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Do disaggregated CPI data improve the accuracy of inflation forecasts?☆

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ABSTRACT

In this paper, we evaluate the role of using consumer price index (CPI) disaggregated data to improve the accuracy of inflation forecasts. Our forecasting approach is based on extracting the factors from the subcomponents of the CPI at the highest degree of disaggregation. The data set contains 54 macroeconomic series and 243 CPI subcomponents from 1992 to 2009 for Mexico. We find that the factor models that include disaggregated data outperform the benchmark autoregressive model and the factor models containing alternative groups of macroeconomic variables. We provide evidence that using disaggregated price data improves forecasting performance. The forecasts of the factor models that extract the information from the CPI disaggregated data are as accurate as the forecasts from the survey of experts.

1. Introduction

Inflation forecasts play an important role in the effective implementation of 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 consequently have important repercussions on the economy.

One possible way to improve the accuracy of inflation forecasts is to employ the information contained in the consumer price index (CPI) disaggregated data. However, traditional models such as vector autoregressions would require a large number of parameters to estimate. Most previous literature about predictions of economic aggregates based on disaggregated information has focused on forecasting the component indices and aggregating such forecasts. Some studies in this line include, for example, Fair and Shiller (1990) for United States GNP; Zellner and Tobias (2000) for industrialized countries' GDP growth; Hubrich (2005) for forecasting euro area inflation; Marcellino et al. (2003) for disaggregation across euro countries; Bruneau et al. (2007) for French inflation; Moser et al. (2007) for Austrian inflation; Duarte and Rua (2007) for Portuguese inflation; and Capistran et al. (2010) for Mexican inflation. Among the papers related to inflation forecasting, the majority of them have used a rather low level of disaggregation, with the exception of Duarte and Rua (2007), who considered almost 60 subcomponents. Some other papers, such as Barhoumi et al. (2010), have investigated whether it is more appropriate to use aggregate or disaggregate data to extract the factors using a general definition of disaggregated data. That is, those authors use a broader set of macroeconomic variables rather than disaggregates of the variable to forecast.

In the spirit of the work by Duarte and Rua (2007), we use an approach based on extracting factors from the subcomponents of the CPI at the highest degree of disaggregation. A factor model is an appealing approach to exploit the disaggregated information, as it allows us to concentrate on a few common factors rather than using a large number of predictors. Existing studies on factor models, including Stock and Watson (2002a), have focused on the role of macroeconomic variables such as output, monetary aggregates and financial variables to forecast the inflation rate. In this paper, we will evaluate the role of using a wide range of macroeconomic variables with a special focus on the importance of using CPI disaggregated data to improve forecasting accuracy.

Our paper focuses on forecasting inflation in Mexico. Most of the empirical applications on factor models to forecast inflation, including Stock and Watson (1999, 2002a), Marcellino et al. (2003), Forni et al. (2003), Angelini et al. (2001), among others, have focused on industrialized countries. An exception is Gupta and Kabundi (2011), who applied large factor models to forecast macroeconomic variables in

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the South African economy. To our knowledge, this is the first application of factor models for Mexico. Mexico is a particularly interesting country to analyze as the inflation process in Mexico is different from that of most industrialized countries. In particular, the inflation rate has recently experienced an important transformation with the adoption of an inflation targeting regime. After the high levels of inflation associated with a fiscal dominance problem that occurred during the late 1970s and most of the 1980s, a gradual disinflation process started in the late 1980s and early 1990s. This process was temporarily interrupted during the 1995 financial crisis. However, inflation resumed its downward trend in a relatively short period of time. In fact, the inflation rate decreased from 52% in 1995 to reach levels close to the inflation target of 3% since 2001. For these reasons, our paper represents an opportunity to evaluate the performance of the factor models that have worked well in economies that have experienced price stability for long periods in a country that has experienced high inflation in the past but has reduced its inflation to low and stable levels.

Our data set contains 243 CPI subcomponents from 1992 to 2009. We also include 54 macroeconomic series including real output, prices, monetary aggregates, financial variables and several components of the balance of payments, thus 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, six, eight and twelve 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 and the survey of professional forecasters.

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 are not necessarily better for forecasting. This suggests the need to evaluate the role of adding the CPI components to the forecasting performance. For this purpose, we estimate the model using data sets containing different blocks of variables and evaluate changes in the forecasting performance when the CPI components are included.

We find that factor models that include the CPI components have a higher predictive accuracy for headline, core and non-core inflation, producing out-of-sample root mean square forecast errors that are lower than those of the benchmark model. We provide evidence that using CPI disaggregated data to extract the factors results in more accurate forecasts of the inflation rate. Once the CPI components are included, the factor model outperforms the benchmark model at most of the forecast horizons. Moreover, we find that the model that extracts the factors from the CPI disaggregated data outperforms the models that extract the factors from alternative blocks of macroeconomic variables. When the CPI components are included, the forecasts of the factor model perform as well as the forecasts from the surveys of experts at all forecast horizons. 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 driving forces of the Mexican economy.

The remainder 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 $t=1, \dots, T$. We can think of the co-movement in these economic time series as arising from 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 $\bar{r} \times 1$ 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. In particular, the factors used in this paper will capture the common component of the CPI disaggregated data and the macroeconomic variables, filtering out the idiosyncratic variations. If the lag polynomials $\lambda_i(L)$ are modeled 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 $F_t = (f'_t, \dots, f'_{t-q})'$ is $r \times 1$, where $r \leq (q+1)\bar{r}$, the ith row of Λ is $\lambda_i = (\lambda_{i0}, \dots, \lambda_{iq})$ and $e_t = (e_{1t}, \dots, e_{Nt})'$.

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.[1]

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 simulations as well as in empirical applications. By imposing fewer constraints and having to estimate a smaller number of auxiliary parameters, this method appears to be less vulnerable to misidentification, thus 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:

$$y^h_{t+h} = \alpha_h + \beta_h(L) F_t + \gamma_h(L) y_t + \varepsilon_{t+h} \tag{3}$$

where $\gamma_h(L)$ and $\beta_h(L)$ are lag polynomials 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 F_t from the predictors. In the second step, we use a linear regression to estimate the parameters given in model 3. Finally, the forecast is estimated as $\hat{y}^h_{t+h} = \alpha_h + \beta_h(L)\hat{F}_t + \gamma_h(L) y_t$.

An important issue is the determination of the number of factors r to include in the model. We apply the Bai and Ng (2002) selection criteria to determine the number of factors to be included in the model.[2] These criteria are similar to other information criteria such as AIC and BIC and depend on a trade-off between parsimony and goodness of fit

[1] The method of principal components minimizes the residual sum of squares, $V(F, \Lambda) = min_{\Lambda,F} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i F_t)^2$, 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 $\hat{\Lambda}' = \left(\hat{F}'\hat{F}\right)^{-1} \hat{F}'X = \frac{\hat{F}'X}{T}$. See Stock and Watson (2002b) for more details.

[2] The results reported in the paper use the IC_2 criterion. We have also computed the IC_1 and IC_3 criteria described in Bai and Ng (2002), as well as the method of Alessi et al. (2010), which is designed for cases when T is not large. The results are similar to those reported in this paper.