Forecasting Brazilian consumer inflation with FAVAR models using targeted variables

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Abstract

We compare the predictive accuracy of FAVAR models for forecasting Brazilian consumer inflation (IPCA) using both two-step by principal component analysis (PCA) and joint estimation using likelihood-based Gibbs sampling technique. The factors are extracted from three different datasets with 40, 64 and 415 economic time series. Overall, the longer the forecasting horizon, the better is the performance of FAVAR models compared to the benchmark AR models. Concerning the estimation methods, models using the joint estimation approach outperforms the PCA models and the advantage of the former widens as the horizon increases.

Key words: Forecasting inflation, FAVAR, Targeted variables, Gibbs sampling.

Classificação JEL: E31, E7

1. Introduction

Currently, thousands of economic time series are available on line in real time. Banco Central do Brasil (BCB), for example, provides electronic access to economic databases included in the *Economic Indicators* which constitutes a very comprehensive description of the Brazilian economy and is currently available to the monetary authorities. However, until some time ago, the vast majority of the models for forecasting inflation used in central banks did not explore this huge amount of information available and usually include a handful of variables. The state of affairs started changing with Stock and Watson (1999, 2002) which introduced the Dynamic Factor Model (DFM) for forecasting in a data-rich environment.

One possible motivation of this strand of literature is well posed by James Stock and Mark Watson's question[1]: "Can we move from small models with forecasts adjusted by judgmental use of additional information, to a more scientific system that incorporates as much quantitative information as possible?"

The results of exploring large datasets to forecast macroeconomic variables seems to be favorable and nowadays there are several methods being employed to do this task such as DFM, Partial Least Squares (PLS), Large Bayesian Vector Autoregression (LBVAR), Bayesian Model Averaging (BMA), etc.

FAVAR methodology which was introduced by Bernanke and Boivin (2003) and further developed by Bernanke, Boivin and Eliasz (2005) (BBE, henceforth) was originally used to assess the impact of monetary policy shocks exploring the advances of dynamic factor models and combine them with VAR methodology. This method and its developments such as Time-varying Parameter FAVAR (TVP-FAVAR) and Factor-augmented Error Correction Model (FECM) have been used to forecast inflation and other macroeconomic variables (see Faust and Wright (2012), Banerjee, Marcellino & Masten (2010), Eickmeier, Lemke & Marcellino (2011), among others).

Our objective is to assess the predictive accuracy of FAVAR models for forecasting Brazilian consumer market price inflation. More specifically, the questions we address in this paper deal with the predictive ability of FAVAR models in two

[1] "What's New in Econometrics – Time Series Lecture 11: Forecasting and Macro Modeling with Many Predictors, Part I" , NBER Summer Institute, 2008.

dimensions: *(i)* estimation method (two-step *versus* joint estimation); and *(ii)* dataset size (targeted dataset *versus* very large dataset)

The rest of the paper is organized as follows. The next section briefly presents the FAVAR methodology. Section 3 describes the VAR models used in BCB to forecast inflation. Discussion about datasets used in our exercises is brought up in section 4. Section 5 briefly mention our forecasting framework and show the results. Finally, in section 6 some concluding remarks are offered and a short sketch of our future research is set forth.

2. FAVAR methodology

The idea behind the FAVAR model is to combine the standard VAR analysis with features of factor models estimating a joint VAR that contains factors extracted from a large panel of informational data with perfectly observable time series that have pervasive effects on the economy.

Following closely BBE, we have that there is an $M \times 1$ observable economic variables (Y_t) assumed to have pervasive effects throughout the economy. Furthermore, there is additional economic information which is not captured by Y_t but may be relevant for the dynamics of these series. It is assumed that this information could be summarized by a $K \times 1$ vector of unobserved factors (F_t). The joint dynamics is given by a VAR in (F_t, Y_t) as shown in (1).

$$(1) \qquad \begin{bmatrix} F_t \\ Y_t \end{bmatrix} = B(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \varepsilon_t$$

Where $B(L)$ is a conformable lag polynomial of finite order d; ε_t is an error term with mean zero and covariance matrix Σ.

The equation above cannot be estimated directly because F_t is not observed. However, we assume that there exists a $N \times 1$ vector of informational time series[2] which relates with F_t, Y_t by (2).

$$(2) \qquad X_t = \Lambda^f F_t + \Lambda^y Y_t + v_t$$

[2] N (the size of X_t) is large and it will be assumed to be much greater than the number of factors.

Where Λ^{f} is an $N \, x \, K$ matrix of factor loading while Λ^{y} is a $N \, x \, M$ vector. v_t is a vector of error terms with zero mean and assumed to be either weakly correlated or uncorrelated, depending upon the estimation approach. ε_t and v_t are independent.

BBE used two approaches to estimate FAVAR models. The first one is a two-step principal component analysis (PCA) approach. In the first step, the common components are extracted from the set X_t and then equation (1) is estimated by standard methods. Despite being computationally simple and easy to implement, this approach implies the presence of "generated regressors" in the second step. The second approach is a single-step Bayesian likelihood approach[3]. BBE performed the joint estimation using likelihood-based Gibbs sampling techniques. The advantage of this approach is that allow us to exploit the structure of the transition (VAR) equation in the estimation of the factors.

The authors argue that is not clear a priori which method is the best one and that the empirical results would tell us whether the advantages of jointly estimating the model are worth the computational costs.

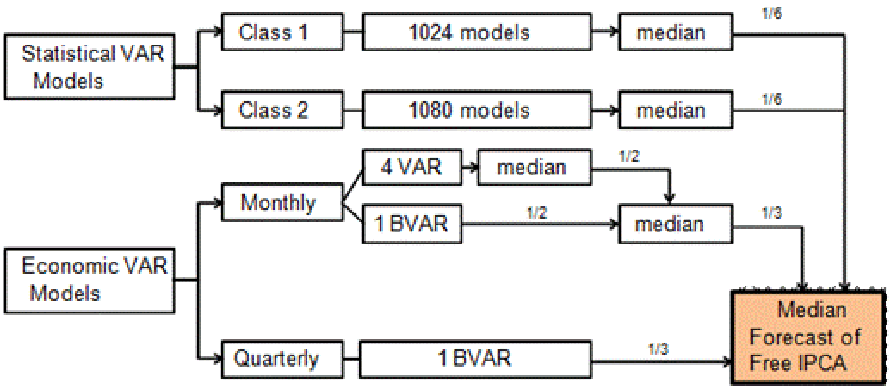
3. BCB auxiliary models

Since the inception of Brazilian inflation targeting, BCB has a set of auxiliary models for forecasting inflation, or more precisely, forecasting price market inflation. After some revisions, the current set of BCB auxiliary models comprises 'Economic" and "Statistical" models as shown in the **Figure 1**.

"Economic" models (last revision in September/2012) consist of VAR type models which includes some economic foundation. They include five monthly models (4 VARs and 1 Bayesian VAR) and one quarterly BVAR model. Besides the market price inflation, the models includes from 3 through 5 endogenous variables including administered price inflation, exchange rate, nominal and real interest rates, monetary aggregate, industrial production and GDP.

[3] As observed by BBE(2005), given the very large dimension of these models, the irregular nature of the likelihood functions makes MLE estimation infeasible in practice. For a complete description of the estimation procedure using Likelihood-based Gibbs sampling, see the appendix of Bernanke, Boivin and Eliasz (2004), the working paper version of Bernanke, Boivin and Eliasz (2005).

Figure 1 - Forecasting market price inflation using BCB auxiliary models



Source: Box "Revisão dos Modelos de Vetores Autoregressivos Estatisticos - 2012", Relatório de Inflação, março de 2013

On the other hand, there are the "statistical" models that seek to explore the information from a larger dataset. They were introduced in the Inflation Report of June/2010 and its current version includes more than 2,000 models including FAVAR and Factor Augmented Error Correction (FECM) models[4]. The dataset is comprised by 40 macroeconomic time series divided into six economic groups as shown in **Table 1**. According to BCB (2010), an important criterion for choosing the variables was the degree of correlation between each variable and market price inflation.

Table 1 – Variables used in the Statistical VAR models

Groups	Selected variables
Economic activity	retail sales, three electricity use indicators, monthly industrial production, capacity utilization, unemployment
External sector	VIX, Embi, exchange rate, U.S. PPI (all commodities), export price index, import price index, export *quantum* index, import *quantum* index
Financial	Real Selic rate calculated in four ways (deflated by IGP and IPCA, with 3 and 12-month expectations), spreads over Selic, calculated for individuals, corporations, total and for credits with BNDES interest rate
Prices	Administered prices, IGP-DI, IPC-BR, IPC-FIPE
Money	M1, M2, M3, M4, currency held by the public, monetary base and demand deposits
Shocks	CRB commodities index, and prices electricity, gasoline, motor oil and petroleum, ratio of consumer and wholesale prices

Relevant features of those models are that the estimation is based on the two step approach using principal component analysis (PCA) and the PCA factors are obtained

[4] For a more complete description of the "statistical" models see BCB(2013).

from the different economic groups mentioned above. In order to distinguish this approach from the more tradition one of extracting the factor from the whole dataset, we call the former as GPCA factors and the latter just as PCA factors.

The market price inflation forecasts by the auxiliary models results from the weighted average of the medians from the different groups of models as shown in **Figure 1**.

4. Datasets and targeting the variables

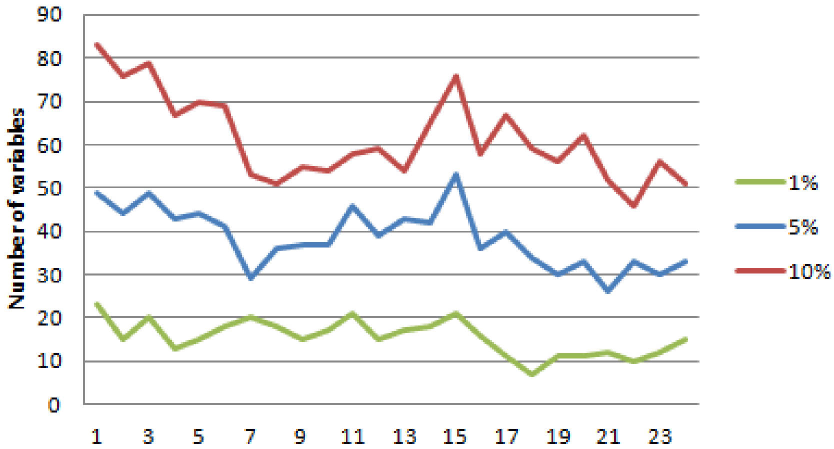
As one of our objectives is to compare the forecasts based on datasets with different sizes, we decided to build a dataset for the Brazilian economy more comprehensive as possible. Additionally, in order to make our analysis somewhat comparable to the models currently used in BCB, we restrict our sample to have a balanced panel of the series whose the initial date is defined by the starting date of the shorter series currently used in the BCB models. We also restrict our analysis by using only monthly series. Thus, our largest dataset contains 415 monthly time series whose sample spans from June/2000 to December/2012.[5]

Boivin and Ng (2006) asserted that there is a natural tendency for researchers to use as much data as are available to extract the factors. However, they demonstrated that increasing the number of series beyond a given number can be harmful and may result in efficiency losses, and extracting factor from larger datasets does not yield better forecasting performance. Then, Bai & Ng (2008) suggested to "target" the variables in order to isolate a subset of the original variables that has predictive ability over the variable to be forecasted. More recently, Caggiano, Kapetanios, and Labhard (2011) found that pre-screening of variables before extracting factors leads to better results in terms of forecast accuracy to forecast GDP growth rates for UK and some euro area countries.

[5] The data and the description (in Portuguese) of all series is provided upon request.

Based on Bai & Ng (2008) and following Figueiredo (2010), we performed the test of Granger-causality between each variable from the large dataset and the variable to be forecasted (market price inflation) to reduce the number of variables to be used for the extraction of factors. The Granger tests were performed using different lags (0-23 months) of the potential variables. The choice criterion was based on the corresponding *p-value* for the test that the variable in question Granger-causes market price inflation. **Figure 2** shows the number of variables that should be retained for each horizon and different significance levels .

Figure 2 - Number of targeted variables



Then, forecasting horizons were classified into three groups: short (1-6 months), medium (7-12 months) and long term (13-24 months). And taking into account the series that satisfied the choice criterion in at least 50% of the horizons in each group, the number of retained variables for the three groups is presented in **Table 2**. We decided to use in our forecast exercises the dataset of 64 variables chosen for the medium term and using significance level of 10%.

Table 2 - Number of targeted variables

	Short	Medium	Long
1%	14	18	9
5%	49	43	31
10%	77	64	62

Furthermore, we also use the dataset currently used in the BCB models. Therefore, our results in the next section are presented for three datasets: the small dataset (SDS) with 40 variables, the targeted dataset (TDS) with 64 variables and the large dataset (LDS) with 415 variables.

We need to mention that our data for IPCA inflation and its components is different from the historical one. Basically it differs in two main respects. First, we rebuilt the series of IPCA and its components from 2008 onwards to incorporate the new structure of the consumption basket, according to the Household Budget Survey (POF) 2008-2009 by the Brazilian Institute of Geography and Statistics (IBGE). Second, the series are put together considering the reclassification of IPCA's components implemented by BCB in January of 2012[6].

5. Forecasting strategy and results

We applied both the two-step (PCA) and the joint estimation approach to the estimation of FAVAR models. As mentioned beforehand our X_t consists of a three balanced panels of time series spanning from July 2000 through December 2012. Y_t is the market price inflation, the variable to be forecasted. We seasonal adjusted the series that presented some seasonal pattern and transformed the variables to induce stationarity.

In the estimation of the models, we used parsimonious specifications setting the maximum number of factors (K) and maximum number of lags (P) in the VAR equation equal to four.

We performed a recursive out-of-sample exercise with the evaluation sample running from January/2008 through December/2012 and the forecasts horizons varying from 1 through 24.

Our results are for root mean square prediction errors (RMSPE) and they are shown in **Table 3** for the two-step estimation and in **Table 4** for the joint estimation. All RMSPE's are reported relative to the best AR benchmark model for a given forecasting horizon and as the benchmark is in the denominator, a relative RMSPE below 1 means that that the forecast outperforms that for the benchmark and it shaded in green in **Table 3** and **Table 4**.

[6] See box "Updates of IPCA's and INPC's Weighting Structure and of IPCA's Classifications" (December 2011 Inflation Report).

The results for the principal component approach show that for the shorter forecasts horizons, the FAVAR models almost always are outperformed by the benchmark models. In terms of longer horizons, the performance of FAVAR gets a little better but usually only marginally superior to the benchmark models.

Table 3: Relative RMSPE for forecasting market inflation - 2008 to 2012

		Principal components											
		Small				Target				Large			
h	*k/p*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
1	*1*	1.28	1.16	1.16	1.28	0.99	0.95	1.03	1.01	1.12	1.04	1.04	1.15
	2	1.20	1.20	1.13	1.34	1.01	1.00	1.02	1.04	1.15	1.28	1.34	1.60
	3	1.32	1.18	1.46	1.49	1.02	1.14	1.07	1.36	1.38	1.64	1.71	1.17
	4	1.39	1.47	1.45	1.79	1.04	0.97	1.04	1.23	1.34	1.45	1.83	1.39
3	*1*	1.12	0.98	1.07	1.10	1.05	1.03	1.06	1.06	0.99	1.03	1.14	1.12
	2	1.36	1.31	1.45	1.24	1.10	1.16	1.08	1.27	1.13	1.35	1.31	1.25
	3	1.68	1.45	1.84	2.22	0.99	1.26	1.40	1.41	1.42	2.09	1.77	2.20
	4	1.89	1.62	2.45	2.58	1.15	1.34	1.67	1.47	1.42	1.83	1.56	1.34
6	*1*	1.21	1.15	1.13	1.15	1.07	1.04	1.05	1.04	1.06	1.03	1.07	1.20
	2	1.67	1.32	1.29	1.06	1.08	1.07	1.11	1.08	1.27	1.39	1.46	1.42
	3	1.68	1.35	1.36	2.90	1.12	1.02	1.10	1.31	1.33	1.86	1.30	3.87
	4	2.07	1.35	1.62	2.32	1.08	1.10	1.08	1.29	1.54	1.83	1.66	2.20
12	*1*	1.09	1.05	1.06	0.98	1.01	1.03	0.97	1.03	1.01	1.02	1.03	1.02
	2	1.42	1.01	1.27	0.99	1.00	1.07	0.98	0.99	0.99	1.32	1.31	1.02
	3	1.46	1.16	1.40	1.51	1.01	1.09	0.97	1.08	1.10	1.96	1.12	1.46
	4	1.86	1.25	1.42	1.89	0.98	0.93	0.93	0.99	1.64	1.97	1.20	2.17
18	*1*	0.98	1.00	0.97	1.00	0.99	1.03	1.02	1.01	0.98	0.97	0.98	1.01
	2	1.06	1.01	0.94	0.97	0.97	0.98	1.00	0.99	1.07	2.07	2.00	0.88
	3	1.16	0.99	1.18	2.88	1.01	0.99	1.02	1.00	1.20	3.34	0.90	1.71
	4	1.13	0.99	1.08	1.58	0.99	0.97	1.03	1.09	1.16	2.51	1.05	1.63
24	*1*	1.00	1.06	0.99	1.01	1.00	0.98	1.00	0.99	1.01	1.00	1.02	0.99
	2	1.20	1.01	1.08	0.97	0.99	1.00	0.99	1.01	0.98	1.80	1.55	0.99
	3	1.03	1.07	1.00	2.01	0.99	1.00	0.99	1.01	0.92	3.30	0.99	1.33
	4	1.44	1.69	1.26	1.17	1.01	1.01	1.01	0.97	2.08	9.51	1.15	1.49

On the other hand, if for shorter horizons, the one-step estimation models display similar results to those from PCA approach, for longer horizons the former present better results with a median RMSPE for h = 24 of 0.75, 0.63 and 0.62 for the small, targeted and large datasets respectively.

Table 4: Relative MSE for forecasting market inflation - 2008 to 2012

		Joint estimation											
		Small				Target				Large			
h	*k/p*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*
1	*1*	1.35	1.29	1.25	1.13	1.07	0.98	0.99	1.21	1.03	1.02	1.05	1.14
	2	1.15	1.16	1.54	1.27	1.15	1.15	1.13	1.06	1.48	1.44	1.54	1.68
	3	1.16	1.57	1.37	1.12	0.95	1.01	1.21	1.18	1.13	1.26	1.36	1.08
	4	1.34	1.41	1.22	1.54	1.21	1.06	1.24	1.16	1.27	1.23	1.32	1.57
3	*1*	1.15	1.21	1.02	1.42	1.05	1.06	1.11	1.26	1.02	0.91	0.97	1.15
	2	1.11	1.40	1.33	1.14	1.16	1.07	1.21	1.07	1.28	1.66	1.72	1.87
	3	1.14	1.21	1.64	1.98	1.09	1.23	1.10	1.44	1.21	1.38	1.37	1.93
	4	1.72	1.36	1.42	2.16	1.24	1.09	1.38	1.19	1.38	1.23	2.04	1.93
6	*1*	1.19	1.11	0.89	1.21	1.00	0.97	0.90	1.04	1.02	0.93	0.96	1.02
	2	1.00	1.35	1.19	1.11	1.02	1.00	1.05	1.09	1.09	1.17	1.18	1.71
	3	1.17	1.26	1.64	1.73	1.07	1.08	1.30	1.12	1.18	1.62	1.72	2.18
	4	1.47	0.91	1.58	1.70	0.99	1.04	1.15	1.25	1.32	1.80	1.84	3.70
12	*1*	0.99	0.93	1.02	0.81	0.81	0.82	0.88	0.82	0.80	0.81	0.80	0.83
	2	1.17	0.89	1.04	1.36	0.82	0.85	0.96	0.87	0.86	0.81	0.75	1.02
	3	0.97	1.04	1.06	2.09	0.75	0.82	0.85	0.85	0.96	1.15	1.78	1.47
	4	1.11	1.46	1.60	1.58	0.95	0.89	1.08	1.14	0.94	0.92	1.30	1.31
	1	0.73	0.75	0.81	0.78	0.71	0.70	0.73	0.74	0.71	0.71	0.71	0.73
	2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 3 displays the medians RMSPE for the three different samples. The models using the targeted dataset have shown the best performance especially for shorter horizons. However, it should also be noted that for such horizons factors regardless of the datasets, the median models present worst performances than the autoregressive models. For the longer horizons, the performance of the median models of targeted and large datasets display similar results. Concerning the models with minimum relative RMSPE, no model is clearly dominated by the others as we can seen in **Figure 4**.

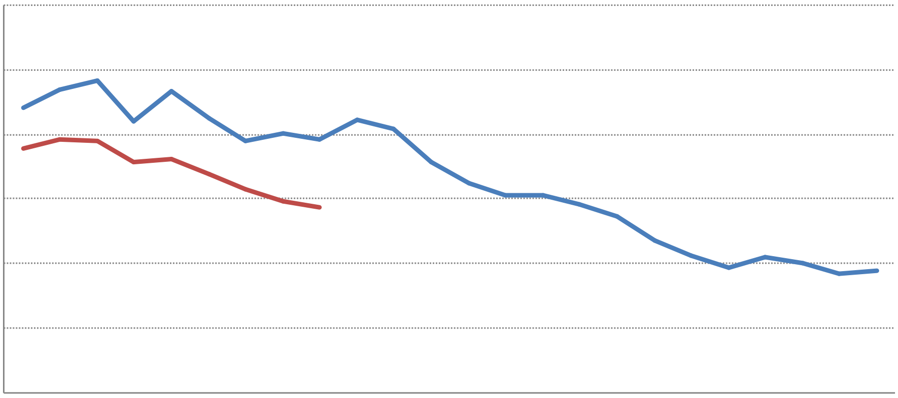
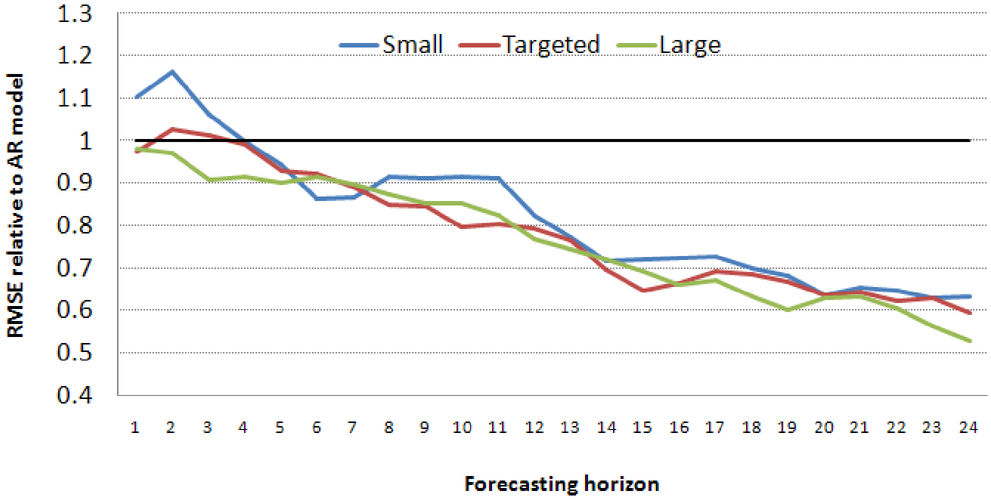


Figure 4: Minimum RMSE for datasets



Regarding the results in terms of estimation technique, joint-estimated models clearly outperformed the two-step approach models either in terms of median models (**Figure 5**) or minimum models (**Figure 6**). Usually the dominance in terms relative RMSPE of the MCMC models started around h = 6 and gets bigger as the forecast horizons increase.

Figure 5: Median RMSE for estimation methods

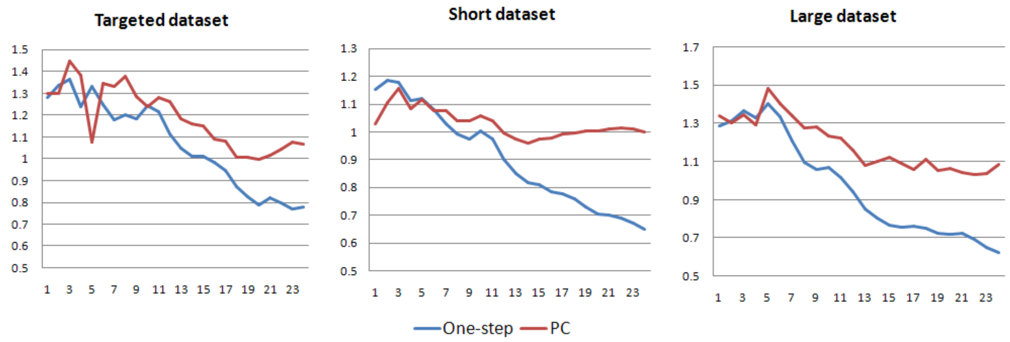
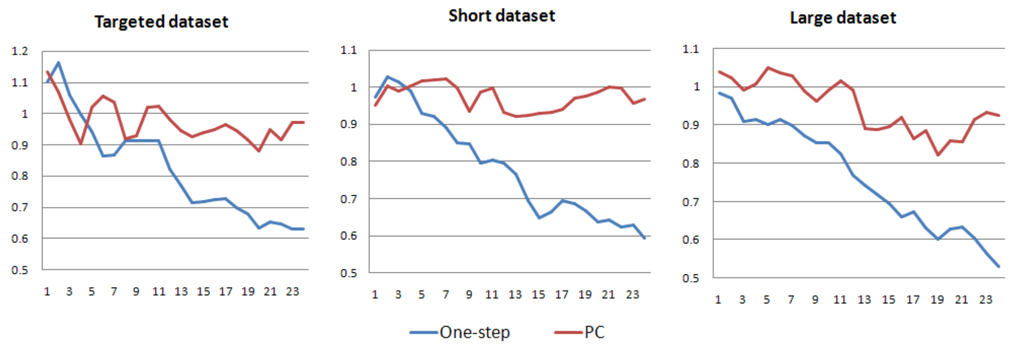


Figure 6: Minimum RMSE for estimation methods



6. Concluding remarks

This paper investigates the performance of FAVAR models using Brazilian data for forecasting market price inflation using different datasets and estimation techniques.

Overall, the longer the forecasting horizon, the better is the performance of FAVAR models compared to the benchmark AR models. Furthermore, targeting variables matters mostly for median forecasts.

Concerning the estimation methods, models using one-step approach outperforms the PCA models and the advantage of the former widens as the horizon increases.

Despite the results presented here being preliminary and the computational costs of joint estimation of FAVAR model not being negligible, we think it is advisable to incorporate this type of model in the set of auxiliary models used by BCB.

In terms of future research in this area, we intend to incorporate different features of the FAVAR models which have been recently discussed in the literature such as time-varying parameters (Eickemeier, Lemke and Marcellino (2011) and

Barnett, Mumtaz and Theodoridis (2012)) and Factor-augmented Error Correction Model (FECM) (Banerjee, Marcellino and Masten (2010)). We also want to test FAVAR models based on grouped factors which are used in the BCB auxiliary models *versus* the more traditional approach used here where the factors are extracted from the whole datasets.

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