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Different Approaches to Inflation Forecasting in Argentina*

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Abstract

We apply some recently developed and more traditional methods to forecast inflation in Argentina and compare their predictive ability at different horizons. Our variety of models includes: (i) Traditional time series models -AR(1) and a monetary VAR-, (ii) a factor model combining a large number of business cycle indicators and (iii) micro-funded models including a conventional New Keynesian Phillips Curve and 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. We find that the monetary VAR outperforms the rest of the models.

JEL Classification: C32, E31, E37

Keywords: Inflation Forecasting, Time Series Models, Phillips Curve, Factor Models

Resumen

Aplicamos metodologías recientes y tradicionales para pronosticar la inflación en la Argentina, comparando su capacidad predictiva para diferentes horizontes. Nuestra variedad de modelos incluye: (i) Modelos tradicionales de series de tiempo -AR (1) y un VAR monetario-, (ii) modelos de factores que combinan un gran número de indicadores del ciclo económico y (iii) modelos microfundados incluyendo una Curva de Phillips nuevo keynesiana convencional y una que incorpora dinero para evaluar su contenido informativo como predictor de la inflación. Comparamos la capacidad predictiva de los diferentes métodos empleando el test de Giacomini-White para horizontes relevantes en la toma de decisiones de política monetaria. Encontramos que el VAR monetario supera al resto de los modelos.

*The opinions expressed in this work are those of the authors, and do not necessarily reflect the opinions of the Central Bank of Argentina or its authorities.

1 Introduction

Inflation forecasting plays a central role in monetary policy formulation but it is also essential for private sector decision making involving long term commitments, as labor contracts, mortgages and other forms of debt.

A growing body of literature has emerged in recent years on inflation forecasting, with an explosion of new methods including those that use a large number of predictors and forecast combination. These methods as well as the emergence of new assets linked to inflation, which incorporate inflation expectations, provide alternative prediction methods to more traditional inflation forecasting models as Phillips Curves (Faust and Wright, 2013) or DSGE models. Whether these different methods and models can serve as complements rather than being rivals depending on the forecasting horizon, the volatility of the economic environment or the presence of structural breaks in the time series of inflation or in its relationship with its determinants is something that has been explored recently (Faust and Wrigth, 2013; Dotsey et al., 2011; Stock and Watson, 2009).

In this paper, we consider a wide range of forecasting models: Traditional time series models as an AR(1) and a monetary VAR, a Factor Model combining a large number of business cycle indicators and micro-funded models, including a conventional New Keynesian Phillips Curve and one that incorporates a money gap to evaluate its information content as a predictor of inflation. We estimate the models for the period 2004:1-2010:12 and then, using rolling windows, we produce pseudo out-of-sample predictions of inflation for the period 2011:1-2015:3 at different horizons and investigate how these alternative models perform in terms of their predictive ability relative to the AR(1) model as a benchmark, depending on the forecast horizon. We test for differences in models' predictive ability using the Giacomini and White (2006) test.

The paper is organized as follows: In Section 1 we describe in detail the empirical approach we use to conduct our forecasting exercise, in Section 2 we present our empirical approach, while in Section 3 the results of our empirical exercise are displayed. Section 4 presents the results of applying the Giacomini-White (2006) test to evaluate the differences in predictive ability of the different models and finally, Section 5 concludes.

2 Our empirical approach

The sample chosen to conduct our forecasting excercise is the period 2004:1-2015:3. We use monthly data to forecast inflation, measured by the Consumer Price Index (CPI). In choosing the sample period as well as the frequency of the data we followed a pragmatic approach. Although ideally one would like to consider a long span to find forecasting models that perform well in all possible macroeconomic conditions, this could be an unattainable objective, taking into account that the parsimonious an predominantly linear time series models in use for forecasting are no more than just local approximations to complicated processes. This is particularly true for Argentina, that has a history of high macroeconomic instability. In this regard we preferred to exclude from our sample the unusual period corresponding to the external and financial crisis of 2001 and the abandoning of the Convertibility regime, that ended with a sharp depreciation of the peso in January 2002. Thus, our sample extends from 2004:1 to 2015:3.

We consider a set of 5 forecasting models of inflation: **(i)** An AR(1) model as benchmark, **(ii)** a monetary VAR model that we describe in detail below, **(iii)** a Factor Model including a large set of business cycle indicators, **(iv)** a conventional New Keynesian Phillips Curve and **(v)** one that incorporates a measure of the real money gap. These models are estimated for the period 2004:1 2010:12 and then used to produce out of sample forecast over the period 2011:1-2015:3 based on rolling windows estimation for different forecasting horizons. We then compare the predictive capacity of the different models and methods based on the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE), considering the AR(1) model as benchmark. Finally, we evaluate the differences in the predictive ability of models using the Giacomini-White (2006) methodology to compare the forecast accuracy of the different models relative to the AR(1). The reason to choose Giacomini-White procedure is that it has some advantages relative to other methods. First, it is a test of conditional predictive ability and thus focuses on the relevant question for forecasters: Which of two forecasts will be more accurate in the future. Second, it is adequate for testing both nested and non-nested models.

2.1 Rivals or complementary models?: Different horizons, different models

Although from the point of view of forecasters, the process of model selection is guided by the search of the best possible predictive accuracy, economic theory also provides a guidance about which models could be preferred depending on the forecasting horizon. Regarding inflation, autorregresive time series models, Dynamic Factor Models which are based on business cycle indicators and Phillips Curves are expected to perform better in the short run, since movements in the inflation rate are supposed to be related to demand pressures or transitory changes in relative prices that cancel out in the mean term. At longer horizons, models accounting for monetary developments as monetary VARs or Phillips Curves incorporating measures of monetary overhang, can add predictive ability, since developments in money aggregates are expected to account for changes in inflation at longer horizons. In this regard, different models can be seen as complementary rather than rivals when forecasting inflation at different horizons. We follow this approach in our forecasting exercise when evaluating and ranking our models.

2.2 Factor Models

Inflation forecast can be conducted through the estimation of common factors from a large set of monthly data and subsequently using them as regressors for inflation (Stock and Watson, 2006). The idea behind this approach is that the variables in the set of interest are driven by a few unobservable factors.

More concretely, the covariance between a large number of n economic time series with their leads and lags can be represented by a reduced number of unobserved q factors, with $n > q$. Disturbances in such factors could in this context represent shocks to aggregate supply or demand.

Therefore, the vector of n observable variables in the cycle can be explained by the distributed lags of q common factors plus n idiosyncratic disturbances which could eventually be serially correlated, as well as being correlated among the $i's$.

A vector X_{it} of n stationary monthly business cycle indicators $x_t = (x_{1t}, ..., x_{nt})'$, with $t = 1, ..., T$ can be explained by the distributed lags of q common latent factors plus n idiosyncratic disturbances which could eventually be serially correlated.

$$X_{it} = \lambda_i(L)' f_t + u_{it} \tag{1}$$

Where f_t is a vector $q\times$ 1 of unobserved factors, λ is a $q \times 1$ vector lag polynomial of *dynamic factor loadings* and the u_{it} are the idiosyncratic disturbances that are assumed to be uncorrelated with the factors in all leads and lags, that is to say $E(f_t u_{it}) = 0 \; \forall \; i, s$.

The objective is therefore to estimate $E(y_t \mid X_t)$ modeling y_t according to

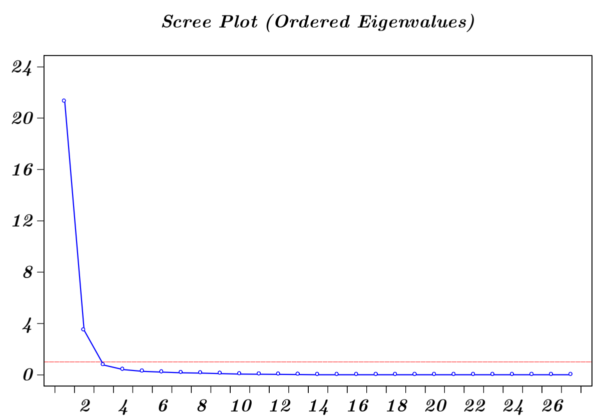
$$y_t = \beta(L)' f_t + \varepsilon_t \tag{2}$$

If the lag polynomials $\lambda_i(L)$ in (1) and $\beta(L)$ in (2) are of finite order p, Stock and Watson (2002a) show that the factors f can be estimated by principal components.

The data set used to extract the factors comprises 27 business cycle indicators, ranging from financial indicators to tax collection data, disaggregated data on industrial production, monetary aggregates and interest rates[1].

The series were seasonally adjusted when needed, de-trended or differentiated to make them stationary and finally log transformed. To apply the factor model methodology we proceeded in the following way: *(i)* We used the indicators to calculate the factors using the principal component methodology, *(ii)* then we used the *scree plot*[2] presented in Figure 1 to determine the number of factors to be used to estimate equation (2). It can be seen from there that it is up to the second factor that the addition of factors contributes to increase the proportion of covariance of the time series explained by the factors. Taking into account this information, we estimated equation (2) using the first two factors.

Figure 1: Scree Plot



2.3 A monetary VAR

VAR models have become an essential tool for out-of-sample macroeconomic forecasting and are widely in use at central banks to produce not only point forecasts but also density forecast. Here we use a VAR model which incorporates a money aggregate and other variables that account for relevant features of a small open economy as Argentina (Basco, D'Amato and Garegnani, 2009). This set of variables includes: *(i)* The change in the M2 money aggregate, *(ii)* the change in the nominal exchange rate, *(iii)* the nominal interest rate, *(iv)* the output gap and (v) CPI inflation. To calculate the output gap at the monthly frequency we use a Markov-random-walk technique as suggested by Litterman (1983) to obtain a monthly measure of GDP and then the Hodrick-Prescott filter to estimate a measure of the output gap.

[1] The indicators included in the data set are detailed in Appendix I.

[2] Developed by R B. Cattel in "The scree test for the number of factors", Multivariate Behav. Res. 1:245-76, 1966. University of Illinois, Urbana-Champaign, ILl.

2.4 Alternative Phillips Curves

2.4.1 A Hybrid New-Keynesian Phillips Curve

D´Amato and Garegnani (2009) estimate a Hybrid New-Keynesian Phillips Curve (HNKPC) for Argentina over the period 1993-2007 which is based on the Galí and Gertler (1999) model extended to the case of a small open economy and considering separately the influence of nominal devaluation and foreign inflation on domestic prices.

We relay on the same specification to estimate a HNKPC for the period 2004:1 2010:12.

$$\pi_t = \phi_1 \pi_{t-1} + \phi_2 E_t(\pi_{t+1}) + \gamma \pi_t^* + \lambda \Delta e_t + \delta x_t + e_t \quad (3)$$

Where $E_t(\pi_{t+1})$ is the expectation of π_{t+1} in t, π_t^* is foreign inflation, Δe_t is nominal devaluation and x_t is the output gap. We measure foreign inflation by a weighted average of CPI inflation of the three main trade partners of Argentina: Brazil, US and the EU. Nominal devaluation is calculated as the change in the log of the nominal exchange rate with the same partners.

2.4.2 Adding a money gap to the HNKPC

Several studies find that while money is not informative about future values of inflation for short-run forecasts, it can improve forecast accuracy at longer horizons. As stressed in Subsection 2.1. this finding is in line with the theoretical idea that money is a relevant determinant of inflation in the medium and long term (Reis, 2013). Assenmacher-Wesche and Gerlach (2006) show a significant contribution of low frequency movements in money growth to forecast inflation using a two-pillar Phillips-curve type dynamic model, while Nicoletti-Altimari (2001), Hofmann (2008), and Scharnagl and Schumacher (2007) all find that M3 growth is useful for inflation forecasts at medium-term horizons. Also, Gerlach and Svensson (2003) find that a real money gap representation of the P* model adds to the predictive power of a conventional Phillips curve approach. Berger and Stavrev (2008) analyze the information content of money in forecasting euro-area inflation, comparing the predictive performance of various classes of structural and empirical models. They find that while money contains relevant information for inflation in some model classes, the marginal contribution of money to forecasting accuracy is often small. Berger and Österholm (2008) use mean-adjusted Bayesian VARs as an out-of-sample forecasting tool to test whether money growth Granger-causes inflation and find strong evidence that including money improves forecast accuracy.

More recently, Valle e Azevedo and Pereira (2010) find that, discarding high frequency movements, money aggregates can be useful to forecast US inflation and that models including it dominate a wide range of competing models.

Coenen et al. (2003) provide an alternative argument for using money as an indicator variable, which is that money demand depends on the true level of aggregate output, whereas the Central Bank only receives a noisy signal of aggregate actual income. Given this link, money can be informative about the real value of aggregate income depending on the relative variability of measurements errors vs. the magnitude of money demand fluctuations in response to unobserved velocity shocks.

Apart from any theoretical support for the use of money as a predictor of inflation, a practical reason to investigate the information content of money for forecasting purpose is that relying on more than one model for forecasting and policy advice is in general beneficial. Taking into account that models' forecast can be biased in different directions, diversifying should add robustness to policy decisions and help to reduce the error's variance in general, which would probably reduce the policy errors too.

The exercise we develop in this paper relates to Gerlach and Svensson (2003) and Assenmacher-Wesche and Gerlach (2006) in that we introduce a real money gap to a New Keynesian Phillips Curve.

The real money gap is defined as the difference between the actual real money stock m_t and its long run equilibrium m_t^*,

$$m_{gap} = m_t - m_t^* \tag{4}$$

At the same time, the long run equilibrium money stock m_t^* is given by the level of real money that is consistent with both, the output y_t^* and nominal interest rate r_t^* long run equilibrium levels. Thus, in the long-run equilibrium, money demand should be equal to

$$m_t^* = \kappa_y y_t^* - \kappa_r r_t^* \tag{5}$$

When introduced into the HNKPC, the real money gap is a measure of demand pressures and can be considered as an indicator of real monetary overhang and the Phillips Curve is then written as

$$\pi_t = \phi_1 \pi_{t-1} + \phi_2 E_t(\pi_{t+1}) + \gamma \pi_t^* + \lambda \Delta e_t + \delta x_t + \varphi m_{gap} + e_t \tag{6}$$

Where m_{gap} is the money gap.

To estimate the money gap we considered the real money demand model estimated in Ahumada and Garegnani (2012) that incorporates the aggregate supply as the measure of real transactions and takes into account three different measures of opportunity cost: inflation, the exchange rate depreciation and the domestic interest rate.

3 The empirical results

All 5 models were estimated for the period 2004:1 -2010:12 and then used to produce out of sample forecast for the period 2011:1 2015:3 for the 1 month, 3 month, 6 month and 12 month horizons. The results of models' estimation are reported in Appendix II. The predictive accuracy of the models is measured by the RMSE and the MAPE[3]. As can be seen from Figure 3 the VAR model notably outperforms the rest of the models for each month and all horizons. From Figure 4 it is also clear the outstanding performance of the VAR model with respect to the AR(1) at the 1 month horizon,[4] although it is also clear that all multivariate models outperform the AR(1), usually considered as benchmark.

[3]The results obtained using the MAPE are similar to those based on the RMSE, as verified when conducting the Giacomini-White test in Section 4. Thus, for brevity, we only present here the results for the RMSE. Those based on the MAPE are available upon request.

[4]See Appendix III for the rest of the horizons.

Figure 3: *RMSE of forecasting models*

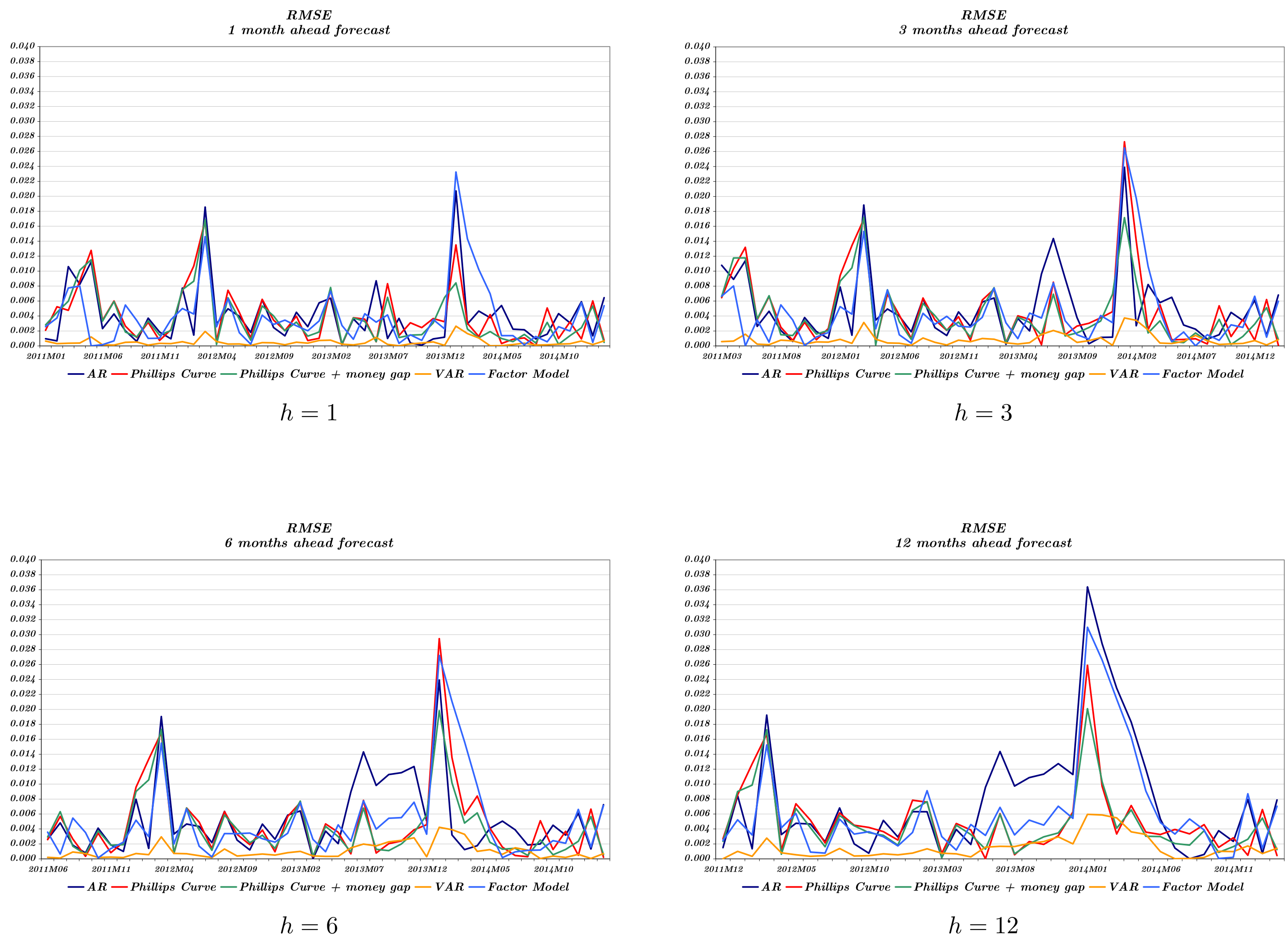
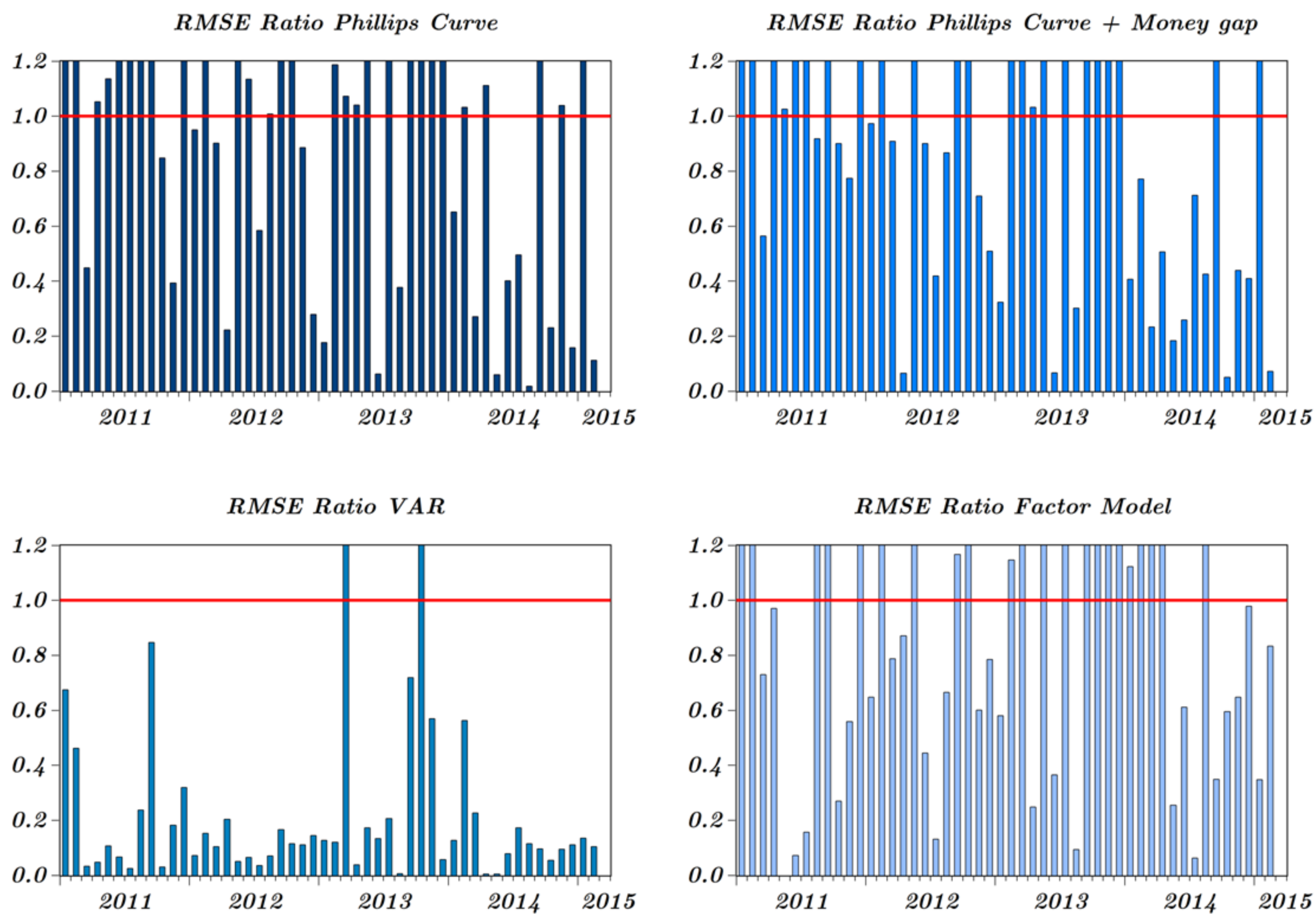


Figure 4: *RMSE ratios* $h = 1$



RMSE model / RMSE AR

4 Testing for differences in predictive ability at different horizons

To test if the differences in predictive accuracy found in the previous section are statistically significant we use the Giacomini and White (2006) test. The Giacomini and White approach differs from that followed by previous tests, as those proposed by Dieblod and Mariano (1995) and West (1996) in what it is based on conditional rather than unconditional expectations. In this regard, the Giacomini and White approach focuses on finding the best forecast method for the following relevant future. Their methodology is relevant for forecasters who are interested in finding methodologies that improve predictive ability of forecast, rather than testing the validity of a theoretical model.[5] Consistently with the aim of the test we estimate all models using rolling windows and in this regard all of them are suitable for conducting the Giacomini and White test, including the VAR, as stressed by Clark and McCracken (2013).

The test has many advantages: (i) it captures the effect of estimation uncertainty on relative forecast performance, (ii) it is useful for forecasts based on both nested and non nested models, **(iii)** it allows the forecasts to be produced by general estimation methods, and (iv) is quite easy to be computed. Following a two-step decision rule that uses current information, it allows to select the best forecast for the future date of interest.

The testing methodology of Giacomini and White consists on evaluating forecast by conducting an exercise using rolling windows. That is, using the R sample observations available at time t, estimates of y_t are produced and used to generate forecast τ step ahead. The test assumes that there are two methods, f_{Rt} and g_{Rt} to generate forecasts of y_t using the available set of information $\mathcal{F}_t$. Models used are supposed to be parametric.

$$\begin{aligned} f_{Rt} &= f_{Rt}(\widehat{\gamma}_{R,t}) \\ g_{Rt} &= g_{Rt}(\widehat{\theta}_{R,t}) \end{aligned}$$

A total of P_n forecasts which satisfy $R + (P_n - 1) + \tau = T + 1$ are generated. The forecasts are evaluated using a loss function $L_{t+\tau}(y_{t+\tau}, f_{R,t})$, that depends on both, the realization of the data and the forecasts. The hypothesis to be tested is:

$$\begin{aligned} H_0 &: E\left[h_t\left(L_{t+\tau}(y_{t+\tau}, f_{R,t}) - L_{t+\tau}(y_{t+\tau}, g_{R,t})\right) \mid \mathcal{F}_t\right] = 0 \\ & \quad \text{or alternatively} \\ H_0 &: E\left[h_t \Delta L_{t+\tau} \mid \mathcal{F}_t\right] = 0 \ \ \forall\ t \geqslant 0 \end{aligned}$$

for all $\mathcal{F}_t$ -measurable function h_t.

In practice, the test consists on regressing the differences in the loss functions on a constant and evaluating its significance using the t statistic for the null of a 0 coefficient, in the case of $\tau = 1$. When τ is greater than one, standard errors are calculated using the Newey-West covariances estimator, that allows for heteroskedasticity and autocorrelation.

The results of applying the Giacomini and White procedure to evaluate the forecasting performance of the two forecasting methods using the RMSE as the loss function are shown in Table 1. Consistently with previous visual inspection, it is clear from the Table that, the VAR model

[5] See Pincheira (2006) for a nice description and aplication of the test.

outperforms the rest of the models across all horizons. This result indicates that nominal variables, such us the rate of growth of money and the nominal interest rate significantly contribute to improve the predictive performance of multivariate models of inflation.[6]

Table 1: *Giacomini-White test-Sample 2011:1-2015:3* ($N = 50$)

Models	*1 month*		*3 months*		*6 months*		*12 months*	
	t-stat.	*p-value*	*t-stat.*	*p-value*	*t-stat.*	*p-value*	*t-stat.*	*p-value*
Phillps Curve vs AR	***4.1388***	***0.0001***	***3.5039***	***0.0010***	***3.5039***	***0.0010***	***3.6186***	***0.0009***
Phillips Curve with Money vs AR	***3.2279***	***0.0022***	***4.5048***	***0.0000***	***4.5048***	***0.0000***	***3.4889***	***0.0012***
Principal Components vs AR	***3.0732***	***0.0035***	***2.4141***	***0.0197***	***2.4141***	***0.0197***	***5.3289***	***0.0000***
VAR vs AR	***3.1489***	***0.0028***	***3.4020***	***0.0014***	***3.4020***	***0.0014***	***3.0324***	***0.0044***
VAR vs Phillps Curve	***4.0168***	***0.0002***	***2.9876***	***0.0045***	***2.9876***	***0.0045***	***2.7548***	***0.0090***
VAR vs Phillips Curve with Money	***3.7328***	***0.0005***	***3.9354***	***0.0003***	***3.9354***	***0.0003***	***3.0393***	***0.0043***
VAR vs Principal Components	***2.8324***	***0.0067***	***3.8666***	***0.0003***	***3.8666***	***0.0003***	***2.6822***	***0.0108***
Phillips Curve with Money vs Phillips Curve	***2.7820***	***0.0076***	***1.7428***	***0.0879***	***1.7428***	***0.0879***	***1.9877***	***0.0541***
Phillips Curve with Money vs Principal Components	***2.9022***	***0.0055***	***3.8307***	***0.0004***	***3.8307***	***0.0004***	***2.6611***	***0.0113***
Phillips Curve vs Principal Components	***3.3597***	***0.0015***	***3.1714***	***0.0027***	***3.1714***	***0.0027***	***2.6317***	***0.0122***

5 Conclusions

We develop an inflation forecasting exercise for Argentina using a variety of inflation models ranging from time series univariate and multivariate models, causal models based on alternative inflation theories, to factor models based on the use of a large set of business cycle indicators. The results indicate that multivariate models outperform the AR(1), usually considered as benchmark. Notably, the VAR model outperforms the rest of the models for each month and all horizons. This result indicates that the nominal variables included in the VAR model, such us the rate of growth of money and the nominal interest rate significantly contribute to improve the predictive performance of multivariate models of inflation.

[6] Similar results are obtained using the Mean Absolute Percentage Error (MAPE) as shown in Appendix IV.

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Appendix I

Figure A.1: Business cycle indicators included in Factor Model

Series		*Source*	*Stationary*
1	*Automobile national production - units*	*ADEFA*	*diff*
2	*Portland cement production*	*AFCP*	*diff*
3	*Total Income revenues*	*MECON*	*trend*
4	*Income revenues DGI*	*MECON*	*trend*
5	*Income revenues DGA (customs)*	*MECON*	*diff*
6	*Total VAT revenues*	*MECON*	*trend*
7	*VAT revenues DGI*	*MECON*	*trend*
8	*IPI - nondurable consumer goods*	*Fiel*	*diff*
9	*IPI - durable consumer goods*	*Fiel*	*diff*
10	*IPI - intermediate goods*	*Fiel*	*diff*
11	*IPI - capital goods*	*Fiel*	*diff*
12	*IPI - food and beverages*	*Fiel*	*diff*
13	*IPI - nonmetallic minerals*	*Fiel*	*diff*
14	*IPI - metalworking*	*Fiel*	*diff*
15	*IPI - automobiles*	*Fiel*	*diff*
16	*M0 (Bills and coins)*	*BCRA*	*diff*
17	*M1*	*BCRA*	*diff*
18	*Private M2* (includes foreign currency deposits)*	*BCRA*	*trend*
19	*M3*	*BCRA*	*diff*
20	*Interest rate on Time Deposits - Private Banks*	*BCRA*	*diff*
21	*Interest rate on Time Deposits - Total Banking system*	*BCRA*	*diff*
22	*Interest rate on Time Deposits - Total Banking system 30-59 days*	*BCRA*	*diff*
23	*Interest rate on Time Deposits - Banking system 60 or more days*	*BCRA*	*diff*
24	*Gross Revenue Tax Collection - City of Buenos Aires*	*Min. Hacienda CABA*	*diff*
25	*Poultry Production*	*CEPA*	*diff*
26	*Used Car Sales*	*CCA*	*diff*
27	*Construction Price Index*	*INDEC*	*diff*

Appendix II:

Estimation Results

Forecasting Models: Dependent Variable - Inflation

Variable	***AR(1)***	***Phillips Curve***	***Phillips Curve with Money***	**Factor Model**
C	0.00504			0.01581
	(0.00068)			(0.00080)
$INFLA_{t-1}$	0.21696	0.51567	0.36045	
	(0.06524)	(0.01052)	(0.03580)	
$INFLA_{t+1}$		0.34558	0.34894	
		(0.01233)	(0.04003)	
$OUTPUTGAP_{t-1}$		0.02090	0.01876	
		(0.00214)	(0.00682)	
$NOMDEV$		0.02954	0.04834	
		(0.00215)	(0.00792)	
$INFLA*$		-0.18879	-0.21818	
		(0.02199)	(0.06701)	
$MONEYGAP$			0.01223	
			(0.00175)	
$D13061503{*}INFLA_{t-1}$	0.52341			
	(0.06499)			
$DUM1401$	0.02526			
	(0.00408)			
$DUM0803$	0.01996			0.02109
	(0.00404)			(0.00410)
$DUM1002$	0.02059			0.02442
	(0.00406)			(0.00409)
$DUM1010$	0.01503			0.01478
	(0.00404)			(0.00412)
$DUM1105$	-0.01205			
	(0.00408)			
$DUM1203$	0.01864			
	(0.00403)			
$D0711305$	0.00749			
	(0.00102)			
$1^{st} Factor_{t-3}$				0.00104
				(0.00017)
$2^{nd} Factor$				0.00038
				(0.00021)

standard error in brackets

Forecasting Models: *Monetary VAR*

Variable	***Dependent variable***				
	D(MONEY)	***NOMDEV***	***D(INTRATE)***	***OUTPUTGAP***	***INFLA***
D(MONEY(-1))	0.07230 (0.10386)	-0.35466 (0.19034)	-0.01501 (0.06532)	0.03280 (0.19852)	-0.01969 (0.04286)
D(MONEY(-2))	0.23379 (0.10019)	-0.02453 (0.1836)	0.17831 (0.06301)	0.31709 (0.1915)	0.07203 (0.04135)
D(MONEY(-3))	0.18482 (0.10114)	0.11665 (0.18533)	-0.13506 (0.06361)	0.06960 (0.1933)	0.05346 (0.04174)
D(MONEY(-4))	-0.16684 (0.09825)	0.64225 (0.18005)	0.02292 (0.06179)	-0.29694 (0.18779)	0.06469 (0.04055)
D(MONEY(-5))	0.16151 (0.10206)	-0.26892 (0.18704)	-0.09049 (0.06419)	0.43249 (0.19508)	-0.03892 (0.04212)
D(MONEY(-6))	0.09683 (0.1025)	0.02281 (0.18783)	0.04784 (0.06446)	0.29723 (0.19591)	0.07682 (0.0423)
NOMDEV(-1)	0.01076 (0.05452)	0.46771 (0.09991)	-0.04165 (0.03429)	0.08484 (0.1042)	0.00206 (0.0225)
NOMDEV(-2)	-0.09804 (0.05924)	-0.05557 (0.10855)	0.01773 (0.03726)	-0.01610 (0.11322)	-0.00797 (0.02445)
NOMDEV(-3)	-0.01761 (0.05535)	0.19510 (0.10143)	-0.00797 (0.03481)	-0.12535 (0.1058)	0.02995 (0.02284)
NOMDEV(-4)	0.06239 (0.0534)	-0.09132 (0.09785)	0.03281 (0.03358)	0.24579 (0.10206)	-0.00437 (0.02204)
NOMDEV(-5)	0.00184 (0.05328)	-0.01664 (0.09763)	-0.06523 (0.03351)	0.18097 (0.10183)	0.00570 (0.02199)
NOMDEV(-6)	-0.01550 (0.04829)	0.00940 (0.0885)	0.01993 (0.03037)	0.06284 (0.0923)	0.03787 (0.01993)
D(INTRATE(-1))	-0.36200 (0.14157)	-0.43129 (0.25944)	0.76207 (0.08904)	0.16725 (0.27059)	0.02536 (0.05843)
D(INTRATE(-2))	0.33436 (0.14794)	0.54099 (0.27111)	-0.31488 (0.09305)	-0.03857 (0.28277)	0.04831 (0.06106)
D(INTRATE(-3))	-0.17055 (0.13365)	0.05511 (0.24492)	-0.17018 (0.08406)	0.00326 (0.25545)	0.04467 (0.05516)
D(INTRATE(-4))	0.02968 (0.13292)	-0.10612 (0.24357)	-0.00598 (0.08359)	0.35874 (0.25404)	0.07971 (0.05485)
D(INTRATE(-5))	0.23387 (0.13806)	-0.09783 (0.253)	0.13378 (0.08683)	0.58693 (0.26388)	0.05790 (0.05698)
D(INTRATE(-6))	0.00478 (0.11899)	0.63751 (0.21806)	-0.18192 (0.07484)	-0.82329 (0.22743)	0.03865 (0.04911)
OUTPUTGAP(-1)	-0.03174 (0.0446)	-0.07058 (0.08173)	0.08491 (0.02805)	0.11292 (0.08525)	-0.03576 (0.01841)
OUTPUTGAP(-2)	0.05979 (0.04287)	0.03593 (0.07855)	-0.02910 (0.02696)	0.11619 (0.08193)	0.00316 (0.01769)
OUTPUTGAP(-3)	0.01294 (0.0402)	-0.17698 (0.07366)	-0.01755 (0.02528)	0.24618 (0.07683)	0.01974 (0.01659)
OUTPUTGAP(-4)	-0.03270 (0.04113)	-0.02091 (0.07537)	0.03059 (0.02587)	0.02779 (0.07861)	0.01737 (0.01697)
OUTPUTGAP(-5)	-0.06999 (0.04099)	0.02477 (0.07511)	-0.03618 (0.02578)	0.24261 (0.07834)	-0.01022 (0.01691)
OUTPUTGAP(-6)	-0.07683 (0.04227)	0.06845 (0.07747)	0.01457 (0.02659)	-0.06690 (0.0808)	0.00792 (0.01745)
INFLA(-1)	-0.01693 (0.18715)	0.46653 (0.34297)	-0.12039 (0.11771)	-0.30198 (0.35771)	0.13018 (0.07724)
INFLA(-2)	0.02321 (0.18752)	-0.88747 (0.34364)	0.32206 (0.11794)	1.04302 (0.35842)	-0.14652 (0.07739)
INFLA(-3)	0.18213 (0.1816)	-0.05812 (0.33279)	0.10118 (0.11421)	-0.25345 (0.34709)	0.13457 (0.07495)
INFLA(-4)	0.13797 (0.17685)	0.21503 (0.32409)	-0.10038 (0.11123)	0.40073 (0.33802)	-0.07783 (0.07299)
INFLA(-5)	-0.05341 (0.17689)	0.01845 (0.32416)	-0.28470 (0.11125)	-0.78573 (0.33809)	0.10363 (0.073)
INFLA(-6)	-0.11379 (0.17008)	-0.30704 (0.31167)	0.25256 (0.10697)	0.01832 (0.32507)	-0.03450 (0.07019)

plus a constant and dummy variables

Appendix III

Figure A.2: *RMSE ratios* $h = 3$

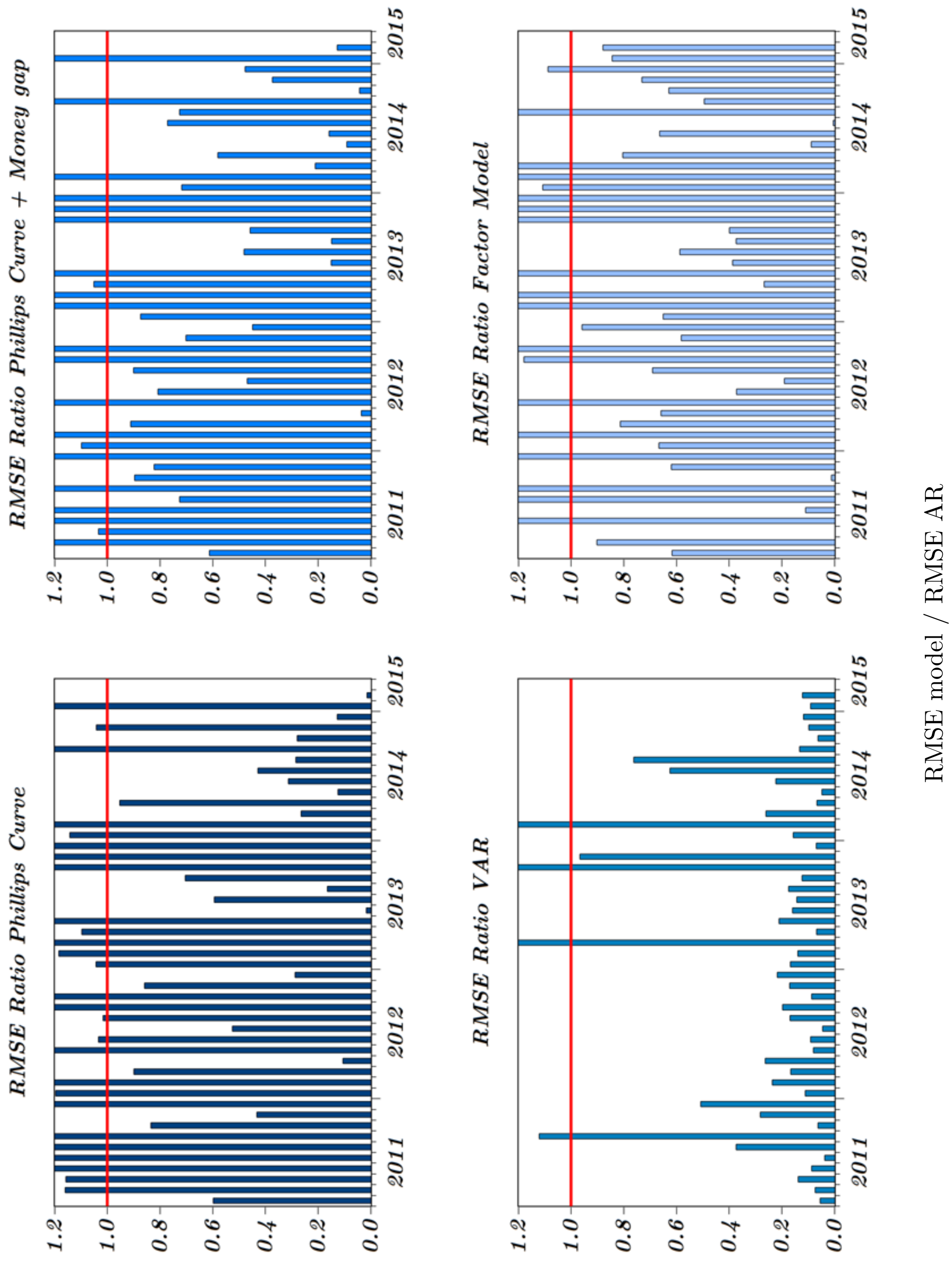
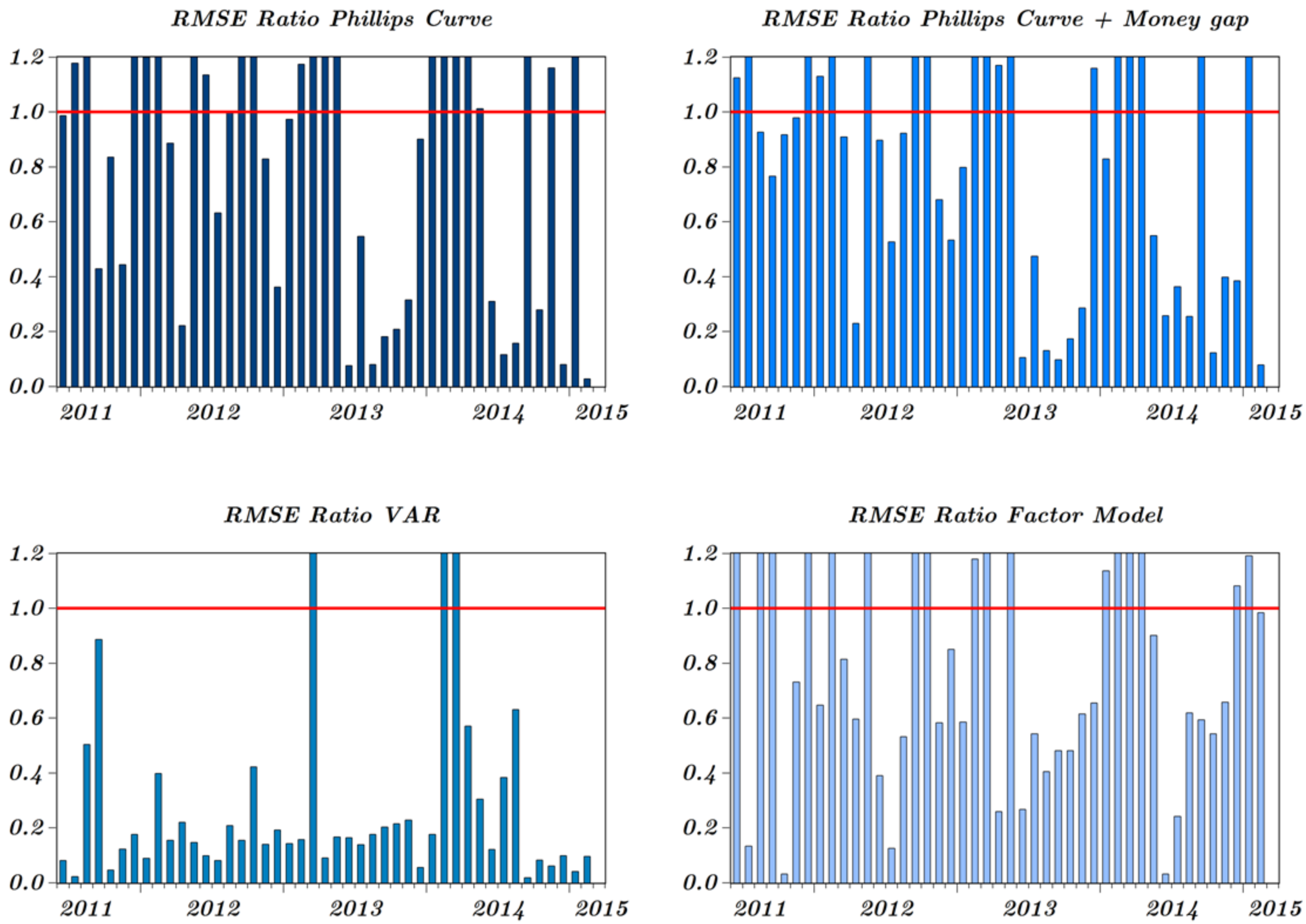
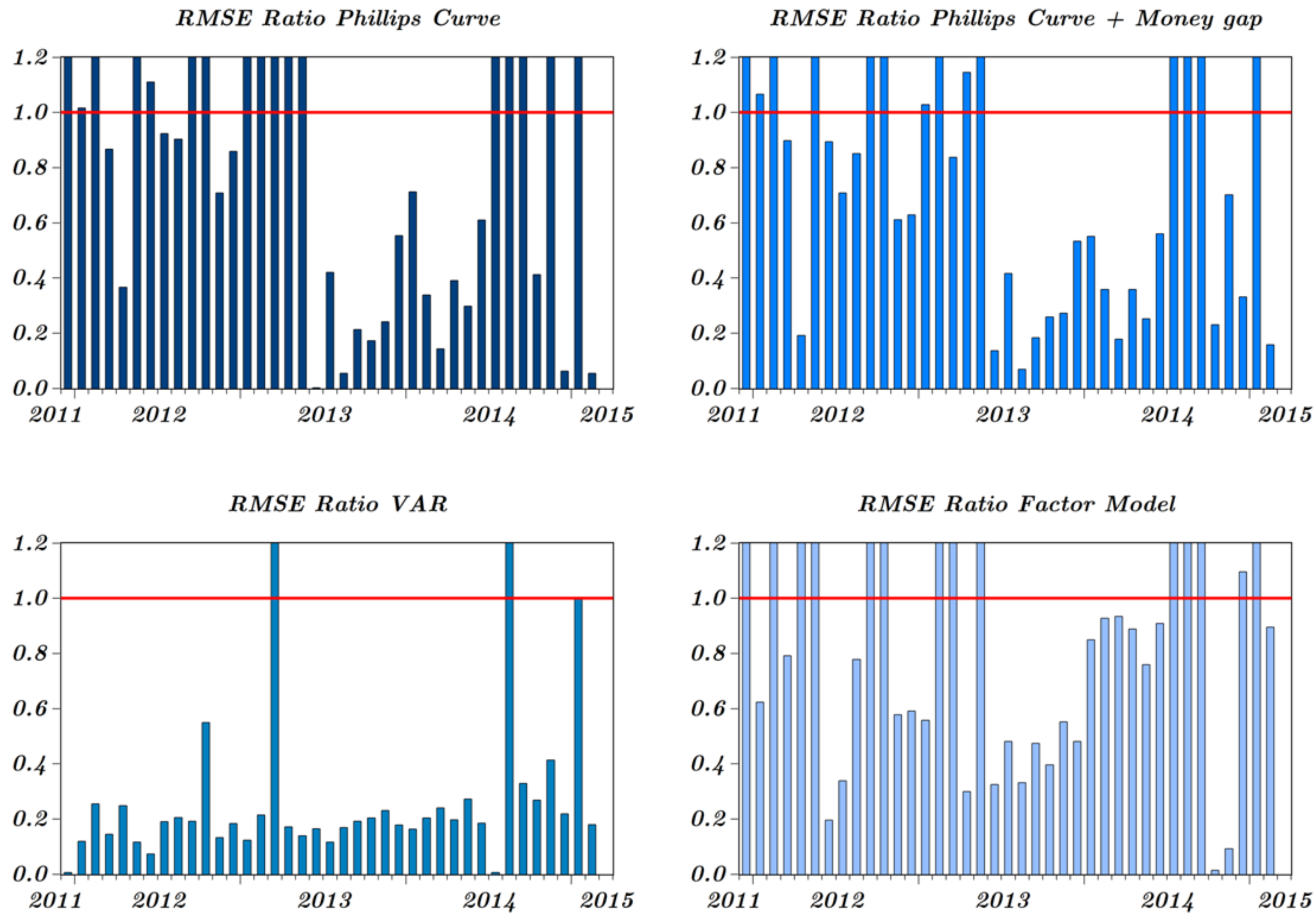


Figure A.3: *RMSE ratios* $h = 6$



RMSE model / RMSE AR

Figure A.4: *RMSE ratios* $h = 12$



RMSE model / RMSE AR

Appendix IV

Table A.1: *Giacomini-White test Sample:2011:1-2015:3* ($N = 50$) - **MAPE**

Models	***1 month***		***3 months***		***6 months***		***12 months***	
	t-stat.	***p-value***	***t-stat.***	***p-value***	***t-stat.***	***p-value***	***t-stat.***	***p-value***
Phillps Curve vs AR	***2.7904***	***0.0075***	***2.6324***	***0.0114***	***3.3457***	***0.0017***	***3.1720***	***0.0030***
Phillips Curve with Money vs AR	***2.5634***	***0.0135***	***2.4468***	***0.0182***	***4.1337***	***0.0002***	***2.6731***	***0.0110***
Principal Components vs AR	***3.1093***	***0.0031***	***3.0856***	***0.0034***	***3.2589***	***0.0022***	***2.7039***	***0.0102***
VAR vs AR	***3.2033***	***0.0024***	***3.2116***	***0.0024***	***3.5347***	***0.0010***	***3.6298***	***0.0008***
VAR vs Phillps Curve	***3.9620***	***0.0002***	***3.1624***	***0.0027***	***4.2146***	***0.0001***	***3.2384***	***0.0025***
VAR vs Phillips Curve with Money	***3.5112***	***0.0010***	***3.7584***	***0.0005***	***3.2683***	***0.0021***	***3.1900***	***0.0028***
VAR vs Principal Components	***4.0772***	***0.0002***	***4.2443***	***0.0001***	***4.4590***	***0.0001***	***2.5248***	***0.0159***
Phillips Curve with Money vs Phillips Curve	***3.9745***	***0.0002***	***1.3676***	***0.1779***	***1.2197***	***0.2291***	***1.5276***	***0.1349***
Phillips Curve with Money vs Principal Components	***3.4158***	***0.0013***	***3.8860***	***0.0003***	***3.8471***	***0.0004***	***3.0296***	***0.0044***
Phillips Curve vs Principal Components	***3.4905***	***0.0010***	***4.0565***	***0.0002***	***3.7040***	***0.0006***	***2.9692***	***0.0051***