INVESTIGATING FORECASTING MODELS OF BRAZILIAN INFLATION

This version: July 2017.

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ABSTRACT

We perform a pseudo real time study on the predictability of Brazilian inflation, measured by the IPCA, using data from January 1995 to December 2015. The main objective of the study is to compare the predictive accuracy of multivariate adaptive VAR models, containing macroeconomic information, against Naive models and against disaggregated data models of inflation, which in the recent literature have been successful in overcoming benchmark models for Brazilian inflation. We found evidence that most models with macroeconomic variables have predictive accuracy higher than the traditional benchmark of the literature, the autoregressive model of order 1. There is also evidence regarding the superiority of forecasts generated by the model with greater data disaggregation. In addition, the ranking of model forecasts changes when we change: the loss function, the forecasts horizons, and the time windows used for evaluations.

Keywords: Inflation. Prediction. Autometrics. Model Confidence Set. SPA Test. Unrestricted VAR. Disaggregated data. Asymmetric loss function.

Área 4: Macroeconomia, Economia Monetária e Finanças

Jel Classification: C53; E31; C52

RESUMO

Realizamos um estudo pseudo em tempo real sobre a previsibilidade da inflação brasileira, medida pelo IPCA, utilizando dados de janeiro de 1995 a dezembro de 2015. O objetivo principal do estudo é comparar a precisão preditiva dos modelos VAR adaptativos multivariados, contendo informações macroeconômicas, contra modelos ingênuos e contra modelos de dados desagregados de inflação, que na literatura recente conseguiram superar os modelos de referência para a inflação brasileira. Encontramos evidências de que a maioria dos modelos com variáveis macroeconômicas possui precisão preditiva maior do que o benchmark tradicional da literatura, o modelo Autorregressivo de ordem 1. Também há evidências quanto à superioridade das previsões geradas pelo modelo com maior desagregação de dados. Além disso, o ranking das previsões do modelo muda quando mudamos: a função de perda, os horizontes de previsão e as janelas de tempo usadas para avaliações.

Keywords: Inflação. Previsão. Autometrics. Model Confidence Set. Teste SPA. VAR irrestrito. Dados desagregados. Função de perda assimétrica.

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1. INTRODUCTION

Forecasting economic series is an extremely important topic for a wide range of agents. Formulators of economic policies, central banks and private agents need to formulate their action plans. Whether economic agents are on the monetary and financial sides, or on the real side of the economy, precise forecasts on the evolution of price index is something important.

Central banks have as their main objective to maintain inflation stable. The fulfillment of this mission depends on optimal forecasts for inflation, and the less information asymmetry the policy will be more effective (ROMER, 2012). According to Faust and Wright (2013), the main tool to achieve the central banks' transparency objective in the implementation of monetary policy is the disclosure of inflation forecasts and other macroeconomic variables. According to the authors, it is agreed that a forecast of accurate inflation is a necessity for households, firms, politicians and, especially, the central bank of a country.

Much research has been done in the area of forecasting economic series in recent years. Large computational and theoretical gains allow the use of a wide range of forecasting models. There is the possibility of using overparameterized models, selection of models and other techniques that require high computational cost. In the field of forecasting, the problem under analysis has come to be the ranking of a huge range of forecasting models, which can be easily constructed by economists.

In this context, the present study aims to evaluate the role of macroeconomic variables in predicting inflation in Brazil. We use univariate and multivariate linear models with the model selection technique developed by Hendry and Doornik (2014), called Autometrics, to obtain parsimonious models and to control possible outliers and structural breaks in the data. Finally, the results were compared with benchmark models and with disaggregated inflation forecasting methods.

Regarding the ranking of the different models, two algorithms were used: the Model Confidence Set (MCS) algorithm and the Superior Predictive Ability (SPA) test, developed by Peter Hansen and co-authors. In addition to the traditional Forecast Mean Squared Error function (FMSE), asymmetric loss functions were evaluated, as monetary authorities may be more concerned not to underestimate inflation.

The rest of the paper is organized as follows: in the next section the theoretical basis is elaborated and the empirical literature on the subject is reviewed; Section 3 presents the methodology of the study and the database; Section 4 presents and discusses the research results, while the conclusion is made in section 5.

2. LITERATURE REVIEW

According to Bodie, Kane and Marcus (2014), fiscal policy is probably the most direct way to stimulate or to slow the economy. A decrease in government spending directly reduces the demand for goods and services. In the same way, an increase in tax burden instantly reduce consumer incomes and result in very rapid decreases in consumption.

A common way to summarize the net impact of government fiscal policy is to look at the government's budget surplus or deficit. A large primary deficit means that the government is spending more than it is taking through taxes. In this way, the Government increases the demand for goods and services more than reduces the demand for goods (via taxes), implying a net effect of increasing demand. When the supply of goods and services does not keep up with this increase in demand, there is a generalized increase in prices in the economy. The effect of fiscal policy is captured through two variables: the public sector borrowing requirement as a percentage of GDP (without exchange devaluation); and the federal public debt in the market. Both variables are among the most frequently selected as relevant for predicting national inflation according to Silva (2016).

Monetary policy affects the economy in a less direct way than fiscal policy, which works through its impact on interest rates. Increases (decreases) in the money supply lead to lower (higher) interest rates. According to Fama (1981), there would be a negative relationship between inflation and economic activity, explained by the combination of money demand theory and the quantity theory of money, a relationship that would have been verified empirically in the work of Fama and also in Nelson (1979). Friedman's monetarist view (1970), as well as Lucas's (1973) theory of rational expectations, also suggest the understanding that the price level can influence and be influenced by the level of activity.

Using a general equilibrium model, Fuerst (1992) shows that an expansionary fiscal policy leads to a fall in the real interest rate, which would lead to an increase in real activity. However, if the supply does not increase, fiscal policy will imply an increase in inflation. In an empirical study with Danish data, Juselius (1994) finds evidence that accumulated nominal interest rate shocks have generated inflation, while Juselius (2006) justifies the use of the variables inflation, nominal interest rate, monetary base and income in VAR models. Regardless of the cause-and-effect relationship between variables, it seems to us that macroeconomic variables may contain some information relevant to the inflation forecast, especially when used together.

Increases (decreases) in the money supply leads to lower (higher) interest rates. The nominal interest rate equals the real rate plus a factor to compensate for the expected inflation. Changes in interest rate expectations may be due either to changes in expectations of real rates or due to changes in inflation expectations (Bodie, Kane and Marcus, 2014). Thus, it is believed that the interest rate swap market contains useful information for forecasting inflation. The fact that this market involves financial investment by economic agents makes forecasts more credible (GARCIA, 1992). Unlike predictions announced in the media or in economic reports, mistaken forecasts in this market generates a high financial cost and serves as a stimulus to the quality of forecasts. Following this reasoning, Garcia (1992) uses pre-fixed interest rates to obtain better forecasts than the CB. To capture this information, in this study we use different maturity dates of swap contracts between DI reference rates and pre-fixed rates.

Focusing on the empirical literature on inflation forecasting models, Swanson and White (1997) made a forecast essay of 9 different macroeconomic variables, including inflation with several "adaptive" and "non-adaptive" univariate and multivariate linear models, as well as nonlinear models called "artificial neural networks". An adaptive model means that a new specification is chosen before each new forecast is made, in a rolling window estimation methodology. Non-adaptive models are also re-estimated for each new window, but the model specification remains fixed throughout the forecast horizon. Unreviewed data have also been used to ensure an *ex ante* forecast, comparable to forecasts by market professionals that are necessarily drawn up on the basis of unverified information. The authors found evidence that *ex ante* predictions, based on rolling window methods of multivariate "adaptive VARs", overcame a variety of: (i) "adaptive" and "non-adaptive" univariate models; (ii) multivariate "non-adaptive" models, (iii) non-linear "adaptive" models and (iv) professionally available research forecasts;

There is evidence that models based on the Phillips curve do not improve inflation prediction. Atkeson and Ohanian (2001) evaluate the prediction of models based on Phillips curves, comparing its prediction to simple mean prediction, over a period of 15 years. The authors found evidence that none of the predictions of different models based on the Phillips curve were more accurate than the naive prediction. Sachsida, Ribeiro and Santos (2009) estimated a Phillips curve with quarterly data, adopting a Markov-Switching model. The authors rejected the hypothesis of linearity in the parameters of the Phillips curve. They further suggest that the Phillips curve would be inadequate to explain the inflationary dynamics in the Brazilian economy.

Stock and Watson (2007) examine changes in the inflation process over time and whether the work of predicting American inflation has become more or less difficult. The main finding was that, in more recent periods, the inflation process was well described by an unobserved component of cyclical trend and stochastic volatility or, equivalently, by a moving average integrated process with time-varying parameters. The authors found evidence that predictions of multivariate models are no better than predictions made using the time-varying univariate model for later periods.

Following the work of Stock and Watson (2007), many others began adopting methodologies that allow coefficients to vary in time, such as recursive estimation and rolling window. Elliot and Timmerman (2008) use these two methodologies to compare 12 different predictors of inflation in a monthly database, from January 1959 to December 2003. The combination of forecasts was the one with the best predictive accuracy, although the difference between the better forecasts has been relatively small. However, the authors found evidence of the inferiority of predictions generated by Smooth Transition Autoregressive (STAR) models. Barnett, Mumtaz and Theodoridis (2014) compare performances of a wide range of time-varying parameter models in English inflation forecasting, and found that the factor-augmented VAR (FAVAR) model with time-varying parameters presents an FMSE 14% lower than that of an AR (p) model in the one year horizon, being the model with the best performance in the sample.

In Brazil, Garcia (1992) analyzed the implicit inflation forecast in fixed interest rate contracts in a period of hyperinflation (between October 1987 and February 1990). According to the author, the future market and the implicit inflation forecast presented better forecasts than those of the Central Bank (CB). The author concluded that the CB estimates are systematically biased downwards with the intention of taxing the inflationary financial profit, or in the belief that optimistic forecasts would play a role of coordinating market expectations, leading to a reduction of official inflation.

Chauvet (2001) make use of a dynamic factor model to extract the common cyclical movements in a group of variables which supposedly have the power to predict inflation. The empirical results confirm that the antecedent indicators signal the alternation of future phases of inflation evolution in a real time exercise. Figueiredo (2010) used a large volume of variables extracted from the CB Economic Indicators database to generate inflation forecasts through two methods, the principal component factor model (PC) and partial least squares factor modeling. The author finds evidence that PC generates better predictions for up to six steps ahead. The author also finds evidence that the estimation with the use of rolling regressions obtains better predictive performance than recursive estimation.

Using Brazilian monthly data, Arruda, Ferreira and Castelar (2011) compared inflation forecasts with using linear and nonlinear time series and the Phillips curve. Among the linear models, a VAR was the model that presented the best predictions, being surpassed only by a nonlinear model based on the Phillips curve. Medeiros, Vasconcelos and Freitas (2016) find evidence that the Phillips curve does not present relevant information for the forecast of inflation. The authors present evidence that models based on Least Absolute Shrinkage and Selection Operator (LASSO) have lower prediction errors for short horizons, whereas the AR model works best for long horizons.

Gaglianone, Issler and Matos (2016) investigates forecast combination models for the period from January 2006 to May 2015. The researchers used the CB Focus's report forecasts combination with and without bias correction, in addition to the combination of Granger and Ramanathan (1984), comparing the results with the naive AR model (1). The authors found evidence that the average of biased corrected forecasts dominate the prediction without bias correction. They also found that forecasts combination presents a lower FMSE compared to the AR model (1).

Garcia, Medeiros and Vasconcelos (2016) used data from 2003 to 2015 in a real-time simulation to compare forecasts of a wide range of models with the AR and random walk benchmark models, in addition to the CB Focus report forecasts. The authors found evidence that prediction combinations based on the MCS shows better predictions than all models individually and also against the simple average combination of all models.

Carlo and Marçal (2016) (C&M from this point forward) use the monthly IPCA from January 1996 to March 2012 to compare the forecast efficiency up to 12 steps ahead of a set disaggregated and aggregated data models. The disaggregated models were estimated by Seasonal Autoregressive Integrated Moving Average (SARIMA), while aggregated models were estimated by time series techniques as SARIMA, state-space structural models and Markov-switching. The authors found evidence of prediction gains in models that use more disaggregated data when compared to models using aggregate data. In this paper we will use

C & M forecast data to test if any of the VAR models estimated here obtains predictive accuracy superior to the SARIMA models of disaggregated inflation.

As described in the methodology section of this paper, the naive models that are tested in this paper can be considered as "adaptive" models and, thus, also allow the coefficients to vary over time, including characteristics of the models used by Swanson and White (1997) and Stock and Watson (2007). In Brazil, as far as the author is aware, no other study has used such a wide window of time for both modeling and forecast comparison. Few Brazilian studies have used the Hansen, Lunde and Nason (2011) Model Confidence Set (MCS) methodology and the Hansen (2005) superior predictive ability test (SPA), for comparison purposes, and none compared models Containing macroeconomic data with disaggregated data models.

3. METODOLOGY

The present work uses the Gets methodology to simplify VAR multivariate models with the use of the Autometrics algorithm. A pseudo real-time simulation is then performed in an attempt to simulate the available information as close as possible to the information available to an agent at the time of forecasting. For each model, forecasts are generated from one to twelve steps ahead. Then we evaluate the accumulated inflation forecast between today (t = 0) and p months ahead $\hat{Y}_{t+p}^{p} \equiv \sum_{i=1}^{p} \hat{Y}_{t+i}^{i}$, where $\hat{Y}_{t}^{1}$ is the inflation forecast of 1 month for month t. Forecasts are then grouped according to time horizons, resulting in 12 forecast groups, one for one month ahead, one for two months ahead and so on for up to twelve months ahead. This procedure leads to the creation of a forecast database. This database is then used to compare the predictive power of the models for Brazilian inflation measured by the IPCA.

To deal with the problem of prediction in the face of structural breaks and outliers, a number of automatic outliers detection methodologies implemented in OxMetrics 7® are used in conjunction with Autometrics algorithm. The methodologies of outliers detection are related to the work of Hendry, Johansen and Santos (2006), which demonstrate that the application of the Gets approach presented in Hendry and Krolzig (2005) can be used successfully for the selection of dummies.

When trying to find the best predictor model of a variable, there is always the possibility that one or more good models will be found by pure chance, and not by their predictive ability. This problem, known as data snooping, was treated by White (2000) as endemic in time series, because there is only one observed realization of the variable and the consequent reuse of this information for the purpose of estimating competing models. Given this problem, Hansen (2005) suggests the Superior Predictive Ability test (SPA test) as an alternative to White's (2000) reality check. The SPA test is a test to verify the predictive superiority of a benchmark model, which is robust to the addition of bad models.

In a different approach to the SPA test, Hansen, Lunde and Nason (2011) present the Model Confidence Set (MCS), which is a set of models that contain the best model with a certain level of confidence. The objective of the MCS determination procedure is to create a set $M*$, consisting of the best model (s) extracted from a group of candidate models, M^0, where the "best" criterion is defined by the lost function. The $\widehat{M}*$ models are evaluated using the sample information of the relative performances of the models contained in M^0. For a given model i belonging to M^0, the p-value of MCS, $\widehat{p_i}$, is the threshold at which i belongs to $\widehat{M}_{1-\alpha}^{*}$ if and only if $\widehat{p_i} \geq \alpha$. Therefore, a model presenting a low $\widehat{p_i}$ is unlikely to be part of the "best" group of models (M^*).

This paper uses the MCS in order to rank models' predictive abilities, and also uses the SPA to give robustness to the results, verifying if any alternative model is superior to the bechmark models.

ADAPTATIVE VAR MODELS

As a consequence of the work of Sims (1980), the VAR model became the starting point for any macroeconomic modeling (ANDERSON and VAHID, 2010). The unrestricted VAR model can conveniently be considered as a summary of the 'stylized facts' of the data (JUSELIUS, 2006). Juselius argues that if the 'true' model satisfies a linear first-order approximation, it is possible to make several hypothesis tests within a valid statistical framework using VAR models.

A problem with VAR models is the large number of parameters to be estimated. In a model of k variables and p lags for each variable, in addition to the constant, there is a need for estimation of $k+k^2p$ parameters. According to Anderson and Vahid (2010), one of the possible ways to deal with the problem is to allow the number of lags in each equation to be determined separately. In this work we use the algorithm of automatic selection of Autometrics models, developed in Hendry and Doornik (2014), in the VAR models to mitigate this problem.

We used the technique of recursive estimation (expanding window) combined with Autometrics algorithm of model selection. The estimated VAR models following this procedure are equivalent to the models that Swanson and White (1997) called "adaptive VAR models", since it allows not only the reestimation of the model parameters to each new set of information, but also allows that some of the variables or lags to be deleted or reinserted into the model. It is also possible to use the recursive estimation technique in so-called "non-adaptive" models, but in this case, it would only be possible to change the coefficients of the model between two data windows used in the estimations, without excluding or including of lags and variables between two or more estimates.

DATA BASE AND DESCRIPTIVE STATISTICS

The database, used in the recursive estimates to generate the predictions, presents data from January 1995 to December 2015, containing 252 observations for the variables with complete data. The last 12 observations were used only for forecasting purposes, so that the maximum size of the series used for the estimates was 240 observations. The minimum size used for the estimates was 144 observations, since the forecasts began in January 2007. The database used for the comparison of the forecasts includes the predictions of 155 models, and for each of the 155 forecast models there are predictions from 1 to 12 steps forward for the period from January 2007 to December 2015. The variables used in the models are listed briefly in Table 1. The series graphs are presented in Figure 5, and their descriptive statistics are presented in Table 2. All variables were collected from the IPEADATA website, with the exception of the Public Debt variable, which was collected through the Secretaria do Tesouro Nacional spreadsheets.

Table 1 – Variables used in the initial general unrestricted models

Variable	Model Name	Name in DB	Description
Inflation		ln_IPCA_IBGE	$Ln(1+\pi)$ Where π is the inflation rate. We used models with 6 different inflation indices other than IPCA to test its predictive power over IPCA
	IPCGV	ln_IPC_FGV	
	IPC	ln_IPC_FIPE	
	INCC	ln_INCC_FGV	
	INPC	ln_INPC_IBGE	
	IGPDI	ln_IGP_DI_FGV	
	IPAEP	ln_IPA_EP_FGV	
SELIC interest rate	J	Lnselic	Sovereign bond interest rate

	DJ	Dlnselic	Variation of the sovereign bond interest rate
Sovereign bond real interest rate	JR	lnjuro-real	Sovereign bond real interest rate. Annualized.
	DJR	Dlnjuro-real	Variation of the annualized sovereign bond interest rate
Industrial production	DPI	Dlnpi_lag2	Second lag of the variation of industrial production
Public sector borrowing requirement	NFSP	Dln_NFSP_lag2	Second lag of the variation of the public sector borrowing requirement
Public debt	Divida	Dln_divida_lag2	Second lag of the variation of public debt
Monetary base	M0	Dln_M0_lag2	Second lag of the variation of monetary base
Income	Renda	Dln_Renda_lag2	Second lag of the variation of Income
Term Structure of the Interest Rate		spread_60	$Ln(1+60\ day\ swap\ rate) - Ln(1+30\ day\ swap\ rate)$
		spread_90	$Ln(1+90\ day\ swap\ rate) - Ln(1+30\ day\ swap\ rate)$
		spread_180	$Ln(1+\ 180\ day\ swap\ rate) - Ln(1+30\ day\ swap\ rate)$
	S	spread_360	$Ln(1+360\ day\ swap\ rate) - Ln(1+30\ day\ swap\ rate)$
	Spreads	(spread_60, spread_90, spread_180, spread_360)	All four variables in the GUM

Note: the column Model Name is the short name of the variable that is included in the final model name. As an example, the model MJDPI1 includes SELIC interest rate and industrial production variables in the initial GUM. The table including the 155 models names and variables included is available as an appendix to this work.

The variable we want to predict is the variation of the Índice Nacional de Preços ao Consumidor Amplo (IPCA), a price index monthly calculated and published by the Brazilian Institute of Geography and Statistics (IBGE). All inflation variables were inserted into the database after transformation $Ln(1+i)$, where i is the monthly inflation rate. Panel A of Figure 1 shows inflation series over time, while in Panel B are the Autocorrelation Function (ACF), and the Partial Autocorrelation Function (PACF).

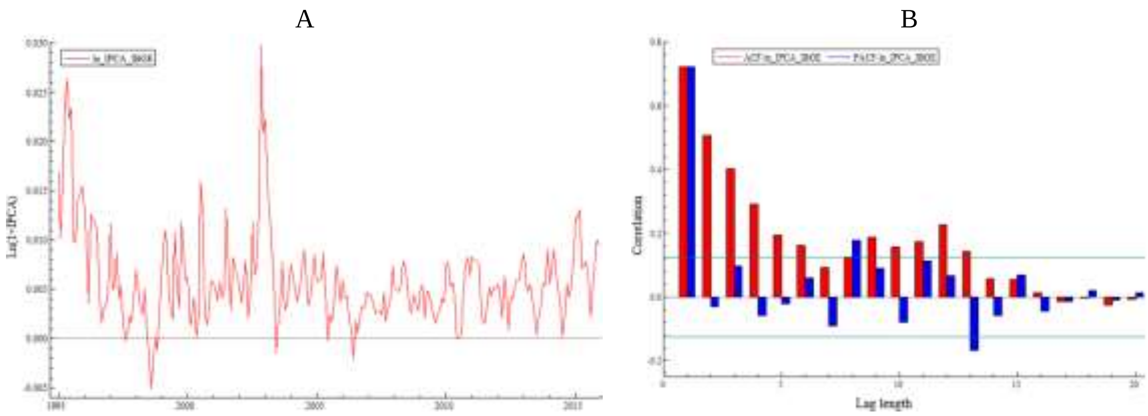

Figure 1: Panel A: Inflation time serie; Panel B: ACF and PACF of inflation time serie.

The naive AR(1) model, as described in equation (1), was used as a benchmark for predicting inflation. We also suggest a more elaborated naive model, to make sure that the improvement in the forecast, if there is none, was due to the inclusion of the macroeconomic variables, and not due to the inclusion of a greater number of lags or seasonal dummies. So the suggested naïve model is an AR(12) model with seasonal dummies (equation 2).

$$IPCA_t = \alpha_1 + \beta_1 IPCA_{t-1} + v_t \tag{1}$$

$$IPCA_t = \alpha_2 + \varphi_1 IPCA_{t-1} + \cdots + \varphi_{12} IPCA_{t-12} + \vartheta s_t + \epsilon_t \tag{2}$$

Were $IPCA_t$ is the dependent variable at time *t*, α_1 e α_2 are intercepts; $\beta_1, \varphi_1, \dots, \varphi_{12}$ are coefficients to be estimated; s_t is an 11 seazonal dummies; ϑ is the vector of coefficients of the seasonal dummies.

The macroeconomic models were VAR type models with 12 lags and seazonal dummies. So the macro general unrestricted models are represented by Equation (3):

$$y_t = \alpha_3 + \theta_1 y_{t-1} + \cdots + \theta_{12} y_{t-12} + \delta s_t + e_t \tag{3}$$

Were y_t is the (*k* x 1) vector of dependent variables, IPCA among them; α_3 is the intercept vector; θ_l is the (*k* x *k*) coefficient matrix to be estimated for the lag *l*; s_t is the 11 seazonal *dummies*; δ is the (*k* x *k*) matrix of coefficients for the seasonal dummies; while e_t is the (*k* x 1) error vector.

Table 2 – Descriptive Statistics.

Variable	**T max-min**	**Av.**	**DP**	**Ass.**	**Curt.**	**Min**	**Max**	**Med**	**JB**	**UR**
ln_IPCA_IBGE	240-144	0,58%	0,47%	1,88	5,74	-0,5%	3,0%	0,50%	0	0
ln_INCC_FGV	240-144	0,69%	0,74%	5,12	45,44	-0,5%	8,4%	0,52%	0	0,005
ln_IPC_FGV	240-144	0,58%	0,58%	2,19	8,62	-0,5%	4,3%	0,52%	0	0,002
ln_IPC_FIPE	240-144	0,52%	0,56%	1,51	5,24	-1,0%	3,7%	0,40%	0	0
ln_INPC_IBGE	240-144	0,59%	0,50%	1,80	5,72	-0,5%	3,3%	0,52%	0	0
ln_IGP_DI_FGV	240-144	0,68%	0,82%	1,76	7,14	-1,1%	5,7%	0,56%	0	0
ln_IPA_EP_FGV	240-144	0,72%	1,17%	1,59	6,87	-2,4%	7,2%	0,52%	0	0
Lnselic	240-144	1,35%	0,66%	1,84	4,29	0,5%	4,2%	1,22%	0	0,047
Dlnselic	239-143	-0,01%	0,19%	1,74	15,24	-1,0%	1,3%	-0,02%	0	0
lnjuro-real	240-144	9,19%	7,57%	0,70	1,36	-17,4%	34,5%	8,30%	0	0,001
Dlnjuro-real	239-143	-0,12%	4,55%	-0,24	2,96	-21,3%	16,8%	-0,48%	0	0
Dlnpi_lag2	237-141	0,14%	6,51%	0,11	0,15	-19,6%	17,5%	-0,02%	0,58	0,004
Dln_NFSP_lag2	237-141	-0,14%	6,78%	-1,69	13,26	-51,2%	24,8%	-0,33%	0	0
Dln_divida_lag2	238-142	0,89%	2,90%	1,68	9,74	-8,6%	20,0%	0,80%	0	0
Dln_M0_lag2	239-143	1,13%	4,98%	0,01	4,24	-10%	21,6%	0,54%	0	0
Dln_Renda_lag2	240-144	0,51%	26,07%	-0,05	1,13	-87,0%	82,0%	0,90%	0	0
spread_60	239-143	0,03%	0,66%	0,01	7,53	-2,6%	3,6%	0,03%	0	0
spread_90	239-143	0,06%	0,97%	0,22	6,47	-3,6%	5,0%	0,08%	0	0
spread_180	239-143	0,31%	1,65%	1,36	8,93	-5,8%	10,8%	0,24%	0	0
spread_360	239-143	0,65%	2,19%	1,19	4,58	-6,4%	11,8%	0,48%	0	0

Note: Tmax-min are the maximum and minimum size of the serie; JB is the p-value of the Jarque-Bera test for normality; UR is the p-value of the Augmented Dickey-Fuller (DICKEY e FULLER, 1979; SAID, e DICKEY, 1984) test for the presence of unity root in the serie.

Figure 2 ilustrate a significant gap between the naïve and the best performance models. We performed the SPA test in addition to the MCS and FMSE rankings. In this case, we test the null hypothesis that the benchmark model is the best forecast model. Consistent p-value SPA indicates whether there is evidence against this hypothesis. A low p-value (less than 0.1 or 0.05 for example) informs that the benchmark model is less than one or more competing models. A high p-value indicates that the sample analyzed does not provide strong evidence that the benchmark model is exceeded. Table 3 shows the result of the SPA test, complementing the information in Figure 2. By the test, it can be stated that there are models with predictive performance superior to the naive model AR(1), MNaive, for forecast windows from 2 to 12 steps forward. In contrast, the naive model AR(12), MAR12_7, was only surpassed in its 1 step forward prediction ability. The SPA test could not reject the null hypothesis of predictive superiority of the AR(12) for the other steps.

Table 4 presents the top ten models for each one the 12 steps according to FMSE lost function. Between parentheses is the MCS p-value. If the p-value is below 0.1 the hypothesis that the model is part of the set of best prediction models is rejected. Stated differently, a p-value below 10% indicates that the model is statistically lower than the others in terms of predictability. Our AR(12) benchmark had the best performance of all 155 models for 8 step ahead, and remain among the top ten best models from 4 to 12 steps ahead forecasts. The traditional benchmark, however, is out of the MCS for 12 months ahead[3]. This result means that there are at least 140 models statistically superior to the traditional benchmark.

Table 3 – SPA test of the benchmark models.

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
MNaive	0,660	0,084	0,013	0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,001
MAR12_7	0,097	0,139	0,594	0,887	0,987	0,996	0,998	0,999	0,999	0,987	0,988	0,944

Note: columns presents the SPA consistent p-values from 1 to 12 steps ahead. Values highlighted in gray indicate that the model is outperformed by one or more competing models in terms of predictive performance with 10% of significance.

[3] The complete set of results are available upon request

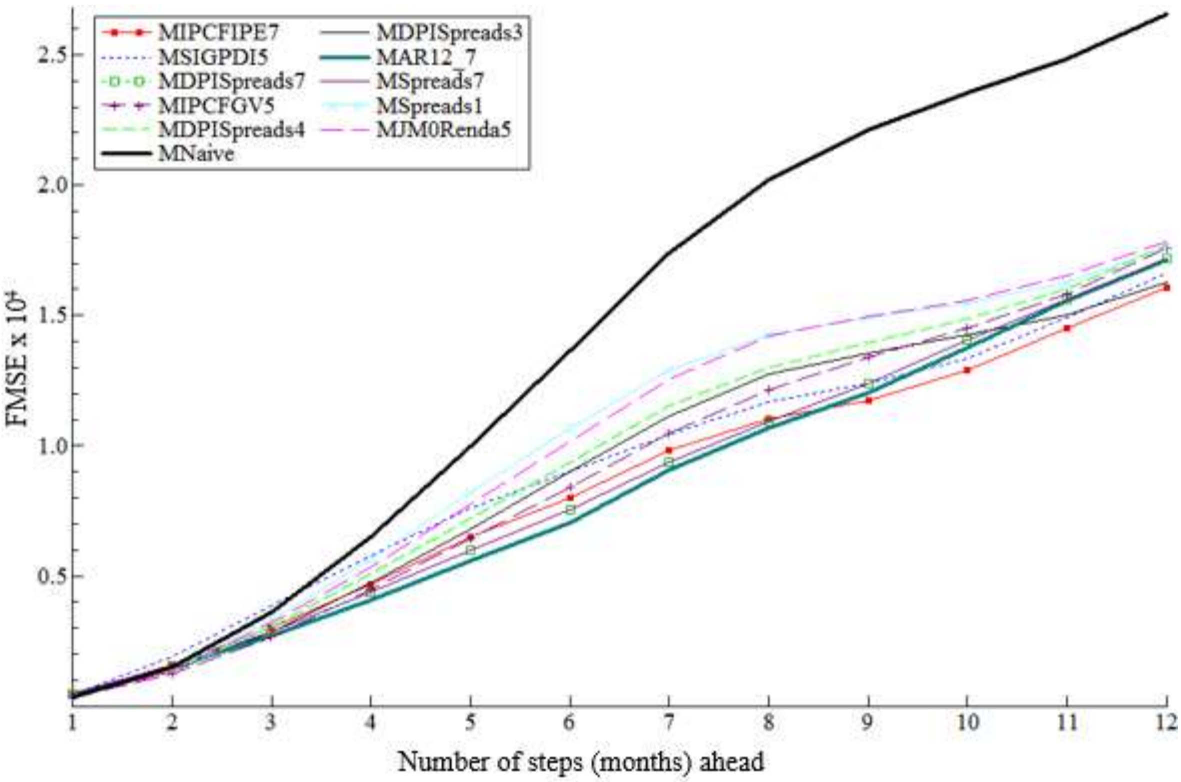

Figure 2: FMSE for 1 to 12 steps ahead forecasts.

One could question how the predictions rankings would be if the available sample were smaller. Figure 3 presents the result of a simulation of the hypothetical situation in which the researcher has only 2 years of forecast data for comparison purposes of the competing models. The figure illustrates how the ranking of models changes according to the period of the forecast window. Although the naive MNaive model has been worse than the others in six of the seven forecast windows, in the last window, which runs from January 2014 to December 2015, the naive model presented the second FMSE minor when compared to The best models of the complete sample (the models in Figure 3 are the same as those shown in Table 3). In addition, in 5 of the 7 windows the best model was different and in all the windows there were changes in the positions of the models.

Table 4 – 10 best models for each one of the 12 forecasts horizons.

	1	2	3	4	5	6	7	8	9	10	11	12
1	**MS1** 0,0318 (1,0000)	**MSIPCGV6** 0,1114 (1,0000)	**MSIPCGV6** 0,2313 (1,0000)	**MSDPI4** 0,3633 (1,0000)	**MSDPI4** 0,5299 (1,0000)	**MS7** 0,6987 (1,0000)	**MS7** 0,8949 (1,0000)	**MAR12_7** 1,0662 (1,0000)	**MIPC7** 1,174 (1,0000)	**MIPC7** 1,289 (1,0000)	**MIPC7** 1,4491 (1,0000)	**MIPC7** 1,6051 (1,0000)
2	**MJM0Renda5** 0,032 (1,0000)	**MSIPCGV5** 0,116 (0,9950)	**MSDPI4** 0,2386 (0,9893)	**MSIPCGV6** 0,3753 (0,9823)	**MSIPCGV6** 0,5326 (0,9996)	**MAR12_7** 0,7062 (0,9999)	**MAR12_7** 0,9044 (0,9997)	**MS7** 1,0783 (0,9981)	**MAR12_7** 1,2028 (0,9988)	**MSIGPDI5** 1,337 (0,9984)	**MSIGPDI5** 1,4914 (0,9846)	**MDPISpreads3** 1,6278 (0,9663)
3	**MAR12_1** 0,0323 (1,0000)	**MSIPCGV1** 0,118 (0,9950)	**MDJDPI3** 0,2387 (0,9893)	**MDJDPI3** 0,387 (0,9823)	**MS7** 0,5438 (0,9996)	**MDPI3** 0,7303 (0,9999)	**MDPISpreads7** 0,9379 (0,9997)	**MDPISpreads7** 1,0909 (0,9981)	**MSIGPDI5** 1,2387 (0,9988)	**MAR12_7** 1,3728 (0,9984)	**MDPISpreads3** 1,4993 (0,9846)	**MSIGPDI5** 1,6625 (0,9663)
4	**MAR12**_3 0,0325 (1,0000)	**MIPCGV4** 0,1229 (0,9950)	**MSIPCGV5** 0,2409 (0,9893)	**MSIPCGV5** 0,3882 (0,9823)	**MDPI1** 0,5455 (0,9996)	**MSDPI4** 0,7323 (0,9999)	**MSpreads7** 0,9379 (0,9997)	**MSpreads7** 1,0909 (0,9981)	**MDPISpreads7** 1,2391 (0,9988)	**MDPISpreads7** 1,4041 (0,9984)	**MAR12_7** 1,5555 (0,9846)	**MAR12_7** 1,7137 (0,9071)
5	**MIPCGV4** 0,0325 (1,0000)	**MIPCGV5** 0,123 (0,9950)	**MSIPCGV1** 0,251 (0,9893)	**MDPI1** 0,389 (0,9823)	**MSIPCGV5** 0,5512 (0,9996)	**MDJDPI3** 0,733 (0,9999)	**MSIPCGV5** 0,9423 (0,9997)	**MIPC7** 1,1053 (0,9981)	**MSpreads7** 1,2391 (0,9988)	**MSpreads7** 1,4041 (0,9984)	**MDPISpreads7** 1,5602 (0,9846)	**MDPISpreads7** 1,7185 (0,9071)
6	**MIPCGV3** 0,0333 (1,0000)	**MSDivida5** 0,1233 (0,9950)	**MDJRDPI1** 0,2528 (0,9893)	**MS7** 0,3936 (0,9823)	**MDJDPI3** 0,5517 (0,9996)	**MSIPCGV5** 0,7332 (0,9999)	**MDJDPI1** 0,9516 (0,9997)	**MSIPCGV4** 1,1061 (0,9981)	**MSIPCGV4** 1,2563 (0,9988)	**MDPISpreads3** 1,4271 (0,9984)	**MSpreads7** 1,5602 (0,9846)	**MSpreads7** 1,7185 (0,9071)
7	**MIPCGV8** 0,0333 (1,0000)	**MIPCGV3** 0,1255 (0,9950)	**MSDPI1** 0,2541 (0,9893)	**MSDPI1** 0,3983 (0,9823)	**MDPI3** 0,5554 (0,9996)	**MDPI1** 0,7334 (0,9999)	**MSDPI4** 0,9524 (0,9997)	**MSIPCGV5** 1,1293 (0,9981)	**MS7** 1,2602 (0,9988)	**MSIPCGV4** 1,4423 (0,9984)	**MSpreads6** 1,5784 (0,9846)	**MIPCGV5** 1,759 (0,9071)
8	**MDPISpreads3** 0,0334 (1,0000)	**MS6** 0,1256 (0,9932)	**MDPI1** 0,2553 (0,9893)	**MDPI3** 0,4001 (0,9823)	**MAR12_7** 0,5571 (0,9996)	**MSIPCGV6** 0,7362 (0,9999)	**MDPI3** 0,9542 (0,9997)	**MDJDPI1** 1,1548 (0,9981)	**MSIPCGV5** 1,307 (0,9988)	**MIPCGV5** 1,4532 (0,9984)	**MIPCGV5** 1,5812 (0,9846)	**MSpreads1** 1,7628 0,8775)
9	**MIPC4** 0,0337 (1,0000)	**MIPC3** 0,1268 (0,9950)	**MSDivida5** 0,2559 (0,9893)	**MDJRDPI3** 0,4048 (0,9823)	**MDJRDPI5** 0,5755 (0,9984)	**MDJDPI1** 0,7464 (0,9999)	**MSIPCGV4** (0,9564 (0,9997)	**MDPI3** 1,1554 (0,9981)	**MS6** 1,3162 (0,9988)	**MIPCGV4** 1,4553 (0,9984)	**MDPISpreads4** 1,6009 (0,9662)	**MDPISpreads4** 1,7683 0,8353)
10	**MINCC1** 0,0339 (1,0000)	**MIPC6** 0,1272 (0,9950)	**MDJRDPI3** 0,2561 (0,9893)	**MAR12_7** 0,4048 (0,9823)	**MSIPCGV3** 0,5764 (0,9947)	**MDJRDPI1** 0,7554 (0,9999)	**MDPI1** 0,9646 (0,9997)	**MDPI1** 1,1623 (0,9981)	**MIPCGV4** 1,3208 (0,9988)	**MS7** 1,4562 (0,9984)	**MSpreads3** 1,6169 (0,9671)	**MJM0Renda5** 1,7855 0,8412)

Note: In each cell, it is shown the name of the model in bold, the FMSE, and the p-value ($\widehat{p}_i$) of the MCS between parentheses.

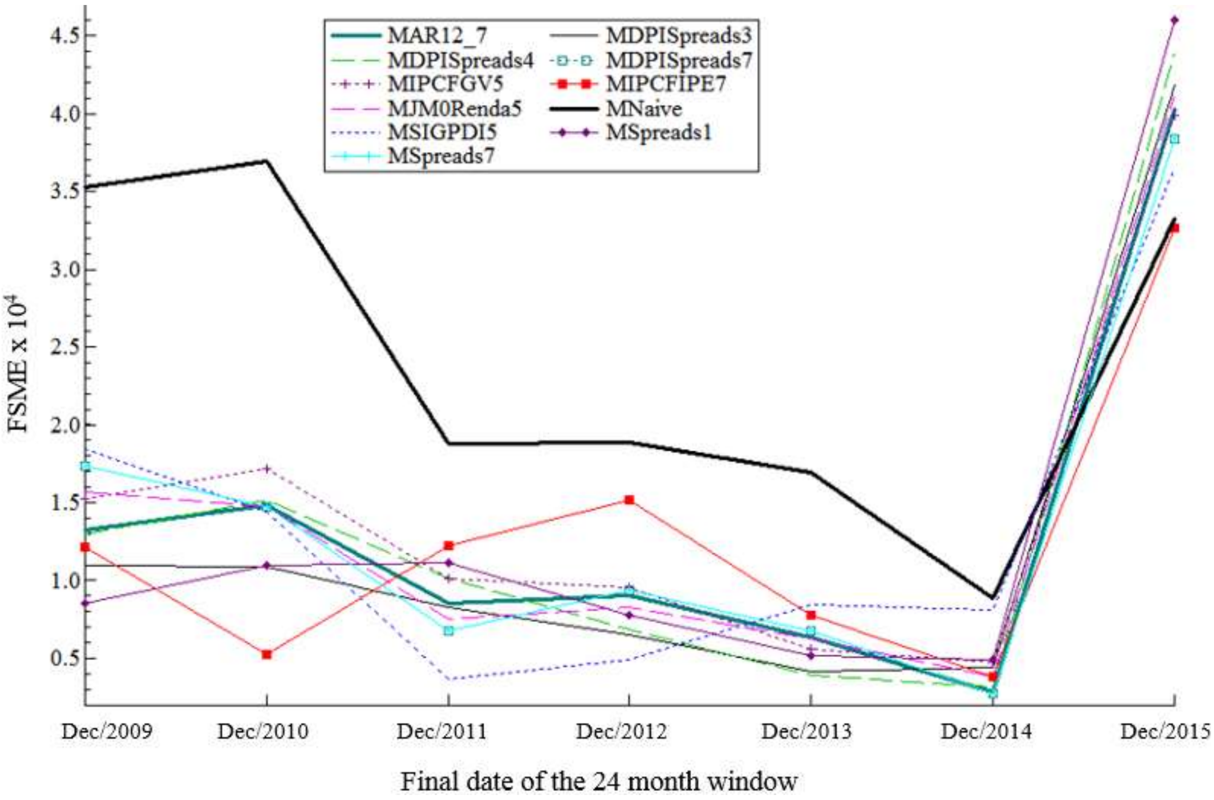

Figure 3: *FMSE* of the inflation forecast, calculated in 2 year windows.

VARIATIONS DUE TO CHANGES IN THE LOSS FUNCTION

The results presented in Tables 3 and 4, and in Figure 2 and 3, were obtained using the FMSE loss function. In this subsection, we analyze the results obtained when the tests are performed with the loss function Assymetric Mean Squared Error with assimetry α ($AMSE_{\alpha}$):

$$\hat{Y}_{AMSE_{\alpha}} \equiv [\alpha + (1 - 2\alpha) \times I(Y - f(Z,\theta) < 0] \times |Y - f(Z,\theta)|^p \qquad (4)$$

Where $I(\cdot)$ is the characteristic function and α and p are parameters chosen by the user. The FMSE loss function can be represented by the function presented in (4), assigning the values of 0.5 and 2 for α and p respectively. Assigning any value other than 0.5 to α causes the function to be asymmetric.

As suggested by Elliott, Timmermann and Komunjer (2008), downward-biased forecasts (underestimation) are considered to have a higher cost for the agent, in which α has values lower than 0.5. We used values of 0.4; 0.33 and 0.25 for α, which means weighting 1.5; 2 and 3 times higher, respectively, for forecast squared errors when there is underestimation, compared to overestimation of observed inflation. We present only the results obtained with α equal to 0.25 in Table 5. Results for different α values are available upon request.

An interesting result is the inclusion of the naive model AR(1) (MNaive) in the set $\widehat{M}*$ when the weight of underestimation losses is increased. This indicates that the AR(1) model can be considered one of the best prediction models when there is a high cost associated to the underestimation of inflation forecast. This result appears for the forecast of accumulated inflation 11 and 12 months ahead, in which the weight of underestimating inflation is 1.5 times greater than the overestimation weight and the higher the weight, the more evident is this result. When the weight of underestimating inflation is 3 times greater than the overestimation weight, as shown in Table 5, the MNaive does not appear in the set of better models only for the 6 to 9 months ahead forecasts.

Table 5 – Best and naive models according to $AMSE_{0,25}$.

Model	1	2	3	4	5	6	7	8	9	10	11	12
MSIGPDI5	0,018	0,071	0,142	0,213	0,291	0,376	0,492	0,591	0,668	0,753	0,850	0,944
	(0,99)	(0,99)	(0,99)	(0,99)	(0,95)	(1,00)	(1,00)	(1,00)	(1,00)	(1,00)	(1,00)	(1,00)
MDPISpreads3	0,023	0,096	0,202	0,309	0,411	0,499	0,591	0,674	0,719	0,778	0,869	0,964
	(0,77)	(0,83)	(0,76)	(0,58)	(0,60)	(0,83)	(0,80)	(0,93)	(0,94)	(0,93)	(0,94)	(0,92)
MIPC7	0,017	0,066	0,133	0,209	0,303	0,398	0,517	0,617	0,689	0,776	0,879	0,971
	(0,99)	(0,99)	(0,99)	(0,99)	(0,95)	(0,85)	(0,86)	(0,93)	(0,94)	(0,93)	(0,94)	(0,92)
MDPISpreads7	0,018	0,071	0,144	0,224	0,313	0,420	0,541	0,642	0,733	0,822	0,901	0,994
	(0,99)	(0,99)	(0,99)	(0,99)	(0,95)	(0,83)	(0,80)	(0,87)	(0,86)	(0,88)	(0,94)	(0,92)
MSpreads7	0,016	0,065	0,133	0,203	0,283	0,384	0,512	0,611	0,687	0,780	0,894	1,005
	(0,99)	(0,99)	(0,97)	(0,51)	(0,35)	(0,20)	(0,33)	(0,40)	(0,53)	(0,77)	(0,93)	(0,92)
MDJDPI5	0,017	0,070	0,164	0,290	0,437	0,590	0,743	0,847	0,896	0,922	0,950	1,011
	(1,00)	(0,99)	(0,98)	(0,77)	(0,64)	(0,58)	(0,61)	(0,64)	(0,69)	(0,82)	(0,94)	(0,92)
MIPCGV5	0,015	0,066	0,163	0,276	0,408	0,556	0,714	0,824	0,870	0,892	0,934	1,013
	(0,77)	(0,61)	(0,97)	(0,98)	(0,95)	(0,85)	(0,86)	(0,93)	(0,90)	(0,88)	(0,94)	(0,92)
MJM0Renda5	0,023	0,082	0,152	0,231	0,322	0,417	0,534	0,633	0,722	0,819	0,917	1,014
	(0,77)	(0,61)	(0,97)	(0,98)	(0,95)	(0,85)	(0,86)	(0,93)	(0,90)	(0,88)	(0,94)	(0,92)
MSIPCGV7	0,023	0,082	0,152	0,231	0,322	0,417	0,534	0,633	0,722	0,819	0,917	1,014
	(0,91)	(0,98)	(0,98)	(0,94)	(0,81)	(0,82)	(0,77)	(0,77)	(0,79)	(0,86)	(0,89)	(0,92)
Benchmarks												
MAR12_7	0,021	0,076	0,142	0,215	0,300	0,384	0,503	0,607	0,690	0,787	0,900	1,007
	(0,90)	(0,97)	(0,99)	(0,99)	(0,95)	(0,90)	(0,86)	(0,93)	(0,94)	(0,93)	(0,94)	(0,92)
MNaive	0,016	0,067	0,159	0,285	0,435	0,599	0,768	0,890	0,954	0,987	1,013	1,061
	(0,99)	(0,99)	(0,98)	(0,39)	(0,15)	(0,08)	(0,04)	(0,04)	(0,07)	(0,36)	(0,83)	(0,92)

Note: Columns show the Asymmetric Mean Squared Error (with alpha = 0.25) multiplied by 10,000 ($AMSE_{0,25} \times 10^4$) of the forecasts of the 10 best models, plus the AR(1) (MNaive), for the predictions of 1 to 12 steps ahead. Below, in parentheses, we present the P-value ($\widehat{p_i}$) of the MCS with the asymmetric loss function. Highlighted in gray are the smallest values for each step.

DISAGGREGATED DATA MODELS

As presented in the methodology section, a specific database with disaggregated inflation models was used to compare disaggregated models, with a higher number of competing models and a lower number of forecast observations. The models that have been added to the database are in Table 4.

Through the analysis of Table 5, one can verify that the model with the highest degree of data disintegration, SARIMA-52, was the best model by the FMSE loss function in all forecast horizons. This result is in line with the findings of C&M. Due to the result of the SPA test in Table 6, the predictive superiority hypothesis of the SARIMA-52 model can not be rejected for any time horizon. It is noticed that, as seen in the previous section, the database that was used to attain these results has the same longitudinal length with respect to the work of C&M, and is smaller than that used in the analysis of the comparison of the 155 original models of this work. Even so, the analysis of Tables 5 and 6 is conclusive regarding the supremacy of the SARIMA-52 disaggregated model. None of the VAR models with macroeconomic variables was superior to SARIMA-52.

With the inclusion of the 17 models presented in C&M work, the MAR12_7 model ceases to be among the 10 best models (as can be seen in Table 5), and it is rejected as the best model by the SPA test for 1 to 10 months ahead time horizons, as observed in Table 6. The naive AR(1) model continues to be rejected as the best model by the SPA test for long-term forecasts (from 3 months ahead, up to 12 months ahead). According to the MCS (Table 5), the AR (1) is no longer part of the best model group from 8 to 12 months ahead forecast, perhaps because this database is smaller longitudinally, which decreases the power of the test.

Table 4 – Models added to forecasts database from C&M.

Name	Composition	Model
DD	Overall Index	Double Difference
Seasonal DD	Overall Index	Seasonal Double Difference
SARIMA_1	Overall Index	SARIMA
SARIMA_9	9 groups	SARIMA
SARIMA_52	52 items	SARIMA
SARIMA_4	Industrials old, Services old, Monitored old and group Food and Beverages	SARIMA
SARIMA_3	Tradables, Non-tradables, Monitored old	SARIMA
SARIMA_5	Durables, Semi-durables, Non-durables, Services old and Monitored old	SARIMA
SARIMA_4N	Industrials new, Services new, Monitored new and subgroup Food at home	SARIMA
BCB_focus	Brazilian Central Bank Survey – FOCUS	-
BCB_QIR_mkt	Brazilian Central Bank Forecast using FOCUS scenario for interest rate	-
BCB_QIR_ref	Brazilian Central Bank Forecast using BCB scenario	-
MS	Overall Index	Markov-Switching
STSM	Overall Index	Structural Time Series Model

Source: Table 3 from Carlo and Marçal (2016)

Table 5 – Best and naive models according to FMSE.

Modelo	1	2	3	4	5	6	7	8	9	10	11	12
SARIMA-52	0,016 (1,00)	0,067 (1,00)	0,132 (1,00)	0,192 (1,00)	0,249 (1,00)	0,318 (1,00)	0,381 (1,00)	0,444 (1,00)	0,524 (1,00)	0,592 (1,00)	0,655 (1,00)	0,732 (1,00)
MIPAEP3	0,030 (0,79)	0,123 (0,74)	0,248 (0,62)	0,363 (0,46)	0,463 (0,44)	0,574 (0,66)	0,625 (0,85)	0,679 (0,86)	0,722 (0,95)	0,743 (0,96)	0,752 (0,98)	0,786 (0,99)
SARIMA-4NxSARIMA-9	0,021 (0,79)	0,080 (0,74)	0,158 (0,72)	0,242 (0,46)	0,310 (0,49)	0,384 (0,69)	0,451 (0,85)	0,523 (0,86)	0,615 (0,95)	0,693 (0,96)	0,749 (0,98)	0,801 (0,99)
SARIMA-9	0,021 (0,79)	0,077 (0,74)	0,154 (0,72)	0,232 (0,46)	0,296 (0,49)	0,364 (0,69)	0,427 (0,85)	0,496 (0,86)	0,590 (0,95)	0,679 (0,96)	0,743 (0,98)	0,802 (0,99)
MDJDPI3	0,035 (0,04)	0,141 (0,27)	0,252 (0,56)	0,365 (0,46)	0,461 (0,47)	0,539 (0,69)	0,613 (0,85)	0,690 (0,86)	0,738 (0,95)	0,801 (0,96)	0,815 (0,98)	0,816 (0,99)
SARIMA-3xSARIMA-9	0,020 (0,79)	0,082 (0,74)	0,167 (0,72)	0,259 (0,46)	0,328 (0,49)	0,402 (0,69)	0,470 (0,85)	0,534 (0,86)	0,620 (0,95)	0,697 (0,96)	0,762 (0,98)	0,836 (0,99)
MIPCGV3	0,026 (0,79)	0,110 (0,74)	0,240 (0,72)	0,381 (0,46)	0,495 (0,49)	0,592 (0,69)	0,666 (0,85)	0,733 (0,86)	0,779 (0,91)	0,812 (0,96)	0,831 (0,98)	0,861 (0,99)
SARIMA-4N	0,023 (0,79)	0,087 (0,74)	0,171 (0,72)	0,265 (0,46)	0,342 (0,49)	0,426 (0,69)	0,504 (0,85)	0,588 (0,86)	0,687 (0,92)	0,764 (0,96)	0,823 (0,98)	0,865 (0,99)
MSDivida3	0,031 (0,28)	0,133 (0,29)	0,274 (0,41)	0,443 (0,42)	0,584 (0,39)	0,679 (0,66)	0,731 (0,85)	0,735 (0,86)	0,742 (0,95)	0,770 (0,96)	0,805 (0,98)	0,874 (0,99)
MIPCGV1	0,030 (0,73)	0,128 (0,65)	0,275 (0,49)	0,417 (0,32)	0,547 (0,32)	0,667 (0,46)	0,742 (0,69)	0,814 (0,71)	0,868 (0,78)	0,892 (0,88)	0,870 (0,98)	0,880 (0,99)
Benchmarks												
MAR12_7	0,037 (0,26)	0,155 (0,18)	0,303 (0,21)	0,437 (0,27)	0,552 (0,32)	0,668 (0,53)	0,739 (0,76)	0,834 (0,76)	0,970 (0,65)	1,090 (0,68)	1,148 (0,90)	1,199 (0,86)
MNaive	0,029 (0,79)	0,139 (0,74)	0,328 (0,62)	0,593 (0,45)	0,900 (0,33)	1,227 (0,21)	1,543 (0,10)	1,847 (0,01)	2,135 (0,00)	2,439 (0,00)	2,715 (0,00)	2,968 (0,00)

Note: Columns show the Forecast Mean Squared Error multiplied by 10,000 ($FMSE \times 10^4$) of the forecasts of the 10 best models, plus the AR(1) (MNaive), for the predictions of 1 to 12 steps ahead. Below, in parentheses, we present the P-value ($\widehat{p_i}$) of the MCS. Highlighted in gray are the smallest values for each step.

Table 6 – SPA test for the naive models and SARIMA-52 model

Modelo	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
MNaive	0,190	0,124	0,097	0,028	0,005	0,001	0,000	0,000	0,000	0,000	0,000	0,000
MAR12_7	0,035	0,030	0,024	0,028	0,024	0,026	0,090	0,030	0,020	0,048	0,259	0,212
SARIMA_52	0,972	0,941	0,925	0,912	0,961	0,965	0,998	1,000	1,000	0,993	0,939	0,637

Note: columns presents the SPA consistent p-values from 1 to 12 steps ahead. Values highlighted in gray indicate that the model is outperformed by one or more competing models in terms of predictive performance with 10% of significance.

5. Conclusions

In this paper we presented new analytical results on the relative forecast accuracy of a variety of macroeconomic unrestricted VAR models for Brazilian inflation in a pseudo real time experiment.

The empirical findings led us to conclude that the usual benchmark model AR(1) has good performance for short periods ahead (one or two months), but can be easily outperformed to longer periods. Most of the performance gain of the macroeconomic models seems to be due to the greater number of lags included and to the seazonal dummies, what led us to propose the AR(12) with seazonal dummies as a new benchmark for forecasting IPCA. Focusing on the macroeconomics models, the spreads variable were the most frequent among the best models, and other inflation indexes also seems to have some predictive power, with the VAR containing the IPC index from FIPE (MIPC7) having the highest forecast accuracy, considering the longer forecast dataset.

The analysis of assymetrics loss functions led us to conclude that the AR(1) model perform better when underestimated forecasts are considered to have a higher cost for the agent. When the weight of underestimating inflation is 3 times greater than the overestimation weight, the AR(1) does not appear in the set of better models only for the 6 to 9 months ahead.

Using the database with disaggregated inflation models, we found evidence that the model with the highest degree of data disaggregation, the SARIMA-52 model, was the best model, considering the FMSE loss function, for all steps analyzed (from 1 to 12). This result is in line with the findings of C&M.

We emphasize that the size and the period of the sample can be determinant for the results found. A simulation was made for the hypothetical situation where the researcher had only 2 years of forecast data for the comparison of the competing models. There was a great variation in the position of the models among the 7 analyzed windows. We believe that a significantly smaller sample could lead to completely different results from those observed here.

Analyzes with different classes of models, such as non-linear models, and particularly Factor-augmented VAR models (FAVAR), which obtained good results in prediction exercises for American inflation (BERNANKE, BOIVIN and ELIASZ, 2005; BARNETT, MUZTAZ and THEODORIDIS, 2014), are beyond the scope of this paper but is a natural suggestion for future research. One could include the use of rolling regressions, in addition to the recursive estimates adopted in this work for the purpose of comparing the performance of the two techniques as another extension.

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