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Forecasting Inflation in Mexico Using Factor Models: Do Disaggregated CPI Data Improve Forecast Accuracy?*

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Abstract
In this paper we apply a dynamic factor model to generate out of sample forecasts for the inflation rate in Mexico. We evaluate the role of using a wide range of macroeconomic variables with particular interest on the importance of using CPI disaggregated data to forecast inflation. Our data set contains 54 macroeconomic series and 243 CPI subcomponents from 1988 to 2008. Our results indicate that: i) Factor models outperform the benchmark autoregressive model at horizons of one, two, four and six quarters, ii) Using disaggregated price data improves forecasting performance, and iii) The factors are related to key variables in the economy such as output growth and inflation.
Keywords: Factor models, inflation forecasting, disaggregate information, principal components, forecast evaluation.
JEL Classification: C22, C53, E37.

Resumen
En este documento se aplica un modelo dinámico de factores para construir pronósticos de inflación en México. Se evalúa el papel que desempeñan diversas variables macroeconómicas, con interés especial en los datos desagregados del Índice Nacional de Precios al Consumidor. Se utiliza una base de datos que contiene 54 series macroeconómicas y 243 componentes del índice de precios, para el periodo de 1988 a 2008. Los resultados indican que: i) El desempeño de los modelos de factores es superior al modelo convencional autorregresivo para horizontes de pronóstico de uno, dos, cuatro y seis trimestres, ii) El uso de datos desagregados del índice de precios mejora el desempeño de los pronósticos, y iii) Los factores están relacionados con variables importantes tales como producción real e inflación.
Palabras Clave: Modelos de factores, pronósticos de inflación, información desagregada, componentes principales, evaluación de pronósticos.

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1 Introduction

Inflation forecasts play an important role to effectively implement an inflation targeting regime (Svensson, 1997). Moreover, many economic decisions, whether made by policymakers, firms, investors, or consumers, are often based on inflation forecasts. The accuracy of these forecasts can thus have important repercussions in the economy.

Our paper focuses on forecasting inflation in Mexico. The forecasting framework is based on the factor model proposed by Stock and Watson (2002a). Factor models incorporate the information content of a wide range of macroeconomic series. Recent advances in data collection have increased the amount of information available for economic analysis. As it is discussed in Bernanke and Boivin (2003), economists have literally thousands of macroeconomic series available from different sources, including data at different frequencies and levels of aggregation, with and without seasonal and other adjustments. This opens the possibility of using a large number of time series to forecast important macroeconomic variables such as inflation in a more accurate and informative way. In spite of this, most empirical studies exploit only a limited amount of information. For example, vector autoregressions typically contain fewer than 10 variables because of the computation burden involved with large models.

The method used in this paper summarizes the information contained in a large number of macroeconomic series into a few predictors of the inflation rate. The underlying assumption in our framework is that a small number of unobservable factors is the driving force behind the series under consideration. This is an appealing feature for forecasting purposes since it allows us to concentrate on a few common factors instead of a large number of explanatory variables. Recent empirical applications on factor models to forecast U.S. and Euro area inflation include Stock and Watson (1999, 2002a), Marcellino et al. (2003), Forni et al. (2003), Angelini et al. (2001), among others. To our knowledge, this is the first application of factor models for Mexico.

Previous applications of factor models including Stock and Watson (2002a) have only considered macroeconomic variables such as output, monetary aggregates and financial variables to forecast the inflation rate. In addition to those macroeconomic variables, our paper exploits the information contained in the subcomponents of the CPI at the highest degree of disaggregation. We investigate whether by pooling this information to construct common factors we can obtain better predictors of the inflation rate. Our dataset contains 243 CPI subcomponents from 1988 to 2008. We also include 54 macroeconomic series including real output, prices, monetary aggregates, financial variables and several components of the balance of payments, providing a complete description of the Mexican economy. Using this information, we estimate the common factors and use those factors to forecast the headline, core and non core inflation rate at the one, two, four and six quarters ahead horizons. Forecasting performances are evaluated through an out-of-sample simulation exercise. The factor forecasts are then compared with the alternative benchmark autoregressive model.

An important determinant of forecasting performance in factor models is the trade off between the information content from adding more data and the estimation uncertainty that is introduced. Boivin and Ng (2006) find that more data to estimate the factors is not necessarily better for forecasting. This suggests the need to evaluate the role of adding the CPI components on forecasting performance. For this purpose, we estimate the model using datasets containing different blocks of variables, and evaluate changes in the forecasting performance when the CPI components are excluded.

We find that factor models have a higher predictive accuracy for headline, core and non-core inflation, in most cases producing out of sample root mean square forecast errors that are one-third less than those of the benchmark model. Our results also suggest that the estimated factors are related to relevant subsets of key macroeconomic variables, such as output and price inflation, which justifies their interpretation as major sources of the Mexican economy. Finally, we provide evidence that using CPI disaggregated data to extract the factors results in more accurate forecasts of the inflation rate.

The reminder of this paper is organized as follows. Section 2 briefly discusses factor models. A description of the data is discussed in Section 3. The forecasting framework is described in Section 4. Section 5 presents the forecasting results. Section 6 concludes the paper.

2 The Factor Model

Suppose we are given time series data on a large number of predictors. Let y_t be the variable to forecast and X_t be the N predictor variables observed for $t = 1, \ldots, T$. We can think of the comovement in these economic time series as arising form a relatively few economic factors. One way of representing this notion is by using a dynamic factor model,

$$X_{it} = \lambda_i(L) f_t + e_{it}, \tag{1}$$

where f_t is a $\overline{r} \times 1$ vector of common factors, $\lambda_i(L)$ are lag polynomials in nonnegative powers of L, representing the factor loadings, and e_{it} is an idiosyncratic disturbance with limited cross sectional and temporal dependence. The factors can be considered as the driving forces of the economy and will therefore be useful for forecasting. If the lag polynomials $\lambda_i(L)$ are modelled as having finite orders of at most q, the factor model can be written as:

$$X_t = \Lambda F_t + e_t, \tag{2}$$

where $F_t = (f_t', \ldots, f_{t-q}')'$ is $r \times 1$, where $r \leq (q+1)\overline{r}$, the ith row of Λ is $\lambda_i = (\lambda_{i0}, \ldots, \lambda_{iq})$ and $e_t = (e_{1t}, \ldots, e_{Nt})'$.

Stock and Watson (2002b) show that, if the number of predictors N and time series T grow large, the factors can be estimated by the principal components of the $T \times T$ covariance matrix of X_t. The method of principal components minimizes the residual sum of squares,

$$V(F, \Lambda) = \min_{\Lambda, F} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i F_t)^2, \tag{3}$$

subject to the normalization that $\frac{F'F}{T} = I_r$, where I_r is a $r \times r$ identity matrix. Concentrating out Λ, the problem is identical to maximizing $tr[F'(XX')F]$. The estimated factor matrix, denoted by $\hat{F}$, is $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix XX'. The corresponding loading matrix is $\hat{\Lambda}' = (\hat{F}'\hat{F})^{-1}\hat{F}'X = \frac{\hat{F}'X}{T}$. See Stock and Watson (2002b) for more details.

Recent empirical applications for the US and Euro Area including Stock and Watson (2002a) and Marcellino et al. (2003) have found important gains from using the factor forecasts based on the method of principal components. An alternative approach to estimate the factors proposed by Forni et al. (2000) is to extract the principal components from the frequency domain using spectral methods. However, Boivin and Ng (2005) conclude that the method proposed by Stock and Watson has smaller forecast errors in the empirical analysis. By imposing fewer constraints, and having to estimate a smaller number of auxiliary parameters, this method appears to be less vulnerable to misidentification, leading to better forecasts than the method of Forni et al. (2000).

We will consider h step ahead forecasts for which the predictive relationship between X_t and y_{t+h} is represented as:

$$y^h_{t+h} = \alpha_h + \beta_h(L)F_t + \gamma_h(L)y_t + \varepsilon_{t+h} \tag{4}$$

where $\gamma_h(L)$ and $\beta_h(L)$ are lag polynomial in non negative powers of L and ε_{t+h} are the forecast errors.

To obtain the forecasts, we use a three step forecast procedure. In the first step, we use the method of principal components to estimate the factors $\hat{F}_t$ from the predictors. In the second step, we use a linear regression to estimate the parameters given in model 4. Finally, the forecast is estimated as $\hat{y}^h_{t+h} = \hat{\alpha_h} + \hat{\beta}_h(L)\hat{F}_t + \hat{\gamma_h}(L)y_t$.

Stock and Watson (2002b) show that the principal components estimators and forecasts are robust to having temporal instability in the model, as long as the instability is relatively small and idiosyncratic (i.e., independent across series).[1]

[1] An empirical application about the stability of the method of principal components using data for the US is investigated in Stock and Watson (2008). The analysis shows that, in spite of the 1984 break for the inflation rate, the factors seem to be well estimated using the full sample period (i.e., 1959-2006).

3 The Data

The dataset consists of 54 quarterly macroeconomic series and 243 CPI subcomponents for the period 1988:I to 2008:IV. The frequency of the dataset is chosen considering that a larger range of macroeconomic variables are available on a quarterly basis than on a monthly basis.

The CPI subcomponents are obtained from Banco de Mexico. Since the CPI data are available on a monthly basis, we use the value for the last month of each quarter as the quarterly value. To form a balanced panel we have only considered the series with available data for the entire period. Therefore, our dataset includes 243 out of the 315 CPI components.

The macroeconomic series are obtained from the OECD main economic indicators. This dataset has been used by Marcellino et al. (2003) to construct forecasts for the Euro Area. The series include output variables (industrial production disaggregated by main sectors), employment, unemployment, prices (consumer and producer indexes), monetary aggregates, interest rates, stock prices, exchange rates and several components of the balance of payments. A complete list of the variables used in this paper is reported in the appendix. The macroeconomic series were selected from a longer list. We select those variables that have been employed in previous studies for the U.S. and Euro area, which are given in the appendix section of Stock and Watson (2002a) and Marcellino et al. (2003). If the series are available with and without seasonal adjustment, only the seasonally adjusted series are selected.

Following Marcellino et al. (2003), the data are preprocessed in several steps before estimating the factors. First, we inspect each variable visually using a time series plot to detect inconsistencies in the series. We drop the series having discrepancies that could not be identified.

Second, the series are transformed to achieve stationarity as required by the factor model. Therefore, we take logs or first differences, as necessary. We apply the same transformation to all variables of the same type. In general, we transform output, prices, exchange rates, monetary aggregates and stock prices in growth rates.[2] Interest rates, unemployment rates and the components of the balance of payments are transformed to first differences. A summary of the transformations applied to the data is reported in the data appendix.[3]

Third, even though most of the series are reported as seasonally adjusted data, we pass all series through a seasonal adjustment procedure. The series are regressed against four seasonal variables and, if the HAC F-test for those coefficients is significant at the 10% level, the series are seasonally adjusted using the Wallis (1974) linear approximation to X-11 ARIMA.

Fourth, the transformed seasonally adjusted series are screened for large outliers, that is, observations exceeding six times the interquartile range from the median. Since most outliers were identified with specific events, such as the 1995 economic crisis, we replace each outlying observation with the median of the series plus six times the interquartile range. Finally, the predictor series are normalized substracting their means and then dividing for their standard deviations.

The dataset described is used to forecast the inflation rate. In addition to forecasting the headline inflation, we will also present the results corresponding to the core and non-core inflation. The core index includes the least volatile components of the CPI. This index is thought to have a lagged response to macroeconomic variables, such as interest rates, exchange rates and wages. On the other hand, the non-core index contains the most volatile components, such as agricultural goods and those administered and concerted prices, such as gasoline, electricity, telephone and local transportation. This index mainly responds to external variables, such as international prices and other domestic non-market forces.

[2]The inflation rate is modelled as being stationary. Chiquiar et al. (2007) find that in 2000 the inflation rate in Mexico has switched from a nonstationary to a stationary process.

[3]Following previous studies in factor forecasting including Stock and Watson (2002a), we have not filtered the series using the method by Hodrick and Prescott (1997). This filtering method has been applied to construct business cycle indices based on common factors by Aiolfi, Catao and Timmermann (2006). However, Cogley and Nason (1995) have shown that when the HP filter is applied to integrated processes, it can generate business cycle fluctuations even if they are not present in the original series, which would potentially misguide our forecasts.

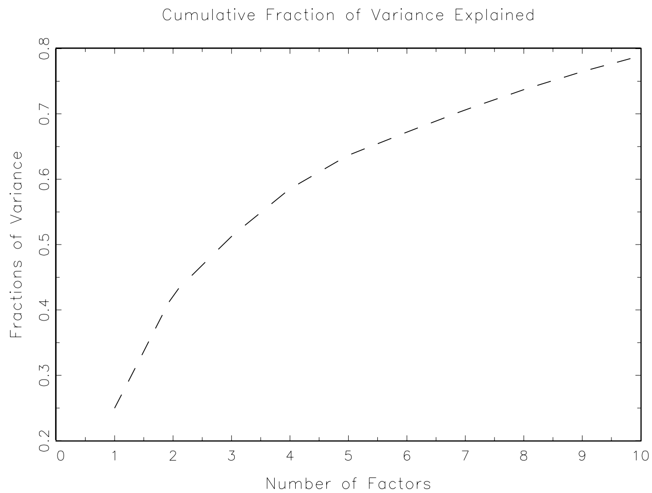

Figure 1: Fractions of Variance

3.1 Estimation and Interpretation of Factors

Figure 1 shows the cumulative percentage of the total variation of the macroeconomic variables explained by the first 10 factors. As can be seen, with only 4 factors we are able to explain about 60% of the variation of the 54 series. One interpretation of this result is that there are only a few important sources of macroeconomic variability.

In order to characterize the first four estimated factors, we regress each variable in the dataset against each factor estimated over the full sample period. High values of R^2 in the resulting regressions suggest that the factor under analysis explains well that particular variable.

The results are shown in Figure 2. The horizontal axis indicates the code of the variables in the dataset as reported in the appendix, while the vertical axis gives the value of the R^2 of the factor corresponding to that particular variable. The vertical lines divide the variables into groups, as in the data appendix. The first factor appears to load primarily on output and employment, the second factor on price inflation, the third factor on trade and the fourth factor on exchange rates. Therefore, the extracted factors from our data are informative and interpretable from an economic point of view. However, it is important to mention that they could be linear combinations of the economic variables.

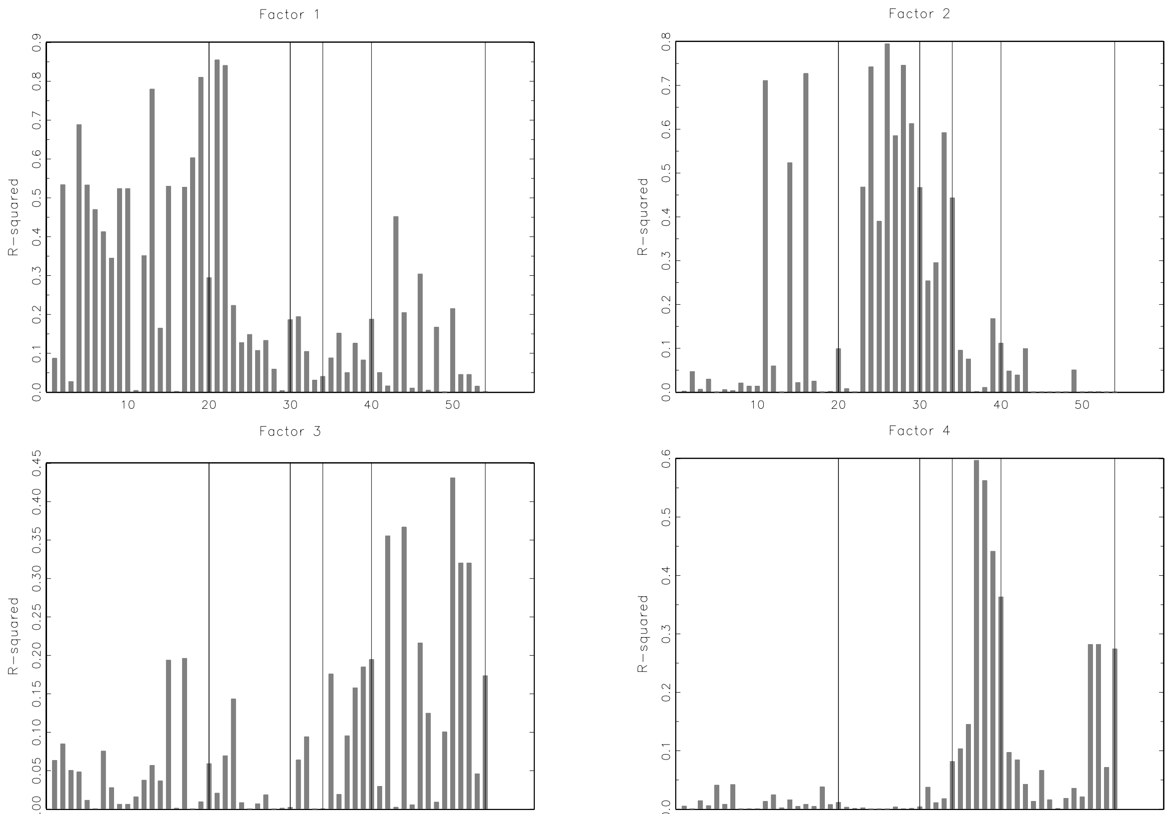

Figure 2: Identification of Factors

4 Forecasting Framework

4.1 Forecasting Design and Forecasting Models

Let π_t be the inflation at time t. We are interested in forecasting π_{t+h}, the annualized value of the inflation rate between t and $t+h$, defined as:

$$\pi_{t+h}^{h} = \frac{400}{h}[\ln(P_{t+h}/P_t)], \tag{5}$$

where P_t is the consumer price index at quarter t. Our factor model is specified as a linear projection of the h-step-ahead inflation rate π_{t+h} onto predictors observed at time t. The forecasting function can be written as:

$$\hat{\pi}_{t+h}^{h} = \hat{\alpha}_h + \sum_{j=1}^{m} \hat{\beta}_{hj}' \hat{F}_{t-j+1} + \sum_{j=1}^{p} \hat{\gamma}_{hj} \pi_{t-j+1} + \hat{\delta}' D_t, \tag{6}$$

where $\hat{F}$ are the estimated factors and the coefficients are defined as in equation 4. The number of factors k, the number of factor lags m and the number of autoregressive lags p are chosen by BIC with $k \leq 3$, $m \leq 4$, and $p \leq 5$.[4] We consider forecasting horizons of h =1, 2, 4 and 6 quarters ahead. The vector D_t contains seasonal dummy variables.[5]

The direct approach used in this paper to construct the forecasts has some advantages over the standard iterative approach. First, it eliminates the need for additional equations to simultaneously forecast the regressors in equation 6. Second, it reduces the potential impact of specification error in the one-step ahead model by using the same horizon for estimation as for forecasting.

In addition to the macroeconomic variables considered by Stock and Watson (2002a), our approach to forecast inflation will extract the factors $\hat{F}_t$ from the the data set comprised of 243 CPI subcomponents. We compare our model with a benchmark univariate autoregressive forecast:

$$\hat{\pi}_{t+h}^{h} = \hat{\alpha}_h + \sum_{j=1}^{p} \hat{\gamma}_{hj} \pi_{t-j+1} + \hat{\delta}' D_t. \tag{7}$$

Capistran et al. (2009) find that the autoregressive model with deterministic seasonality produces forecasts of equal performance compared to those taken from surveys of experts at the monthly frequency. The later in turn outperform other type of inflation forecasts in Mexico according to the evidence (Capistran and Lopez-Moctezuma,

[4]We have also constructed our forecasts including only contemporaneous values of the factors (i.e, m =1), although the results are not reported in this paper. The number of factors was estimated by the Bai and Ng (2002) criterion and the number of autoregressive lags by BIC. Although the model yields similar conclusions, we find that including the lags of the factors results in more accurate forecasts.

[5]Capistran et al. (2009) provide empirical evidence that the seasonal components explain nearly 60% of the total variation of inflation rate during the period 2000-2005. For the core and non core inflation rate, the seasonal component explains above 60% and nearly 50% of their respective total variation.

2008).[6]

To analyze forecasting performance, we conduct a simulated real time forecasting exercise. For each model, we estimate the factors and model parameters to obtain the forecasts of the inflation rate using a rolling scheme. According to Giacomini and White (2006), the rolling windows scheme might be preferable if there are structural changes in the sample.

The out-of-sample forecasts are made for 2005:I to 2008:IV. The forecasting period is chosen considering the structural change in 2000, when the inflation rate switched from a non-stationary to a stationary process. Therefore, one part of the observations for the period when inflation is stationary is included in the estimation window and the remaining part is included in the forecasting period.

The length of the estimation window is 36 quarters. For instance, to construct the one step ahead forecast for 2005:I, we use data from 1996:I to 2004:IV to estimate the factors by the method of principal components. Then, we choose the number of factors, the number of factor lags and the number of autoregressive lags by BIC. Finally, we estimate the coefficients in equation 6 and use them to generate the out of sample forecast for 2005:I. Following the same forecasting procedure, we use data from 1996:II to 2005:I to make a one step ahead forecast for 2005:II. Notice that we drop the first observation and add a new observation at the end of the sample. This exercise is repeated until we obtain the forecast for 2008:IV using data from 1999:IV to 2008:III.[7]

To ensure that the length of the estimation windows and the number of out of sample forecasts is constant for the h steps ahead forecasts, we add $h-1$ observations at the beginning of the estimation period for $h = 2$, 4, and 6 quarters. For instance, to construct the $h = 2$ steps ahead forecast for 2005:I, we use data from 1995:IV to 2004:III. In moving forward the rolling procedure, the models are re-estimated each

[6]For the case of US inflation, Stock and Watson(2007) find that since 1984 it has been difficult to outperform univariate models. Simple univariate models appear to generate relatively smooth and stable forecasts without suffering from large parameter estimation error.

[7]The results are robust for recursive forecasts and for different rolling window lengths. The forecasting results for windows lengths of 34, 38 and 40 quarters can be found in the Appendix B.

period. Therefore, the estimated factors as well as the number of factors, factor lags and autoregressive lags will be specific for each period and forecast horizon.

4.2 Forecast Comparison

To compare the forecast accuracy of the models, we calculate the root mean square error (RMSFE) of the factor models relative to the benchmark autoregressive model. To investigate whether the differences in the forecasting performance of the models are statistically significant, we use a test of equal predictive ability. Commonly used tests such as Diebold and Mariano (1995) can only be applied to compare non-nested models. We apply the test by Giacomini and White (2006) which is also useful to compare nested models.

The Giacomini and White (GW) test is a test of conditional forecasting ability. The test is constructed under the assumption that the forecasts are generated using a moving data window. Consider the loss differential $d_t = e_{1t}^2 - e_{2t}^2$, where e_{it} is the forecast error for forecast i.[8] The null hypothesis of equal forecasting accuracy can be written as:

$$H_0 : E[d_{t+\tau}|h_t] = 0, \tag{8}$$

where h_t is a $p \times 1$ vector of test functions or instruments and τ is the forecast horizon. If a constant is used as instrument, the test can be interpreted as an unconditional test of equal forecasting accuracy. The GW test statistic GW_T can be computed as the Wald statistic:

$$GW_T = T\left(T^{-1}\sum_{t=1}^{T-\tau} h_t d_{t+\tau}\right)' \hat{\Omega}_T^{-1}\left(T^{-1}\sum_{t=1}^{T-\tau} h_t d_{t+\tau}\right) \tag{9}$$

where $\hat{\Omega}_T$ is a consistent HAC estimator for the asymptotic variance of $h_t d_{t+\tau}$. Under the null hypothesis given in equation 8, the test statistic GW_T is asymptotically

[8] The results reported in this paper are based on a MSE loss function which is the most common in the factor forecasting literature. We have also compared our results with those based on a Mean Absolute Error (MAE) loss, yielding similar conclusions. Those can be found in the Appendix B.

Table 1: Forecasting Results: Headline Inflation

Excluded Block	h =1	h =2	h =4	h =6
Output	0.620 (0.018)	0.744 (0.001)	0.656 (0.007)	0.640 (0.006)
Prices	0.617 (0.025)	0.737 (0.001)	0.614 (0.009)	0.620 (0.004)
Mon. aggregates	0.615 (0.025)	0.723 (0.001)	0.616 (0.007)	0.622 (0.004)
Financial Var.	0.606 (0.025)	0.714 (0.000)	0.607 (0.006)	0.693 (0.001)
Bal. of Payments	0.619 (0.025)	0.721 (0.000)	0.664 (0.006)	0.620 (0.004)
CPI Components	0.849 (0.349)	0.848 (0.267)	0.957 (0.573)	0.807 (0.166)
None	0.611 (0.024)	0.719 (0.001)	0.611 (0.006)	0.618 (0.003)
RMSFE AR	2.522	2.188	1.612	1.598

Note: The table reports the RMSFE from using the factors for each dataset relative to the benchmark AR Model. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The RMSFE are calculated using out of sample forecasts from 2005:I-2008:IV with a rolling window of 36 quarters.

distributed as χ^2_p.

5 Forecasting Results

To estimate the model, we organize the data into six blocks: real output variables, price inflation, monetary aggregates, financial variables (interest rates, exchange rates and stock prices), balance of payments and CPI components. Then we follow Forni et al. (2003) to analyze the marginal predictive content of these different groups of variables. That is, we estimate the factor model considering seven alternative datasets: The first group contains all variables except those in the real output block, the second group contains all variables except those in the price block, and so for the first six blocks. The seventh group contains all variables. In this way, we are able to evaluate the change in forecasting performance when each of the six groups of variables is excluded.

Table 1 presents the RMSFE of the factor model estimated for each group of variables relative to the benchmark AR for the case of headline inflation. In general, the factors models outperform the benchmark AR model at all horizons, with an average gain in the range 30-40% with respect to the benchmark.

Results about the role of disaggregated CPI components are of particular interest.

Table 2: Forecasting Results: Core Inflation

Excluded Block	h =1	h =2	h =4	h =6
Output	0.683 (0.141)	0.925 (0.299)	0.828 (0.048)	0.765 (0.000)
Prices	0.875 (0.492)	0.885 (0.250)	0.812 (0.038)	0.748 (0.000)
Mon. aggregates	0.915 (0.656)	0.879 (0.205)	0.840 (0.070)	0.804 (0.000)
Financial	0.765 (0.180)	0.865 (0.172)	0.830 (0.069)	0.819 (0.000)
Bal. of Payments	0.834 (0.189)	0.902 (0.335)	0.811 (0.042)	0.973 (0.830)
CPI Components	1.072 (0.042)	0.986 (0.880)	1.136 (0.149)	0.957 (0.615)
None	0.870 (0.471)	0.876 (0.203)	0.831 (0.063)	0.746 (0.000)
RMSFE AR	1.693	1.705	1.245	1.539

Note: The table reports the RMSFE from using the factors for each dataset relative to the benchmark AR Model. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The RMSFE are calculated using out of sample forecasts from 2005:I-2008:IV with a rolling window of 36 quarters.

Excluding these variables results in a deterioration of forecasting performance at all horizons. The same is not true however, for the rest of the variables, since the forecasting performance sometimes improves when these variables are excluded. In other words, once the CPI components are considered, the real output variables, monetary aggregates, financial variables and the balance of payments components seem to have only a marginal effect on the forecasting ability of the model.

Table 1 also reports the results of the predictive ability test for each model relative to the benchmark AR Model. More specifically, we present the p-values of the Giacomini and White (2006) tests using a constant as an instrument. In general, we reject the null hypothesis of equal predictive ability for those models which include the CPI disaggregated data. However, when the factor model excludes the CPI components, the differences in forecasting performance with respect to the benchmark AR model are not statistically significant at any forecasting horizon.[9] In sum, the results show evidence of superior performance of the factor model over the benchmark AR model provided that the CPI components are included.

The forecasting results for core inflation and non-core inflation are reported in Tables

[9]This conclusion is consistent with the study by Giacomini and White (2006) for the US. The authors find the null hypothesis of equal forecasting accuracy between the factor model that includes only the macroeconomic variables and the AR model cannot be rejected.

Table 3: Forecasting Results: Non-core Inflation

Excluded Block	h =1	h =2	h =4	h =6
Output	0.816 (0.111)	0.650 (0.042)	0.792 (0.006)	0.798 (0.000)
Prices	0.829 (0.128)	0.655 (0.044)	0.778 (0.001)	0.673 (0.000)
Mon. aggregates	0.828 (0.139)	0.652 (0.044)	0.765 (0.007)	0.680 (0.000)
Financial Var.	0.827 (0.133)	0.649 (0.042)	0.779 (0.002)	0.677 (0.000)
Bal. of Payments	0.830 (0.137)	0.652 (0.042)	0.772 (0.001)	0.621 (0.000)
CPI Components	0.855 (0.109)	0.629 (0.066)	1.069 (0.719)	0.883 (0.060)
None	0.828 (0.135)	0.651 (0.043)	0.778 (0.002)	0.678 (0.000)
RMSFE AR	6.814	4.630	2.615	2.117

Note: The table reports the RMSFE from using the factors for each dataset relative to the benchmark AR Model. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The RMSFE are calculated using out of sample forecasts from 2005:I-2008:IV with a rolling window of 36 quarters.

2 and 3 respectively. The results suggest that the factor models consistently outperform the benchmark model at all horizons. The Giacomini and White test rejects the null hypothesis of equal predictive ability for horizons of h = 4 and 6 quarters ahead for the case of core inflation for those models including CPI disaggregated data. For the case of non-core inflation, we obtain the same conclusion for horizons of h = 2, 4 and 6 quarters ahead. According to this evidence, the CPI components are especially useful for medium horizon forecasts of h = 4 and 6 quarters of the core and non-core inflation. For horizons of h = 1 quarter ahead, the non-core index seems to be more difficult to predict since this index is subject to temporary shocks.[10]

In general, the relative performance of the factor models that include the CPI components improves as the forecast horizon increases. The factors capture the common component of the CPI disaggregated data, filtering out the idiosyncratic variations. This common component has a good predictive content especially for the long run component of inflation, resulting in higher improvements over the benchmark model as the horizon increases. In addition, the parameter uncertainty for the factor model is

[10]Notice that for horizons of h = 1 quarters ahead, the null hypothesis of equal predictive ability is rejected for headline inflation, but the same hypothesis is not rejected for core and non-core inflation. As it is shown by Lutkepohl (1984), the forecasts from aggregated series might be superior to the forecasts from the disaggregated series when there the data generation process is unknown due to parameter uncertainty, which is commonly found in empirical applications.

likely to be reduced at longer horizons, resulting in higher improvements.[11]

6 Conclusion

In this paper we use the dynamic factor model proposed by Stock and Watson (2002a) to forecast inflation in Mexico. This method exploits the information contained in a large number of economic series using a few common factors to construct the forecasts. We also investigate the role of using CPI disaggregated data to improve forecasting performance.

We use a large dataset consisting of 243 CPI components and 54 macroeconomic variables to extract the factors and simulate out of sample predictions of inflation. We estimate the model using datasets containing different blocks of variables to evaluate the gains of including the CPI disaggregated data.

Our results indicate that factors model outperform the benchmark AR model at the one, two, four and six quarters ahead horizons, with gains of above 30% in terms of the RMSFE. Those gains are especially strong considering that Capistran et al. (2009) have shown that the autoregressive model with deterministic seasonality performs as well as the surveys of experts. These results are in line with those from previous studies for the US and the Euro area. In addition, we provide evidence that using information from the CPI components contributes to substantial improvements in the accuracy of the inflation forecasts.

The results presented in this paper are promising enough to warrant further research. The Stock and Watson (2002a) methodology can be combined with more structural approaches to improve forecasting still further. The method can also be applied to generate forecasts of inflation at the monthly frequency. The dynamic model proposed by Forni et al (2000) can also be applied to our dataset to compare the forecasting performance of the method used in this paper with an alternative factor model. Finally,

[11]These results are in line with the simulations shown by Boivin and Ng (2005) which suggest that the factor model significantly outperforms the autoregressive model at longer horizons. The results are also consistent with Stock and Watson (2002a).

we can also use the method of weighted principal components explained in Boivin and Ng (2006) which considers the quality of the series to construct the factors.

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Appendix A: Data Description

This appendix lists the variables used to construct the estimated factors. The total number of series is 243 CPI components and 54 macroeconomic variables. The sample period is 1988:I to 2008:IV. The macroeconomic series are obtained from the OECD main economic indicators, and the CPI subcomponents are obtained from Banco de Mexico. The format is as follows: series number, transformation code, and series description. The transformations codes are 1= no transformation, 2=first difference, 5=first difference in logarithms.

Macroeconomic Variables

Real Output

1 . 5 Production in total mining sa - units: 2005=100
2 . 5 Production in total manufacturing sa - units: 2005=100
3 . 5 Production of total energy sa - units: 2005=100
4 . 5 Production of total industry including construction sa - units: 2005=100
5 . 5 Production of total construction sa - units: 2005=100
6 . 5 Total retail trade (Volume) sa - units: 2005=100
7 . 5 Total wholesale trade (Volume) sa - units: 2005=100
8 . 5 Insured workers - units: persons '000
9 . 2 Harmonized unemployment rate: all persons sa - units: %
10 . 2 Unemployment rate: survey-based (all persons) sa - units: %
11 . 5 Monthly earnings: manufacturing sa - units: 2005=100
12 . 5 Real monthly earnings: manufacturing - units: 2005=100
13 . 5 Benchmarked real output - Total - units: MXN mln
14 . 5 Benchmarked real output - Manufacturing - units: MXN mln
15 . 5 Benchmarked real output - Industry - units: MXN mln
16 . 5 Benchmarked real output - Construction - units: MXN mln
17 . 5 Benchmarked real output - Trade, transport and communication - units: MXN mln
18 . 5 Benchmarked real output - Financial and business services - units: MXN mln
19 . 5 Benchmarked real output - Market services - units: MXN mln
20 . 5 Benchmarked real output - Business sector - units: MXN mln

Prices

21 . 5 Benchmarked total labour costs - Manufacturing - units: MXN mln
22 . 5 Benchmarked unit labour costs - Manufacturing - units: 2005=100
23 . 5 Domestic PPI Finished goods - units: 2005=100
24 . 5 CPI All items Mexico - units: 2005=100

25 . 5 CPI Energy - units: 2005=100
26 . 5 CPI All items non-food non-energy - units: 2005=100
27 . 5 CPI Food excl. restaurants - units: 2005=100
28 . 5 CPI Services less housing - units: 2005=100
29 . 5 CPI Housing - units: 2005=100
30 . 5 Cost of construction: social housing - units: 2005=100

Monetary Aggregates

31 . 5 Narrow money (M1a) sa - units: 2005=100
32 . 5 Monetary aggregate M1 sa - units: MXN bln
33 . 5 Broad money (M3) sa - units: 2005=100
34 . 5 Monetary aggregate M4 sa - units: MXN mln

Financial Variables

35 . 2 Rate 91-day treasury certificates - units: % p.a.
36 . 5 Share prices: MSE IPC share price index - units: 2005=100
37 . 5 USD/MXN exchange rate end period - units: USD/MXN
38 . 5 MXN/USD exchange rate monthly average - units: MXN/USD
39 . 5 Real effective exchange rates - CPI Based - units: 2005=100
40 . 5 Real effective exchange rates - ULC Based - units: 2005=100

Balance of Payments

41 . 5 SDR Reserve assets - units: SDR bln
42 . 5 ITS Exports f.o.b. total sa - units: USD bln
43 . 5 ITS Imports f.o.b. total sa - units: USD bln
44 . 2 ITS Net trade (f.o.b. - f.o.b) sa - units: USD bln
45 . 1 Current account as a % of GDP - units: %
46 . 2 BOP Current balance USD sa - units: USD bln
47 . 2 BOP Balance on income sa - units: USD bln
48 . 2 BOP Balance on services sa - units: USD bln
49 . 2 BOP Balance on current transfers sa - units: USD mln
50 . 2 BOP Balance on goods sa - units: USD bln
51 . 2 BOP Cap. and fin. balance incl. reserves - units: USD bln
52 . 2 BOP Financial balance incl. reserves - units: USD mln
53 . 2 BOP Other investment, assets - units: USD mln
54 . 2 BOP Net errors and omissions - units: USD mln

CPI Components

1 . 5 Corn tortilla
2 . 5 Flour
3 . 5 Corn
4 . 5 Sweet bread
5 . 5 White bread
6 . 5 Loaf of Bread
7 . 5 Cakes and pastries
8 . 5 Pasta soup
9 . 5 Popular cookies
10 . 5 Other cookies
11 . 5 Wheat flour
12 . 5 Cereal flakes
13 . 5 Rice
14 . 5 Chicken pieces
15 . 5 Whole chicken
16 . 5 Pork meat
17 . 5 Chops and lard
18 . 5 Loin
19 . 5 Pork Leg
20 . 5 Steak
21 . 5 Ground beef
22 . 5 Pork shoulder
23 . 5 Special cuts of beef
24 . 5 Beef liver
25 . 5 Other beef offal
26 . 5 Ham
27 . 5 Sausages
28 . 5 Chorizo
29 . 5 Other meats
30 . 5 Dried meat
31 . 5 Bacon
32 . 5 Other fish
33 . 5 Shrimp
34 . 5 Mojarra
35 . 5 Other seafood
36 . 5 Sea bass and grouper
37 . 5 Red snapper
38 . 5 Canned tuna and sardines
39 . 5 Other canned fish and seafood
40 . 5 Pasteurized and fresh milk
41 . 5 Milk powder

42 .	5	Evaporated and condensed milk
43 .	5	Cheese
44 .	5	Yogurt
45 .	5	Cream
46 .	5	Manchego or Chihuahua cheese
47 .	5	Other cheeses
48 .	5	Ice cream
49 .	5	American cheese
50 .	5	Butter
51 .	5	Egg
52 .	5	Edible oils and fats
53 .	5	Apple
54 .	5	Bananas
55 .	5	Orange
56 .	5	Avocado
57 .	5	Mango
58 .	5	Papaya
59 .	5	Lime
60 .	5	Grape
61 .	5	Melon
62 .	5	Watermelon
63 .	5	Pear
64 .	5	Peach
65 .	5	Grapefruit
66 .	5	Pineapple
67 .	5	Guava
68 .	5	Tomato
69 .	5	Potato
70 .	5	Onion
71 .	5	Green tomato
72 .	5	Zucchini
73 .	5	Serrano pepper
74 .	5	Carrot
75 .	5	Poblano chile
76 .	5	Lettuce and cabbage
77 .	5	Pea
78 .	5	Chayote
79 .	5	Cucumber
80 .	5	Bean
81 .	5	Dried chile
82 .	5	Other pulses
83 .	5	Packaged juice or nectar
84 .	5	Processed peppers

85 . 5 Packaged vegetables
86 . 5 Mashed tomatoes and canned soups
87 . 5 Other canned fruit
88 . 5 Fruits and vegetables for babies
89 . 5 Sugar
90 . 5 Coffee
91 . 5 Roasted coffee
92 . 5 Soda
93 . 5 Mayonnaise and mustard
94 . 5 Chicken and salt concentrates
95 . 5 Potato chips and similar
96 . 5 Concentrates for soft drinks
97 . 5 Chocolate
98 . 5 Candies, honey and caramel topping
99 . 5 Jelly powder
100 . 5 Pieces of barbequed pork
101 . 5 Roasted Chicken
102 . 5 Barbecue or Birria
103 . 5 Beer
104 . 5 Tequila
105 . 5 Other liquors
106 . 5 Rum
107 . 5 Brandy
108 . 5 Wine
109 . 5 Cigarettes
110 . 5 Shirts
111 . 5 Men's Underwear
112 . 5 Socks
113 . 5 Cotton trousers for men
114 . 5 Suits
115 . 5 Men's Pants
116 . 5 Men's clothes
117 . 5 Blouses for women
118 . 5 Women's Underwear
119 . 5 Stockings and panties
120 . 5 Cotton trousers for women
121 . 5 Pants for women
122 . 5 Sets and other clothing for women
123 . 5 Women's Dresses
124 . 5 Women's Skirts
125 . 5 Children cotton trousers
126 . 5 Pants for children
127 . 5 Shirts and T-shirts for kids

128 . 5 Girl dresses
129 . 5 Children's underwear
130 . 5 Underwear for girls
131 . 5 Baby Costumes
132 . 5 Baby Shirts
133 . 5 Jackets and coats
134 . 5 Hats
135 . 5 Sweater for children
136 . 5 Uniforms for boy
137 . 5 Uniforms for girls
138 . 5 Tennis shoes
139 . 5 Women's Shoes
140 . 5 Men's Shoes
141 . 5 Children's Shoes
142 . 5 Other footwear expenses
143 . 5 Bags, suitcases and belts
144 . 5 Watches, jewelry and fashion jewelry
145 . 5 Rental housing
146 . 5 Electricity
147 . 5 Domestic gas
148 . 5 Domestic service
149 . 5 Kitchen furniture
150 . 5 Dining furniture
151 . 5 Stoves
152 . 5 Water heaters
153 . 5 Sofa sets
154 . 5 Dining Furniture
155 . 5 Mattresses
156 . 5 Bed sets
157 . 5 Refrigerators
158 . 5 Laundry Machine
159 . 5 Irons
160 . 5 Blenders
161 . 5 Stereo equipments
162 . 5 Radios and tape recorders
163 . 5 Bulbs
164 . 5 Matches
165 . 5 Candles
166 . 5 Brooms
167 . 5 Glassware
168 . 5 Cooking Batteries
169 . 5 Plastic utensils for the home
170 . 5 Bedspreads

171 . 5 Sheets
172 . 5 Blankets
173 . 5 Towels
174 . 5 Curtains
175 . 5 Detergents
176 . 5 Soap for washing
177 . 5 Deodorants
178 . 5 Antibiotics
179 . 5 Analgesics
180 . 5 Nutrition
181 . 5 Contraceptives
182 . 5 Gastrointestinal
183 . 5 Expectorants and decongestants
184 . 5 Flu Medicine
185 . 5 Medical Service
186 . 5 Surgery
187 . 5 Dental Care
188 . 5 Haircut
189 . 5 Beauty Salon
190 . 5 Hair products
191 . 5 Lotions and perfumes
192 . 5 Toilet soap
193 . 5 Toothpaste
194 . 5 Personal deodorants
195 . 5 Skin cream
196 . 5 Razors and shavers
197 . 5 Toilet paper
198 . 5 Diapers
199 . 5 Sanitary towels
200 . 5 Paper napkins
201 . 5 Bus
202 . 5 Taxi
203 . 5 Subway or electric transportation
204 . 5 Interstate bus
205 . 5 Air transportation
206 . 5 Cars
207 . 5 Bicycles
208 . 5 Lubrication
209 . 5 Tires
210 . 5 Other parts
211 . 5 Accumulators
212 . 5 Auto Insurance
213 . 5 Road Tax

214 . 5 Car Maintenance
215 . 5 Parking
216 . 5 University
217 . 5 Primary school
218 . 5 High school
219 . 5 Secondary school
220 . 5 Community college
221 . 5 Kindergarten
222 . 5 Textbooks
223 . 5 Other books
224 . 5 Notebooks and folders
225 . 5 Pens, pencils and others
226 . 5 Hotels
227 . 5 Movies
228 . 5 Nightclub
229 . 5 Sports Club
230 . 5 Sports shows
231 . 5 Newspapers
232 . 5 Journals
233 . 5 Toys
234 . 5 Discs and cassettes
235 . 5 Film Equipment
236 . 5 Musical instruments and other
237 . 5 Sporting goods
238 . 5 Snack bars
239 . 5 Restaurants
240 . 5 Bars
241 . 5 Cafeterias
242 . 5 Funerals
243 . 5 License fee and other documents

Appendix B: Forecasting Results using alternative Windows Sizes and MAE Loss Function

Table 4: Forecasting Results: Headline Inflation

Excluded Block	h =1	h =2	h =4	h =6
		Windows size=34 quarters		
Output	0.720 (0.020)	0.762 (0.036)	0.738 (0.034)	0.849 (0.150)
Prices	0.749 (0.020)	0.805 (0.060)	0.734 (0.032)	0.948 (0.542)
Mon. aggregates	0.730 (0.028)	0.797 (0.043)	0.744 (0.036)	0.913 (0.470)
Financial Var.	0.723 (0.025)	0.798 (0.055)	0.726 (0.028)	0.883 (0.333)
Bal. of Payments	0.714 (0.025)	0.785 (0.043)	0.727 (0.025)	0.865 (0.239)
CPI Components	0.968 (0.658)	1.031 (0.803)	1.123 (0.162)	1.284 (0.058)
None	0.723 (0.025)	0.797 (0.054)	0.730 (0.027)	0.882 (0.326)
RMSFE AR	2.454	2.126	1.392	1.030
		Windows size=38 quarters		
Output	0.628 (0.008)	0.831 (0.024)	0.751 (0.028)	0.788 (0.042)
Prices	0.642 (0.010)	0.787 (0.021)	0.716 (0.056)	0.797 (0.031)
Mon. aggregates	0.630 (0.010)	0.774 (0.016)	0.704 (0.040)	0.800 (0.034)
Financial Var.	0.624 (0.011)	0.778 (0.013)	0.674 (0.024)	0.795 (0.032)
Bal. of Payments	0.629 (0.011)	0.778 (0.013)	0.694 (0.029)	0.782 (0.036)
CPI Components	1.303 (0.458)	0.985 (0.858)	1.077 (0.309)	0.979 (0.444)
None	0.623 (0.010)	0.769 (0.012)	0.672 (0.024)	0.793 (0.031)
RMSFE AR	2.522	2.021	1.515	2.622
		Windows size=40 quarters		
Output	0.561 (0.038)	0.690 (0.062)	0.731 (0.097)	0.765 (0.044)
Prices	0.630 (0.066)	0.590 (0.148)	0.572 (0.125)	0.765 (0.037)
Mon. aggregates	0.593 (0.049)	0.739 (0.094)	0.732 (0.095)	0.768 (0.039)
Financial Var.	0.611 (0.060)	0.725 (0.086)	0.716 (0.087)	0.765 (0.038)
Bal. of Payments	0.607 (0.057)	0.742 (0.095)	0.717 (0.085)	0.757 (0.040)
CPI Components	1.560 (0.312)	0.980 (0.776)	1.469 (0.208)	1.176 (0.180)
None	0.616 (0.063)	0.733 (0.089)	0.716 (0.086)	0.765 (0.039)
RMSFE AR	2.248	2.401	1.939	2.982

Note: The table reports the RMSFE from using the factors for each dataset relative to the benchmark AR Model at different forecast horizons h. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The RMSFE are calculated using out of sample forecasts from 2005:I-2008:IV.

Table 5: Forecasting Results: Core Inflation

Excluded Block	h =1	h =2	h =4	h =6
		Windows size=34 quarters		
Output	0.666 (0.122)	0.894 (0.455)	0.781 (0.006)	0.922 (0.322)
Prices	0.744 (0.162)	0.889 (0.280)	0.739 (0.000)	0.805 (0.043)
Mon. aggregates	0.801 (0.271)	0.906 (0.352)	0.759 (0.000)	0.793 (0.025)
Financial Var.	0.800 (0.241)	0.883 (0.244)	0.743 (0.000)	0.788 (0.036)
Bal. of Payments	0.798 (0.182)	0.880 (0.282)	0.731 (0.000)	0.740 (0.006)
CPI Components	0.984 (0.826)	1.006 (0.912)	1.186 (0.207)	1.090 (0.452)
None	0.723 (0.139)	0.884 (0.249)	0.743 (0.000)	0.778 (0.023)
RMSFE AR	1.753	1.691	1.333	1.291
		Windows size=38 quarters		
Output	1.117 (0.296)	0.929 (0.571)	0.896 (0.524)	0.841 (0.002)
Prices	0.885 (0.468)	0.858 (0.282)	0.805 (0.229)	0.875 (0.008)
Mon. aggregates	0.921 (0.588)	0.819 (0.164)	0.785 (0.178)	0.880 (0.013)
Financial Var.	0.935 (0.644)	0.769 (0.033)	0.897 (0.616)	0.834 (0.000)
Bal. of Payments	0.887 (0.413)	0.906 (0.506)	0.802 (0.223)	0.860 (0.009)
CPI Components	1.050 (0.120)	0.870 (0.255)	1.206 (0.075)	0.933 (0.413)
None	0.908 (0.539)	0.934 (0.645)	0.779 (0.175)	0.871 (0.006)
RMSFE AR	1.510	1.620	1.233	2.625
		Windows size=40 quarters		
Output	1.051 (0.792)	0.846 (0.038)	0.942 (0.605)	0.895 (0.001)
Prices	1.024 (0.908)	0.964 (0.754)	0.937 (0.596)	0.898 (0.000)
Mon. aggregates	0.872 (0.481)	0.955 (0.666)	0.945 (0.640)	0.901 (0.000)
Financial Var.	0.928 (0.737)	0.913 (0.274)	0.941 (0.625)	0.899 (0.000)
Bal. of Payments	0.815 (0.457)	0.921 (0.398)	0.913 (0.455)	0.892 (0.001)
CPI Components	1.091 (0.224)	0.878 (0.439)	0.793 (0.189)	1.012 (0.591)
None	0.953 (0.799)	0.935 (0.532)	0.937 (0.595)	0.898 (0.000)
RMSFE AR	1.499	1.670	1.476	2.890

Note: The table reports the RMSFE from using the factors for each dataset relative to the benchmark AR Model at different forecast horizons h. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The RMSFE are calculated using out of sample forecasts from 2005:I-2008:IV.

Table 6: Forecasting Results: Non-core Inflation

Excluded Block	h =1	h =2	h =4	h =6
		Windows size=34 quarters		
Output	0.834 (0.107)	0.712 (0.051)	0.691 (0.000)	0.752 (0.000)
Prices	0.821 (0.106)	0.725 (0.051)	0.696 (0.001)	0.779 (0.007)
Mon. aggregates	0.819 (0.108)	0.723 (0.052)	0.702 (0.000)	0.768 (0.001)
Financial Var.	0.819 (0.103)	0.720 (0.050)	0.687 (0.000)	0.757 (0.000)
Bal. of Payments	0.820 (0.105)	0.719 (0.051)	0.658 (0.000)	0.730 (0.000)
CPI Components	0.930 (0.168)	0.783 (0.101)	1.077 (0.385)	1.074 (0.297)
None	0.820 (0.105)	0.720 (0.050)	0.711 (0.001)	0.772 (0.005)
RMSFE AR	6.846	4.559	2.693	1.948
		Windows size=38 quarters		
Output	0.859 (0.221)	0.704 (0.020)	0.698 (0.068)	0.610 (0.041)
Prices	0.866 (0.220)	0.712 (0.021)	0.644 (0.032)	0.601 (0.045)
Mon. aggregates	0.812 (0.094)	0.710 (0.022)	0.662 (0.033)	0.617 (0.044)
Financial Var.	0.807 (0.083)	0.708 (0.020)	0.683 (0.056)	0.614 (0.044)
Bal. of Payments	0.862 (0.226)	0.710 (0.020)	0.682 (0.059)	0.607 (0.044)
CPI Components	0.956 (0.628)	0.840 (0.253)	0.974 (0.923)	0.703 (0.123)
None	0.863 (0.220)	0.708 (0.020)	0.651 (0.032)	0.615 (0.044)
RMSFE AR	6.559	4.344	2.766	3.269
		Windows size=40 quarters		
Output	0.851 (0.065)	0.642 (0.007)	0.535 (0.103)	0.589 (0.049)
Prices	0.844 (0.160)	0.642 (0.007)	0.553 (0.094)	0.565 (0.041)
Mon. aggregates	0.823 (0.134)	0.642 (0.007)	0.556 (0.095)	0.604 (0.049)
Financial Var.	0.766 (0.031)	0.638 (0.006)	0.514 (0.094)	0.655 (0.051)
Bal. of Payments	0.828 (0.149)	0.640 (0.007)	0.552 (0.092)	0.603 (0.052)
CPI Components	0.942 (0.561)	0.787 (0.103)	0.795 (0.285)	0.885 (0.289)
None	0.837 (0.160)	0.639 (0.007)	0.551 (0.094)	0.602 (0.049)
RMSFE AR	6.827	5.116	3.741	3.451

Note: The table reports the RMSFE from using the factors for each dataset relative to the benchmark AR Model at different forecast horizons h. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The RMSFE are calculated using out of sample forecasts from 2005:I-2008:IV.

Table 7: Forecasting Results using a MAE Loss Function

Excluded Block	h =1	h =2	h =4	h =6
		Headline Inflation		
Output	0.605 (0.012)	0.716 (0.000)	0.631 (0.057)	0.567 (0.001)
Prices	0.606 (0.020)	0.690 (0.000)	0.634 (0.072)	0.617 (0.000)
Mon. aggregates	0.613 (0.019)	0.686 (0.000)	0.638 (0.056)	0.601 (0.000)
Financial Var.	0.584 (0.016)	0.674 (0.000)	0.623 (0.049)	0.703 (0.000)
Bal. of Payments	0.595 (0.018)	0.677 (0.000)	0.676 (0.068)	0.599 (0.000)
CPI Components	0.822 (0.320)	0.806 (0.146)	0.946 (0.592)	0.816 (0.154)
None	0.587 (0.016)	0.680 (0.000)	0.630 (0.052)	0.600 (0.000)
MAE AR	2.095	1.936	1.257	1.262
		Core Inflation		
Output	0.773 (0.220)	0.936 (0.579)	0.771 (0.022)	0.803 (0.027)
Prices	0.923 (0.702)	0.891 (0.355)	0.794 (0.044)	0.808 (0.070)
Mon. aggregates	0.932 (0.741)	0.875 (0.282)	0.841 (0.100)	0.859 (0.118)
Financial Var.	0.813 (0.290)	0.856 (0.218)	0.844 (0.144)	0.909 (0.340)
Bal. of Payments	0.924 (0.623)	0.892 (0.361)	0.796 (0.047)	1.039 (0.795)
CPI Components	1.181 (0.024)	0.899 (0.352)	1.086 (0.271)	0.970 (0.649)
None	0.899 (0.597)	0.884 (0.329)	0.838 (0.104)	0.816 (0.090)
MAE AR	1.240	1.460	1.040	1.164
		Non-core Inflation		
Output	0.767 (0.042)	0.663 (0.025)	0.691 (0.007)	0.666 (0.000)
Prices	0.806 (0.096)	0.661 (0.023)	0.617 (0.000)	0.578 (0.000)
Mon. aggregates	0.806 (0.113)	0.659 (0.026)	0.592 (0.000)	0.592 (0.000)
Financial Var.	0.806 (0.112)	0.655 (0.023)	0.609 (0.000)	0.585 (0.000)
Bal. of Payments	0.811 (0.117)	0.656 (0.022)	0.622 (0.000)	0.540 (0.000)
CPI Components	0.820 (0.100)	0.667 (0.115)	0.981 (0.919)	0.840 (0.032)
None	0.806 (0.112)	0.657 (0.024)	0.607 (0.000)	0.589 (0.000)
MAE AR	5.708	3.495	2.254	1.767

Note: The table reports the MAE from using the factors for each dataset relative to the benchmark AR Model at different forecast horizons h. The p-value for the Giacomini and White test of equal forecasting accuracy is presented in parenthesis. The MAE are calculated using out of sample forecasts from 2005:I-2008:IV.