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Bayesian Combination for Inflation Forecasts:

The Effects of a Prior Based on Central Banks' Estimates*

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Abstract

Typically, central banks use a variety of individual models (or a combination of models) when forecasting inflation rates. Most of these require excessive amounts of data, time, and computational power; all of which are scarce when monetary authorities meet to decide over policy interventions. In this paper we use a rolling Bayesian combination technique that considers inflation estimates by the staff of the Central Bank of Colombia during 2002-2011 as prior information. Our results show that: 1) the accuracy of individual models is improved by using a Bayesian shrinkage methodology, and 2) priors consisting of staff's estimates outperform all other priors that comprise equal or zero-vector weights. Consequently, our model provides readily available forecasts that exceed all individual models in terms of forecasting accuracy at every evaluated horizon.

Key Words: Bayesian shrinkage, inflation forecast combination, internal forecasts, rolling window estimation

JEL Codes: C22, C53, C11, E31

*The views expressed herein are those of the authors and not necessarily those of the Banco de la República nor its Board of Directors.

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1 Introduction

The demise of the Bretton Woods system in the early 1970's marked the most coordinated exchange rate liberalization in monetary history. It also prompted new policy strategies aimed at achieving long-run price stability. Two decades later, this approach further materialized (denoted as inflation targeting) and was first adopted by New Zealand in 1990. Soon afterwards, a number of industrialized countries became advocates of this approach including Canada, Israel, United Kingdom, Finland and Sweden. Emerging markets followed.

Within the purview of inflation targeting, central banks seek accurate forecasts when deciding over policy interventions. Therefore, tailored forecasting methodologies are warranted in order to elicit salient features of inflation. To date, a common practice employed by monetary authorities has been to use either individual models or a combination of models when forecasting inflation rates. Namely, individual models contain information on the data-generating process such as persistence, non-linearities, and asymmetries. But one single model cannot capture all of the relevant information and it is often the case that the combination of forecasts outperforms individual models (see Granger and Newbold (1974)).

Forecast combination methodologies date back to the pioneering works of Reid (1968) and Bates and Granger (1969) and reviews of the most relevant contributions can be found in Clemen (1989) and Timmermann (2006). Additionally, studies that center on how the averaging is computed include Kapetanios et al. (2006), Eklund and Karlson (2005), and Clemen (1989). Recently, Bayesian Model Averaging, which account for the uncertainty involved in model selection, has gained terrain in the related literature and include the works of Kapetanios et al. (2008), Koop and Potter (2003) and Wright (2003). However, most of these models require excessive amounts of data and a significant amount of time and computational power; all of which are exceptionally scarce when monetary authorities meet to decide over policy interventions.

Consequently, the main objective of this paper is to use a rolling Bayesian forecast combination technique to provide readily available forecasts. We improve on the predictive performance of all individual models used by the Central Bank of Colombia (**CBoC** henceforth) by using a prior based on staff's estimates. These estimates, which are conducted by the Macroeconomic Department of the CBoC, differ from all other internal forecasts that target inflation. Specifically, they contain non-conventional information that ranges from the price of potatoes (key to the representative consumer basket of Colombians) to the scheduling of national soccer championships. Thus, they contain additional information that can potentially complement existing forecasting techniques. To our knowledge, few empirical studies have examined forecast combination and only a handful have centered on the Colombian case.[1] Moreover, a Bayesian approach has not been used in this context. Thus, we believe that our investigation will provide an improved and more accessible toolkit for central bankers in emerging markets.

We follow Diebold and Pauly (1990) in adopting a Bayesian shrinkage methodology which allow us to incorporate our chosen prior in a linear setting. In the empirical application, we employ proprietary data from the CBoC which allow us to compare the accuracy of our model with respect to nine internal models that target inflation. The implications of our findings are twofold: 1) we confirm that the forecasting accuracy of individual models can be improved by using a Bayesian shrinkage forecast combination technique and 2) we show that priors consisting of staff's estimates outperform all other priors that comprise equal or zero-vector weights. A caveat however, is that the forecasting performance of staff's estimates depends on the magnitude of the shrinkage parameter and window size.

The rest of the paper is organized as follows. Section 2 explains the Bayesian shrinkage methodology in terms of forecast combination and the specification of the prior distribution. Sections 3 and 4 describe the data and present results, respectively. Finally, Section 5 concludes.

2 Methodology

Let $f^1_{t|t-h}, \ldots, f^m_{t|t-h}$ be the set of m $h-$step ahead forecasts of y_t. Following Granger and Ramanathan (1984), a typical way to combine these forecasts is as follows:

$$y_t = \boldsymbol{\beta}' \boldsymbol{f}_{t|t-h} + \varepsilon_t, \tag{1}$$

where $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_m)'$ is the regression coefficient vector, and $\boldsymbol{f}_{t|t-h} = (1, f^1_{t|t-h}, \ldots, f^m_{t|t-h})'$ is a $m+1$ vector that comprises the intercept and the m forecasts. The intercept plays an important role in this model because it ensures that the bias correction of the combined forecast is optimally determined.

Diebold and Pauly (1990) consider a methodology that allows prior information to be incorporated into a regression-based forecast combination framework. The authors use the g-prior model of Zellner (1986) for a Bayesian estimation of the parameters in equation (1). They assume that the error term is normally distributed, $\varepsilon_t \overset{iid}{\sim} N(0, \sigma^2)$, and use a natural conjugate normal-gamma prior

[1] See Castaño and Melo (2000) and Melo and Núñez (2004).

of the form:

$$P_0(\boldsymbol{\beta},\sigma) \propto \sigma^{-K-\nu_0-1} \exp\left\{-\tfrac{1}{2}\sigma^2 \left[\nu_0 s_0^2 + \left(\boldsymbol{\beta}-\underline{\boldsymbol{\beta}}\right)' M \left(\boldsymbol{\beta}-\underline{\boldsymbol{\beta}}\right)\right]\right\} \tag{2}$$

where $K = m+1$. Consequently, the resulting likelihood is presented as:

$$L\left(\boldsymbol{\beta},\sigma \mid \boldsymbol{Y}, F\right) \propto \sigma^{-T} \exp\left\{-\tfrac{1}{2}\sigma^2 \left(\boldsymbol{Y}-F\boldsymbol{\beta}\right)' \left(\boldsymbol{Y}-F\boldsymbol{\beta}\right)\right\} \tag{3}$$

where $\boldsymbol{Y} = (y_1,\ldots,y_{t-h})'$ and $F = (\boldsymbol{f}_{1|1-h},\ldots,\boldsymbol{f}_{t-h|t-2h})'$. As follows, the marginal posterior of $\boldsymbol{\beta}$ is given by equation (4):

$$P_1\left(\boldsymbol{\beta} \mid \boldsymbol{Y}, F\right) \propto \left[1+\tfrac{1}{\nu_1}\left(\boldsymbol{\beta}-\overline{\boldsymbol{\beta}}\right)' s_1^{-2}\left(M+F'F\right)\left(\boldsymbol{\beta}-\overline{\boldsymbol{\beta}}\right)\right]^{-\frac{K+\nu_1}{2}} \tag{4}$$

where the marginal posterior mean corresponds to $\overline{\boldsymbol{\beta}} = \left(M+F'F\right)^{-1}\left(M\underline{\boldsymbol{\beta}}+F'F\widehat{\boldsymbol{\beta}}\right)$, and where $\nu_1 = T+\nu_0$, $s_1^2 = \frac{1}{\nu_1}\left[\nu_0\ s_0^2 + \boldsymbol{Y}'\boldsymbol{Y} + \underline{\boldsymbol{\beta}}'M\underline{\boldsymbol{\beta}} - \overline{\boldsymbol{\beta}}'\left(M+F'F\right)\overline{\boldsymbol{\beta}}\right]$ and $\widehat{\boldsymbol{\beta}} = \left(F'F\right)^{-1}F'\boldsymbol{Y}$.

Finally, under the $g-$prior analysis (with $M = gF'F$), Diebold and Pauly (1990) show that:

$$\overline{\boldsymbol{\beta}} = \tfrac{g}{1+g}\underline{\boldsymbol{\beta}} + \tfrac{1}{1+g}\widehat{\boldsymbol{\beta}}, \tag{5}$$

where $g \in [0,\infty)$ corresponds to the shrinkage parameter that controls the relative weight between the prior mean and the maximum likelihood estimator in the posterior mean.

However, Diebold and Pauly (1990) do not control for the possible presence of structural breaks. Nonetheless, equation (1) can be extended to consider these instabilities by using time-varying forecast combination weights, as follows:

$$y_t = \boldsymbol{\beta}_t'\boldsymbol{f}_{t|t-h} + \varepsilon_t. \tag{6}$$

The Bayesian shrinkage forecast combination methodology can then be generalized to consider equation (6) by using rolling estimates with a w-window size. This procedure yields the following posterior mean:

$$\overline{\boldsymbol{\beta}}_t = \tfrac{g}{1+g}\underline{\boldsymbol{\beta}}_{\ t} + \tfrac{1}{1+g}\widehat{\boldsymbol{\beta}}_t, \tag{7}$$

where $\widehat{\boldsymbol{\beta}}_t = \left(F'_{t-h-w+1,t-h}F_{t-h-w+1,t-h}\right)^{-1} F'_{t-h-w+1,t-h}\boldsymbol{Y}_{t-h-w+1,t-h}$, $F_{t-h-w+1,t-h} = (\boldsymbol{f}_{t-h-w+1|t-2h-w+1}, \ldots, \boldsymbol{f}_{t-h|t-2h})'$, and $\boldsymbol{Y}_{t-h-w+1,t-h} = (y_{t-h-w+1}, \ldots, y_{t-h})$.

In the related literature, Diebold and Pauly (1990) use equal weights as the prior mean $\left(\underline{\boldsymbol{\beta}}_{\ t}\right)$. Alternatively, Wright (2008) uses zero-weights as the prior mean in a Bayesian shrinkage exercise. In this paper we follow Geweke and Whiteman (2006) in order to incorporate inflation estimates from the staff of the CBoC as prior information. Thus, we propose to use the OLS estimated parameters of the regression between the staff's $h-$step forecast series $f^{ex}_{t|t-h}$ and the set of individual $h-$ step model forecasts as prior weights.[2] Formally, we compute the prior mean as follows:

$$f^{ex}_{t|t-h} = \boldsymbol{\beta}'_t\boldsymbol{f}_{t|t-h} + \varepsilon_t. \tag{8}$$

Accordingly, the prior mean equals $\underline{\boldsymbol{\beta}}_t = \left(F'_{t-w+1,t}F_{t-w+1,t}\right)^{-1} F'_{t-w+1,t}\boldsymbol{F}^{ex}_{t-w+1,t}$ where $F_{t-w+1,t} = (\boldsymbol{f}_{t-w+1|t-h-w+1}, \ldots, \boldsymbol{f}_{t|t-h})'$, and $\boldsymbol{F}^{ex}_{t-w+1,t} = (f^{ex}_{t-w+1|t-h-w+1}, \ldots, f^{ex}_{t|t-h})$.

When the forecasting series are non-stationary, Coulson and Robins (1993) propose a combination method based on the following linear model:

$$y_t - y_{t-h} = \boldsymbol{\beta}'\widetilde{\boldsymbol{f}}_{t|t-h} + \varepsilon_t, \tag{9}$$

where $\widetilde{\boldsymbol{f}}_{t|t-h} = (1, f^1_{t|t-h} - y_{t-h}, \ldots, f^m_{t|t-h} - y_{t-h})'$. Therefore, equations (6), (7) and (8), equation (9) can be easily modified to consider a rolling Bayesian shrinkage methodology. In this case, $\underline{\boldsymbol{\beta}}_t$ is obtained as the rolling OLS estimation of $\boldsymbol{\beta}_t$:

$$f^{ex}_{t|t-h} - f^{ex}_{t-h|t-2h} = \boldsymbol{\beta}'_t\ \widetilde{\widetilde{\boldsymbol{f}}}_{t|t-h} + \varepsilon_t, \tag{10}$$

where $\widetilde{\widetilde{\boldsymbol{f}}}_{t|t-h} = \left(1, f^1_{t|t-h} - f^{ex}_{t-h|t-2h}, \ldots, f^m_{t|t-h} - f^{ex}_{t-h|t-2h}\right)'$.

The polar (or extreme) cases of the posterior mean in terms of the shrinkage parameter are

[2] Higher prior weights are assigned to forecasts that are highly correlated with the staff's estimates.

obtained under the Coulson and Robins modified methodology presented in Table 1. Cases are shown for different priors.

Table 1: Posterior mean polar cases for the Coulson and Robins modified methodology

Prior	Shrinkage Parameter $g = 0$	$g \to \infty$
Zero weights	GR-CR	Random walk weights
Equal weights	GR-CR	Equal weights
Staff's Estimates	GR-CR$^{(-1)}$	Staff's Estimates weights

GR-CR indicates the MLE weights obtained by rolling estimation of the parameters in (9) including estimates by the staff of the CBoC as a covariate. GR-CR$^{(-1)}$ indicates the MLE weights obtained by rolling estimation of the parameters in (9), excluding staff's estimates as a covariate.

Two results of Table 1 are noted. First, when $g \to \infty$ with a zero weights prior, the posterior mean is equal to a zero-weight vector. In this case, equation (9) implies a random walk forecast. Second, when $g = 0$, the posterior mean corresponds to the MLE weights. However, the posterior mean of the three priors differ since they do not have the same information. The Bayesian combination with zero and equal-weight priors is calculated using the staff's inflation estimates as a covariate, whereas the staff's estimates prior does not include this covariate.

3 Data

Our data consist of monthly Colombian inflation, measured as the log-difference of the Consumer Price Index (CPI) and nine competing (internal) forecasts employed by the CBoC. The latter comprise 1-step to 9-steps ahead forecasts during the period of September 2002 - December 2011.[3] In addition, inflation estimates by the staff of the CBoC were used to specify the prior in the shrinkage methodology.[4] These estimates use non-conventional indicators that affect inflation such as the price of potatoes, the scheduling of national soccer championships, and national and local election dates, among others.

Our data is divided into two subsamples. The first subsample is used to estimate the rolling Bayesian forecast combination model. Alternatively, the second subsample is used to evaluate the predictive accuracy of the nine individual models as well as their combination. The first rolling window estimation of size w goes up until September 2007. With this information, an h-step

[3]See Table 11 of Appendix B for a brief description of the nine competing forecasts.
[4]These estimates were provided by the Macroeconomic Department of the CBoC.

forecast is estimated. Next, the parameters of the combination are re-estimated after rolling over the next period's observation. A new set of forecasts is obtained until the last available observation is considered.

4 Empirical Results

The Root Mean Square Error (RMSE) criterion is used to compare the models' forecasting accuracy. Similarly, the U-Theil statistic is also computed to assess the performance of each model vis-a-vis a random walk. Table 2 and Tables 3 - 10 of Appendix A, show the performance statistics for windows size $w = 20, 30, 40$ and 50 months[5], shrinkage parameters $g = 0, 1, 3, 5, 20$ and $g \to \infty$, and forecast horizons ranging from 1 to 9-months. In addition to our proposed prior (based on inflation estimates by the staff of the CBoC), we consider equal and zero-weight priors as benchmark comparisons.

The upper panels of Tables 2 - 10 present results of all individual models while the lower panels present results for the combined forecasts. The nine individual models which are currently employed by the CBoC consist of Autoregressive Integrated Moving Averages (ARIMAs), non-parametric regressions, neural networks, Logistic Smooth Transition Regressions (LSTR), and Flexible Least Square Regressions (FLS). For a more detailed description of these models see Table 11 of Appendix B.

As can be observed in the upper panels, inflation estimates by the staff of the CBoC outperform all nine individual models at every horizon and window size. This can be construed as evidence of relevant (and systematic) information within these estimates that are not being captured by the nine competing models. It also validates our decision to incorporate these estimates as prior information.

Results for the lower panels show that the forecasting accuracy is improved by using a rolling Bayesian shrinkage forecast combination methodology with staff's estimates as prior information (**RSFC methodology**, henceforth). This result follows from having the lowest RMSE and U-Theil values. For example, for a 1-month forecast horizon, Table 2 shows that the minimum RMSE is 0.177, which corresponds to the RSFC methodology with a shrinkage parameter $g = 20$ and a rolling window size $w = 20$. However, the forecast performance of the RSFC methodology depends on the magnitude of the shrinkage parameter and the window size. For the longest forecast horizons, $h = 6, 7, 8$ and 9, the best performance is obtained when $g \to \infty$, as shown in Tables 7 to 10. This result suggests that staff's estimates are more informative when considering longer horizons.

[5]The maximum possible rolling window size for forecast horizon $h = 7, 8$ and 9 months ahead is 40.

Results also indicate that the RSFC methodology produces the most accurate inflation forecasts when compared with the shrinkage methodology that uses other priors as equal and zero-vector weights. In the few cases that the other priors have better performance, almost all are associated with a zero-shrinkage parameter because the equal and zero priors contain more information when $g = 0$, as noted in section 2.

As expected, when the shrinkage parameter is zero, $g = 0$, all three Bayesian shrinkage forecast have similar performance because the prior mean has zero-weight in the posterior mean. As explained previously, in this case, the forecast statistics of our chosen prior (containing staff's estimates) differ slightly because they are computed with less information. Morevoer, when $g \to \infty$, the U-Theil statistic is equal to unity for the Bayesian shrinkage forecast combination methodology that uses a zero-weight prior. In this case, equation (9) implies a random walk forecast (i.e. the U-Theil statistic is one).

Table 2: Performance of Colombian inflation for 1-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40		Window Size=50	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS									
ARIMA		0.280	0.751	0.280	0.751	0.280	0.751	0.280	0.751
ARIMA.C4		0.276	0.740	0.276	0.740	0.276	0.740	0.276	0.740
ARIMA.C6		0.216	0.579	0.216	0.579	0.216	0.579	0.216	0.579
ARIMA.C10		0.258	0.690	0.258	0.690	0.258	0.690	0.258	0.690
FLS		0.267	0.715	0.267	0.715	0.267	0.715	0.267	0.715
LSTR		0.353	0.946	0.353	0.946	0.353	0.946	0.353	0.946
Neural.Network		0.248	0.665	0.248	0.665	0.248	0.665	0.248	0.665
Neural.Network.C		0.249	0.668	0.249	0.668	0.249	0.668	0.249	0.668
Non.Parametric		0.351	0.941	0.351	0.941	0.351	0.941	0.351	0.941
Staff's Estimates		0.185	0.495	0.185	0.495	0.185	0.495	0.185	0.495
COMBINED MODELS									
Shrinkage	Prior								
	Staff's Estimates	0.296	0.793	0.246	0.660	0.240	0.643	0.244	0.653
g=0	Equal Weights	0.305	0.818	0.254	0.680	0.230	0.617	0.223	0.598
	Zero Weights	0.305	0.818	0.254	0.680	0.230	0.617	0.223	0.598
	Staff's Estimates	0.207	0.555	0.208	0.557	0.208	0.557	0.215	0.575
g=1	Equal Weights	0.220	0.589	0.217	0.581	0.208	0.556	0.207	0.555
	Zero Weights	0.258	0.691	0.254	0.679	0.247	0.661	0.248	0.665
	Staff's Estimates	0.182	0.488	0.197	0.527	0.198	0.530	0.205	0.551
g=3	Equal Weights	0.210	0.564	0.217	0.580	0.213	0.570	0.214	0.572
	Zero Weights	0.301	0.806	0.304	0.814	0.302	0.809	0.304	0.814
	Staff's Estimates	0.178	0.478	0.194	0.520	0.196	0.524	0.203	0.545
g=5	Equal Weights	0.214	0.572	0.219	0.588	0.217	0.582	0.218	0.583
	Zero Weights	0.323	0.864	0.325	0.872	0.324	0.869	0.326	0.873
	Staff's Estimates	0.177*	0.476	0.192	0.514	0.193	0.518	0.201	0.539
g=20	Equal Weights	0.223	0.599	0.226	0.605	0.225	0.603	0.225	0.604
	Zero Weights	0.358	0.959	0.359	0.962	0.359	0.961	0.359	0.963
	Staff's Estimates	0.179	0.479	0.191	0.513	0.193	0.517	0.200	0.537
$g\to\infty$	Equal Weights	0.229	0.614	0.229	0.614	0.229	0.614	0.229	0.614
	Zero Weights	0.373	1.000	0.373	1.000	0.373	1.000	0.373	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

5 Conclusion

Within the purview of inflation targeting, central banks seek accurate forecasts when deciding over policy interventions. Therefore, tailored forecasting methodologies are warranted in order to elicit salient features of inflation.

This study implements a Bayesian shrinkage forecast combination methodology for an emerging country case, using Colombian inflation data from September 2002 - December 2011. Our estimation method takes into account two important characteristics: instability (by using rolling a estimation), and non-stationarity (by implementing methods for series integrated of order one).

We improve on the predictive performance of all individual models used by the Central Bank of Colombia by using a prior based on staff's estimates. As such, we follow Diebold and Pauly (1990) in adopting a Bayesian shrinkage methodology which allow us to incorporate our chosen prior in a linear setting. The implications of our findings are twofold: 1) we confirm that the forecasting accuracy of individual models can be improved by using a Bayesian shrinkage forecast combination technique and 2) we show that priors consisting of staff's estimates outperform all other priors that comprise equal or zero-vector weights. However, the forecast performance of staff's estimates depends on the magnitude of the shrinkage parameter and window size.

To date, forecasting models used by central banks generally require excessive amounts of data and a significant amount of time and computational power; all of which are exceptionally scarce when monetary authorities meet to decide over policy interventions. Thus, we believe that our investigation will provide an improved and more accessible toolkit (which provides readily available forecasts) for central bankers in emerging markets.

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A Performance of Colombian inflation for 2-month to 9-month ahead forecasts

Table 3: Performance of Colombian inflation for 2-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40		Window Size=50	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS									
ARIMA		0.540	0.816	0.540	0.816	0.540	0.816	0.540	0.816
ARIMA.C4		0.554	0.837	0.554	0.837	0.554	0.837	0.554	0.837
ARIMA.C6		0.486	0.735	0.486	0.735	0.486	0.735	0.486	0.735
ARIMA.C10		0.485	0.734	0.485	0.734	0.485	0.734	0.485	0.734
FLS		0.536	0.810	0.536	0.810	0.536	0.810	0.536	0.810
LSTR		0.643	0.972	0.643	0.972	0.643	0.972	0.643	0.972
Neural.Network		0.444	0.671	0.444	0.671	0.444	0.671	0.444	0.671
Neural.Network.C		0.497	0.751	0.497	0.751	0.497	0.751	0.497	0.751
Non.Parametric		0.644	0.974	0.644	0.974	0.644	0.974	0.644	0.974
Staff's Estimates		0.430	0.650	0.430	0.650	0.430	0.650	0.430	0.650
COMBINED MODELS									
Shrinkage	Prior								
	Staff's Estimates	0.595	0.899	0.492	0.744	0.440	0.666	0.427	0.646
g=0	Equal Weights	0.605	0.914	0.506	0.765	0.422	0.639	0.414	0.626
	Zero Weights	0.605	0.914	0.506	0.765	0.422	0.639	0.414	0.626
	Staff's Estimates	0.428	0.647	0.411	0.621	0.401	0.606	0.400	0.604
g=1	Equal Weights	0.453	0.685	0.432	0.654	0.401	0.607	0.403	0.609
	Zero Weights	0.504	0.762	0.485	0.733	0.450	0.681	0.457	0.692
	Staff's Estimates	0.389	0.588	0.395	0.597	0.399	0.603	0.400	0.605
g=3	Equal Weights	0.433	0.654	0.432	0.654	0.421	0.637	0.423	0.640
	Zero Weights	0.556	0.841	0.555	0.839	0.542	0.819	0.547	0.828
	Staff's Estimates	0.385*	0.583	0.394	0.595	0.401	0.606	0.402	0.609
g=5	Equal Weights	0.436	0.660	0.438	0.663	0.432	0.653	0.434	0.656
	Zero Weights	0.586	0.886	0.587	0.888	0.579	0.876	0.583	0.882
	Staff's Estimates	0.389	0.588	0.396	0.599	0.406	0.614	0.408	0.616
g=20	Equal Weights	0.450	0.681	0.452	0.683	0.450	0.681	0.451	0.682
	Zero Weights	0.638	0.965	0.639	0.966	0.637	0.963	0.638	0.965
	Staff's Estimates	0.393	0.595	0.399	0.603	0.409	0.619	0.410	0.620
$g \to \infty$	Equal Weights	0.459	0.693	0.459	0.693	0.459	0.693	0.459	0.693
	Zero Weights	0.661	1.000	0.661	1.000	0.661	1.000	0.661	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 4: Performance of Colombian inflation for 3-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40		Window Size=50	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS									
ARIMA		0.799	0.875	0.799	0.875	0.799	0.875	0.799	0.875
ARIMA.C4		0.832	0.911	0.832	0.911	0.832	0.911	0.832	0.911
ARIMA.C6		0.777	0.852	0.777	0.852	0.777	0.852	0.777	0.852
ARIMA.C10		0.751	0.823	0.751	0.823	0.751	0.823	0.751	0.823
FLS		0.778	0.852	0.778	0.852	0.778	0.852	0.778	0.852
LSTR		0.938	1.028	0.938	1.028	0.938	1.028	0.938	1.028
Neural.Network		0.695	0.762	0.695	0.762	0.695	0.762	0.695	0.762
Neural.Network.C		0.749	0.820	0.749	0.820	0.749	0.820	0.749	0.820
Non.Parametric		0.900	0.986	0.900	0.986	0.900	0.986	0.900	0.986
Staff's Estimates		0.695	0.761	0.695	0.761	0.695	0.761	0.695	0.761
COMBINED MODELS									
Shrinkage	Prior								
	Staff's Estimates	1.167	1.279	0.840	0.920	0.690	0.756	0.613	0.672
g=0	Equal Weights	1.333	1.461	0.924	1.013	0.724	0.793	0.625	0.685
	Zero Weights	1.333	1.461	0.924	1.013	0.724	0.793	0.625	0.685
	Staff's Estimates	0.798	0.874	0.694	0.761	0.633	0.694	0.601*	0.658
g=1	Equal Weights	0.855	0.937	0.727	0.797	0.648	0.711	0.612	0.671
	Zero Weights	0.926	1.015	0.799	0.875	0.696	0.763	0.657	0.720
	Staff's Estimates	0.695	0.762	0.654	0.717	0.631	0.691	0.614	0.673
g=3	Equal Weights	0.711	0.779	0.685	0.751	0.655	0.718	0.642	0.703
	Zero Weights	0.856	0.938	0.827	0.906	0.781	0.856	0.766	0.840
	Staff's Estimates	0.681	0.746	0.647	0.709	0.634	0.695	0.621	0.681
g=5	Equal Weights	0.689	0.755	0.682	0.747	0.665	0.728	0.657	0.720
	Zero Weights	0.861	0.944	0.850	0.931	0.821	0.899	0.812	0.890
	Staff's Estimates	0.679	0.745	0.642	0.704	0.642	0.703	0.634	0.695
g=20	Equal Weights	0.685	0.751	0.687	0.753	0.683	0.749	0.681	0.747
	Zero Weights	0.892	0.978	0.892	0.978	0.885	0.970	0.883	0.967
	Staff's Estimates	0.685	0.751	0.642	0.704	0.646	0.708	0.640	0.701
$g \to \infty$	Equal Weights	0.692	0.759	0.692	0.759	0.692	0.759	0.692	0.759
	Zero Weights	0.912	1.000	0.912	1.000	0.912	1.000	0.912	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 5: Performance of Colombian inflation for 4-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40		Window Size=50	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS									
ARIMA		1.025	0.899	1.025	0.899	1.025	0.899	1.025	0.899
ARIMA.C4		1.066	0.935	1.066	0.935	1.066	0.935	1.066	0.935
ARIMA.C6		1.039	0.912	1.039	0.912	1.039	0.912	1.039	0.912
ARIMA.C10		0.978	0.858	0.978	0.858	0.978	0.858	0.978	0.858
FLS		1.000	0.877	1.000	0.877	1.000	0.877	1.000	0.877
LSTR		1.231	1.080	1.231	1.080	1.231	1.080	1.231	1.080
Neural.Network		0.909	0.797	0.909	0.797	0.909	0.797	0.909	0.797
Neural.Network.C		0.951	0.834	0.951	0.834	0.951	0.834	0.951	0.834
Non.Parametric		1.126	0.988	1.126	0.988	1.126	0.988	1.126	0.988
Staff's Estimates		0.896	0.786	0.896	0.786	0.896	0.786	0.896	0.786
COMBINED MODELS									
Shrinkage	Prior								
	Staff's Estimates	1.852	1.624	1.236	1.084	0.943	0.827	0.807	0.708
g=0	Equal Weights	2.019	1.771	1.314	1.152	1.030	0.904	0.890	0.781
	Zero Weights	2.019	1.771	1.314	1.152	1.030	0.904	0.890	0.781
	Staff's Estimates	1.168	1.025	0.961	0.843	0.831	0.729	0.777*	0.681
g=1	Equal Weights	1.297	1.138	1.048	0.919	0.908	0.797	0.851	0.746
	Zero Weights	1.433	1.257	1.153	1.012	0.970	0.851	0.915	0.803
	Staff's Estimates	0.925	0.812	0.855	0.750	0.801	0.703	0.777	0.682
g=3	Equal Weights	1.026	0.900	0.954	0.837	0.887	0.779	0.863	0.757
	Zero Weights	1.232	1.081	1.127	0.988	1.029	0.903	1.008	0.884
	Staff's Estimates	0.874	0.766	0.826	0.725	0.796	0.698	0.780	0.684
g=5	Equal Weights	0.963	0.845	0.930	0.816	0.887	0.778	0.872	0.765
	Zero Weights	1.187	1.041	1.127	0.988	1.061	0.931	1.048	0.920
	Staff's Estimates	0.836	0.733	0.793	0.695	0.792	0.695	0.785	0.689
g=20	Equal Weights	0.907	0.796	0.905	0.794	0.893	0.783	0.889	0.780
	Zero Weights	1.147	1.007	1.134	0.995	1.116	0.979	1.112	0.976
	Staff's Estimates	0.833	0.731	0.782	0.686	0.792	0.695	0.788	0.691
$g \to \infty$	Equal Weights	0.897	0.787	0.897	0.787	0.897	0.787	0.897	0.787
	Zero Weights	1.140	1.000	1.140	1.000	1.140	1.000	1.140	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 6: Performance of Colombian inflation for 5-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40		Window Size=50	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS									
ARIMA		1.224	0.895	1.224	0.895	1.224	0.895	1.224	0.895
ARIMA.C4		1.272	0.931	1.272	0.931	1.272	0.931	1.272	0.931
ARIMA.C6		1.266	0.926	1.266	0.926	1.266	0.926	1.266	0.926
ARIMA.C10		1.170	0.856	1.170	0.856	1.170	0.856	1.170	0.856
FLS		1.205	0.882	1.205	0.882	1.205	0.882	1.205	0.882
LSTR		1.477	1.081	1.477	1.081	1.477	1.081	1.477	1.081
Neural.Network		1.123	0.822	1.123	0.822	1.123	0.822	1.123	0.822
Neural.Network.C		1.134	0.830	1.134	0.830	1.134	0.830	1.134	0.830
Non.Parametric		1.348	0.986	1.348	0.986	1.348	0.986	1.348	0.986
Staff's Estimates		1.056	0.773	1.056	0.773	1.056	0.773	1.056	0.773
COMBINED MODELS									
Shrinkage	Prior								
	Staff's Estimates	2.112	1.545	1.760	1.288	1.365	0.999	1.053	0.770
g=0	Equal Weights	2.251	1.647	1.821	1.333	1.485	1.086	1.198	0.877
	Zero Weights	2.251	1.647	1.821	1.333	1.485	1.086	1.198	0.877
	Staff's Estimates	1.361	0.996	1.263	0.924	1.067	0.781	0.958	0.701
g=1	Equal Weights	1.505	1.102	1.359	0.994	1.193	0.873	1.077	0.788
	Zero Weights	1.673	1.224	1.480	1.083	1.292	0.945	1.164	0.851
	Staff's Estimates	1.108	0.811	1.077	0.788	0.980	0.717	0.937	0.686
g=3	Equal Weights	1.225	0.896	1.185	0.867	1.108	0.810	1.060	0.776
	Zero Weights	1.472	1.077	1.389	1.016	1.295	0.948	1.240	0.907
	Staff's Estimates	1.058	0.774	1.031	0.754	0.963	0.705	0.935*	0.684
g=5	Equal Weights	1.157	0.847	1.140	0.834	1.091	0.798	1.062	0.777
	Zero Weights	1.425	1.042	1.373	1.005	1.312	0.960	1.277	0.934
	Staff's Estimates	1.026	0.751	0.981	0.718	0.951	0.696	0.935	0.684
g=20	Equal Weights	1.091	0.798	1.091	0.798	1.078	0.788	1.071	0.783
	Zero Weights	1.378	1.008	1.365	0.999	1.348	0.986	1.339	0.980
	Staff's Estimates	1.027	0.752	0.968	0.708	0.950	0.695	0.936	0.685
$g \to \infty$	Equal Weights	1.076	0.787	1.076	0.787	1.076	0.787	1.076	0.787
	Zero Weights	1.367	1.000	1.367	1.000	1.367	1.000	1.367	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 7: Performance of Colombian inflation for 6-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40		Window Size=50	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS									
ARIMA		1.416	0.888	1.416	0.888	1.416	0.888	1.416	0.888
ARIMA.C4		1.455	0.912	1.455	0.912	1.455	0.912	1.455	0.912
ARIMA.C6		1.460	0.916	1.460	0.916	1.460	0.916	1.460	0.916
ARIMA.C10		1.346	0.844	1.346	0.844	1.346	0.844	1.346	0.844
FLS		1.430	0.897	1.430	0.897	1.430	0.897	1.430	0.897
LSTR		1.741	1.091	1.741	1.091	1.741	1.091	1.741	1.091
Neural.Network		1.346	0.844	1.346	0.844	1.346	0.844	1.346	0.844
Neural.Network.C		1.283	0.804	1.283	0.804	1.283	0.804	1.283	0.804
Non.Parametric		1.570	0.984	1.570	0.984	1.570	0.984	1.570	0.984
Staff's Estimates		1.223	0.767	1.223	0.767	1.223	0.767	1.223	0.767
COMBINED MODELS									
Shrinkage	Prior								
	Staff's Estimates	2.452	1.537	2.345	1.470	1.798	1.127	1.273	0.798
g=0	Equal Weights	2.618	1.641	2.442	1.531	1.932	1.211	1.400	0.878
	Zero Weights	2.618	1.641	2.442	1.531	1.932	1.211	1.400	0.878
	Staff's Estimates	1.642	1.030	1.648	1.033	1.378	0.864	1.129	0.708
g=1	Equal Weights	1.834	1.150	1.741	1.092	1.515	0.950	1.258	0.789
	Zero Weights	2.038	1.278	1.905	1.195	1.661	1.041	1.357	0.850
	Staff's Estimates	1.333	0.836	1.350	0.847	1.213	0.761	1.083	0.679
g=3	Equal Weights	1.501	0.941	1.454	0.912	1.357	0.851	1.236	0.775
	Zero Weights	1.792	1.124	1.712	1.073	1.599	1.002	1.445	0.906
	Staff's Estimates	1.257	0.788	1.265	0.793	1.169	0.733	1.073	0.672
g=5	Equal Weights	1.405	0.881	1.375	0.862	1.315	0.824	1.237	0.775
	Zero Weights	1.720	1.078	1.664	1.043	1.591	0.997	1.489	0.934
	Staff's Estimates	1.181	0.740	1.160	0.727	1.116	0.700	1.061	0.665
g=20	Equal Weights	1.289	0.808	1.281	0.803	1.266	0.794	1.245	0.781
	Zero Weights	1.628	1.021	1.611	1.010	1.591	0.998	1.563	0.980
	Staff's Estimates	1.162	0.729	1.125	0.705	1.099	0.689	1.058*	0.664
$g \rightarrow \infty$	Equal Weights	1.250	0.784	1.250	0.784	1.250	0.784	1.250	0.784
	Zero Weights	1.595	1.000	1.595	1.000	1.595	1.000	1.595	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 8: Performance of Colombian inflation for 7-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS							
ARIMA		1.634	0.895	1.634	0.895	1.634	0.895
ARIMA.C4		1.652	0.905	1.652	0.905	1.652	0.905
ARIMA.C6		1.656	0.907	1.656	0.907	1.656	0.907
ARIMA.C10		1.542	0.845	1.542	0.845	1.542	0.845
FLS		1.673	0.916	1.673	0.916	1.673	0.916
LSTR		1.989	1.090	1.989	1.090	1.989	1.090
Neural.Network		1.527	0.836	1.527	0.836	1.527	0.836
Neural.Network.C		1.472	0.806	1.472	0.806	1.472	0.806
Non.Parametric		1.801	0.987	1.801	0.987	1.801	0.987
Staff's Estimates		1.388	0.760	1.388	0.760	1.388	0.760
COMBINED MODELS							
Shrinkage	Prior						
	Staff's Estimates	4.065	2.227	3.306	1.811	2.568	1.407
g=0	Equal Weights	4.215	2.309	3.452	1.891	2.709	1.484
	Zero Weights	4.215	2.309	3.452	1.891	2.709	1.484
	Staff's Estimates	2.472	1.354	2.184	1.197	1.835	1.005
g=1	Equal Weights	2.651	1.452	2.314	1.268	1.972	1.080
	Zero Weights	2.909	1.594	2.525	1.383	2.147	1.176
	Staff's Estimates	1.773	0.971	1.686	0.924	1.518	0.832
g=3	Equal Weights	1.957	1.072	1.818	0.996	1.667	0.913
	Zero Weights	2.319	1.270	2.132	1.168	1.947	1.066
	Staff's Estimates	1.577	0.864	1.540	0.844	1.426	0.781
g=5	Equal Weights	1.756	0.962	1.675	0.918	1.581	0.866
	Zero Weights	2.140	1.172	2.018	1.105	1.896	1.039
	Staff's Estimates	1.354	0.742	1.358	0.744	1.310	0.718
g=20	Equal Weights	1.517	0.831	1.500	0.822	1.477	0.809
	Zero Weights	1.908	1.045	1.875	1.027	1.842	1.009
	Staff's Estimates	1.292	0.708	1.297	0.711	1.270*	0.696
$g\to\infty$	Equal Weights	1.442	0.790	1.442	0.790	1.442	0.790
	Zero Weights	1.825	1.000	1.825	1.000	1.825	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 9: Performance of Colombian inflation for 8-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS							
ARIMA		1.846	0.904	1.846	0.904	1.846	0.904
ARIMA.C4		1.832	0.898	1.832	0.898	1.832	0.898
ARIMA.C6		1.835	0.899	1.835	0.899	1.835	0.899
ARIMA.C10		1.731	0.848	1.731	0.848	1.731	0.848
FLS		1.920	0.941	1.920	0.941	1.920	0.941
LSTR		2.190	1.073	2.190	1.073	2.190	1.073
Neural.Network		1.729	0.847	1.729	0.847	1.729	0.847
Neural.Network.C		1.642	0.805	1.642	0.805	1.642	0.805
Non.Parametric		2.014	0.987	2.014	0.987	2.014	0.987
Staff's Estimates		1.515	0.742	1.515	0.742	1.515	0.742
COMBINED MODELS							
Shrinkage	Prior						
	Staff's Estimates	4.659	2.283	3.531	1.730	2.866	1.404
g=0	Equal Weights	4.679	2.292	3.514	1.722	3.133	1.535
	Zero Weights	4.679	2.292	3.514	1.722	3.133	1.535
	Staff's Estimates	2.869	1.406	2.375	1.164	2.098	1.028
g=1	Equal Weights	2.938	1.439	2.380	1.166	2.258	1.106
	Zero Weights	3.163	1.550	2.574	1.261	2.470	1.210
	Staff's Estimates	2.045	1.002	1.864	0.913	1.757	0.861
g=3	Equal Weights	2.172	1.064	1.921	0.941	1.892	0.927
	Zero Weights	2.516	1.233	2.233	1.094	2.216	1.086
	Staff's Estimates	1.797	0.881	1.714	0.840	1.654	0.810
g=5	Equal Weights	1.954	0.957	1.798	0.881	1.788	0.876
	Zero Weights	2.333	1.143	2.150	1.053	2.148	1.052
	Staff's Estimates	1.489	0.729	1.526	0.748	1.520	0.745
g=20	Equal Weights	1.697	0.832	1.660	0.813	1.661	0.814
	Zero Weights	2.112	1.035	2.064	1.011	2.067	1.013
	Staff's Estimates	1.388*	0.680	1.462	0.716	1.471	0.721
$g \rightarrow \infty$	Equal Weights	1.619	0.793	1.619	0.793	1.619	0.793
	Zero Weights	2.041	1.000	2.041	1.000	2.041	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

Table 10: Performance of Colombian inflation for 9-month ahead forecasts

		Window Size=20		Window Size=30		Window Size=40	
		RMSE	U-Theil	RMSE	U-Theil	RMSE	U-Theil
INDIVIDUAL MODELS							
ARIMA		2.019	0.904	2.019	0.904	2.019	0.904
ARIMA.C4		1.960	0.877	1.960	0.877	1.960	0.877
ARIMA.C6		1.971	0.882	1.971	0.882	1.971	0.882
ARIMA.C10		1.880	0.841	1.880	0.841	1.880	0.841
FLS		2.129	0.953	2.129	0.953	2.129	0.953
LSTR		2.402	1.075	2.402	1.075	2.402	1.075
Neural.Network		1.904	0.852	1.904	0.852	1.904	0.852
Neural.Network.C		1.792	0.802	1.792	0.802	1.792	0.802
Non.Parametric		2.199	0.984	2.199	0.984	2.199	0.984
Staff's Estimates		1.709	0.764	1.709	0.764	1.709	0.764
COMBINED MODELS							
Shrinkage	Prior						
	Staff's Estimates	4.628	2.071	3.638	1.628	3.375	1.510
g=0	Equal Weights	4.574	2.047	3.628	1.623	3.473	1.554
	Zero Weights	4.574	2.047	3.628	1.623	3.473	1.554
	Staff's Estimates	2.941	1.316	2.497	1.117	2.451	1.097
g=1	Equal Weights	2.954	1.322	2.543	1.138	2.510	1.123
	Zero Weights	3.198	1.431	2.771	1.240	2.745	1.228
	Staff's Estimates	2.185	0.978	2.002	0.896	2.034	0.910
g=3	Equal Weights	2.260	1.011	2.093	0.937	2.096	0.938
	Zero Weights	2.632	1.178	2.446	1.095	2.453	1.097
	Staff's Estimates	1.963	0.878	1.858	0.832	1.907	0.853
g=5	Equal Weights	2.066	0.924	1.969	0.881	1.976	0.884
	Zero Weights	2.476	1.108	2.362	1.057	2.371	1.061
	Staff's Estimates	1.691	0.756	1.681	0.752	1.739	0.778
g=20	Equal Weights	1.841	0.824	1.820	0.814	1.825	0.817
	Zero Weights	2.293	1.026	2.265	1.013	2.270	1.015
	Staff's Estimates	1.602*	0.717	1.621	0.725	1.677	0.751
$g \to \infty$	Equal Weights	1.773	0.793	1.773	0.793	1.773	0.793
	Zero Weights	2.235	1.000	2.235	1.000	2.235	1.000

Source: Authors' calculations. The symbol (*) indicates the smallest RMSE.

B Forecast models

Table 11: Forecast models included in the combination

Forecast model	Abbreviation	Characteristics	Reference
ARIMA by components	$ARIMA.C4$, $ARIMA.C6$, $ARIMA.C10$	Weighted average between ARIMA models with different aggregation levels of the CPI basket	Gmez et al. (2012)
ARIMA	$ARIMA$	ARIMA model	–
Non parametric	$Non.Parametric$	Non-parametric regression model	Rodríguez and Siado (2003)
Neural Networks	$Neural.Network$	Neural Networks model	Misas et al. (2002)
Neural Networks by components	$Neural.Network.C$	Weighted average between an NN for food inflation and an NN for non-food inflation	–
LSTR	$LSTR$	Logistic smooth transition regression model	Jalil and Melo (1999)
FLS	FLS	Flexible Least Squares approach	Melo and Misas (2004)