventional New Keynesian Phillips Curves including one that incorporates money to evaluate its information content as a predictor of inflation. We compare the predictive performance of the different methods using the Giacomini-White test over the relevant horizons for monetary policy decisions.

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1   Introduction

In recent decades, forecasts of relevant macroeconomic variables have been a fundamental tool both to Central Banks and the general public. While the monetary authority needs them as an input for monetary policy decisions, the private sector also employs these forecasts as input when taking expenditure and investment decisions. In particular, in an inflation targeting scheme, monetary policy should be guided with a forward-looking perspective considering that transmission mechanisms take some time to induce an effect in the economy. From this point of view, the monetary authority should guide its decisions in advance of future developments to be effective.

This paper develops a wide range of models and assesses their forecasting performance for different horizons. We implement vector autoregressions (both in frequentist and Bayesian flavors), time-varying parameters vector autoregressions, and a hybrid New Keynesian Philips curve. We use different variables in each model to account for the many possible causes of inflation and the transmission mechanisms that take place in a complex economy. So, we arrive at 14 models and compare their performance to a benchmark Random Walk. For this purpose, we evaluate the models according to a standard measure, the Root Mean Square Forecast Error (RMSFE) and compare the predictive ability with the standard testing methodology. We find that for short term horizons, no models are statistically different from the benchmark. In contrast, for further horizons, this is reversed.

The remainder of the paper is organized as follows. The next section describes each of the models and variables used in the paper. Section 3 presents the results in relation to the predictive power of the models, and finally, section 4 concludes.

2   Forecasting Models and Dataset

2.1   Models

Each type of forecasting model has its own advantages and caveats. On the one hand, it is reasonable to argue that univariate time series models cannot capture the dynamic interactions among the different macroeconomic variables that could be jointly driven by different shocks. On the other hand, the literature related to forecasting inflation has found that smaller, parsimonious and univariate models, in particular,

the Random Walk, usually outperform or at least match more sophisticated models (Atkeson & Ohanian, 2001; Faust & Wright, 2009; Duncan & Martínez-García, 2018). We consider both univariate and multivariate models. In this subsection we briefly describe the structure and main characteristics of the models employed.

2.1.1 Random Walk (RW)

The first model employed is the Random Walk:

$$\pi_t = \pi_{t-1} + u_t. \tag{1}$$

This specification considers π_{t-1} as the forecast for π_{t+h} for $h = 1, \ldots, 6$. We chose this as the benchmark due to its simplicity and good predictive power according to the literature.

2.1.2 Vector Autoregression (VAR)

Moving on to multivariate models, the VAR consists in a linear system of equations. This type of model became popular since the Sims' critique (Sims, 1980) as a simple and flexible alternative to large scale econometric models. Each variable of the system is represented as a function of its own lags and lags of the rest of the variables. This assumes that the endogenous variables are treated symmetrically and that there is a feedback effect between them. An unrestricted VAR of order p can be expressed in reduced form:

$$\mathbf{y}_t = \boldsymbol{\nu} + \mathbf{A}_1 \mathbf{y}_{t-1} + \ldots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \tag{2}$$

where $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous random variables; $\boldsymbol{\nu}$ is a fixed $n \times 1$ vector of intercept terms allowing for the possibility of a nonzero mean; $\mathbf{A}_1$ to $\mathbf{A}_p$ are $n \times n$ coefficient matrices; and $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$ is a $n \times 1$ vector of serially uncorrelated exogenous shocks with constant covariance matrix $\boldsymbol{\Sigma}$ of size $n \times n$ (all of whose elements are time independent). This last assumption implies a white-noise or innovation process, that is, $\mathrm{E}[\mathbf{u}_t] = \mathbf{0}$, where $\mathrm{E}[\mathbf{u}_t \mathbf{u}_t'] = \boldsymbol{\Sigma}$ and $\mathrm{E}[\mathbf{u}_t \mathbf{u}_s'] = \mathbf{0}$ for $s \neq t$. D'Amato, Garegnani, & Blanco (2008), for example, test a bivariate monetary VAR to forecast headline inflation in Argentina.

2.1.3 Bayesian Vector Autoregression (BVAR)

One weakness of standard VARs is that the dense number of parameters to estimate increases exponentially as the number of variables increases; and hence, the finite sample estimates become less accurate with higher variances, resulting in unstable inference and less accurate forecasts. Litterman (1986) among others proposed to rethink standard VARs and combine the likelihood function (the data) with some informative prior distributions (the researcher's belief about the values of coefficients) to improve the forecasting performance, introducing a Bayesian approach into VAR modeling. The coefficients of the BVAR result in a weighted average of the prior mean (researcher's belief) and the maximum likelihood estimators (inferred from the data) where the inverse covariance of the prior and the maximum likelihood estimators are the respective weights. In this paper we follow this strategy.

The (conditional) posterior distribution of the coefficients of the BVAR is then

$$\boldsymbol{\beta}|\boldsymbol{\Omega} \sim \mathcal{N}(\boldsymbol{\beta_0}, \boldsymbol{\Omega}^{-1}\xi), \tag{3}$$

where $\boldsymbol{\beta} \equiv \text{vec}(\mathbf{B})$ and $\mathbf{B} \equiv [\boldsymbol{\nu}'\mathbf{A}_1' \dots \mathbf{A}_p']'$, the vector $\boldsymbol{\beta}_0$ is the prior mean, the matrix $\boldsymbol{\Omega}$ is the known variance of the prior and ξ is a scalar parameter controlling the tightness of the prior information. Even though $\boldsymbol{\Omega}$ could have many shapes, Gamma and Wishart distributions are frequently used in the literature, since they ensure a normally distributed posterior. The conditional posterior of $\boldsymbol{\beta}$ can be obtained by multiplying the prior by the likelihood function. So, if the information contained in the data is good enough to describe the process behind it, the posterior will move towards the maximum likelihood estimates. There is plenty of literature on applications of these models. Some examples include Giannone, Lenza, Momferatou, & Onorante (2014); Giannone, Lenza, & Primiceri (2015) and Mandalinci (2017). An application for Argentina can be found in Garegnani & Gómez Aguirre (2018).

2.1.4 Time-Varying Parameter Vector Autoregression (TVP-VAR)

Another extension of the standard VAR is to allow for time-varying coefficients. The time-varying parameter model implies that the underlying structure of the model evolves over time, while maintaining that such changes in the dynamic behavior should occur smoothly.

The TVP-VAR can be expressed in the following form:

$$\mathbf{y}_t = \boldsymbol{\nu}_t + \mathbf{A}_{1,t}\mathbf{y}_{t-1} + \dots + \mathbf{A}_{p,t}\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{4}$$

where $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$. If we define $\mathbf{X}_t = \mathbf{I}_n \otimes [1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-p}]$ and $\boldsymbol{\beta}_t = \text{vec}(\mathbf{B}_t)$, we can rewrite the system as:

$$\mathbf{y}_t = \mathbf{X}_t \boldsymbol{\beta}_t + \mathbf{u}_t. \tag{5}$$

The parameters $\boldsymbol{\beta}_t$ are assumed to evolve as a Random Walk

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \mathbf{w}_t \tag{6}$$

where $\mathbf{w}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$ and the initial conditions for $\boldsymbol{\beta}_t$ are treated as parameters. We formulate the simplifying assumption that the covariance matrix $\mathbf{Q}$ is diagonal, i.e., $\mathbf{Q} = \text{diag}(q_1, \ldots, q_{kn})$. The model specification[1] is fulfilled with independent priors for $\boldsymbol{\Sigma}$, $\boldsymbol{\beta}_0$ and the diagonal elements of $\mathbf{Q}$:

$$\boldsymbol{\Sigma} \sim \mathcal{W}^{-1}(\nu_0, \mathbf{S}_0) \qquad \boldsymbol{\beta}_0 \sim \mathcal{N}(0, \boldsymbol{\Sigma}) \qquad q_i \sim \mathcal{G}^{-1}(\nu_{0,q_i}, s_{0,q_i})$$

To estimate the TVP-VAR, we employed an MCMC approach similar to Koop & Korobilis (2013). Barnett, Mumtaz, & Theodoridis (2014) show an application of these TVP-VARs to forecast inflation.

2.1.5 Phillips Curve

Another model that we employ is the Phillips curve (PC). In the hybrid version proposed by Galí & Gertler (1999), the inflation rate is assumed to follow the process:

$$\pi_t = \phi \pi_{t-1} + (1 - \phi) \text{E}_t[\pi_{t+1}] + \delta mc_t + u_t \tag{7}$$

where π_t is the inflation rate at time t, $\text{E}_t[\pi_{t+1}]$ is the expectation of inflation of the next period at time t, mc_t is the "marginal cost" and u_t is a random shock. The assumption that $0 < \phi < 1$ implies a vertical Phillips curve in the long-run.

We adapted the specification of Galí and Gertler to the case of a small open economy. As pointed out by Svensson (2000), changes in the nominal exchange rate and foreign prices have a direct effect on domestic inflation. In addition, since the nominal exchange rate is in essence the price of an asset, it is inherently a forward-looking variable. Thus, as a determinant of domestic inflation it influences expectations and domestic price formation.

We estimate an open economy version of the "Hybrid New Keynesian Phillips Curve" that modifies the previous equation in two directions: (i) introducing measures of

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[1]All the multivariate model specifications include only one lag of each variable.

nominal devaluation and foreign inflation and (ii) using a measure of the output gap as a proxy for marginal costs rather than the labor income share. Thus, the final model is:

$$\pi_t = \phi_1 \pi_{t-1} + \phi_2 \mathrm{E}_t[\pi_{t+1}] + \gamma \pi_t^* + \lambda \Delta e_t + \delta x_t + u_t, \tag{8}$$

where π_t is domestic inflation, measured by the change in the logarithm of the price index; $\mathrm{E}_t[\pi_{t+1}]$ is inflation expectation for $t + 1$ at time t; π_t^* is foreign inflation, measured by the change in the log of the US Producer Price Index; Δe_t is the nominal devaluation computed as the log difference of the nominal ARS-USD exchange rate and x_t is the output gap.

We then consider that a relevant empirical question beyond the ongoing debate on the role of money in monetary policy is whether money can contribute to forecast inflation and if so, at which frequency. We evaluate the information content of money by introducing a "real" money gap into the previous Phillips curve model. This additional variable is defined as the difference between the actual real money stock and its long-run equilibrium,

$$m_t^{gap} = m_t - m_t^*, \tag{9}$$

where m_t^* is the level of real money balances that is consistent with both, potential output and the long-run equilibrium interest rate. When introduced into the Phillips curve equation, the real money gap is a measure of demand pressures and can be considered as an indicator of the real monetary overhang.

Under rational expectations, economic agents are supposed to use current and past information efficiently. In terms of equation (8) this implies that the error in forecasting future inflation is uncorrelated with the information set $\mathbf{z}_t$ available at date t. The following moment conditions needs to hold,

$$\mathrm{E}[(\pi_t - \phi_1 \pi_{t-1} - \phi_2 \mathrm{E}_t[\pi_{t+1}] - \gamma \pi_t^* - \lambda \Delta e_t + \delta x_t)\mathbf{z}_t] = 0, \tag{10}$$

where $\mathbf{z}_t$ is a vector of variables (instruments) dated at t and earlier. A natural way to deal with the estimation of the Phillips curve is to use the Generalized Method of Moments (GMM) developed by Hansen (1982), which is a generalization of the method of moments. The model with the money gap is also estimated with the GMM methodology.[2] There is a wide economic literature that employs Phillips curves to forecast inflation. We can mention, for example, the extensive work of Stock & Watson (1999) and Faust & Wright (2009) for the US economy, and an application for Argentina in D'Amato et al. (2008).

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[2]For a detailed description of GMM estimation see D'Amato & Garegnani (2009).

Forecasting with Phillips curves implies the use of inflation expectations that are not available at the time the forecasts are made. To circumvent this problem, we use the forecasts of the Random Walk as a proxy of inflation expectations for all forecast horizons.

2.2 Variables and Dataset

This section describes the variables included in all the models. The dataset was constructed using many sources and starts in January 2004 and ends in May 2018. The following list describes all the variables in the dataset:

- **CPIX:** A price index constructed combining the index the National Institute of Statistics and Census of Argentina (INDEC) and the Price Index of the City of Buenos Aires. This index excludes seasonal and regulated prices.

- **NEER:** Multilateral Nominal Exchange Rate Index. Is is constructed by the Central Bank of Argentina.

- **EMAE:** Estimador Mensual de Actividad Económica (EMAE). A Monthly Economic Activity Indicator published by the INDEC. This variable tries to replicate quarterly GDP but at a monthly frequency.

- **Interest Rate:** 30 to 59-day fixed term deposit rates. The source is the Central Bank of Argentina (BCRA).

- **Wages:** Mean wage of Registered Private Sector workers. The source is the Ministry of Labor, Employment and Social Security of Argentina.

- **Reg. Prices:** A price index of regulated prices. This index is composed of public utility services (electricity, natural gas and running water of households).

- **ARS-USD ER:** It indicates the nominal exchange rate peso-dollar. The source is the Central Bank of Argentina.

- **US PPI:** Producer Price Index of the US. The source is the Federal Reserve Bank of St. Louis.

- **Output Gap:** The gap between real GDP and the potential output of Argentina. The estimation methodology is based on a multivariate filter based on Beneš, Clinton, García-Saltos, Johnson, Laxton, Manchev, & Matheson (2010).

- **Monetary Gap:** The difference between the actual real money stock and its long-run equilibrium. The long-run equilibrium money stock is the level of real money that is consistent with both, the observed output and the nominal interest rate long-run equilibrium levels.

Table 1: Variables Included in Each Model

	CPIX	NEER	EMAE	Int. Rate	Wages	Reg. Prices	ARS-USD ER	US PPI	Output Gap	Monetary Gap
VAR-1	X	X	X	X						
VAR-2	X	X			X					
VAR-3	X	X	X	X		X				
VAR-4	X	X			X	X				
BVAR-1	X	X	X	X						
BVAR-2	X	X			X					
BVAR-3	X	X	X	X		X				
BVAR-4	X	X			X	X				
TVP-VAR-1	X	X	X	X						
TVP-VAR-2	X	X			X					
TVP-VAR-3	X	X	X	X		X				
TVP-VAR-4	X	X			X	X				
PC-1	X						X	X	X	
PC-2	X						X	X	X	X
RW	X									

Notes: The hyperparameters of the BVARs can be found in the appendix.

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2.2.1 Comparison Strategy

We first estimated the models presented so far with a rolling window of 88 observations. The evaluation period we considered goes from January 2012 to December 2017. We computed the root mean square forecast error (RMSFE) for one-, three- and six-step-ahead point forecasts with the formula below

$$\text{RMSFE}_{m,h} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{y}_{m,t+h} - y_{t+h})^2} \tag{11}$$

where $m = 1, \ldots, 14$ are the models, and $h = 1, \ldots, 6$ are the forecast horizons, N is the evaluation sample size, $\hat{y}_{m,t+h}$ is the forecast and y_{t+h} is the observed value. Then we compared the RMSFE of each model relative to the benchmark and tested their predictive ability with the methodology of Giacomini & White (2006). This requires the computation of the difference of the times series of squared losses of the model under evaluation and the benchmark for each desired forecast horizon, $\Delta L_{t+h}(\hat{\boldsymbol{\theta}})$, where $\hat{\boldsymbol{\theta}}$ contains all the estimated parameters, assuming a rolling window sample of estimation. This series is then modeled and a standard Wald test is conducted on the coefficients to determine the difference in forecast accuracy between the two competing models. The unconditional version of the test assumes that the series is constant, and thus

$$\Delta L_{t+h}(\hat{\boldsymbol{\theta}}) = \mu + u_t. \tag{12}$$

Standard errors may be computed using the Newey-West covariance estimator, controlling for heteroskedasticity and autocorrelation. The Giacomini-White test has many advantages: i) it captures the effect of estimation uncertainty on relative forecast performance, ii) it allows for comparison between either nested or non-nested models, and finally, iii) it is relatively easy to calculate.

3 Results

Here we present three plots of observed inflation in addition to one-, three- and six-step-ahead forecasts.
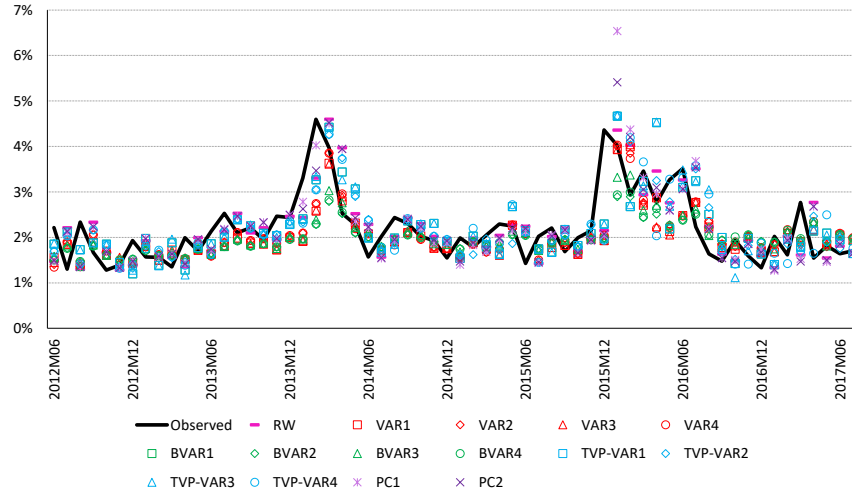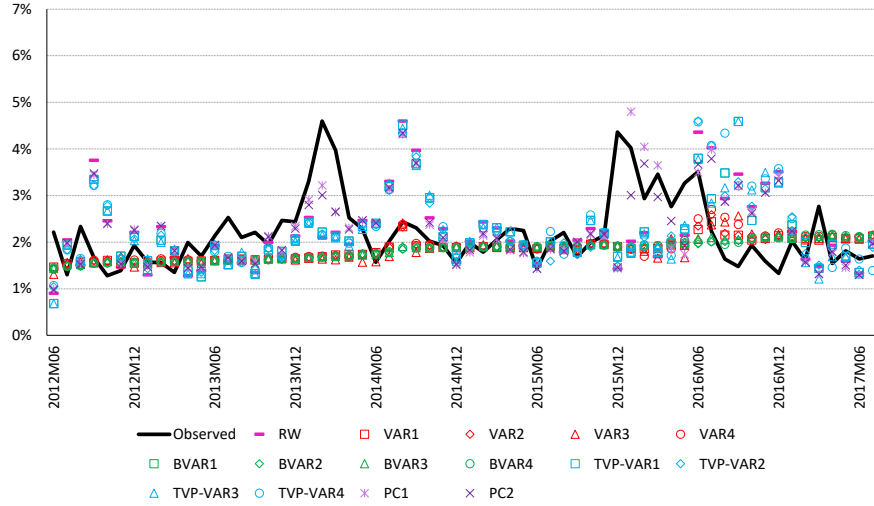

(a) Evolution of Observed Inflation and One-Step-Ahead Forecasts
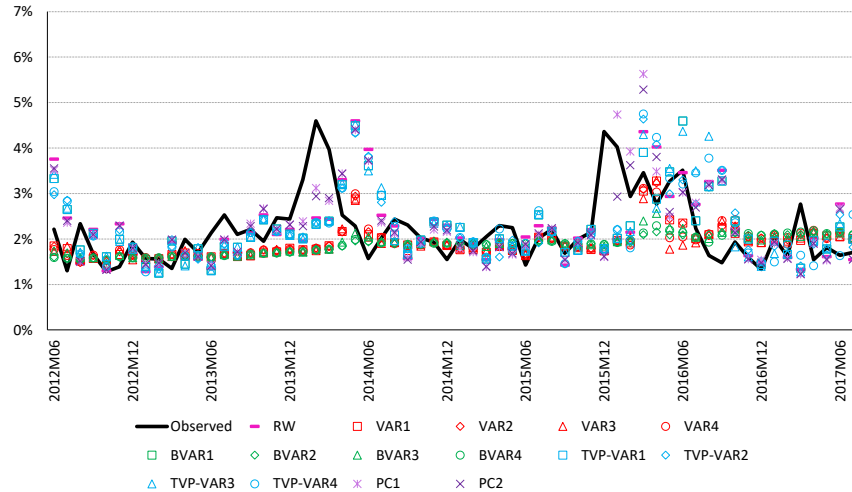
(b) Evolution of Observed Inflation and Three-Step-Ahead Forecasts

We can observe that as the forecast horizon goes further into the future, the performance of the models tends to deteriorate.

(c) Evolution of Observed Inflation and Six-Step-Ahead Forecasts

Table 2 reports out-of-sample RMFSE of alternative h-step-ahead forecasts of inflation, all relative to the benchmark Random Walk. A relative RMSFE below 1 indicates better performance than the benchmark. The cases in which deviations in RMSFE are significantly different from zero at 10%, 5% and 1% significance levels are denoted with one, two and three asterisks ($*$), respectively. These are based on the aforementioned Giacomini-White test, described earlier in the paper.

Results of Table 2 show that in 72 out of 84 ratios the RMSFE are less than 1, which could indicate that causal and multivariate models outperform in forecasting capacity the benchmark. Using the Giacomini-White test we find that the differences in forecasting performance of the Random Walk and the rest of the forecasting models are not significant (at 1%, 5% and 10%) for one- and two-step-ahead horizons. However, when the differences in predictive capacity are evaluated for three- to six-step-ahead forecast horizons, in 23 out of 56 of the cases, these are significant at traditional levels. Only in two of the cases of significant differences in predictive performance, the benchmark outperforms the TVP-VAR for three- and six-step-ahead horizons. In the other 21 cases the causal and multivariate models present better forecast capacity than the benchmark. We want to emphasize that 9 of these 21 significant differences in favor of causal and multivariate forecasting models correspond to the six-step-ahead forecast horizon.

The results indicate that when the forecast horizon grows, the causal and multivariate models tend to outperform the benchmark. Taking a look into the subset of 21

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Table 2: Out-of-Sample Predictive Performance, RMSFE Ratios

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
VAR-1	0.941	0.893	0.831*	0.800*	0.842	0.791*
VAR-2	0.920	0.895	0.836*	0.806*	0.841	0.791*
VAR-3	0.946	0.927	0.867	0.833	0.876	0.831
VAR-4	0.927	0.920	0.860	0.819	0.853	0.801*
BVAR-1	0.975	0.988	0.958*	0.971*	1.016	0.992*
BVAR-2	0.970	0.941	0.866	0.819	0.864	0.800*
BVAR-3	0.931	0.896	0.838	0.802	0.850	0.793*
BVAR-4	0.961	0.930	0.857	0.810	0.856	0.794*
TVP-VAR-1	0.975	0.988	0.958	0.971	1.016	0.992
TVP-VAR-2	0.976	0.981	0.961	0.961	0.971	0.968
TVP-VAR-3	0.984	1.017	1.013	1.014	1.075	1.009
TVP-VAR-4	0.986	1.031	0.996	0.984	1.058	1.029
PC-1	1.056	0.982	0.929	0.849**	0.836***	0.857***
PC-2	1.006	0.978	0.929*	0.873**	0.835***	0.848***

significant differences, 7 corresponds to VARs, 7 to Phillips curves, 6 to BVARs y 1 to a TVP-VAR. Particularly, forecasts from Phillips curves are quite different (1% significance level) from the ones of the Random Walk for five- and six-step-ahead forecast horizons.

If we want to make a difference among the transmission mechanism that generate better forecasting performance, 8 of the cases are in line with financial mechanisms (VAR-1 and VAR-3) and the other 13 are connected with the cost-push channel of monetary policy (VAR-2, VAR-4, PC-1 and PC-2). We also find that the inclusion of regulated prices as an exogenous variable in the VAR models does not make any difference in predictive performance relative to the benchmark.

4   Conclusions

We conducted an exercise to forecast inflation in Argentina using a wide set of models that includes a Random Walk as a benchmark, various VARs, BVARs and TVP-VARs, as well as two versions of the Phillips curve. We then compared the relative predictive accuracy of those forecasts using the Giacomini-White test. The results indicate that no model dominates the others at all horizons. The forecasting performance of the Random Walk and the rest of the models is not statistically different at very short horizons (one- to two-step-ahead). As we forecast further into the future (three- to six-step-ahead), univariate and multivariate models outperform the benchmark in predictive capacity. In particular, forecasts from Phillips curves, are significantly better, at the 1% level, for five- and six-month-ahead forecast horizons. Finally, it should also be noted that these models could complement each other when conducting inflation forecasts, in the sense that they make it possible to answer different questions and guide policy decisions. In this regard, exploring forecast combinations could be relevant for future research.

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Appendix: Specification for BVARs

We followed the strategy suggested by Bańbura, Giannone, & Reichlin (2010); Carriero, Clark, & Marcellino (2015) and Giannone et al. (2015) to select the hyperparameters and the lag length of the BVARs. Suppose that a model is described by a likelihood function $p(\mathbf{y}|\boldsymbol{\theta})$ and a prior distribution $p_{\boldsymbol{\gamma}}(\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is the vector of parameters of the model and $\boldsymbol{\gamma}$ is a vector of hyperparameters affecting the distribution of all the priors of the model; then it is natural to choose these hyperparameters by interpreting the model as a hierarchical one, i.e. replacing $p_{\boldsymbol{\gamma}}(\boldsymbol{\theta})$ with $p(\boldsymbol{\theta}|\boldsymbol{\gamma})$ and evaluating their posterior (Berger, 1985; Koop, 2003). In this way, the posterior can be obtained by applying Bayes' law

$$p(\boldsymbol{\gamma}|\mathbf{y}) \approx p(\mathbf{y}|\boldsymbol{\gamma})p(\boldsymbol{\gamma}), \tag{13}$$

where $p(\boldsymbol{\gamma})$ is the density of the hyperparameters and $p(\mathbf{y}|\boldsymbol{\gamma})$ is the marginal likelihood. In turn, the marginal likelihood is the density that comes from the data when the hyperparameters change. In other words, the marginal likelihood can be obtained after integrating out the uncertainty about the parameters in the model,

$$p(\boldsymbol{\gamma}|\mathbf{y}) = \int p(\mathbf{y}|\boldsymbol{\theta}, \boldsymbol{\gamma})p(\boldsymbol{\theta}|\boldsymbol{\gamma})d\boldsymbol{\theta}. \tag{14}$$

For every conjugate prior, the density $p(\boldsymbol{\gamma}|\mathbf{y})$ can be computed in closed form. To obtain the Bayesian hierarchical structure, it is necessary to obtain the distribution of $p(\boldsymbol{\theta})$ by integrating out the hyperparameters

$$p(\boldsymbol{\theta}) = \int p(\boldsymbol{\theta}, \boldsymbol{\gamma})p(\boldsymbol{\gamma})d\boldsymbol{\gamma}. \tag{15}$$

More precisely, we can find different values of the prior distribution from different hyperparameter values, and, in this way, we can represent the posterior as:

$$p(\boldsymbol{\theta}, \boldsymbol{\gamma}|\mathbf{y}) = p(\mathbf{y}|\boldsymbol{\theta}, \boldsymbol{\gamma})p(\boldsymbol{\theta}, \boldsymbol{\gamma})p(\boldsymbol{\gamma}). \tag{16}$$

The marginal likelihood should be sufficient to discriminate among models. In this sense, we can choose models with different hyperparameters and different likelihood specifications (more precisely, lag length structure). To make this point operational, we estimate different models, following Giannone et al. (2015) who introduce a procedure allowing to find the values of the hyperparameters that maximize the value of the marginal likelihood of the model. This implies that the hyperparameter values

are not set a priori but are estimated. Then the marginal likelihood can be estimated for every combination of hyperparameter values within specified ranges and for different lag length structures, and the optimal combination is retained as the one that maximizes that value.

We work with a Normal-Wishart BVAR specification. In this type of specification there are two hyperparameters and two parameters. We estimate the overall tightness λ_1, lag decay λ_3 and the lag length as described below, and then we impose the value of the prior mean (the autoregressive coefficient) equal to zero.

The hyperparameter of the overall tightness λ_1 is the standard deviation of the prior of all the coefficients in the system different from the constant. In other words, it determines how all the coefficients are concentrated around their prior means.

The term λ_3 is a decay factor, and $1/(L^{\lambda_3})$ controls the tightness on lag "L" relative to the first lag. Since the coefficients of higher order lags are more likely to be close to zero than those of lower order lags, the prior for the standard deviations of the coefficients decrease as the lag length increases. The values usually used in the literature are 1 or 2, but in our case, we settle for $\lambda_3 = \lambda_2 = 0$.

The prior variance of the parameters of $\hat{\boldsymbol{\beta}}(\xi)$ is set according to:

$$\sigma_{ij}^2 = \left(\frac{1}{\sigma_j^2}\right)\left(\frac{\lambda_1}{L^{\lambda_3}}\right)^2 \tag{17}$$

where σ_j^2 denotes OLS residual variance of the autoregressive coefficient for variable "j". For exogenous variables, we define variances as $\sigma_x^2 = (\lambda_1\lambda_4)^2$.

The characteristics of the hyperparameters after the optimization and prior means of the BVAR-1, BVAR-2, BVAR-3 and BVAR-4 models are shown in the next table:

Table 3: List of Hyperparameter Values

	BVAR-1	BVAR-2	BVAR-3	BVAR-4
Autoregressive Coefficient	0.50	0.30	0.40	0.30
Overall Tightness (λ_1)	0.05	0.21	0.07	0.17
Lag Length	1	1	1	1

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