Mexico: Combining monthly inflation predictions from surveys

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ABSTRACT

We examine the problem of combining Mexican inflation predictions or projections provided by a biweekly survey of professional forecasters. Consumer price inflation in Mexico is measured twice a month. We consider several combining methods and advocate the use of dimension reduction techniques whose performance is compared with different benchmark methods, including the simplest average prediction. Missing values in the database are imputed by two different databased methods. The results obtained are basically robust to the choice of the imputation method. A preliminary analysis of the data was based on its panel data structure and showed the potential usefulness of using dimension reduction techniques to combine the experts' predictions. The main findings are: the first monthly predictions are best combined by way of the first principal component of the predictions available; the best second monthly prediction is obtained by calculating the median prediction and is more accurate than the first one.

KEYWORDS Inflation, economic projections, Mexico

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I
Introduction

By all accounts, Mexico's monetary policy for the last 25 years has been successful in achieving price stability: inflation declined from a monthly average rate of 4.3% during the 1980s to 0.4% during the early years of the twenty-first century. To pursue price stability, Mexico's monetary authorities have used different monetary instruments ranging from exchange-rate control to control of the monetary base and inflation targeting. It was at the end of the 1980s, during a period characterized by high macroeconomic instability that the Mexican monetary authorities decided to generate a biweekly inflation index. The underlying idea of the biweekly data is to incorporate more timely information on price dynamics during volatile periods, so that economic agents, private and public alike, may monitor closely the evolution of prices in the economy in order to make decisions that allow them to optimize the use of their resources.

Frequent inflation forecasting is important for both market and institutional operators. On the one hand, financial market operators tend to update their expectations continuously as new information is released and to use this information to modify their investment strategies; on the other hand, according to Woodford (2003), a timely update of the macroeconomic projection is essential for conducting monetary policy based on market expectations. The accuracy and timeliness of short-run inflation forecasts can thus have a significant influence on these strategies.

The aim of this paper is to generate an efficient combination of inflation forecasts for Mexico. The forecast framework is based on the dimension reduction techniques proposed by Poncela and others (2011), which allow us to obtain a single, more accurate forecast of inflation rather than several individual forecasts. Dimension reduction techniques are used to extract the common information contained in the experts' forecasts in order to produce a consensus forecast and to reveal the level of disagreement between the different forecasters.

It is well known that the combination of forecasts improves forecasting accuracy by taking advantage of the availability of information from multiple sources. Since Bates and Granger's (1969) seminal article, we have seen the development of many combining methods, ranging from the simple average to the most recent alternatives, such as dimension reduction techniques (more information on this topic can be found in Aiolfi, Capistrán and Timmermann (2011), Timmermann (2006) and Newbold and Harvey (2002), among others).

In Mexico, there are two surveys of professional forecasters (SPF): the first one conducted by the central bank of Mexico and the second one by Banco Nacional de Mexico (BANAMEX) (the second largest private bank in Mexico). Since the central bank survey is not publicly available, our forecasts of Mexican inflation are based on data provided by BANAMEX twice a month since 2007. This survey provides regular forecasts of macroeconomic variables relating to investment and production. Here, we only consider one-period-ahead forecasts of monthly inflation from 2007 to 2011. After the first forecast of each month is given, forecasts are revised in response to new information from one survey to the next, thus providing two forecasts for the same month. We have few observations, so the so-called "forecast combination puzzle" (the fact that the sample average of forecasts gives better forecasting results than more sophisticated weighting schemes) might arise. See, for instance, Smith and Wallis (2009) and Aiolfi, Capistrán and Timmermann (2011). We would like to suggest forecast combination procedures that might work better in situations in which the sample is quite short. Our assumption is also that the second forecast is more accurate than the first since it has information about the measured inflation for the first half of the month. Thus there is no need to use mixed frequency methods (such as MIDAS; see, for instance, Ghysles et al., 2004) in which we could combine higher frequency forecasts (biweekly in our case), since we can replace the inflation forecast for the first half of the month by its actual measurement. The following section explains the data provided by this SPF in detail.

There are some papers related to this one; for instance, Poncela and Senra (2006) used two principal

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components to combine United States inflation forecasts and related the second component to the level of expected inflation. The papers by Capistrán and López-Moctezuma (2010a and 2010b) are also related to forecasting of Mexican inflation, but they used the monthly SPF conducted by the central bank of Mexico and their objective was quite different from ours. In their first paper, the main concern was to show that the consensus forecast of a set of macroeconomic variables, among them inflation, does not pass tests of unbiasedness, lack of serial correlation and efficient use of available information. The second paper studies the extent to which information available to forecasters is incorporated efficiently into forecasts of inflation and GDP growth.

The remainder of this paper is organized as follows. Section II introduces the notation used throughout the study and presents information relating to the treatment of missing data, as well as the panel structure of the SPF. Section III outlines the dimension reduction techniques used here to produce a single forecast; while section IV presents the results of applying those techniques to the Mexican data and, lastly, section V presents some concluding remarks.

II

Notation and preparation of data

In the following calculations, p_τ denotes percentage inflation through biweekly variation in the consumer price index (b*CPI*) for $\tau = 2t\text{-}1, 2t,$ where $t = 1, \ldots, T$ indexes months, that is, $p_\tau = 100(\text{bCPI}_\tau - \text{bCPI}_{\tau\text{-}1})/\text{bCPI}_{\tau\text{-}1}$, while monthly percent inflation, $\pi t = 100(\text{CPI}_t - \text{CPI}_{t\text{-}1})/\text{CPI}_{t\text{-}1}$, is based on the monthly *CPI* given by $CPI_t = (\text{b}CPI_{2t\text{-}1} + \text{b}CPI_{2t})/2$. The official inflation figures are released by the National Statistical Institute in charge of calculating the *CPI* by the 9th of each month, for the previous month and by the 24th for the first half of the month. The official figures of πt and p_τ are available at the website: www.inegi.org.mx.

The survey provides predictions of several macroeconomic variables, but we focus on percent inflation predictions made by each of $i = 1, \ldots, N$ experts: the inflation forecast for the first half of the month, $y_{i,\tau|\tau-1}$, and two inflation forecasts, $z_{i,t|\tau}$, which differ according to the time when they are obtained and the information used by the forecasters. To highlight this difference, the notation used for the monthly inflation forecasts $z_{i,t|\tau}$ is as follows: the first subindex t is measured in monthly units while the second one, τ, is measured on a biweekly basis. The three inflation forecasts are obtained as follows: (i) around the 20th of each month (three or four days before the figure for the first half of the month is published), the experts provide an inflation forecast for the first half of that month. Hence, the information up to the second half of the previous month is available to the experts and we denote such a forecast as $y_{i,2t\text{-}1|2(t\text{-}1)}$. At the same time, the experts predict monthly inflation for the current month, which we call the Monthly 1 prediction and denote as $z_{i,t|2(t\text{-}1)}$. Then, (ii) around day six of each month (again three or four days before the official monthly figure is released) the experts provide another monthly inflation prediction for the previous month, say Monthly 2 prediction, and call it $z_{i,t|2t\text{-}1}$.

The forecasts (either for the first half or for the whole month) are always conditioned on information relating to the previous half month and the forecast generation scheme can be seen in table 1. Thus, the SPF provides forecasts for the first half of each month, $y_{i,2t\text{-}1|2(t\text{-}1)}$, as well as monthly predictions $z_{i,t|2(t\text{-}1)}$ and $z_{i,t|2t\text{-}1}$ for months $t = 1, \ldots, T,$ with $T = 60$ (covering the period January 2007-December 2011) and $N = 18$ experts. The number of experts participating in the survey has changed over the years, but there have been approximately 18 regular respondents in each survey (this study does not consider experts who have left the group or those who have entered recently).

Since the original survey database has missing values for all experts at different dates, we decided to employ a systematic estimation procedure to fill in the gaps. In order to check for the sensitivity of results we proposed two different procedures, each of these was selected with the criteria that: (i) it makes use only of the historical record of predictions for the expert in consideration and (ii) it takes into account some salient features of the observed data. The procedure that comes to mind is the easy-to-use optimal missing estimation procedure contained in the Time Series Regression with ARIMA Noise, Missing Observations and Outliers (TRAMO) program (see Gómez and Maravall, 1996), available at the Bank of Spain website. However, this procedure does not satisfy the aforementioned criterion

TABLE 1

Inflation forecasting scheme for the first half of the month and the whole month provided by expert *i*

Period		Percent inflation predictions			Prediction made on the...
Month	Half month	First half	Whole month		
T	τ	$y_{i,2t\text{-}1\mid 2(t\text{-}1)}$	$z_{i,t\mid 2(t\text{-}1)}$	$z_{i,t\mid 2t\text{-}1}$	
1	1	$y_{i,1\mid 0}$	$z_{i,1\mid 0}$	-	20th of month 1
	2	-	-	$z_{i,1\mid 1}$	6th of month 2
2	3	$y_{i,3\mid 2}$	$z_{i,2\mid 2}$	-	20th of month 2
	4	-	-	$z_{i,2\mid 3}$	6th of month 3
…	…	…	…	…	…
T	2T-1	$y_{i,2T\text{-}1\mid 2(T\text{-}1)}$	$z_{i,T\mid 2(T\text{-}1)}$	-	20th of month T
	2T	-	-	$z_{i,T\mid 2T\text{-}1}$	6th of month T+1

Source: prepared by the authors.

(i) and its application was therefore discarded. The first procedure we use is based on the fact that the series of predictions for all the experts do not show a trend, as can be seen in figure 1 for the case of a particular expert (BANAMEX). Thus, the series' first differences can be considered reasonably constant over time, so that the average of past differences provides a reasonable estimate of the current difference for the respective prediction, be it monthly or biweekly. Hence, for the first monthly prediction of the whole month we have

$$z_{i,t\mid 2(t-1)} - z_{i,t-1\mid 2(t-1)-2} = \sum_{j=1}^{t-2} \frac{z_{i,t-j\mid 2(t-j)-2} - z_{i,t-1-j\mid 2(t-j-1)-2}}{t-2} \quad (1)$$

so that the prediction for month t, given data up to time 2(t-1), is given by

$$z_{i,t\mid 2(t-1)} = z_{i,t-1\mid 2(t-1)-2} + \frac{\left(z_{i,t-1\mid 2(t-1)-2} - z_{i,1\mid 0}\right)}{\left(t-2\right)} \quad (2)$$

and for the second monthly prediction we get

$$z_{i,t\mid 2t-1} = z_{i,t-1\mid 2(t-1)-1} + \frac{\left(z_{i,t-1\mid 2(t-1)-1} - z_{i,1\mid 1}\right)}{\left(t-2\right)} \quad (3)$$

Similarly, for a first half of the month prediction we have

$$y_{i,2t-1\mid 2(t-1)} - y_{i,2(t-1)\mid 2(t-1)-1} = \sum_{j=1}^{2(t-1)-1} \frac{y_{i,2t-1-j\mid 2(t-1)-j} - y_{i,2(t-1)-j\mid 2(t-1)-1-j}}{2\left(t-1\right)-1} \quad (4)$$

this leads us to

$$y_{i,2t-1\mid 2(t-1)} = y_{i,2(t-1)\mid 2(t-1)-1} + \frac{\left(y_{i,2(t-1)\mid 2(t-1)-1} - y_{i,1\mid 0}\right)}{2\left(t-1\right)-1} \quad (5)$$

The second procedure arises from inspection of the autocorrelation structure of the official inflation figures. There we see that a seasonal difference of order 12 is required to render the series approximately stationary. Then, since the predictions try to resemble the official figures, we assume the series of predictions of all the experts share the same order of integration. Hence, we use the following expressions to estimate missing values of first and second monthly predictions

$$z_{i,t\mid 2(t-1)} = z_{i,t-12\mid 2t-26} + \sum_{j=1}^{t-13} \frac{\left(z_{i,t-j\mid 2(t-j)-2} - z_{i,t-12-j\mid 2(t-j)-26}\right)}{\left(t-13\right)} \quad (6)$$

and

$$z_{i,t\mid 2t-1} = z_{i,t-12\mid 2t-25} + \sum_{j=1}^{t-13} \frac{\left(z_{i,t-j\mid 2(t-j)-1} - z_{i,t-12-j\mid 2(t-j)-25}\right)}{\left(t-13\right)} \quad (7)$$

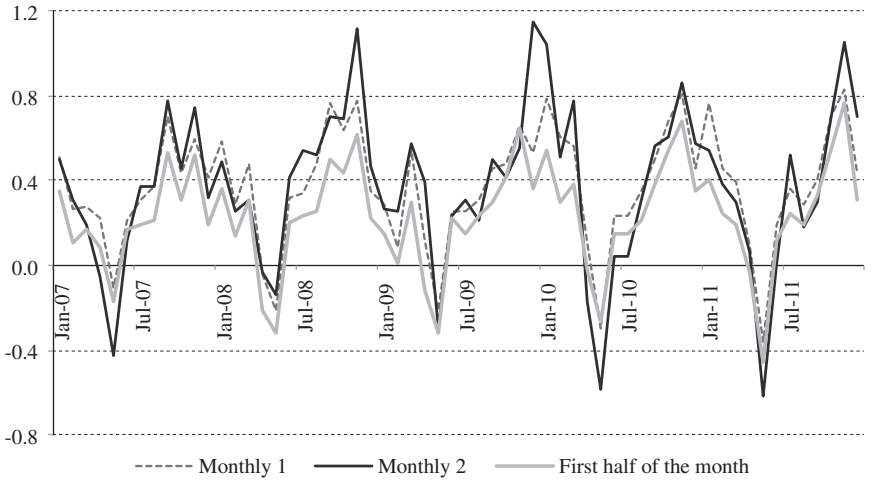
which are valid for $t = 14, \ldots, T$. Similarly, the estimate of a missing prediction for the first half of the month is given by

$$y_{i,2t-1\mid 2(t-1)} = y_{i,2t-13\mid 2t-14} + \sum_{j=1}^{t-7} \frac{\left(y_{i,2(t-j)-1\mid 2(t-j-1)} - y_{i,2(t-j)-13\mid 2(t-j)-14}\right)}{\left(t-7\right)} \quad (8)$$

for $t = 7, \ldots, T$, with the sum equal to *0* if $t = 7$. When the previous expressions cannot be calculated (for $t < 7$), we replaced the missing values with the official figures. An example of the application of method 2 appears in figure 1, where the following missing values were estimated: the first monthly predictions for December 2007 and October 2011; the second monthly predictions for April 2008, December 2008, December 2009 and December 2010; and the first-half-of-the-month predictions for December 2007 and October 2011. In fact, the observations may be said to be missing for all the experts because the survey was not sent out on those dates, for different reasons. Thus, strictly speaking, they are not missing values.

FIGURE 1

First and second monthly forecasts (monthly 1 and monthly 2) and forecasts for the first half of the month
(Percentages)



Source: prepared by the authors.

It is interesting to note that inflation forecasts for the second half of each month, say $y_{i,2t|2t-1}$, can be derived from the monthly forecasts $z_{i,t|2t-1}$, since at the time this forecast is made, the official biweekly inflation figure for the first half of the month, p_{2t-1}, is already available. In the annex we show how these forecasts are derived. However, it should be clear that a prediction for the second half of each month does not really add more information to that in table 1, since it is derived from the second monthly prediction.

Panel data analysis

As mentioned above, the SPF data used in this paper have a panel structure, with 18 individual units —the experts— and 60 time periods, that is, their monthly forecasts (or those for the first half of the month) from January 2007 to December 2011. We can exploit the panel data structure to decompose the prediction made by the expert i at time t in several components. Focusing on the monthly predictions, we can write

$$z_{i,t|\tau} = z_i + z_t + \varepsilon_{i,t|\tau} \quad (9)$$

where $\tau = 2(t-1)$ for the first monthly forecasts and $\tau = 2t-1$ for the second ones.

The first component, z_i, represents the time-invariant individual effect. It captures the intrinsic characteristics of expert i and can be written as

$$z_i = \frac{1}{T}\sum_{t=1}^{T} z_{i,t|\tau} \quad (10)$$

for $i = 1,\ldots,N$. It captures the average level of the predictions made by forecaster i over the sample period. The second component, z_t, is an individual-invariant aggregate effect that captures the common dynamics

of the predictions provided by the experts. It can be written as

$$z_t = \frac{1}{N}\sum_{i=1}^{N}\left(z_{i,t|\tau} - z_i\right) \qquad (11)$$

for $t = 1,\ldots, T$. This component averages across experts the predictions provided by all of them for period t, once the individual effects have been eliminated. The third component is an error term given by $\varepsilon_{i,t|\tau} = z_{i,t|\tau} - z_i - z_t$. It has both time and individual variation, representing the part of the forecast that cannot be isolated either as a time-invariant effect or as an individual-invariant effect.

The individual (time-invariant) effect and the aggregate (individual-invariant) effect are orthogonal by construction. The error term is the residual of the projection of $z_{i,t|\tau}$ into these components, and thus, it is orthogonal to them. The orthogonality of the components allows the variance of the forecast $z_{i,t|\tau}$ to be written as the sum of the variance of each component. This decomposition provides information about the contribution of the individual-specific effects and the common beliefs of the experts to the total variance. The panel decomposition can also be applied to the forecast errors, with analogous interpretation of the components. Taking into account the patterns of the predictions, we have performed this decomposition for the forecast errors. The results are shown in table 2. We show the total variance of the forecast errors, for the two imputation methods we use, for the first monthly predictions (columns 1 and 2) and for the second monthly predictions (columns 3 and 4). We also show the percentage contribution of the individual, aggregate and residual components to this variance.

As expected, the variance of the forecast errors is lower in the second monthly prediction than in the first one, since the experts have more information when they do the second forecast. Regarding the panel decomposition, it is clear that the individual effect does little to explain the total variance of the forecast errors. The most important component is the aggregate effect. The most relevant feature of these results is the information they provide on the potential usefulness of the different forecast combination schemes. In the second monthly predictions, the contribution of the aggregate effect to the variance of the forecast error is lower than in the first ones. In terms of the variance of the forecast, this means that the contribution of the aggregate effect is higher in the second monthly prediction than in the first one. Thus, in the second case almost all of the variability of the forecasts comes from common beliefs, from the commonality among experts, represented by the aggregate effect. We would expect that simple combination schemes, such as the average or the median would perform well. In the first monthly predictions, the contribution of the aggregate effect is higher in the forecast error (i.e., lower in the forecast) and thus, more sophisticated combination schemes, such as the dimension reduction techniques shown in the next section, may have a chance to surpass the simple methods.

TABLE 2

Panel decomposition of the variance of the forecast errors

	Forecast error from			
	First monthly prediction $\pi_t - z_{i,t\|2(t-1)}$		Second monthly prediction $\pi_t - z_{i,t\|2t-1}$	
	Imputation method 1	Imputation method 2	Imputation method 1	Imputation method 2
Total variance	0.044	0.042	0.025	0.026
Contribution to the total variance of the forecast error (*percentage*)				
Individual effect	1.08	1.12	2.54	0.55
Aggregate effect	77.29	78.21	55.52	74.35
Residual term	21.63	20.67	41.94	25.10

Source: prepared by the authors.

III

A summary of dimension reduction techniques

Dimension reduction techniques were introduced for forecast combination by Poncela and Senra (2006) and extended in Poncela and others (2011). The key insight is to see the forecast combination as a way to reduce the dimension from N (the number of forecasters at each period of time) to a single one. This can be done in two steps: in a first step, reduce the number of individual forecasts to just $r \geq 1$ linear combinations of them. Each linear combination is formed as

$$f_{js} = w_{js}'x_s, \qquad j = 1,\ldots, r \tag{12}$$

where w_{js} is the weighting vector for the j-th linear combination for forecast period s and $x_s = (x_{1,s}, \ldots, x_{N,s})'$ is the N-vector of forecasts for time period s with any of the three possible types of forecasts available within the survey. That is, $x_{i,s}$ could be equal to $y_{i,2t-1|2(t-1)}$ if we work with forecasts made for the first half of the month with data up to the previous month; $z_{i,t|2(t-1)}$ if we use the monthly forecasts at t with data up to the previous month; or $z_{i,t|2t-1}$ if we are interested in the previous biweekly forecast of the present month.

In a second step, regress the linear combinations on previous known data of the type to be forecasted, where we can add an intercept for bias correction. In the present case, we used just one linear combination, $r = 1$, since there is a large commonality among forecasters (all of them try to forecast inflation for a certain period), and that is what we want to pick up through dimension reduction techniques. Besides, this choice was also empirically supported by an analysis with up to three components aimed at finding out which option provided the minimum root mean square error (RMSE) forecast. Then,

$$\pi_{s-1} = \beta_0 + \beta_1 f_{s-1} + e_{s-1} \tag{13}$$

where the coefficients are estimated by ordinary least squares (OLS), with observed data up to period $s-1$ in order to generate a true ex-ante forecast for period s. When the variable to be predicted and its forecasts are non-stationary they must be co-integrated as we emphasized when presenting imputation method 2.

With regard to the dimension reduction techniques in the first step of our procedure, we used the following: principal components (PC), both static and dynamic factor models (FM) and partial least squares (PLS). The main difference between PC and PLS is that the former do not take into account the variable to be forecasted when reducing the dimension of the problem to form the linear combination, while the last ones do. A brief review of these methods is given below.

1. Principal components

Let z_s be an $N\times 1$ vector of random variables such that $\text{var}(z_s) = S$ for all $s = 1, 2,\ldots, T$. The first principal component (PC) is defined as the linear combination given by the weighting vector $w = (w_1,\ldots, w_N)'$ such that w is the maximizer of $w'Sw$ subject to $w'w = 1$. A non-stationary PC was proposed by Lee and Carter (1992).

2. Factor models

Poncela and others (2011) demonstrated that simple factor models (FMs) are better suited for forecast combination than more complicated factor schemes, probably because the number of parameters estimated to form the weights for the combination is lower than in more complex factor alternatives. In particular, they found that static FMs performed quite well. When there is one factor, we decompose the x_s vector as the sum of two orthogonal components: a common factor f_s plus an idiosyncratic error η_s, as

$$x_s = Pf_s + \eta_s \tag{14}$$

where P is the $(N\times 1)$ factor loading matrix and $Q = \text{var}(\eta_s)$ is a diagonal matrix.

In dynamic FMs both the common and idiosyncratic components can exhibit dynamic behaviour. We assume auto-regressive (AR) processes for both the common factor and the idiosyncratic component. In other words, the equation for the common factor is

$$\phi(B)f_s = u_s \tag{15}$$

where $\phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ with B the backshift operator, $p < \infty$ and the error u_s comes from a white noise process. The equation for the idiosyncratic components is

$$\Phi(B)\eta_s = v_s \tag{16}$$

where $\Phi(B) = I - \Phi_1 B - \ldots - \Phi_q B^q$ is a diagonal polynomial matrix with $q < \infty$ and v_s comes from a multivariate white noise process with diagonal variance matrix $R = \text{var}(v_s)$. If in dynamic FMs, the idiosyncratic component is white noise, the model is of the type given in Peña and Box (1987). In that case, the variance-covariance structure of the data is

$$C(k) = E(x_s - \mu_x)(x_{s-k} - \mu_x)' = E(f_s - \mu_f)(f_{s-k} - \mu_f)PP' \tag{17}$$

where $\mu_x = E(x_s)$ and $\mu_f = E(f_s)$. Then, the factor loading vector P is associated with the non-zero eigenvalue of the lagged covariance matrices and it is the same for all non-zero lags. If the idiosyncratic components are not white noises, the above decomposition is only approximate. We shall denote this type of FMs by L1FM in the forecasting exercise. This model was extended to the non-stationary case by Peña and Poncela (2004 y 2006) and Lam, Yao and Bathia (2011), while seasonal dynamic FMs were analysed in Alonso and others (2011).

3. Partial least squares

The first partial least squares (PLS) component is built by projecting each forecast in the direction of the observed variable (inflation in our case). The goal is to explicitly take into account the variable being forecast when forming the pooled forecast. In fact, PLS regression analysis assumes that both the X variables (inflation forecasts in our case) and the response variable Y (that is, the variable being forecast) depend on latent variables that are related. Recall that x_s is the N-vector of forecasts for period s and the response is measured inflation π_s. Then,

$$x_s = Pl_s + u_s \tag{18}$$

$$\pi_s = Qm_s + v_s \tag{19}$$

where P and Q are the loadings, l_s and m_s are the latent variables, and u_s and v_s are the error terms. The first PLS component is obtained by projecting the mixed products between the variable being forecasted and the forecast themselves, $\sum_s \pi_s x_{i,s}$, in the direction of the forecasts.

IV
Analysis of the forecasting results

This section presents some of the most important results obtained during a forecasting exercise that mimics a real-time forecasting application with a recursive factor and a parameter estimation. The available predictions cover the period January 2007 through December 2011 (60 months). We decided to start the estimation with 36 pre-sample values and obtained one-step-ahead predictions recursively from there on, so that a forecasting sample of 24 values was used in the exercise. Since the first PC accounts for 89% of total variation and the second PC increases this amount only by 2 percentage points, we decided to use only one component in the combining methods.

For comparative purposes, we also used two common methods for combining forecasts: OLS and the bias corrected mean (BC_mean) of the forecasts at each period s. The OLS forecast combination is found by fitting the multiple linear regression model

$$\pi_s = c + \beta' x_s + e_s \tag{20}$$

where the estimated coefficients found with data up to period s were used to form the true ex ante forecast combination at $s+1$. Similarly, to obtain the BC_mean of the forecasts, we fitted the simple linear regression model

$$\pi_s = c + \beta\overline{x_s} + e_s \tag{21}$$

imposing $\beta = 1$, where $\overline{x_s} = \frac{1}{N}\sum_{i=1}^{N} x_{i,s}$ is the average forecast at time s. The benchmark methods for the

comparisons below are the median and the average of the forecasts.

The results shown in table 3 correspond to the first monthly predictions with missing data imputed with either of the two methods described before. ME denotes the mean prediction error that allows us to appreciate potential biases in the prediction method; RMSE is the root mean square error employed as a measure of absolute precision, since it is expressed in the same units of the inflation rate; and Theil's U is used to establish comparisons of relative precision against the average prediction, considered as the benchmark since it is the simplest combining method. We used precision as the main measure to qualify the predictions and it can be seen that, with $N = 18$, the second imputation method is only slightly better than the first imputation method, so that the imputation method is not really that important. Then, since five experts had up to 20% missing first monthly predictions and up to 35% missing second monthly predictions, we used only the 13 remaining experts for this exercise. In the rightmost part of table 3, we report the results pertaining to $N = 13$, where it becomes clear that reducing the number of experts does not affect the conclusions that can be obtained with the second method of imputation and $N = 18$.

Some conclusions from table 3 follow. According to the MEs, there is no important bias in any of the combining methods. In fact, the signal to noise ratio $|\sqrt{24}\text{ME}/\text{RMSE}|$ similar to a $|t|$ statistic lies in (0.77, 1.40) for the first method of imputation and $N = 18$, in (1.17, 1.40) for the second method of imputation and $N = 18$, and in (0.98, 1.40) for $N = 13$. The highest of these ratios is always obtained with the average, irrespective of the method of imputation or the number of experts used. The RMSEs and Theil's U statistics point towards the combining methods (PC, FM, L1FM and PLS) as the best in terms of accuracy when using the second method of imputation and to OLS when using the first one. As a result, we decided to use the simplest combining method, that is, PC.

As a complement of table 3, we present figure 2 where we can visually appreciate the performance of the combined prediction, as well as the corresponding prediction errors. In this figure, it is clear that there are no systematic patterns present in the prediction errors and that the behaviour is similar whether inflation goes up or down, although it seems that the combined prediction tends to exaggerate in the lowest and highest episodes of inflation. The level and variance of the prediction errors are reasonably stable, showing no evidence of inadequacy.

As with the previous exercise, in table 4 and figure 3, we provide a summary of the results for the combination of second monthly predictions (with missing data imputed with methods 1 and 2). Table 4 reveals that, in general, the MEs are smaller than those in table 3 so that, again, none of the combining methods induce important biases. The RMSEs are also smaller in general than those in table 3 (in a ratio of about 11:18, except for the OLS method, whose performance is poor in comparison with the others), indicating that the combined second monthly predictions are more accurate than the previous ones. This

TABLE 3

First monthly forecasting results[a]

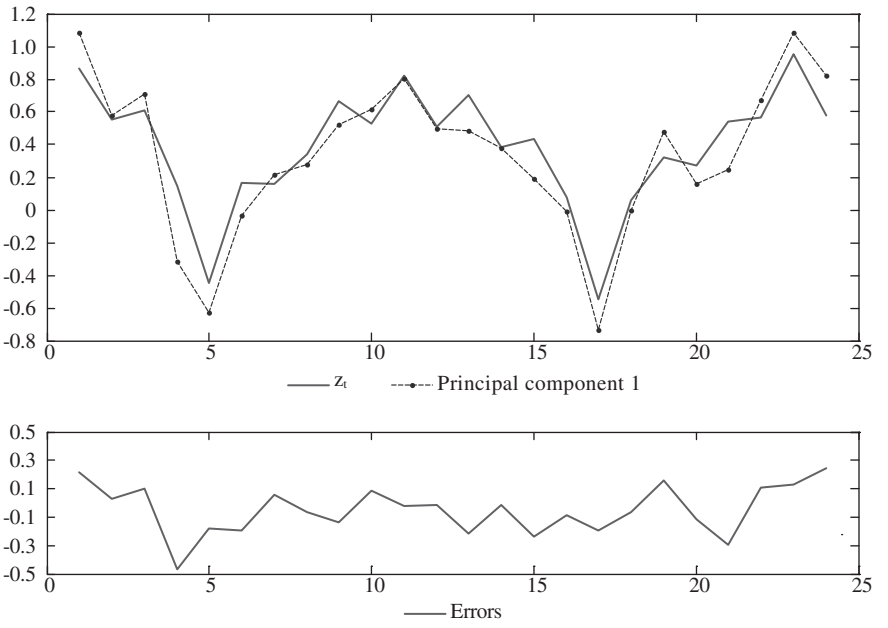
Experts	Imputation method 1			Imputation method 2					
	$N^b = 18$			$N^b = 18$			$N^b = 13$		
Combining methods	ME	RMSE	Theil's U	ME	RMSE	Theil's U	ME	RMSE	Theil's U
Principal components	-0.03	0.19	0.80	-0.05	0.18	0.73	-0.04	0.18	0.75
Factor models	-0.04	0.19	0.76	-0.05	0.18	0.73	-0.05	0.18	0.74
L1FM	-0.03	0.19	0.79	-0.05	0.18	0.73	-0.04	0.18	0.74
Partial least squares	-0.04	0.19	0.78	-0.05	0.18	0.72	-0.04	0.18	0.75
OLS	-0.05	0.18	0.72	0.06	0.23	1.25	0.04	0.20	0.91
Bias corrected_mean	-0.04	0.21	0.98	0.06	0.21	1.00	-0.04	0.21	1.00
Median	-0.05	0.21	0.95	-0.05	0.21	1.00	-0.05	0.20	0.97
Average	-0.06	0.21	-	-0.06	0.21	-	-0.06	0.21	-

Source: prepared by the authors.

[a] Based on information up to the previous month. Forecasting sample = 24.
[b] N = number of experts under consideration.
RMSE: root mean square error.
ME: mean forecast error.
OLS: ordinary least squares.

FIGURE 2

First monthly combined predictions obtained with principal components
(Percentages)



Source: prepared by the authors.

happens mainly for the average and median combining methods, and the only combining method that surpasses the average is the median. On the other hand, figure 3 is clear in showing the closeness between the combined prediction —the median— and the observed inflation. Even the exaggeration that was evident in the combined first monthly predictions is substantially diminished when combining the second monthly predictions.

In summary, on the basis of tables 3 and 4, we may say that the choice of an imputation method is basically irrelevant when comparing the combining methods; nevertheless we prefer to use the second method because it allows us to see things a little bit more clearly. Besides, it does not make sense to discard the data from the five experts that exhibit more missing data than the others because the results of the combining procedures are robust to the presence of these experts (with their missing data imputed by the second imputation method, of course). With respect to the choice of a combining method it is clear that there is room for improvement on the average to combine the experts' predictions. On the one hand, the first monthly predictions are best combined by way of PC, which is chosen because it is easy to use and provides a reasonably simple interpretation of the combination employed. On the other hand, the second monthly predictions should be combined by way of the median, which is also a very simple and easy-to-use technique. These results are in line with the conclusions stemming from the panel decomposition shown in table 2: in short samples, when the contribution of the common beliefs to the total variance of the forecast is higher, the simple methods are more suitable than the multivariate dimension reduction techniques, since they do not convey the estimation of any parameters. On the contrary, when the contribution of the common beliefs to the total variance of the forecast error is higher, dimension reduction techniques seem to outperform simpler benchmarks.

To complement the previous analysis of forecast bias and precision we now focus on forecast accuracy. Table 5 presents Diebold-Mariano test statistics (see Diebold and Mariano, 1995) for the null hypothesis of no difference in the accuracy of two competing forecasts, that is, each one of the combining methods versus the average. Each calculated statistic should be compared with a standard, normal distribution in order to declare statistical significance. The test results for imputation method 2 are all significant at the 5% level for all the dimension reduction techniques, with a negative sign for the first monthly forecast and a positive sign for the second monthly forecast. Since the difference is given by d = forecast square error of the combining method-

TABLE 4

Second monthly forecasting results[a]

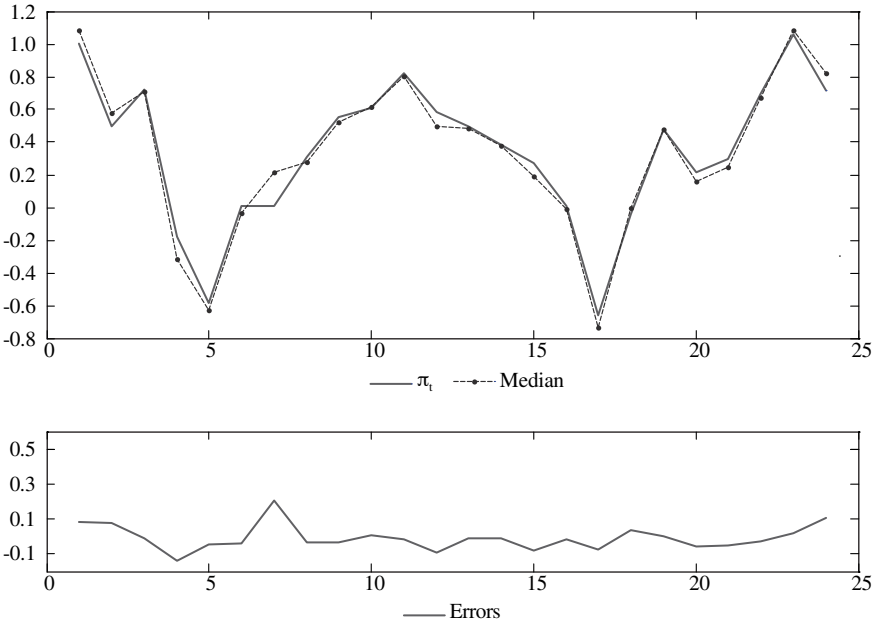
Experts	Imputation method 1			Imputation method 2					
	$N^b = 18$			$N^b = 18$			$N^b = 13$		
Combining methods	ME	RMSE	Theil's U	ME	RMSE	Theil's U	ME	RMSE	Theil's U
Principal components	-0.01	0.12	1.17	-0.01	0.11	1.70	-0.01	0.11	1.99
Factor models	-0.01	0.11	0.99	-0.01	0.10	1.45	-0.01	0.10	1.92
L1FM	-0.01	0.12	1.17	-0.01	0.11	1.72	-0.01	0.11	2.01
Partial least squares	-0.01	0.12	1.17	-0.01	0.11	1.70	-0.01	0.11	1.92
Ordinary least squares	-0.06	0.15	1.85	-0.04	0.17	3.98	-0.05	0.16	4.31
Bias corrected_mean	-0.01	0.11	1.02	-0.01	0.09	1.01	-0.01	0.08	1.00
Median	-0.02	0.10	0.78	-0.01	0.07	0.67	-0.01	0.07	0.89
Average	-0.01	0.11	-	-0.01	0.09	-	-0.02	0.08	-

Source: prepared by the authors.

[a] Information up to the first half of the month. Forecasting sample = 24.
[b] N = number of experts under consideration.
RMSE: root mean square error.
ME: mean forecast error.

FIGURE 3

Second monthly combined with the median predictions
(Percentages)



Source: prepared by the authors.

forecast square error of the average, the results can be interpreted as saying that, with the former forecast, such techniques provide a statistically significant improvement on forecasting accuracy over the average, while the opposite occurs with the latter.

Conversely, with imputation method 1, it is shown that significantly different accuracies occur only for the first monthly forecasts (at the 5% level, except for FM). Besides, the forecast accuracy of the other combining methods employed does not differ from that of the average at the 5% level, except in the case of the second monthly forecasts, where OLS is significantly less accurate than the average for both imputation methods and for the median, which is more accurate than the average at the 5.4% level. Again, these results provide empirical support for the use of reduction techniques for combining the first monthly predictions and for the use of the median for the second monthly predictions.

TABLE 5

Diebold-Mariano test statistics for equal predictive accuracy of each combining method versus the average[a]

Combining methods	First monthly forecasts			Second monthly forecasts		
	Imputation 1	Imputation 2		Imputation 1	Imputation 2	
	$N^b = 18$	$N^b = 18$	$N^b = 13$	$N^b = 18$	$N^b = 18$	$N^b = 13$
Principal component	-2.26	-2.29	-2.24	1.79	2.19	2.18
Factor model	-1.94	-2.28	-2.26	1.79	2.13	2.16
L1FM	-2.21	-2.31	-2.26	1.80	2.20	2.20
Partial least squares	-2.25	-2.32	-2.28	1.79	2.17	2.17
OLS	-1.53	0.34	-0.29	2.48	2.66	3.02
Bias corrected_mean	-0.32	-0.14	-0.10	0.92	0.73	-0.13
Median	-0.95	-0.01	-0.80	-1.89	-1.93	-1.40

Source: prepared by the authors.

[a] Forecasting sample = 24.
[b] N = number of experts.
OLS: ordinary least squares.

V
Conclusions

The main purpose of this study is to show that the information on monthly inflation predictions provided by the SPF carried out by BANAMEX can be best exploited by means of reduction dimension and forecast combination techniques. In fact, two of the simplest techniques used here (PC and median) were shown to outperform the average and therefore also outperform each individual expert's predictions. To establish this fact we considered as the benchmark the average prediction, which is typically hard to beat by more sophisticated combining techniques.

The combined first monthly predictions are seen to be reasonably unbiased and precise, but the second monthly predictions are even better. This suggests that the experts do, indeed, incorporate the most recent information into their second predictions. This is corroborated by the fact that the second monthly predictions do not require an application of dimension reduction techniques in order to get the combined forecast, but just a simple median calculation. Moreover, we do not need to estimate any weighting vector when using the median. In the first survey, the heterogeneity among individuals could be the reason why optimal estimated weights give better forecasting results than assigning the same weight to all the forecasters (and therefore, treating the panellists as homogeneous). In the second survey, the homogeneity across forecasters is greater (as was demonstrated by the panel analysis). In this case, both the sample of forecasts and the median outperform the dimension reduction techniques. In this particular second survey, the median gave the best forecasting results.

ANNEX

Predictions for the second half of the month

To obtain the required forecast we first see that

$$\pi_t = 100\left[\frac{\left(bCPI_{2t-1}+bCPI_{2t}\right)/2-\left(bCPI_{2(t-1)-1}+bCPI_{2(t-1)}\right)/2}{\left(bCPI_{2(t-1)-1}+bCPI_{2(t-1)}\right)/2}\right]$$

so that

$$p_{2t} = \frac{\left(2\pi_t CPI_{t-1}-2p_{2t-1}bCPI_{2(t-1)}-p_{2(t-1)}bCPI_{2(t-1)-1}\right)}{\left(bCPI_{2t-1}\right)}.$$

Thus, for each expert $i = 1, \ldots, N$, we can get predictions for the second half of the month by means of

$$y_{i,2t|2t-1} = \frac{\left(2z_{i,t|2t-1}CPI_{t-1}-2p_{2t-1}bCPI_{2(t-1)}-p_{2(t-1)}bCPI_{2(t-1)-1}\right)}{\left(bCPI_{2t-1}\right)}$$

in such a way that we can obtain a biweekly time series of predictions for the first and second half of each month, that is, for $2t\text{-}1 = 1, 3, \ldots, 2T\text{-}1$, as well as for $2t = 2, 4, \ldots, 2T$.

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