Forecasting With Many Predictors. An Empirical Comparison

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FORECASTING WITH MANY PREDICTORS. AN EMPIRICAL COMPARISON *

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BANCO DE LA REPÚBLICA

ABSTRACT. Three methodologies of estimation of models with many predictors are implemented to forecast Colombian inflation. Two factor models, based on principal components, and partial least squares, as well as a Bayesian regression, known as Ridge regression are estimated. The methodologies are compared in terms of out-sample RMSE relative to two benchmark forecasts, a random walk and an autoregressive model. It was found, that the models that contain many predictors outperformed the benchmarks for most horizons up to 12 months ahead, however the reduction in RMSE is only statistically significant for the short run. Partial least squares outperformed the other approaches based on large datasets.

Key words and phrases. Partial least squares, Principal components, Ridge regression.

JEL clasification. C11, C15, C52, C53.

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1. Introduction

For monetary policy it is important to have a precise knowledge about the state of the economy and large amounts of data available at each period of time are analized in order to achieve this. On the other hand, it is necessary to count with reliable forecasts for some key macroeconomic variables so that the monetary authority makes appropriate decisions. However, most forecasts are obtained from small dimension models, leaving out some relevant and available information that may reduce the forecasting error. The main reason for this is that under standard econometric techniques, when there are many regressors there is a lack of degrees of freedom issue, specially when the number of observations is smaller than the number of regressors in which case it is not possible to estimate a model in a traditional way. This problem might be solved by using methods that account for large data set and summarize the information in some way to include it in a forecasting equation. Those alternative methods include factor models, bayesian regression and forecast combination. Another useful approach to work with large data sets but different in spirit, is based on variable selection algorithms. In this case, a representative small number of regressors is chosen among the complete set of variables based on some criterion, moving from data-rich environment to a small dimension model.

In this paper the focus is exploiting the forecast ability of the complete set of predictors. In this regard, factor models is an alternative that exploit the co-movement of a set of variables and efficiently reduce the dimension of the data set to a few underlying factors that can be used to construct forecasting models with small dimension. There exist several methodologies of estimation of factor models, the widely used principal components method, popularized by Stock and Watson [2002a], Stock and Watson [2002b], Watson [2003] works; the method based on the frequency domain by Forni et al. [2000], Forni et al. [2005]; the work of Kapetanios and Marcellino [2006] based on subspace algorithms using a state-space representation and the less known partial least squares proposed by Wold [1982], but recently used as a methodology to extract common factors from large data sets by Groen and Kapetanios [2009].

Principal components (hereafter PC) has the advatange over the other methodologies of easy implementation for both extracting factors and forecasting. However, compared to Partial least squares (hereafter PLS), the former has the disadvatage that the common factors are chosen so that they provide the best fit for the dataset but does not take into account the variable to be forecast, while in PLS the common factors are linear, orthogonal combinations of the predictor variables such that they maximize the covariance between the target variable and each of the common factors. Groen and Kapetanios [2009], evaluated the asymptotic properties of PLS compared to PC when both the number of observations and the number of predictors become large. They also showed that when the commonality (colinearity) among variables is strong, the forecasting performance of the two methods is statistically indistinguishable, however when a weak factor structure exists, the performance of PLS improves as the number of predictors increases. On the other hand, De Mol et al. [2008] found the equivalence between Bayesian regression and

PC with the difference that the former considers all the predictor variables in the forecasting equation with some coefficients shrunk towards zero, while the later summarizes the predictors in a few common factors that enter the forecasting equation.

There have had many empirical applications of factor models for forecasting macroeconomic variables in many economies, mainly using principal components. Eickmeier and Ziegler [2006] gathered the results of several applications of factor models to evaluate their ability to forecast inflation and output, comparing the first three methodologies mentioned above, founding mixing results. There is not a clear advantage of any of the methods reducing forecast errors. More recently, De Mol et al. [2008] compared PC and Bayesian regression using US data to forecast inflation and industrial production. Their results suggest that when there is sparsity, using a gaussian prior distribution, Ridge regression, is a good alternative to PC. However, when the predictors are highly collinear, then using a double exponential prior, Lasso regression (least absolute shrinkage and selection operator), which becomes a variable selection method, seems to perform better. On the other hand, PLS has only been recently used for forecasting purposes. Groen and Kapetanios [2009] applied PLS using US montlhy data to forecast CPI inflation, industrial production, unemployment and federal funds rate and compared the forecasting perfomance to PC and Ridge regression, founding supportive results for PLS for most evaluating samples and target variables. Rodrigues [2010] applied PLS to forecast inflation in Brazil.

For the Colombian case, González et al. [2009] estimated a factor model to forecast Colombian inflation using principal components, following Stock and Watson [2002a] and Stock and Watson [2002b]. They used monthly data from 1999:01 to 2008:06 and estimated several factors models with different number of factors as well as different number of lags of the target variable and factors in the forecasting equation, selected according to different criteria. Out-sample forecast for horizons up to one year were generated, showing good forecasting performance of the factor models relative to an autoregressive model, except for the short run, one-month ahead.

In this paper, an empirical comparison of the forecasting performance of factor models estimated by principal components and partial least squares is performed for Colombian inflation, using monthly data and considering a larger dataset of variables related to economic activity, monetary, credit and exchange rate, prices and external variables. Additionally, having into account the relation between principal components and bayesian regression, also Ridge regression is implemented and evaluated with the same data. The forecasting evaluation is carried out using the RMSE relative to two benchmark forecasting models, a random walk and autoregressive model.

The results favor PLS over PC and also PLS outperformed the random walk and autoregressive benchmarks for all horizons. It seems that the set of predictor variables is characterized by collinearity and that a small number of factors is needed to capture the common structure. The evaluation of the forecasts is done for two periods, Jan-2006 to Jun-2010 and during the recent crisis Jun-2008 to Jun-2010. It was found that for the two out-sample periods, PLS outperformed both PC and Ridge regression as well as the benchmark models, however for the later period, inflation was harder to forecast and the RMSE is higher for all models, but still models with many predictors performed well.

The remainder of the paper is structured as follows. Section 2 describes the different methodologies to forecast with many predictors used in the empirical exercise. Section 3 describes the data and variable to be forecast as well as details of the implementation of the estimation methods. Section 4 shows the results of the out-sample forecasts evaluation obtained by the different approaches. Section 5 concludes.

2. METHODOLOGIES OF FORECASTING WITH MANY PREDICTORS

In this section, a brief description of the two estimation methodologies of factor models, principal components and partial least squares as well as the bayesian regression method known as Ridge regression is addressed.

The general problem consists on the estimation of the following model

$$\mathbf{Y}_t = \alpha \mathbf{X}_t + \epsilon_t \tag{2.1}$$

where $\mathbf{Y}_t$ is the target variable to be forecast, $\mathbf{X}_t$ is a vector of N predictors and α is a vector of N coefficients. The issue is that N might be too large and even larger than T, the number of observations, what makes difficult the estimation of the model using traditional econometric techniques.

2.1. **Principal Components - PC.**

In the case of factor models, the N predictor variables does not enter the forecasting equation directly but a reduced number, r, of unobserved common factors that summarize the information content in all the predictors. Thus, the factors $F_t = (F_{1t}, F_{2t}, ..., F_{rt})$ are linear combinations of X_t, such that $F_t = \Lambda X_t$. The difference among factor methods is the way Λ is constructed.

In general, let $\tilde{X}_t$ the vector of predictors transformed such that for each variable the mean is zero and variance equal one, which may contain also lags and leads of X_t, then

$$\tilde{X}_t = \Lambda' \mathbf{F}_t + e_t \tag{2.2}$$

where Λ are the factor loadings, $\mathbf{F}_t$ is the vector of r common factors, with $r < \min{(N, T)}$, and e_t is the vector of idiosyncratic components, which is a zero-mean vector that contains the fraction of $\tilde{X}_t$ unexplained by $\mathbf{F}_t$.

For the principal components methodology, Λ and $\mathbf{F}_t$ are obtained by solving:

$$V(r) = \min{[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (\tilde{x}_{it} - \lambda_i \mathbf{F}_t)^2]} \tag{2.3}$$

A non-unique solution of (2.3) consists on taking the eigenvectors corresponding to the r largest eigenvalues of the var-cov matrix of $\tilde{X}_t$. Thus, $\hat{\Lambda} = (\lambda_1, ..., \lambda_N)$, λ_i a $r \times 1$ vector and $\hat{\mathbf{F}}_t = \hat{\Lambda}\tilde{X}_t$.

In terms of α in equation (2.1), the estimate becomes

$$\hat{\alpha} = \hat{\Lambda}'(\hat{\Lambda}X'X\hat{\Lambda}')^{-1}\hat{\Lambda}X'\mathbf{Y} \tag{2.4}$$

2.2. **Partial Least Squares - PLS.** As in the case of principal components, the factors are linear combinations of the regressors. However, a major difference with the former method is that the factors are constructed taking into account the relation between the target variable $\mathbf{Y}_t$ and $\tilde{X}_t$.

A simple algorithm to construct k PLS factors is discussed in detail in Helland [1990] and is summarized as follows:

(1) Set $u_t = \tilde{\mathbf{Y}}_t$ and $v_{it} = \tilde{x}_{it}$, $i = 1, \cdots, N$, with $\tilde{\mathbf{Y}}_t$ the demeaned target variable. $v_t = (\tilde{x}_{1t} \cdots \tilde{x}_{Nt})$. Set $j = 1$
(2) Construct the loadings or vector of weights $w_j = (w_{1j} \cdots w_{Nj})'$, where $w_{ij} = cov(u_t, v_{it})$. Then the j-th PLS factor is the linear combination $f_{jt} = w_j' v_t$
(3) Regress u_t and v_{it}, $i = 1, \cdots, N$ on f_{jt}. Denote the residuals of these regressions by $\tilde{u}_t$ and $\tilde{v}_{it}$, respectively.
(4) If $j = k$ then stop. Else, set $u_t = \tilde{u}_t$ and $v_{it} = \tilde{v}_{it}$ for $i = 1, \cdots, N$. Set $j = j + 1$ and go to step (2).

Helland [1988] shows that the estimate obtained using the algorithm is mathematically equivalent to the following estimate of α in equation (2.1)

$$\hat{\alpha} = V_k(V_k'X'XV_k)^{-1}V_k'X'\mathbf{Y} \tag{2.5}$$

where $V_k = (X'\mathbf{Y} \quad (X'X)X'\mathbf{Y} \quad \cdots \quad (X'X)^{k-1}X'\mathbf{Y})$

2.3. **Ridge Regression - RR.** An alternative methodology to estimate α in equation (2.1) is Bayesian regression, where the whole set of predictors is considered in the equation. The starting point is a prior distribution for α, that when Gaussian distribution is assumed, it is well known as Ridge Regression. Using the likelihood of the observed data and the prior distribution, then the posterior distribution of α is obtained and sampling from this distribution, α is estimated as the posterior mode.

Another simpler way to implement Ridge Regression is considering the shrinkage estimator of α in equation (2.1) given by

$$\hat{\alpha} = (X'X + vI)^{-1}X'\mathbf{Y} \tag{2.6}$$

where υ is a shrinkage scalar parameter, which when assuming that $\epsilon_t \sim i.i.d\ N(0, \sigma^2_\epsilon)$ and $\alpha \sim i.i.d\ N(0, \sigma^2_\alpha I)$[1], i.e. all parameters are shrunk to zero, then $\upsilon = \frac{\sigma^2_\epsilon}{\sigma^2_\alpha}$.

In practice, the parameter υ is set as proportional to the dimension of the data set N, $\upsilon = \eta N$, and is chosen according to some criterion based on the in-sample fit or out-sample performance of the model.

3. Empirical Application

3.1. **Data.** The dataset used for the empirical application consists on 164 monthly Colombian time series from Jan-2000 to Jun-2010. This sample was chosen given the availability of all series and to avoid a structural change observed in several macroeconomic variables at the end of the 90's as shown in Melo and Nuñez [2004] among others. The data are grouped into four categories: economic activity (70 series), Prices (34 series), Credit and Money indicators (37 series) and external variables (23 series)

The series are seasonally adjusted using Tramo-Seats methodology proposed by Caporello and Maravall [2004], then the variables are transformed to achieve stationarity[2]. The target series is inflation, measured as the twelve-month growth rate of total CPI. The dependant variable is not included in the set of predictors.

3.2. **Implementation.** Recursive estimation of the following models is performed and forecasts for one to twelve months ahead are generated. The initial estimation sample is from Jan-2000 to Dec-2005. So, pseudo out-sample forecasts for the sample Jan-2006 to Jun-2010 are obtained.

$$\Delta\mathbf{Y}_{t+h,t} = \alpha^h + \sum_{i=1}^{p} \rho_i \Delta\mathbf{Y}_{t-i+1,t-i} + \epsilon_{t+h} \tag{3.1}$$

$$\Delta\mathbf{Y}_{t+h,t} = \alpha^h + \sum_{i=1}^{p} \rho_i \Delta\mathbf{Y}_{t-i+1,t-i} + \beta^h F(X_t) + \epsilon_{t+h} \tag{3.2}$$

where $\Delta\mathbf{Y}_{t+h,t} = \pi_{t+h} - \pi t$ is the difference of order h of the twelve-month variation of total CPI,π_t, $\Delta\mathbf{Y}_{t,t-1} = \pi_t - \pi t - 1$ is the difference of order 1 of the twelve-month variation of total CPI. $F(X_t)$ are the linear combinations of X_t constructed by any of the three methodologies described above, PC, PLS or RR. Notice that $F(X_t)$ is of dimension $r \times 1$ for PC and PLS, but $N \times 1$ for Ridge Regression.

[1] Homogenous variance and zero mean are justified by the fact that all variables in the panel are standarized and demeaned.

[2] See Table A.10 in Appendix A for a detailed description of the variables and the transformation applied to each variable

Two versions of model (3.2) are estimated using both PC and PLS. For the first one, $r = \{1, 2\}$ [3] factors are extracted from the complete dataset, while for the second version, one factor is extracted from each category of variables, so a total of 4 factors are included in the forecasting equation. Thus, the second version of the model has the form:

$$\Delta \mathbf{Y}_{t+h,t} = \alpha^h + \sum_{i=1}^{p} \rho_i \Delta \mathbf{Y}_{t-i+1,t-i} + \sum_{j=1}^{4} \beta_j^h F(X_{jt}) + \epsilon_{t+h} \tag{3.3}$$

where X_{jt} is the vector of predictors in category $j = 1, \cdots, 4$

All possible models with up to $p = \{0, 1, \cdots, 6\}$ lags are considered. The parameters of the models and the factors are estimated for each horizon and each period, starting with the sample from Jan-2000 to Dec-2005 and adding one observation at a time. For details of the implementation and generation of the forecasts, see Groen and Kapetanios [2009].

For Ridge Regression all the regressors are considered at once, so only version one of the model is estimated. In order to determine the degree of shrinkage, different values of υ, proportional to the dimension of the data set, were considered. Having into account the findings of De Mol et al. [2008], values between N and $5N$ explain an important fraction of the in-sample variance of the target variable in model (3.2), producing appropriate forecasts and a high correlation with those of principal components.

4. Empirical Results

The forecasting performace of model (3.2), estimated by each of the three methodologies described in section 2 are evaluated in terms of the RMSE relative to both an autoregressive model (3.1) and the random walk (model (3.1) with $p = 0$). Two out-sample periods are considered. First, the period from Jan-2006 to Jun-2010 and the second from Jun-2008 to Jun-2010 in order to evaluate the performance of the models with many predictors during the recent crisis when inflation was harder to forecast (See Figure 5.2).

The main results are summarized as follows. Table 5.1 contains the forecast evaluation of the best model (3.2), estimated by each of the three methodologies, and the best model (3.3), relative to the random walk model. For most horizons, the model estimated by PLS outperform the other two methodologies for both out-sample periods. Between Ridge regression and PC the ranking is less clear. Ridge regression does not reduce the RMSE relative to the random walk for horizons further than 8 months in the large out-sample period. When comparing the two versions of factor models, equations (3.2) and (3.3), the forecasts evaluation shows that the model with one factor extracted from the complete data set is more suitable than the model containing a factor extracted from each category of predictors, when the factors are estimated by principal components. However, when factors are estimated by PLS, it is the other way around.

[3] Up to $r = 4$ factors were considered, however both, Bai and Ng and BIC criteria lead to r=1. This result is according to the finding in González et al. [2009]

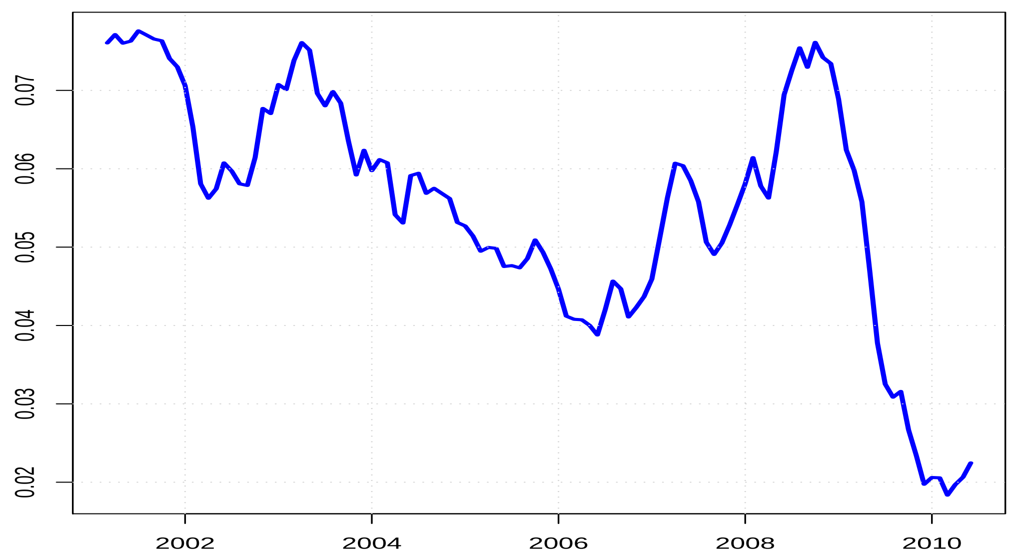

FIGURE 4.1. Inflation in Colombia

On the other hand, Table 5.2 contains the RMSE of the best models (3.2) and (3.3), relative to the best AR model for each horizon. The results are quite similar to those relative to the random walk. Models with many predictors have better forecast ability than an autoregressive model, especially in the short run. Additionally, the forecasting performance seems to be better during the recent crisis. Again, PLS outperformed both, PC and Ridge regression for most horizons, and model (3.2) is more accurate than (3.3) when the estimation is made by principal components and the other way around for partial least squares.

Considering two issues of the modified Diebold and Mariano test for equal forecast ability, the small evaluation out-sample period and the inaccuracy for comparing nested models, a boostrapping exercise is performed in order to determine whether the reduction in RMSE of the best model with many predictors relative to an autoregressive and random walk models is statistically significant. Tables A.8 and A.9 in the Appendix show the 90% confidence interval for the relative RMSE, obtained from a bootstrapping sample of the forecasting errors, for the large and small out-sample periods, respectively. The sampling is done taking into account the serial correlation of the forecasting errors up to order h, drawing 5000 replications[4]. The results suggest that there is not reduction in the RMSE of the models with many predictors relative to the AR model for all horizons and all analysed models. However, there is a significant reduction in RMSE for the two factor

[4]In footnote of Table A.8 are details of the sampling process

models estimated by PLS and the Ridge regression for horizon 1-month ahead relative to the random walk for the small out-sample period. The Tables also include a t type test for the null hypothesis of relative RMSE equals the unity, against the alternative that the relative RMSE is less than one. The results of the t-statistics confirm the conclusions drawn from the confidence intervals.

More detailed results of all individual models evaluated are found in Tables A.3, A.4 and A.5 in the Appendix A. Those tables contain forecast evaluation of model (3.2) estimated by PLS, PC and Ridge Regression, respectively, for both out-sample periods, for different number of lags p and different number of factors, for the first two methods, and different value of the shrinkage parameter υ, for the Ridge regression. The evaluation criterion is the RMSE relative to the autoregressive model (3.1) with the same number of lags. Although the best out-sample autoregressive model (3.1) seems to be with $p = 1$ lag for most horizons and for both out-sample periods, the same number of lags not necessarily is the one with better out-sample performance when estimating model (3.2).

From the evaluation of models estimated by PLS some results can be outlined. it is found for the large out-sample period, that for all horizons the PLS model outperformed the AR model and the reduction in RMSE is significant, except for 8 to 10 months ahead. One factor and one lag of the target variable seem to do a good job in forecasting inflation, except for 1 to 3 months, when the model with two factors performed best. For the short out-sample period, PLS model outperformed the AR model for all horizons and the reduction in RMSE is significant for 1 to 8 month-ahead. Again a model with one factor have good performance for horizons further than 3 months, and a model with two factors performed well for the short-run horizons (1-3 months).

For the models estimated by PC and for the large out-sample, it is found that for all horizons there is a factor model that outperformed the AR model, however the reduction in RMSE with the factor model statistically significant for horizons 2, and 9 to 12-month ahead. A model with two factor seems to be enough to explain the dynamics of inflation, except for horizons 2, and 10 to 12. For the short out-sample period, PC model outperformed the AR model for all horizons, but the reduction in RMSE is not significant.Again, a model with two factors performed best for most horizons.

For the models estimated by Ridge regression, a grid of values for the parameter $\upsilon = \eta N$, with $\eta = 0.5, 1, 1.5, \cdots, 6$ and N the dimension of the data set, are evaluated along with different lag order p. The fraction of explained in-sample variance of the target variable fluctuates between 50% and 5% for all horizons[5]. The smaller the parameter υ, the higher the fraction of explained in-sample variance of the target variable and the closer to OLS estimation. On the other extreme, the larger the parameter υ, the smaller the explained variability of the variable to be forecast and more parameters are shrunk to zero. Table A.5 reports the forecast evaluation, for both out-sample periods. It is worth mentioning that for the large out-sample period, for all horizons there is a reduction in the RMSE with a ridge regression relative to the AR model, however this reduction is not

[5]This results are available under request

statistically significant. The degree of shrinkage of the model that performs best, varies with the horizon, but for most horizons $\upsilon = 6$ performed best. On the other hand, for the small out-sample period, the results are more promising. For all horizon there is a ridge regression that out performs the AR model and for horizons 1 to 8 months the reduction in RMSE with the Ridge regression is statistically significant. The degree of shrinkage is high, the parameter υ varies between 4.5 and 6 times N for most horizons.

The second version of the factor model, (3.3), where one factor for each category of variables is included in the model, is estimated using both, principal components and partial least squares. A.6 and A.7 in Appendix A contain the forecast evaluation of these models. For models estimated by PLS, the results show that for the large out-sample period, for all horizons, there is at least one factor model that outperforms the AR model. The factor model significantly reduces the RMSE relative to the AR model for horizons 3 to 7, 11 and 12 months ahead. For the short out-sample period, a factor model outperformed the AR model for all horizon, being the reduction in RMSE significant for horizons 1 to 5, 7 and 10. On the other hand, for models estimated by PC, it was found that none of the factor models outperforms the AR model for any forecast horizon for the long out-sample. In fact, when looking at the estimation results, only the factor associated to credit and money indicators is significant in most models and also in some cases the factor associated to prices [6]. When looking at the evaluation of the forecast for the short out-sample period, a factor model estimated by principal components generates better forecasts in terms of RMSE than an AR model for horizons 1, 6,7, and 9 to 12 months. However the reduction in RMSE is only significant for horizon 10-month ahead. The performance of the factors models for the small out-sample have improved.

5. Concluding Remarks

In this work, different methodologies of estimating models with many predictors are applied as alternative methods for forecasting inflation in Colombia in the short run. In particular, factor models estimated by principal components and partial least squares, in which the complete set of predictors is sumarized in a small number of common factors that enter the forecasting equation and a Bayesian approach, which considers the complete set of preditors but shrinks some parameters to zero. The later method assumes a prior gaussian distribution for the parameteres of the model and is known as ridge regression. The methodologies are compared in terms of forecasting performance using the RMSE relative to an autoregressive model and a random walk.

Our forecasting analysis includes two versions of the factor model. In the first version, factors extracted from the complete data set are included in the forecasting equation, while in the second version, one factor extracted from each category of variables (economic activity, prices, credit and monetary indicators and external variables) is included in the forecasting equation. On the other hand, for the ridge regression, different values of the shrinkage parameter are evaluated.

[6] The estimation results of each model is available under request.

The models are estimated in a recursive way and out-sample forecasts are generated for one to twelve month ahead. Two out-sample forecast periodos are evaluated. The first one, from Jan-2006 to Jun-2010 and the second from Jun-2008 to Jun-2010 in order to evaluate the forecasting ability of the different economic variables to predict inflation in the recent crisis.

The results show that, in average, one factor is appropriate to capture the commonality of the economic variables considered in this study and help to explain the dynamics of Colombian inflation. On the other hand, when factors are estimated by principal components, a model with factor extracted from the complete set of predictors seems to have more predictive power than factors extracted from each category of variables separately. However, partial least squares favors the second type of models.

Regarding Ridge regression, although it seems that a high degree of shrinkage is needed to produced good forecast for inflation and although it is a good alternative to forecast inflation relative to and autoregressive and random walk models, comparing to factor models there is not significant gain in using this methodology.

In general, models that include many predictors have good forecasting performance compared to an autoregressive and random walk models for all horizons, especially in the short run. Models estimated by PLS outperformed the other two methodologies for most horizons. The predictive ability of those models, relative to the benchmark models, seems to have improved over the last part of the sample. However, the forecasting error has increased, as expected by the economic conditions during the evaluation period.

TABLE 5.1. Forecast Evaluation relative to a Random walk model

out - sample period: Jan-2006 to Jun-2010					
Horizon	**Best PLS**	**Best PC**	**Best RR**	**Best PLS - V.II**	**Best PC - V.II**
1	**0.551***	0.677	0.729	0.749	0.720
2	**0.725***	0.839	0.833	0.819	1.076
3	0.760	0.823	**0.746**	0.750	1.197
4	0.761	0.870	0.783	**0.702***	1.113
5	0.775	0.943	0.880	**0.709***	1.048
6	0.793	0.960	0.930	**0.676***	1.025
7	**0.829**	0.979	0.991	0.925	1.063
8	0.918	0.986	1.010	**0.807**	1.112
9	0.969	0.983	1.020	**0.909**	1.096
10	**0.943**	0.963	1.009	0.979	1.054
11	0.930	0.969	1.033	**0.909***	1.080
12	0.962	0.960	1.065	**0.925***	1.125
out - sample period: Jun-2008 to Jun-2010					
Horizon	**Best PLS**	**Best PC**	**Best RR**	**Best PLS - V.II**	**Best PC - V.II**
1	**0.477***	0.644	0.517	0.531	0.623
2	0.661	0.808	**0.610***	0.657	1.007
3	0.680	0.818	**0.581***	0.662	1.166
4	0.706	0.869	0.661	**0.593***	0.992
5	0.711	0.918	0.756	**0.640***	0.960
6	0.768	0.929	0.808	**0.595**	0.932
7	0.805	0.963	0.853	**0.762***	0.966
8	0.860	0.980	0.888	**0.823**	1.012
9	0.906	0.974	0.883	**0.822**	1.006
10	0.908	0.941	0.834	**0.810***	0.942
11	0.921	0.914	**0.858**	0.894	0.955
12	0.895	**0.845***	0.897	0.900	0.930

The numbers correspond to the ratio of the RMSE of the best model (3.2) according to each estimation methodology, vis-a-vis the random walk model.
V-II makes reference to model (3.3).
The best performing model for each horizon is highlighted in bold italic.
* means a significant reduction in RMSE according to the modified Diebold-Mariano test for equal forecast ability (Harvey et al. [1997])

TABLE 5.2. Forecast Evaluation relative to an Autoregressive model

out - sample period: Jan-2006 to Jun-2010					
Horizon	**Best PLS**	**Best PC**	**Best RR**	**Best PLS - V.II**	**Best PC - V.II**
1	**0.827***	1.016	1.082	1.125	1.082
2	**0.843***	0.976	0.965	0.952	1.252
3	0.880	0.952	0.872	**0.868***	1.385
4	0.857	0.980	0.886	**0.790***	1.253
5	0.835	1.016	0.946	**0.763***	1.129
6	0.839	1.016	0.981	**0.716**	1.085
7	**0.854**	1.007	1.018	0.953	1.094
8	0.918	0.986	1.010	**0.807**	1.112
9	0.969	0.983	1.020	**0.909**	1.096
10	**0.948**	0.967	1.010	0.983	1.060
11	0.936	0.976	1.034	**0.915***	1.087
12	0.962	0.960	1.065	**0.925***	1.125

out - sample period: Jun-2008 to Jun-2010					
Horizon	**Best PLS**	**Best PC**	**Best RR**	**Best PLS - V.II**	**Best PC - V.II**
1	**0.788***	1.064	0.848	0.878	1.029
2	0.818	1.001	**0.754**	0.814	1.248
3	0.816	0.982	**0.701**	0.795	1.399
4	0.804	0.989	0.754	**0.675***	1.13
5	0.778	1.004	0.826	**0.700***	1.051
6	0.817	0.988	0.857	**0.633**	0.992
7	0.827	0.989	0.875	**0.782***	0.993
8	0.860	0.980	0.888	**0.823**	1.012
9	0.906	0.974	0.883	**0.822**	1.006
10	0.917	0.95	0.839	**0.818***	0.951
11	0.931	0.924	**0.865**	0.904	0.965
12	0.944	**0.891***	0.934	0.949	0.981

The numbers correspond to the ratio of the RMSE of the best model (3.2), according to each estimation methodology, vis-a-vis the best AR model for each horizon.

V-II makes reference to model (3.3).

The best performing model for each horizon is highlighted in bold italic.

* means a significant reduction in RMSE according to the modified Diebold-Mariano test for equal forecast ability (Harvey et al. [1997])

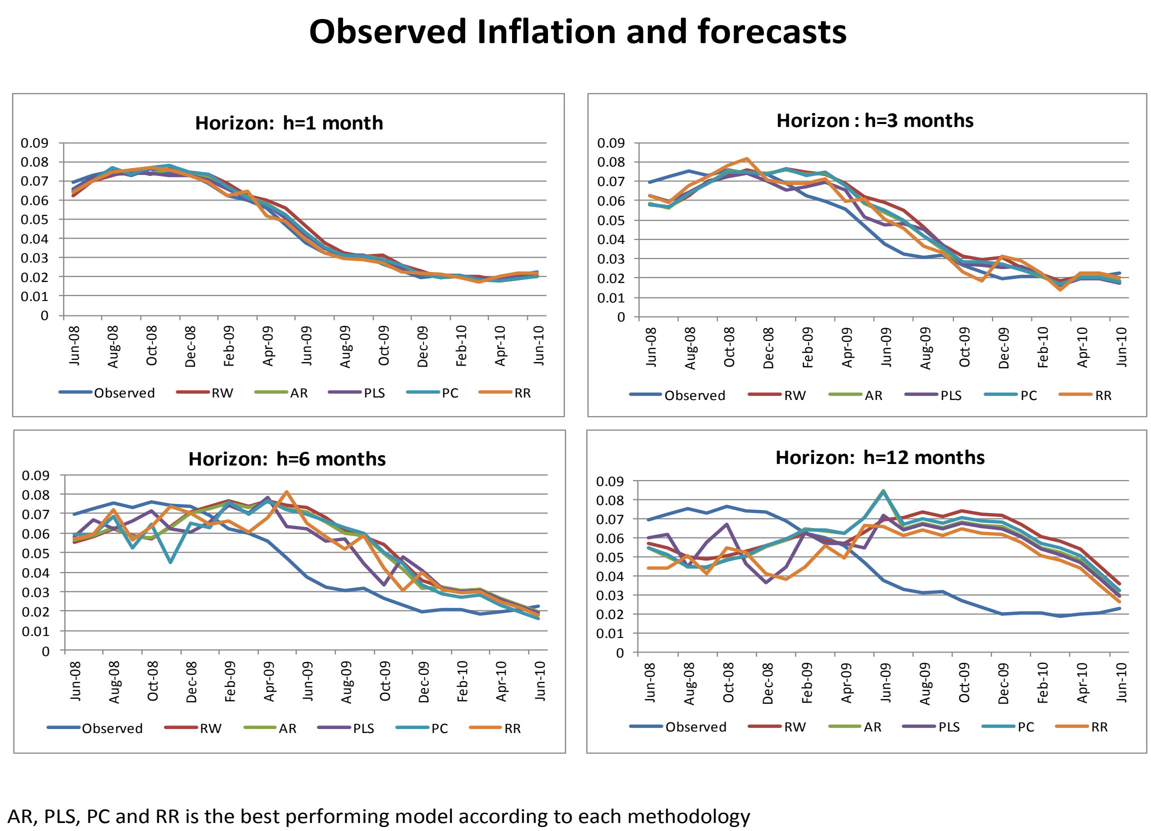

FIGURE 5.2. Inflation Forecasts

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APPENDIX A. FORECAST EVALUATION OF INDIVIDUAL MODELS

TABLE A.3. Forecast evaluation of models estimated by PLS

out - sample period: Jan-2006 to Jun-2010													
Lags	**Factors**	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	1	0.917	0.967	0.963	0.924	0.906	0.926	0.938	0.959	0.979	0.988	1.017	1.057
0	2	0.862	0.914	0.951	0.913	0.916	0.946	0.982	1.023	1.047	1.055	1.111	1.158
1	1	0.838	0.848	**0.836***	**0.829***	**0.835***	**0.839***	0.854	0.918	0.963	0.948	**0.936***	**0.943***
1	2	**0.827***	**0.843***	0.835	0.831	0.838	0.845	0.861	0.923	0.964	0.953	0.946	0.958
2	1	1.024	1.007	1.004	0.974	0.952	0.967	0.968	0.976	0.983	0.993	1.016	1.047
2	2	1.089	1.045	1.095	1.037	1.016	1.024	1.041	1.047	1.06	1.082	1.133	1.148
3	1	1.04	1.019	1.021	0.982	0.945	0.957	0.951	0.952	0.956	0.971	1.007	1.037
3	2	1.104	1.047	1.108	1.04	0.99	0.997	1.012	1.024	1.034	1.047	1.109	1.126
4	1	1.039	1.017	1.011	0.97	0.934	0.932	0.923	0.916	0.925	0.955	0.995	1.023
4	2	1.109	1.051	1.105	1.038	0.981	0.974	0.987	0.99	0.999	1.023	1.087	1.104
5	1	1.032	1.01	1.005	0.965	0.928	0.924	0.908	0.897	0.91	0.944	0.987	1.018
5	2	1.09	1.036	1.101	1.036	0.978	0.964	0.966	0.971	0.984	1.011	1.071	1.094
6	1	1.055	1.01	0.98	0.926	0.885	0.862	0.849	0.855	0.878	0.91	0.947	0.979
6	2	1.088	1.032	1.073	0.999	0.933	0.901	0.902	0.909	0.931	0.964	1.021	1.039

out - sample period: Jun-2008 to Jun-2010													
Lags	**Factors**	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	1	0.764	0.809	0.764	**0.706***	**0.711***	0.768	0.805	0.86	0.906	0.931	0.952	0.975
0	2	**0.700***	**0.717**	**0.711***	0.711	0.763	0.809	0.847	0.896	0.941	0.969	1.019	1.033
1	1	0.804	0.828	0.787	0.794	0.808	0.837	0.858	0.941	0.959	1.025	0.986	0.99
1	2	0.788	0.818	0.778	0.791	0.809	0.837	0.859	0.938	0.95	1.012	0.973	0.978
2	1	0.943	0.912	0.849	0.804	0.799	0.84	0.853	0.872	0.886	0.893	**0.902**	**0.914**
2	2	1.088	0.935	0.901	0.889	0.914	0.93	0.93	0.922	0.944	0.962	0.988	0.98
3	1	0.965	0.937	0.878	0.822	0.803	0.835	0.842	0.855	0.871	0.882	0.905	0.919
3	2	1.101	0.946	0.916	0.89	0.896	0.905	0.911	0.918	0.942	0.951	0.988	0.984
4	1	0.974	0.948	0.879	0.816	0.796	0.812	0.817	0.824	0.846	0.873	0.906	0.923
4	2	1.102	0.958	0.916	0.89	0.887	0.882	0.887	0.891	0.921	0.943	0.994	0.998
5	1	0.967	0.941	0.871	0.813	0.8	0.818	0.817	0.82	0.844	0.873	0.914	0.934
5	2	1.092	0.96	0.916	0.882	0.883	0.877	0.881	0.891	0.923	0.947	0.995	0.997
6	1	0.926	0.884	0.816	0.753	0.747	**0.761***	**0.786***	**0.803***	**0.835**	**0.864**	0.910	0.944
6	2	1.02	0.879	0.841	0.81	0.828	0.82	0.853	0.863	0.903	0.938	0.995	1.008

The numbers correspond to the ratio of the RMSE of model (3.2) with different number of factors and lags, vis-a-vis the AR model with equal number of lags.

The best performing model for each horizon is highlighted in bold.

* means a significant reduction in RMSE according to modified Diebold- Mariano test for equal forecast ability (Harvey et al. [1997])

TABLE A.4. Forecast evaluation of models estimated by PC

out - sample period: Jan-2006 to Jun-2010													
Lags	**Factors**	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	1	1.024	1.003	1.016	1.011	1.02	1.013	1.008	0.991	0.983	0.981	0.983	0.970
0	2	1.017	1.011	1.024	1.036	1.048	1.056	1.062	1.024	0.985	0.977	0.988	0.982
1	1	1.050	1.000	1.011	1.013	1.020	1.016	1.007	0.986	0.98	0.98	0.982	0.948
1	2	1.016	1.009	1.020	1.039	1.05	1.063	1.061	1.019	0.978	0.967	0.977	0.97
2	1	0.98	**0.937***	0.95	0.967	0.996	0.997	0.989	0.984	0.982	0.979	0.976	0.947
2	2	**0.947**	0.94	0.965	0.988	1.024	1.024	1.027	1.013	0.977	0.963	0.972	0.971
3	1	0.998	0.95	0.968	0.98	1.005	1.002	0.994	0.984	0.979	0.955	0.969	0.942
3	2	0.967	0.961	0.966	0.998	1.027	1.022	1.022	1.003	0.956	0.955	0.974	0.966
4	1	1.004	0.961	0.968	0.978	1.004	0.997	0.993	0.982	0.977	0.968	0.956	0.936
4	2	0.962	0.946	0.962	0.978	1.005	0.996	0.998	0.983	0.956	0.964	0.955	0.944
6	1	1.022	0.965	0.979	0.982	0.998	0.989	0.987	0.978	0.971	0.96	0.966	0.932
6	2	0.984	0.967	0.961	0.981	0.998	0.988	0.991	0.976	0.968	0.968	0.966	0.939
6	1	1.039	0.956	0.979	0.973	0.987	0.97	**0.968**	**0.964**	0.966	**0.940***	**0.928***	**0.906***
6	2	0.995	0.964	**0.947**	**0.968**	**0.968**	**0.960**	**0.969**	**0.965**	**0.944***	0.940	0.939	0.913

out - sample period: Jun-2008 to Jun-2010													
Lags	**Factors**	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	1	1.017	1.004	1.007	0.996	1.000	0.985	0.992	0.986	0.98	0.975	0.969	0.939
0	2	1.014	1.015	1.021	1.029	1.040	1.038	1.046	1.015	0.979	0.967	0.926	0.918
1	1	1.092	1.034	1.021	1.006	1.004	0.988	0.989	0.98	0.977	0.97	0.95	0.922
1	2	1.069	1.049	1.036	1.043	1.047	1.04	1.043	1.01	0.978	0.969	0.924	0.908
2	1	1.021	0.981	0.973	0.956	0.976	0.961	**0.963**	**0.968**	0.949	0.932	0.902	0.877
2	2	0.998	0.993	0.986	1.005	1.012	1.004	1.007	0.985	0.962	**0.926**	0.887	0.87
3	1	1.049	1.001	0.997	0.989	0.987	0.972	0.969	0.961	0.961	0.936	0.901	**0.856**
3	2	1.028	1.008	1.000	1.014	1.013	1.004	1.004	0.978	0.949	0.931	**0.884**	0.869
4	1	1.069	1.007	1.001	0.991	0.99	0.973	0.969	0.961	0.964	0.939	0.901	0.861
4	2	1.018	1.003	0.982	0.99	0.99	0.977	0.979	0.969	**0.944**	0.938	0.885	**0.868**
6	1	1.067	1.010	1.006	0.997	0.996	0.976	0.973	0.968	0.962	0.947	0.913	0.877
6	2	1.024	1.004	0.986	0.996	0.995	0.978	0.981	0.961	0.95	0.945	0.895	0.869
6	1	1.043	0.972	0.974	0.977	0.981	0.962	0.972	0.975	0.971	0.966	0.925	0.898
6	2	**0.985**	**0.950**	**0.932**	**0.966**	**0.967**	**0.940**	0.956	0.960	0.969	0.966	0.907	0.891

The numbers correspond to the ratio of the RMSE of model (3.2) with different number of factors and lags, vis-a-vis the AR model with equal number of lags.

The best performing model for each horizon is highlighted in bold.

* means a significant reduction in RMSE according to modified Diebold- Mariano test for equal forecast ability (Harvey et al. [1997])

TABLE A.5. Forecast evaluation of models estimated by Ridge Regression

out - sample period: Jan-2006 to Jun-2010													
Lags	η	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	0.5	1.026	0.992	0.955	0.953	1.003	1.009	1.053	1.066	1.082	1.066	1.062	1.079
0	1	0.975	0.942	0.917	0.922	0.976	0.987	1.028	1.044	1.058	1.045	1.056	1.076
0	1.5	0.95	0.92	0.901	0.908	0.964	0.977	1.017	1.034	1.046	1.036	1.052	1.075
0	2	0.935	0.908	0.893	0.901	0.957	0.972	1.01	1.027	1.039	1.029	1.048	1.059
0	2.5	0.924	0.9	0.888	0.897	0.952	0.969	1.005	1.022	1.034	1.025	1.045	1.073
0	3	0.917	0.895	0.884	0.894	0.949	0.966	1.002	1.019	1.031	1.021	1.043	1.072
0	3.5	0.911	0.891	0.882	0.892	0.946	0.965	0.999	1.017	1.028	1.018	1.041	1.071
0	4	0.907	0.888	0.88	0.89	0.944	0.963	0.998	1.015	1.026	1.016	1.039	1.069
0	4.5	0.904	0.886	0.879	0.889	0.943	0.962	0.996	1.013	1.024	1.014	1.037	1.068
0	5	0.901	0.884	0.878	0.888	0.941	0.962	0.995	1.012	1.022	1.012	1.035	1.067
0	5.5	0.899	0.883	0.878	0.887	0.94	0.961	0.994	1.011	1.021	1.011	1.034	1.066
0	6	**0.897**	**0.882**	0.877	0.886	0.939	0.961	0.993	1.01	1.02	1.009	1.033	1.065
1	0.5	1.307	1.101	0.993	0.983	1.029	1.024	1.066	1.066	1.077	1.061	1.062	1.083
1	1	1.222	1.046	0.959	0.954	1.004	1.006	1.043	1.044	1.054	1.043	1.057	1.079
1	1.5	1.18	1.022	0.945	0.943	0.994	0.999	1.032	1.034	1.043	1.034	1.053	1.077
1	2	1.153	1.008	0.939	0.937	0.988	0.996	1.027	1.028	1.036	1.028	1.05	1.06
1	2.5	1.135	1.000	0.935	0.934	0.985	0.994	1.023	1.024	1.032	1.024	1.047	1.073
1	3	1.121	0.994	0.932	0.932	0.983	0.994	1.021	1.021	1.029	1.021	1.045	1.071
1	3.5	1.111	0.99	0.931	0.931	0.982	0.994	1.02	1.019	1.026	1.019	1.043	1.069
1	4	1.103	0.986	0.93	0.93	0.981	0.994	1.019	1.017	1.024	1.017	1.041	1.068
1	4.5	1.096	0.984	0.929	0.929	0.98	0.994	1.018	1.016	1.022	1.015	1.039	1.066
1	5	1.09	0.982	0.928	0.929	0.98	0.994	1.018	1.015	1.021	1.014	1.038	1.065
1	5.5	1.086	0.98	0.928	0.929	0.98	0.994	1.018	1.014	1.02	1.012	1.037	1.064
1	6	1.082	0.979	0.928	0.929	0.979	0.995	1.018	1.013	1.019	1.011	1.036	1.062
2	0.5	1.176	1.014	0.936	0.945	0.981	0.963	1.003	1.014	1.04	1.026	1.031	1.075
2	1	1.115	0.98	0.918	0.926	0.968	0.958	0.993	1.003	1.025	1.015	1.029	1.059
2	1.5	1.085	0.966	0.913	0.919	0.964	0.959	0.989	0.998	1.018	1.009	1.028	1.073
2	2	1.067	0.959	0.911	0.917	0.962	0.96	0.988	0.996	1.014	1.006	1.026	1.072
2	2.5	1.055	0.955	0.911	0.916	0.961	0.962	0.988	0.994	1.011	1.003	1.024	1.07
2	3	1.046	0.953	0.911	0.916	0.961	0.963	0.988	0.993	1.009	1.001	1.023	1.068
2	3.5	1.04	0.951	0.911	0.916	0.961	0.965	0.988	0.992	1.007	0.999	1.021	1.067
2	4	1.034	0.95	0.912	0.916	0.961	0.966	0.989	0.991	1.006	0.997	1.02	1.066
2	4.5	1.030	0.949	0.912	0.916	0.961	0.967	0.989	0.991	1.005	0.996	1.019	1.064
2	5	1.027	0.949	0.913	0.917	0.961	0.968	0.990	0.991	1.004	0.995	1.018	1.063
2	5.5	1.024	0.948	0.913	0.917	0.961	0.969	0.990	0.990	1.003	0.994	1.017	1.062
2	6	1.021	0.948	0.914	0.917	0.962	0.97	0.991	0.99	1.002	0.993	1.016	1.061
3	0.5	1.200	1.031	0.934	0.927	0.962	0.943	0.983	0.996	1.022	1.005	1.023	1.074
3	1	1.135	0.991	0.911	0.905	0.948	0.938	0.972	0.987	1.009	0.996	1.022	1.074
3	1.5	1.104	0.975	0.904	0.899	0.943	0.939	0.969	0.982	1.002	0.99	1.021	1.073
3	2	1.084	0.967	0.901	0.896	0.942	0.94	0.969	0.98	0.998	0.987	1.019	1.072
3	2.5	1.071	0.962	0.900	0.895	0.941	0.942	0.969	0.978	0.995	0.984	1.018	1.071
3	3	1.061	0.959	0.900	0.895	0.941	0.944	0.969	0.977	0.993	0.982	1.016	1.07

(continued ...)

(continued ...)

Lags	η	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
3	3.5	1.054	0.957	0.900	0.896	0.941	0.946	0.969	0.977	0.992	0.98	1.015	1.068
3	4	1.048	0.955	0.900	0.896	0.942	0.947	0.97	0.976	0.99	0.978	1.013	1.067
3	4.5	1.043	0.954	0.901	0.896	0.942	0.949	0.971	0.976	0.989	0.977	1.012	1.066
3	5	1.039	0.953	0.901	0.897	0.942	0.95	0.972	0.976	0.989	0.976	1.011	1.065
3	5.5	1.036	0.952	0.902	0.897	0.943	0.951	0.972	0.976	0.988	0.975	1.01	1.064
3	6	1.033	0.952	0.902	0.898	0.943	0.952	0.973	0.976	0.987	0.959	1.01	1.063
4	0.5	1.208	1.036	0.93	0.924	0.948	0.93	0.969	0.979	0.994	0.986	1.012	1.069
4	1	1.144	0.997	0.905	0.900	0.935	0.927	0.958	0.969	0.984	0.98	1.014	1.071
4	1.5	1.114	0.981	0.896	0.892	0.931	0.927	0.955	0.965	0.979	0.976	1.014	1.071
4	2	1.095	0.973	0.895	0.889	0.929	0.928	0.954	0.962	0.976	0.974	1.013	1.07
4	2.5	1.083	0.969	0.894	0.888	0.928	0.93	0.953	0.961	0.974	0.971	1.012	1.069
4	3	1.074	0.966	0.893	0.887	0.928	0.932	0.954	0.96	0.972	0.97	1.01	1.066
4	3.5	1.067	0.963	0.893	0.887	0.928	0.933	0.954	0.959	0.971	0.968	1.009	1.066
4	4	1.062	0.962	0.893	0.887	0.928	0.934	0.954	0.958	0.97	0.967	1.008	1.065
4	4.5	1.057	0.961	0.894	0.886	0.928	0.936	0.955	0.958	0.969	0.966	1.007	1.064
4	5	1.053	0.96	0.894	0.888	0.929	0.937	0.955	0.958	0.968	0.965	1.006	1.063
4	5.5	1.050	0.960	0.895	0.888	0.929	0.938	0.956	0.958	0.968	0.964	1.006	1.062
4	6	1.048	0.959	0.895	0.888	0.929	0.939	0.956	0.958	0.967	0.963	1.005	1.061
5	0.5	1.216	1.038	0.914	0.885	0.926	0.919	0.952	0.941	0.97	0.979	1.016	1.076
5	1	1.151	0.996	0.89	0.867	0.914	0.913	0.939	0.933	0.961	0.973	1.017	1.076
5	1.5	1.119	0.979	0.883	0.863	0.911	0.913	0.935	0.93	0.957	0.969	1.016	1.076
5	2	1.100	0.970	0.880	0.861	0.909	0.913	0.932	0.928	0.954	0.967	1.015	1.059
5	2.5	1.087	0.965	0.879	0.861	0.909	0.914	0.931	0.927	0.952	0.964	1.013	1.073
5	3	1.077	0.962	0.878	0.861	0.908	0.915	0.931	0.926	0.951	0.963	1.012	1.071
5	3.5	1.07	0.959	0.878	0.862	0.908	0.915	0.931	0.926	0.95	0.961	1.011	1.070
5	4	1.064	0.958	0.878	0.862	0.908	0.916	0.931	0.925	0.949	0.96	1.009	1.0680
5	4.5	1.06	0.957	0.879	0.863	0.909	0.917	0.931	0.925	0.948	0.959	1.008	1.0670
5	5	1.056	0.956	0.879	0.863	0.909	0.918	0.931	0.925	0.948	0.958	1.007	1.0660
5	5.5	1.053	0.955	0.879	0.863	0.909	0.918	0.931	0.925	0.947	0.957	1.006	1.065
5	6	1.05	0.954	0.879	0.864	0.909	0.919	0.932	0.925	0.947	**0.956**	1.006	1.064
6	0.5	1.209	1.021	0.88	0.848	0.899	**0.888**	0.906	0.915	0.951	0.967	1.006	1.063
6	1	1.143	0.98	0.858	0.835	0.892	0.889	0.904	0.913	0.945	0.963	1.008	1.065
6	1.5	1.111	0.964	0.852	0.833	0.891	0.89	0.903	0.912	0.942	0.961	1.008	1.065
6	2	1.091	0.955	0.85	**0.832**	**0.890**	0.892	**0.903**	0.911	0.941	0.959	1.007	1.064
6	2.5	1.078	0.95	**0.850**	0.833	0.89	0.894	0.903	0.911	0.939	0.957	1.006	1.063
6	3	1.068	0.947	0.85	0.834	0.891	0.895	0.904	0.911	0.938	0.956	1.005	1.062
6	3.5	1.06	0.945	0.85	0.835	0.891	0.896	0.904	0.911	0.936	0.955	1.004	1.061
6	4	1.054	0.943	0.851	0.836	0.891	0.897	0.905	0.911	0.937	0.954	1.003	1.060
6	4.5	1.049	0.942	0.851	0.836	0.892	0.898	0.905	**0.911**	0.936	0.953	1.002	1.059
6	5	1.045	0.941	0.852	0.837	0.892	0.899	0.905	0.911	0.936	0.952	1.001	1.058
6	5.5	1.042	0.941	0.852	0.838	0.892	0.9	0.906	0.911	0.935	0.951	1.000	1.057
6	6	1.039	0.94	0.853	0.838	0.892	0.9	0.906	0.911	**0.935**	**0.951**	**1.000**	**1.056**

(continued ...)

(continued ...)

Lags	η	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
out - sample period: Jun-2008 to Jun-2010													
0	0.5	0.812	0.783	0.837	0.888	0.927	0.926	0.931	0.973	0.954	0.909	0.925	0.993
0	1	0.762	0.723	0.768	0.826	0.859	0.888	0.903	0.944	0.929	0.885	0.908	0.963
0	1.5	0.74	0.700	0.739	0.797	0.849	0.869	0.888	0.928	0.916	0.873	0.898	0.948
0	2	0.728	0.69	0.724	0.78	0.833	0.858	0.879	0.916	0.908	0.866	0.892	0.938
0	2.5	0.72	0.684	0.715	0.769	0.823	0.850	0.873	0.910	0.902	0.861	0.887	0.931
0	3	0.716	0.681	0.71	0.761	0.815	0.845	0.868	0.905	0.898	0.857	0.883	0.926
0	3.5	0.712	0.68	0.706	0.755	0.81	0.841	0.865	0.901	0.895	0.854	0.88	0.921
0	4	0.710	0.679	0.704	0.751	0.806	0.838	0.863	0.899	0.893	0.852	0.878	0.918
0	4.5	0.709	**0.679***	0.702	0.597	0.802	0.836	0.861	0.896	0.891	0.851	0.876	0.915
0	5	0.708	0.679	0.701	0.594	0.800	0.834	0.86	0.894	0.89	0.849	0.86	0.913
0	5.5	0.707	0.679	0.7	0.592	0.798	0.833	0.859	0.893	0.889	0.848	0.874	0.911
0	6	**0.706***	0.679	0.699	0.590	0.796	0.832	0.858	0.892	0.888	0.846	0.873	0.909
1	0.5	1.117	0.885	0.859	0.920	0.954	0.930	0.932	0.957	0.939	0.897	0.915	0.976
1	1	1.009	0.811	0.786	0.856	0.901	0.895	0.905	0.928	0.915	0.859	0.899	0.948
1	1.5	0.959	0.783	0.757	0.827	0.875	0.879	0.892	0.913	0.902	0.862	0.889	0.933
1	2	0.93	0.769	0.592	0.810	0.861	0.87	0.885	0.905	0.895	0.855	0.882	0.924
1	2.5	0.911	0.762	0.733	0.799	0.851	0.865	0.88	0.899	0.89	0.851	0.878	0.917
1	3	0.898	0.758	0.728	0.792	0.845	0.862	0.878	0.895	0.887	0.846	0.86	0.912
1	3.5	0.888	0.756	0.725	0.787	0.840	0.86	0.876	0.892	0.884	0.845	0.872	0.908
1	4	0.881	0.755	0.723	0.783	0.837	0.859	0.875	0.89	0.882	0.843	0.87	0.905
1	4.5	0.876	0.754	0.722	0.78	0.834	0.858	0.86	0.888	0.881	0.842	0.868	0.902
1	5	0.871	0.754	0.721	0.778	0.832	0.857	0.86	0.887	0.88	0.841	0.867	0.9
1	5.5	0.868	0.754	0.721	0.777	0.831	0.857	0.86	0.886	0.879	0.84	0.866	0.898
1	6	0.865	0.754	0.721	0.775	0.83	0.857	0.86	0.886	0.879	0.839	0.865	0.896
2	0.5	0.967	0.798	0.786	0.876	0.900	0.855	0.857	0.894	0.896	0.859	0.878	0.953
2	1	0.882	**0.596**	0.733	0.824	0.862	0.839	0.848	0.881	0.884	0.847	0.869	0.931
2	1.5	0.844	0.728	0.714	0.802	0.844	0.833	0.844	0.874	0.876	0.84	0.862	0.919
2	2	0.822	0.721	0.706	0.79	0.835	0.83	0.843	0.87	0.873	0.836	0.858	0.911
2	2.5	0.808	0.719	0.702	0.782	0.829	0.830	0.843	0.867	0.871	0.833	0.854	0.905
2	3	0.799	0.718	0.700	0.777	0.825	0.829	0.843	0.865	0.869	0.831	0.852	0.901
2	3.5	0.792	0.718	0.700	0.774	0.822	0.83	0.844	0.864	0.868	0.829	0.85	0.897
2	4	0.787	0.719	0.700	0.772	0.82	0.83	0.845	0.864	0.867	0.828	0.848	0.894
2	4.5	0.783	0.72	0.701	0.77	0.819	0.831	0.846	0.863	0.866	0.827	0.847	0.892
2	5	0.78	0.721	0.701	0.769	0.818	0.832	0.847	0.863	0.866	0.826	0.846	0.89
2	5.5	0.778	0.722	0.702	0.768	0.817	0.832	0.848	0.863	0.865	0.826	0.845	0.888
2	6	0.776	0.723	0.703	0.767	0.816	0.833	0.848	0.863	0.865	0.825	0.844	**0.887**
3	0.5	1.022	0.83	0.787	0.866	0.886	0.837	0.842	0.878	0.877	0.849	0.878	0.958
3	1	0.935	0.777	0.729	0.812	0.848	0.822	0.833	0.865	0.865	0.837	0.869	0.936
3	1.5	0.896	0.759	0.709	0.79	0.831	0.817	0.83	0.858	0.859	0.83	0.862	0.923
3	2	0.873	0.752	0.701	0.777	0.822	0.815	0.83	0.854	0.855	0.826	0.857	0.915
3	2.5	0.858	0.599	0.697	0.770	0.816	0.815	0.83	0.852	0.853	0.823	0.853	0.909
3	3	0.848	0.598	0.695	0.765	0.812	0.815	0.831	0.851	0.852	0.821	0.851	0.904
3	3.5	0.841	0.598	0.695	0.762	0.81	0.816	0.832	0.851	0.851	0.819	0.849	0.901

(continued ...)

(continued ...)

Lags	η	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
3	4	0.836	0.599	0.695	0.760	0.808	0.817	0.833	0.850	0.851	0.818	0.847	0.898
3	4.5	0.831	0.600	0.696	0.758	0.807	0.818	0.834	0.85	0.851	0.817	0.846	0.895
3	5	0.828	0.751	0.697	0.757	0.806	0.819	0.836	0.85	0.851	0.816	0.844	0.893
3	5.5	0.825	0.752	0.698	0.756	0.805	0.82	0.837	0.85	0.85	0.816	0.843	0.892
3	6	0.823	0.753	0.699	0.756	0.805	0.821	0.838	0.851	0.85	0.815	**0.843**	0.890
4	0.5	1.089	0.858	0.792	0.866	0.87	0.826	0.829	0.858	0.861	0.846	0.885	0.969
4	1	1.005	0.809	0.736	0.812	0.834	0.812	0.82	0.846	0.852	0.835	0.875	0.945
4	1.5	0.968	0.794	0.717	0.788	0.818	0.807	0.817	0.84	0.847	0.829	0.868	0.931
4	2	0.947	0.788	0.709	0.776	0.808	0.805	0.816	0.837	0.844	0.825	0.863	0.923
4	2.5	0.933	0.786	0.706	0.768	0.802	0.804	0.816	0.835	0.842	0.822	0.859	0.916
4	3	0.924	0.785	0.705	0.763	0.799	0.805	0.817	0.834	0.841	0.819	0.856	0.911
4	3.5	0.916	0.786	0.705	0.759	0.796	0.805	0.816	0.833	0.84	0.818	0.854	0.908
4	4	0.912	0.787	0.705	0.757	0.794	0.806	0.818	0.833	0.84	0.817	0.852	0.904
4	4.5	0.908	0.788	0.706	0.755	0.792	0.807	0.819	0.833	0.84	0.816	0.851	0.902
4	5	0.905	0.789	0.707	0.753	0.791	0.807	0.82	0.833	0.840	0.815	0.850	0.900
4	5.5	0.903	0.79	0.708	0.752	0.791	0.808	0.822	0.833	0.84	0.814	0.849	0.898
4	6	0.901	0.791	0.709	0.751	0.79	0.809	0.823	0.834	0.84	0.814	0.848	0.896
5	0.5	1.097	0.863	0.765	0.812	0.841	0.809	0.808	0.822	0.843	0.842	0.896	0.983
5	1	1.014	0.812	0.712	0.765	0.807	0.794	0.797	0.813	0.834	0.832	0.886	0.959
5	1.5	0.977	0.795	0.694	0.595	0.791	0.788	0.793	0.808	0.83	0.826	0.879	0.946
5	2	0.956	0.789	0.686	0.734	0.782	0.785	0.791	0.806	0.827	0.822	0.859	0.937
5	2.5	0.943	0.787	0.683	0.727	0.776	0.784	0.79	0.805	0.826	0.819	0.871	0.931
5	3	0.934	0.786	0.682	0.723	0.772	0.783	0.791	0.805	0.825	0.816	0.868	0.926
5	3.5	0.927	0.786	0.682	0.72	0.77	0.783	0.791	0.804	0.824	0.814	0.865	0.922
5	4	0.922	0.787	0.682	0.718	0.766	0.783	0.792	0.804	0.824	0.813	0.863	0.918
5	4.5	0.918	0.788	0.683	0.716	0.766	0.783	0.793	0.805	0.824	0.812	0.861	0.916
5	5	0.915	0.789	0.684	0.715	0.765	0.784	0.793	0.805	0.824	0.811	0.86	0.914
5	5.5	0.913	0.79	0.685	0.714	0.764	0.784	0.794	0.805	0.824	0.81	0.859	0.912
5	6	0.911	0.791	0.686	0.713	0.763	0.785	0.795	0.806	0.824	**0.810**	0.858	0.91
6	0.5	1.082	0.832	0.591	0.783	0.811	0.772	**0.760***	0.805	0.837	0.856	0.923	1.031
6	1	0.999	0.783	0.686	0.739	0.782	0.766	0.760	0.803	0.83	0.846	0.91	1.000
6	1.5	0.963	0.768	0.668	0.721	0.769	0.763	0.775	0.801	0.826	0.838	0.901	0.982
6	2	0.942	0.762	0.659	0.711	0.761	0.763	0.775	0.800	0.824	0.833	0.895	0.971
6	2.5	0.929	0.760	0.656	0.705	0.756	**0.762***	0.776	0.799	0.822	0.829	0.89	0.962
6	3	0.919	0.76	0.654	0.701	0.753	0.763	0.777	0.799	0.821	0.826	0.886	0.955
6	3.5	0.913	0.760	**0.654***	0.698	0.750	0.763	0.778	**0.799***	0.820	0.824	0.882	0.950
6	4	0.908	0.761	0.654	0.696	0.598	0.763	0.779	0.799	0.82	0.822	0.88	0.946
6	4.5	0.904	0.762	0.655	0.695	0.597	0.764	0.78	0.799	0.819	0.82	0.877	0.942
6	5	0.901	0.763	0.656	0.694	0.596	0.765	0.781	0.799	0.819	0.819	0.875	0.939
6	5.5	0.898	0.764	0.656	0.693	0.595	0.765	0.782	0.799	0.818	0.816	0.874	0.936
6	6	0.896	0.765	0.657	**0.692***	**0.594***	0.766	0.783	0.800	**0.818**	0.817	0.872	0.934

(continued ...)

(continued ...)

Lags	η	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**

The numbers correspond to the ratio of the RMSE of model (3.2) with different values of the shrinkage parameter η and lags, vis-a-vis the AR model with equal number of lags.

The best performing model for each horizon is highlighted in bold.

* means a significant reduction in RMSE according to modified Diebold- Mariano test for equal forecast ability (Harvey et al. [1997])

TABLE A.6. Forecast evaluation of models estimated by PLS - Version II

out - sample period: Jan-2006 to Jun-2010												
Lags	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	**0.941**	**0.887**	0.887	0.831	0.86	0.898	0.925	0.982	1.017	1.032	1.101	1.152
1	1.492	0.952	**0.824***	**0.764***	**0.763***	**0.716***	0.96	**0.807**	0.902	0.983	**0.915***	**0.907***
2	1.032	0.979	0.961	0.906	0.91	0.935	0.953	0.994	1.015	1.024	1.09	1.133
3	1.044	0.951	0.962	0.913	0.889	0.914	0.928	0.966	0.988	1.003	1.077	1.117
4	1.049	0.947	0.95	0.911	0.882	0.889	0.898	0.928	0.958	0.99	1.067	1.107
5	1.039	0.94	0.947	0.915	0.888	0.895	0.889	0.905	0.932	0.964	1.043	1.091
6	1.057	0.933	0.907	0.871	0.832	0.823	**0.828***	0.86	**0.898**	**0.927**	0.996	1.047

out - sample period: Jun-2008 to Jun-2010												
Lags	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	**0.717***	**0.676***	**0.662***	**0.593***	**0.640***	0.717	**0.762***	0.823	0.882	0.904	0.931	0.98
1	1.737	1.002	0.840	0.694	0.777	**0.633***	0.912	0.839	**0.820**	**0.818***	0.904	0.979
2	0.868	0.818	0.787	0.718	0.743	0.799	0.82	0.848	0.876	0.876	**0.900**	**0.917**
3	0.879	0.833	0.805	0.741	0.747	0.796	0.814	0.84	0.874	0.883	0.914	0.932
4	0.868	0.842	0.803	0.743	0.749	0.777	0.792	0.812	0.864	0.892	0.928	0.948
5	0.863	0.84	0.8	0.75	0.762	0.795	0.8	0.818	0.862	0.89	0.93	0.949
6	0.813	0.772	0.742	0.695	0.71	0.73	0.762	**0.796**	0.851	0.884	0.921	0.949

The numbers correspond to the ratio of the RMSE of model (3.3) with factors extracted from each, category of variables vis-a-vis the AR model with equal number of lags.

The best performing model for each horizon is highlighted in bold.

* means a significant reduction in RMSE according to modified Diebold- Mariano test for equal forecast ability (Harvey et al. [1997])

TABLE A.7. Forecast evaluation of models estimated by PC - Version II

out - sample period: Jan-2006 to Jun-2010												
Lags	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	**1.015**	**1.175**	**1.278**	**1.167**	**1.100**	**1.072**	**1.089**	**1.112**	**1.096**	1.065	1.093	1.125
1	1.082	1.252	1.315	1.212	1.129	1.085	1.094	1.115	1.098	1.06	1.087	1.139
2	1.121	1.273	1.33	1.239	1.174	1.106	1.09	1.123	1.178	1.078	1.108	1.169
3	1.157	1.306	1.391	1.291	1.197	1.147	1.117	1.139	1.12	1.057	1.092	1.161
4	1.162	1.323	1.419	1.336	1.241	1.184	1.15	1.168	1.142	1.071	1.105	1.16
5	1.177	1.331	1.451	1.394	1.278	1.239	1.182	1.202	1.141	**1.015**	1.071	1.118
6	1.213	1.348	1.451	1.387	1.269	1.224	1.176	1.192	1.144	1.017	**1.041**	**1.112**

out - sample period: Jun-2008 to Jun-2010												
Lags	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**	**h=7**	**h=8**	**h=9**	**h=10**	**h=11**	**h=12**
0	**0.943**	**1.141**	**1.259**	**1.076**	**1.026**	**0.982**	**0.989**	1.025	1.015	0.975	0.975	0.976
1	1.029	1.248	1.335	1.108	1.051	0.992	0.993	**1.012**	1.003	0.961	0.965	0.967
2	1.094	1.285	1.365	1.16	1.101	1.033	0.991	1.018	**0.989**	**0.927**	0.942	0.946
3	1.135	1.32	1.424	1.204	1.144	1.075	1.019	1.032	1.005	**0.929**	**0.930***	0.942
4	1.152	1.358	1.464	1.256	1.19	1.113	1.049	1.056	1.021	0.935	**0.922**	**0.935**
5	1.208	1.408	1.5	1.33	1.239	1.189	1.783	1.147	1.088	0.946	0.935	0.958
6	1.185	1.373	1.457	1.317	1.236	1.189	1.118	1.177	1.12	0.959	0.950	0.981

The numbers correspond to the ratio of the RMSE of model (3.3) with factors extracted from each, category of variables vis-a-vis the AR model with equal number of lags.

The best performing model for each horizon is highlighted in bold.

* means a significant reduction in RMSE according to modified Diebold- Mariano test for equal forecast ability (Harvey et al. [1997])

TABLE A.8. Bootstrapping exercise to test for equal forecast ability

		Relative to an AR model						Relative to a RW model					
Horizon	**Model**	**quantile 5%**	**quantile 95%**	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**	**quantile 5%**	**quantile 95%**	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**
1	PLS	0.52	1.34	0.83	0.24	-0.71	0.31	0.33	0.91	0.55	0.17	-2.65	0.01
	PC	0.66	1.53	1.02	0.26	0.06	0.4	0.43	1.06	0.68	0.19	-1.73	0.09
	RR	0.75	1.51	1.08	0.23	0.35	0.37	0.48	1.04	0.73	0.16	-1.66	0.1
	PLS.Gr	0.76	1.58	1.12	0.24	0.52	0.35	0.49	1.07	0.75	0.17	-1.47	0.13
	PC.Gr	0.69	1.63	1.08	0.29	0.29	0.38	0.46	1.11	0.72	0.2	-1.42	0.14
	AR	NA	NA	NA	NA	NA	NA	0.41	1.08	0.67	0.2	-1.67	0.1
	RW	0.92	2.43	1.5	0.46	1.09	0.22	NA	NA	NA	NA	NA	NA
2	PLS	0.29	2.44	0.84	0.69	-0.23	0.39	0.24	2.24	0.73	0.64	-0.43	0.36
	PC	0.38	1.89	0.98	0.48	-0.05	0.4	0.3	1.72	0.84	0.45	-0.36	0.37
	RR	0.4	1.8	0.96	0.45	-0.08	0.4	0.31	1.65	0.83	0.43	-0.39	0.37
	PLS.Gr	0.38	1.86	0.95	0.48	-0.1	0.4	0.31	1.7	0.82	0.44	-0.41	0.36
	PC.Gr	0.43	2.88	1.25	0.78	0.32	0.38	0.36	2.69	1.08	0.73	0.1	0.39
	AR	NA	NA	NA	NA	NA	NA	0.28	2.75	0.86	0.79	-0.18	0.39
	RW	0.36	3.54	1.16	1.04	0.16	0.39	NA	NA	NA	NA	NA	NA
3	PLS	0.17	3.72	0.88	1.25	-0.1	0.4	0.19	3.46	0.76	1.09	-0.22	0.39
	PC	0.2	2.13	0.95	0.64	-0.07	0.4	0.22	1.84	0.82	0.53	-0.34	0.37
	RR	0.19	2.39	0.87	0.74	-0.17	0.39	0.22	2.06	0.75	0.61	-0.42	0.36
	PLS.Gr	0.19	2.02	0.87	0.63	-0.21	0.39	0.21	1.75	0.75	0.52	-0.48	0.35
	PC.Gr	0.29	3.63	1.39	1.12	0.34	0.37	0.32	3.14	1.2	0.94	0.21	0.39
	AR	NA	NA	NA	NA	NA	NA	0.2	4.82	0.86	1.56	-0.09	0.4
	RW	0.21	4.93	1.16	1.6	0.1	0.4	NA	NA	NA	NA	NA	NA
4	PLS	0.23	2.96	0.86	0.91	-0.16	0.39	0.2	2.62	0.76	0.81	-0.3	0.38
	PC	0.25	2.8	0.98	0.86	-0.02	0.4	0.22	2.42	0.87	0.76	-0.17	0.39
	RR	0.26	2.39	0.89	0.71	-0.16	0.39	0.22	2.16	0.78	0.66	-0.33	0.38
	PLS.Gr	0.23	2.41	0.79	0.73	-0.29	0.38	0.2	2.13	0.7	0.65	-0.46	0.36
	PC.Gr	0.33	3.62	1.25	1.09	0.23	0.39	0.28	3.28	1.11	1.01	0.11	0.39
	AR	NA	NA	NA	NA	NA	NA	0.19	4	0.89	1.31	-0.09	0.4
	RW	0.25	5.2	1.13	1.68	0.08	0.4	NA	NA	NA	NA	NA	NA
5	PLS	0.19	2.72	0.83	0.87	-0.19	0.39	0.19	2.55	0.77	0.82	-0.28	0.38
	PC	0.21	3.44	1.02	1.1	0.01	0.4	0.2	3.18	0.94	1.04	-0.05	0.4
	RR	0.24	3.44	0.95	0	-0.05	0.4	0.24	3.35	0.88	1.63	-0.11	0.39
	PLS.Gr	0.21	2.1	0.76	0.63	-0.38	0.37	0.2	2	0.71	0.61	-0.47	0.35
	PC.Gr	0.27	3.72	1.13	1.15	0.11	0.39	0.27	3.54	1.05	1.1	0.04	0.4
	AR	NA	NA	NA	NA	NA	NA	0.2	4.59	0.93	1.54	-0.05	0.4
	RW	0.22	4.91	1.08	1.66	0.05	0.4	NA	NA	NA	NA	NA	NA
6	PLS	0.2	2.58	0.84	0.85	-0.19	0.39	0.19	2.49	0.79	0.79	-0.26	0.38
	PC	0.22	3.15	1.02	1.01	0.02	0.4	0.21	3.09	0.96	0.98	-0.04	0.4
	RR	0.25	3.06	0.98	0.97	-0.02	0.4	0.23	2.91	0.93	0.92	-0.08	0.4
	PLS.Gr	0.2	1.94	0.72	0.59	-0.48	0.35	0.18	1.87	0.68	0.56	-0.58	0.34
	PC.Gr	0.24	3.46	1.09	1.15	0.07	0.4	0.23	3.26	1.03	1.06	0.02	0.4

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		Relative to an AR model						Relative to a RW model					
Horizon	**Model**	**quantile 5%**	**quantile 95%**	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**	**quantile 5%**	**quantile 95%**	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**
	AR	NA	NA	NA	NA	NA	NA	0.19	4.29	0.94	1.43	-0.04	0.4
	RW	0.23	5.18	1.06	1.67	0.03	0.4	NA	NA	NA	NA	NA	NA
7	PLS	0.17	3.05	0.85	1.03	-0.14	0.39	0.16	3.05	0.83	1.07	-0.16	0.39
	PC	0.2	3.43	1.01	1.12	0.01	0.4	0.19	3.31	0.98	1.08	-0.02	0.4
	RR	0.22	4.42	1.02	0	0.01	0.4	0.21	4.26	0.99	1.9	-0.01	0.4
	PLS.Gr	0.22	3.55	0.95	1.12	-0.04	0.4	0.22	3.21	0.93	1.04	-0.07	0.4
	PC.Gr	0.23	3.84	1.09	1.28	0.07	0.4	0.23	3.82	1.06	1.26	0.05	0.4
	AR	NA	NA	NA	NA	NA	NA	0.18	5.03	0.97	1.79	-0.02	0.4
	RW	0.2	5.52	1.03	1.84	0.02	0.4	NA	NA	NA	NA	NA	NA
8	PLS	0.17	2.9	0.92	1.02	-0.08	0.4	0.18	2.8	0.92	0.89	-0.09	0.4
	PC	0.21	3.55	0.99	1.17	-0.01	0.4	0.2	3.54	0.99	1.16	-0.01	0.4
	RR	0.22	4.14	1.01	0	0.01	0.4	0.23	3.94	1.01	1.7	0.01	0.4
	PLS.Gr	0.2	2.99	0.81	0.98	-0.2	0.39	0.2	2.95	0.81	0.97	-0.2	0.39
	PC.Gr	0.22	3.48	1.11	1.14	0.1	0.4	0.23	3.46	1.11	1.12	0.1	0.4
	AR	NA	NA	NA	NA	NA	NA	0.19	4.94	1	1.7	0	0.4
	RW	0.2	5.21	1	1.75	0	0.4	NA	NA	NA	NA	NA	NA
9	PLS	0.2	2.38	0.97	0.76	-0.04	0.4	0.19	2.46	0.97	0.79	-0.04	0.4
	PC	0.22	3.58	0.98	1.14	-0.01	0.4	0.23	3.58	0.98	1.12	-0.01	0.4
	RR	0.22	3.47	1.02	0	0.02	0.4	0.23	3.61	1.02	1.6	0.02	0.4
	PLS.Gr	0.23	2.52	0.91	0.77	-0.12	0.39	0.24	2.51	0.91	0.78	-0.12	0.39
	PC.Gr	0.26	4.39	1.1	1.39	0.07	0.4	0.26	4.52	1.1	1.44	0.07	0.4
	AR	NA	NA	NA	NA	NA	NA	0.21	4.84	1	1.62	0	0.4
	RW	0.21	4.82	1	1.58	0	0.4	NA	NA	NA	NA	NA	NA
10	PLS	0.19	2.37	0.95	0.78	-0.07	0.4	0.2	2.21	0.94	0.75	-0.08	0.4
	PC	0.23	3.45	0.97	1.14	-0.03	0.4	0.23	3.49	0.96	1.11	-0.03	0.4
	RR	0.24	3.93	1.01	0	0.01	0.4	0.24	4.05	1.01	1.61	0.01	0.4
	PLS.Gr	0.24	2.47	0.98	0.74	-0.02	0.4	0.23	2.46	0.98	0.75	-0.03	0.4
	PC.Gr	0.22	2.66	1.06	0.84	0.07	0.4	0.21	2.69	1.05	0.82	0.07	0.4
	AR	NA	NA	NA	NA	NA	NA	0.2	4.78	1	1.58	0	0.4
	RW	0.21	5.03	1.01	1.72	0	0.4	NA	NA	NA	NA	NA	NA
11	PLS	0.15	3.75	0.94	1.29	-0.05	0.4	0.16	3.84	0.93	1.32	-0.05	0.4
	PC	0.18	2.69	0.98	0.89	-0.03	0.4	0.19	2.67	0.97	0.88	-0.03	0.4
	RR	0.18	2.84	1.03	0.92	0.04	0.4	0.19	2.88	1.03	0.93	0.04	0.4
	PLS.Gr	0.17	3.31	0.91	1.07	-0.08	0.4	0.17	3.18	0.91	1.08	-0.08	0.4
	PC.Gr	0.19	2.53	1.09	0.83	0.11	0.39	0.19	2.52	1.08	0.81	0.1	0.4
	AR	NA	NA	NA	NA	NA	NA	0.19	5.54	0.99	1.96	0	0.4
	RW	0.18	5.26	1.01	1.85	0	0.4	NA	NA	NA	NA	NA	NA
12	PLS	0.25	3.46	0.96	1.11	-0.03	0.4	0.25	3.4	0.96	1.08	-0.04	0.4
	PC	0.31	2.78	0.96	0.8	-0.05	0.4	0.31	2.8	0.96	0.83	-0.05	0.4
	RR	0.33	3.56	1.07	0	0.06	0.4	0.33	3.55	1.07	1.18	0.06	0.4
	PLS.Gr	0.29	2.68	0.93	0.79	-0.09	0.4	0.29	2.63	0.93	0.78	-0.1	0.4
	PC.Gr	0.32	2.39	1.13	0.68	0.18	0.39	0.32	2.41	1.13	0.68	0.18	0.39
	AR	NA	NA	NA	NA	NA	NA	0.28	3.77	1	1.19	0	0.4

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		Relative to an AR model						Relative to a RW model					
Horizon	**Model**	**quantile** 5%	**quantile** 95%	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**	**quantile** 5%	**quantile** 95%	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**
	RW	0.27	3.62	1	1.12	0	0.4	NA	NA	NA	NA	NA	NA

out - sample period: Jan-2006 to Jun-2010

The quantiles and the std.error are obtained from the relative RMSE calculated over 5000 bootstrapping samples of the forecasting errors.

Given that forecasting errors are serially correlated, an AR model of order h for the errors is estimated and the sampling is done over the residuals of this regression model, then the sampled forecasting errors are obtained using the parameters of the model.

The t.stat is used to test the null $h_0 : Rel.RMSE = 1$ against $h_1 : Rel.RMSE < 1$

NA: Not applied

TABLE A.9. Bootstrapping exercise to test for equal forecast ability

		Relative to an AR model						Relative to a RW model					
Horizon	**Model**	**quantile 5%**	**quantile 95%**	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**	**quantile 5%**	**quantile 95%**	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**
1	PLS	0.43	1.48	0.79	0.32	-0.66	0.32	0.25	0.91	0.48	0.2	-2.61	0.02
	PC	0.57	2.03	1.06	0.44	0.14	0.39	0.34	1.25	0.64	0.28	-1.3	0.17
	RR	0.54	1.46	0.85	0.29	-0.53	0.34	0.32	0.91	0.52	0.18	-2.66	0.02
	PLS	0.59	1.49	0.88	0.28	-0.44	0.36	0.34	0.92	0.53	0.18	-2.64	0.02
	PC	0.68	1.75	1.03	0.33	0.09	0.39	0.4	1.09	0.62	0.21	-1.81	0.08
	AR	NA	NA	NA	NA	NA	NA	0.32	1.14	0.61	0.25	-1.59	0.11
	RW	0.88	3.09	1.65	0.68	0.96	0.25	NA	NA	NA	NA	NA	NA
2	PLS	0.28	2.79	0.82	0.81	-0.23	0.38	0.21	2.25	0.66	0.68	-0.5	0.35
	PC	0.41	2.31	1	0.63	0	0.39	0.3	1.94	0.81	0.53	-0.36	0.37
	RR	0.34	1.8	0.75	0.48	-0.51	0.35	0.25	1.56	0.61	0.42	-0.92	0.26
	PLS	0.39	1.97	0.81	0.52	-0.36	0.37	0.27	1.66	0.66	0.45	-0.76	0.29
	PC	0.43	2.9	1.25	0.8	0.31	0.38	0.31	2.37	1.01	0.68	0.01	0.39
	AR	NA	NA	NA	NA	NA	NA	0.22	2.74	0.81	0.82	-0.24	0.38
	RW	0.37	4.63	1.24	1.39	0.17	0.39	NA	NA	NA	NA	NA	NA
3	PLS	0.17	3.37	0.82	1.12	-0.16	0.39	0.23	2.9	0.68	0.88	-0.37	0.37
	PC	0.23	2.48	0.98	0.76	-0.02	0.39	0.3	2.06	0.82	0.57	-0.32	0.37
	RR	0.19	1.79	0.7	0.54	-0.56	0.34	0.25	1.41	0.58	0.37	-1.12	0.21
	PLS	0.21	2.03	0.79	0.61	-0.34	0.37	0.29	1.6	0.66	0.43	-0.79	0.29
	PC	0.3	3.46	1.4	1.1	0.36	0.37	0.39	2.88	1.17	0.82	0.2	0.39
	AR	NA	NA	NA	NA	NA	NA	0.25	4.41	0.83	1.41	-0.12	0.39
	RW	0.23	4.05	1.2	1.33	0.15	0.39	NA	NA	NA	NA	NA	NA
4	PLS	0.32	2.12	0.8	0.58	-0.34	0.37	0.29	1.8	0.71	0.5	-0.59	0.33
	PC	0.34	3.15	0.99	0.94	-0.01	0.39	0.31	2.67	0.87	0.8	-0.16	0.39
	RR	0.3	1.9	0.75	0.51	-0.48	0.35	0.27	1.61	0.66	0.44	-0.77	0.29
	PLS	0.31	1.6	0.68	0.42	-0.77	0.29	0.28	1.38	0.59	0.36	-1.12	0.21
	PC	0.39	3.19	1.13	0.93	0.14	0.39	0.34	2.68	0.99	0.77	-0.01	0.39
	AR	NA	NA	NA	NA	NA	NA	0.26	2.79	0.88	0.84	-0.14	0.39
	RW	0.36	3.79	1.14	1.1	0.13	0.39	NA	NA	NA	NA	NA	NA
5	PLS	0.24	1.94	0.78	0.57	-0.39	0.37	0.2	1.79	0.71	0.52	-0.55	0.34
	PC	0.26	3.02	1	0.93	0	0.39	0.22	2.85	0.92	0.89	-0.09	0.39
	RR	0.25	2.17	0.83	0.68	-0.26	0.38	0.22	2.04	0.76	0.63	-0.39	0.37
	PLS	0.23	1.7	0.7	0.49	-0.61	0.33	0.2	1.66	0.64	0.48	-0.75	0.29
	PC	0.31	2.57	1.05	0.73	0.07	0.39	0.26	2.33	0.96	0.7	-0.06	0.39
	AR	NA	NA	NA	NA	NA	NA	0.25	3.22	0.91	0.98	-0.09	0.39
	RW	0.31	3.99	1.09	1.25	0.08	0.39	NA	NA	NA	NA	NA	NA
6	PLS	0.26	1.98	0.82	0.56	-0.33	0.37	0.27	1.92	0.77	0.55	-0.42	0.36
	PC	0.33	3.42	0.99	1.02	-0.01	0.39	0.31	3.45	0.93	1.04	-0.07	0.39
	RR	0.28	2.22	0.86	0.63	-0.23	0.38	0.29	2.22	0.81	0.62	-0.31	0.38
	PLS	0.2	1.33	0.63	0.37	-1	0.24	0.21	1.25	0.59	0.34	-1.19	0.19
	PC	0.29	2.61	0.99	0.76	-0.01	0.39	0.29	2.57	0.93	0.73	-0.09	0.39

(continued ...)

(continued ...)

		Relative to an AR model						Relative to a RW model					
Horizon	Model	quantile 5%	quantile 95%	Rel.RSME	Std.error	t.stat	p.value	quantile 5%	quantile 95%	Rel.RSME	Std.error	t.stat	p.value
	AR	NA	NA	NA	NA	NA	NA	0.32	3.13	0.94	0.92	-0.07	0.39
	RW	0.32	3.11	1.06	0.93	0.07	0.39	NA	NA	NA	NA	NA	NA
7	PLS	0.36	2.07	0.83	0.55	-0.31	0.38	0.34	1.98	0.81	0.53	-0.37	0.37
	PC	0.41	2.8	0.99	0.76	-0.01	0.39	0.41	2.73	0.96	0.75	-0.05	0.39
	RR	0.38	2.74	0.87	0.76	-0.17	0.39	0.37	2.75	0.85	0.75	-0.19	0.39
	PLS	0.34	1.97	0.78	0.52	-0.42	0.36	0.33	1.92	0.76	0.51	-0.47	0.35
	PC	0.41	2.23	0.99	0.58	-0.01	0.39	0.4	2.22	0.97	0.58	-0.06	0.39
	AR	NA	NA	NA	NA	NA	NA	0.38	2.44	0.97	0.66	-0.04	0.39
	RW	0.41	2.65	1.03	0.72	0.04	0.39	NA	NA	NA	NA	NA	NA
8	PLS	0.37	1.86	0.86	0.48	-0.29	0.38	0.33	1.85	0.86	0.49	-0.29	0.38
	PC	0.44	2.65	0.98	0.69	-0.03	0.39	0.39	2.56	0.98	0.7	-0.03	0.39
	RR	0.35	2.2	0.89	0.58	-0.19	0.39	0.35	2.19	0.89	0.58	-0.19	0.39
	PLS	0.35	1.79	0.82	0.46	-0.38	0.37	0.31	1.71	0.82	0.45	-0.39	0.36
	PC	0.43	2.32	1.01	0.6	0.02	0.39	0.38	2.17	1.01	0.57	0.02	0.39
	AR	NA	NA	NA	NA	NA	NA	0.38	2.27	1	0.6	0	0.39
	RW	0.44	2.66	1	0.71	0	0.39	NA	NA	NA	NA	NA	NA
9	PLS	0.32	1.73	0.91	0.45	-0.21	0.39	0.33	1.74	0.91	0.45	-0.21	0.39
	PC	0.4	2.83	0.97	0.76	-0.03	0.39	0.4	2.81	0.97	0.77	-0.03	0.39
	RR	0.35	1.91	0.88	0.5	-0.23	0.38	0.35	1.92	0.88	0.49	-0.24	0.38
	PLS	0.36	2.36	0.82	0.64	-0.28	0.38	0.37	2.31	0.82	0.63	-0.28	0.38
	PC	0.4	2.31	1.01	0.62	0.01	0.39	0.38	2.32	1.01	0.63	0.01	0.39
	AR	NA	NA	NA	NA	NA	NA	0.37	2.58	1	0.7	0	0.39
	RW	0.39	2.72	1	0.73	0	0.39	NA	NA	NA	NA	NA	NA
10	PLS	0.45	2.06	0.92	0.52	-0.16	0.39	0.45	2.06	0.91	0.51	-0.18	0.39
	PC	0.52	2.83	0.95	0.73	-0.07	0.39	0.51	2.86	0.94	0.73	-0.08	0.39
	RR	0.47	2.19	0.84	0.54	-0.3	0.38	0.49	2.2	0.83	0.55	-0.3	0.38
	PLS	0.47	1.86	0.82	0.43	-0.43	0.36	0.47	1.87	0.81	0.44	-0.43	0.36
	PC	0.48	2.5	0.95	0.63	-0.08	0.39	0.48	2.52	0.94	0.64	-0.09	0.39
	AR	NA	NA	NA	NA	NA	NA	0.47	2.14	0.99	0.52	-0.02	0.39
	RW	0.47	2.11	1.01	0.52	0.02	0.39	NA	NA	NA	NA	NA	NA
11	PLS	0.16	1.84	0.93	0.57	-0.12	0.39	0.37	2.26	0.92	0.62	-0.13	0.39
	PC	0.17	2.39	0.92	0.77	-0.1	0.39	0.38	3.09	0.91	0.9	-0.1	0.39
	RR	0.15	1.97	0.86	0.62	-0.22	0.39	0.39	2.58	0.86	0.7	-0.2	0.39
	PLS	0.14	1.75	0.9	0.55	-0.17	0.39	0.33	2.15	0.89	0.6	-0.18	0.39
	PC	0.14	1.64	0.97	0.54	-0.06	0.39	0.33	2.14	0.95	0.59	-0.08	0.39
	AR	NA	NA	NA	NA	NA	NA	0.48	6.32	0.99	1.95	-0.01	0.39
	RW	0.16	2.08	1.01	0.66	0.02	0.39	NA	NA	NA	NA	NA	NA
12	PLS	0.14	1.06	0.94	0.32	-0.18	0.39	0.4	2.06	0.89	0.53	-0.2	0.39
	PC	0.22	2.61	0.89	0.81	-0.14	0.39	0.65	5.05	0.84	1.37	-0.11	0.39
	RR	0.18	1.22	0.93	0.36	-0.18	0.39	0.45	2.13	0.9	0.56	-0.19	0.39
	PLS	0.18	1.35	0.95	0.39	-0.13	0.39	0.52	2.48	0.9	0.62	-0.16	0.39
	PC	0.15	1.15	0.98	0.36	-0.05	0.39	0.42	2.26	0.93	0.61	-0.12	0.39
	AR	NA	NA	NA	NA	NA	NA	0.82	6.6	0.95	1.81	-0.03	0.39

(continued ...)

(continued ...)

		Relative to an AR model						**Relative to a RW model**					
Horizon	**Model**	**quantile** 5%	**quantile** 95%	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**	**quantile** 5%	**quantile** 95%	**Rel.RSME**	**Std.error**	**t.stat**	**p.value**
	RW	0.15	1.22	1.05	0.36	0.15	0.39	NA	NA	NA	NA	NA	NA

out - sample period: Jun-2008 to Jun-2010

The quantiles and the std.error are obtained from the relative RMSE calculated over 5000 bootstrapping samples of the forecasting errors.

Given that forecasting errors are serially correlated, an AR model of order h for the errors is estimated and the sampling is done over the residuals of this regression model, then the sampled forecasting errors are obtained using the parameters of the model.

The t.stat is used to test the null $h_0 : Rel.RMSE = 1$ against $h_1 : Rel.RMSE < 1$

NA: Not applied

TABLE A.10. Data set description

Code	Despcription	Transformation
Economic activity		
ISRTRILL	Index of Real Wage (ISR) Manufacturing industries with cofee threshing	5
ISRSINT	ISR Manufacturing industries excluding cofee threshing	5
ISNCOMIN	Index of Nominal Wage (ISN) by economic activity - retails	5
ISNIMAEM	ISN by economic activity - Manufacturing Industries - Employees	5
ISNIMAOB	ISN by economic activity - Manufacturing Industries - Workers	6
PCVIS	Building Permits for Housing of Social Interes (VIS)	4
PCNOVIS	Building Permits for Housing - NO VIS	5
PCOTROS	Building Permits for Housing - Others	6
CHBRUTA	Gross Mortgage Portfolio	6
IPI	Industrial Production Index	5
DdaEnerg	Energy Demand	2
LicConstr	Construction licensing	2
Empleo	Employment	2
Horastr	Index of Hours Worked	2
Horasex	Index of Extra Hours Worked	5
ProdHoratr	Productivity per Hour Worked	2
ProdMedre	Average Productivity	2
MBCNODU	Consumption goods Import - durable	5
MBCDUR	Consumption goods Import - non durable	5
MBICOMLU	Intermediate goods Import and raw materials - Fuels and lubricants	5
MBISA	Intermediate goods Import and raw materials - Agriculture	5
MBISI	Intermediate goods Import and raw materials -Industrial sector	2
MBKMATCO	Capital goods import - Building materials	2
MBKSA	Capital goods import - Agriculture sector	2
MBKSI	Capital goods import - Industrial sector	2
MBKEQTRA	Capital goods import - Transportation equipment	2
XBTCAFE	Traditional goods exports - Coffee	5
XBTCARBO	Traditional goods exports - Coal	5
XBTPETR	Traditional goods exports - Petroleum	5
XBTFERR	Traditional goods exports - Ferronickel	5
XBNTSA	Traditional goods exports - Agriculture	5
XBNTSMIN	Traditional goods exports - Mining	5
XBNTSI	Traditional goods exports - Industrial sector	5
INGRES	Income	5
GAST	Expenses (including Interest) Central National Government	5
INTERGC	Interests Central National Government	5
SUPERAVI	Superavit Central National Government	5
FININTER	Internal Financing Central National Government	5
FINEXTER	External Financing Central National Government	5
MINORVENTAS	Retail sales Colombia	5
MINOREMPL	Retail employees Colombia	5

(continued ...)

(continued ...)

Code	Despcription	Transformation
MINORSREAL	Retail real wage Colombia	5
ICI	Industrial Confidence Index	5
ICCV	Cost Index for Housing Construction	5
SECONOM	Current economic condition	2
ACTPROD	Production activity	1
EXISTEN	Stocks	1
VOLACTPE	Number of orders at the end of the month	1
CAPINVOP	Installed capacity, given the current situation of demand	5
EXPPRO	Production expectations for the next 3 months	5
EXPSITEC	Price expectations for the next three months	5
CAPINDE	Actual Installed capacity	2
EOEC01	Current economic condition (Commerce survey)	2
EOEC02	Sales compared to last month (Commerce survey)	1
EOEC03	Sales compared to same month last year (Commerce survey)	2
EOEC04	Stocks (Commerce survey)	2
EOEC05	Current demand (Commerce survey)	2
EOEC06	Number of orders at the end of the month (Commerce survey)	2
EOEC08	Production expectations for the next 3 months compared to last year (Commerce survey)	2
EOEC09	Economic expectations for the next 6 months (Commerce survey)	1
EOC1	Current economic conditions in the Household (households survey)	2
EOC2	Household economic conditions expectations for next 12 months (households survey)	2
EOC3	country economic contions expectations for next 12 months (households survey)	2
EOC4	Perception of country economic conditions of present year compared to last year (households survey)	2
EOC5	Expectations of country economic conditions of next year compared to current year (households survey)	1
EOC6	Unemployment perception (households survey)	1
EOC7	Interest rates perception (households survey)	1
EOC8	Prices perception (households survey)	1
EOC10	Is it a good time to buy house? (households survey)	2
EOC11	Is it a good time to buy durable goods? (households survey)	2
EOC12	Is it a good time to buy cars? (households survey)	2
EOC13	Savings capacity (households survey)	2
EOC14	Have someone in your home ask for a credit to the financial institutions? (households survey)	2
EOC15	Have someone in your home ask for a credit to a friend or relative? (households survey)	2
ICC	Consumer Confidence Index	2
IEC	Consumer Expectation Index	2
ICE	Economic Condition Index	2
Prices		
GALIM	Group Activity (GA) Food	7
GAVIV	Group Activity (GA) Housing	7
GAVES	Group Activity (GA) Apparel	7
GASAL	Group Activity (GA) Health	7
GAEDU	Group Activity (GA) Education	7
GACUL	Group Activity (GA) Leisure and Culture	7
GATRAN	Group Activity (GA) Shipping	7

(continued ...)

(continued ...)

Code	Despcription	Transformation
GAOTGA	Group Activity (GA) Other Expenses	7
NCNOTRAN	New Clasification (NC) Non-Transables	7
NCTRAN	NCTransables	7
NCREGUL	NC Regulated	7
IPP	Producer Price Index	7
AEA	Economic Activity(EA) Food	7
AEMIN	EA Mining	7
AEIMAN	EA Manufacturing Industries	7
PBPRODCO	Origin of Goods (PB) Produced and Consumed	7
PBM	PBImports	7
PBX	PB Exports	7
PBXSINCA	PB excluding Cofee	7
UECINTER	Use of Economic Destiny (UE) Intermediate Consumption	7
UECFINAL	UE Final consumption	7
UEFORK	UE Capital formation	7
UEMATCO	UE Building materials	7
EXPAUMPR	Price rise expectations	1
Global	Commodities price index - Global	2
FatsOils	Commodities price index - Fats and Oils	2
Foodstuffs	Commodities price index - Foodstuffs	2
Livestock	Commodities price index - Livestock	2
Metals	Commodities price index - Metals	2
RawIndustrial	Commodities price index - Raw Industrial	2
Textiles	Commodities price index - Textiles	2
Money, credit and exchange rates		
BASEMON	Monetary Base	7
RESNETAS	Net International Reserve	5
M1	M1	7
M2	M2	7
M3	M3	7
CREDBR	Gross Credit	5
EFECTIV	Currency in Circulation	7
TOTALDEP	Total Deposits	5
DEPCTAHO	Deposits in Saving Accounts	5
DEPCTCOR	Deposits in Current accounts	5
CDT90DBA	Interest rates of 90 - day certificate of deposits for banks and corporations	3
TIBPROME	Interbank rate - monthly average	3
DTFNO90D	Nominal Interest rate of 90-day deposits	2
TASACTIV	Active Interest Rate	3
CRBTES	Gross Credit of Treasury	5
CRBBAN	Gross Credit of Banks	5
CRBCORP	Gross Domestic Credit Financial sector	4
CRDOBPRI	Gross Domestic Credit Private Sector	6
CRDONEPR	Net Gross Domestic Private Sector	2

(continued ...)

(continued ...)

Code	Despcription	Transformation
TCNMPROM	Nominal Exchange Rate - Average	5
TERMINTE	Terms of Trade	5
ITCRIPPN	Real exchange rate index Deflacted by PPI (Non Traditional import and exports)	5
ITCRIPCN	Real exchange rate index Deflacted by CPI (Non Traditional import and exports)	5
ITCRIPPT	Real exchange rate index Deflacted by PPI (total Import and exports)	5
ITCRIPCT	Real exchange rate index Deflacted by CPI (Total import and exports)	5
TCOLOCACION	Lending interest rate	2
TCConsumo	Lending gross interest rate for consumption	2
TCOrdinario	Ordinary Lending gross interest rate	2
TCPreferencial	Preferential Credit Interest Rate	2
TCTESORERIA	Treasury interest rate	2
TCDE	Dolar / EURO nominal Exchange Rate	2
Consumo	Total loans for consumption	5
Comercial	Total commercial loans	5
Hipotecario	Total loans for housing	5
carteraTotal	Outstanding loans in Colombian pesos	5
IGBCREAL	Real Stock exchange Colombian idex	5
C1	Outstanding Gross loans (Colombian pesos)	2
C5	Outstanding loans for consumption plus microcredits (Colombian pesos)	5
C13	Microcredits (Colombian pesos)	5
C17	Oustanding Consumption credits (colombian pesos)	2
C21	Outstanding Commercial credits (colombian pesos)	2
Colombia	EMBIS Colombia	2
External variables		
EURIPC	CPI EUROPE	7
USAIPC	CPI USA	7
EURIPI	IPI EURPE	5
USIPI	IPI USA	5
TB5	TB 5 years	2
TB10	TB 10 years	2
TB15	TB 15 years	2
TB30	TB 30 years	2
Yankees5	Yankees 5 years	2
Yankees10	Yankees 10 years	2
Yankees15	Yankees 15 years	2
Yankees30	Yankees 30 years	2
Sp5	Sp 5 years	2
Sp10	Sp 10 years	2
Sp15	Sp 15 years	2
Sp30	Sp 30 years	2
EMBIplus	EMBI plus	2
Brazil	EMBI	2
Fed Funds	Federal funds rate	2
ECB	European central bank short term interest rate	2

(continued ...)

(continued ...)

Code	Despcription	Transformation
Libor	Libor rate	2

* Transformation code: Y_t is the original series

1: no transformation $X_t = Y_t$;

2: first difference $X_t = \Delta Y_t$;

3: Second difference $X_t = \Delta^2 Y_t$;

4: Logarithms $X_t = \log Y_t$;

5: first difference of logs $x_t = \Delta \log Y_t$;

6: second difference of logs $X_t = \Delta^2 \log Y_t$;

7: differece of annual variation $x_t = \Delta \log Y_{t,t-12} - \Delta \log Y_{t-1,t-13}$