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Abstract

The combination of individual forecasts is often a useful tool to improve forecast accuracy. The most commonly used technique for forecast combination is the mean, and it has frequently proved hard to surpass. This paper considers factor analysis to combine US inflation forecasts showing that just one factor is not enough to beat the mean and that the second one is necessary. The first factor is usually a weighted mean of the variables and it can be interpreted as a consensus forecast, while the second factor generally provides the differences among the variables and, since our observations are forecasts, it may be related with the dispersion in forecasting expectations and, in a sense, with its uncertainty. Within this approach, the paper also revisits Friedman's hypothesis relating the level of inflation with expectations uncertainty at the beginning of the 21st century.

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1 Introduction

It may be common to have several sources of information that can be used to build different forecasts for the same economic indicator. The combination of such forecasts might be a useful tool to improve forecast accuracy. This paper considers the combination of individual forecasts for US inflation from the Survey of Professional Forecasters, provided since 1990 by the Federal Reserve Bank of Philadelphia.

The combination of individual forecasts is known to improve forecast accuracy since the work of Bates and Granger (1969) and Newbold and Granger (1974), among others. Recent surveys on this topic can be found, for instance, in Clemen (1989), Diebold and Lopez (1996) and Newbold and Harvey (2002). There are a large number of alternatives to combine forecasts. The most commonly used is the equal weights for all the panelists (mean), that has been proved hard to beat by most sophisticated alternatives, like basing the weighting mechanism in the variance-covariance matrix of the forecast errors or ridge regressions, among others, (see, for instance, Stock and Watson, 2004).

One of the most frequently tools used to achieve dimensionality reduction is Factor Analysis. In the context of time series analysis, some references related to this topic are, for instance, Anderson (1963), Priestley *et al.* (1974), Box and Tiao (1977), Geweke and Singleton (1981), Brillinger (1981), Velu *et al.* (1986), Peña and Box (1987), Stock and Watson (2002a), Tiao and Tsay (1989), Reinsel (1993) and Ahn (1997), among others. Some applications using price data are Stock and Watson (1999) and Nath (2004).

As the combination of forecasts can be seen as a dimension reduction problem (from I panelists forecasts to just a single forecast), we consider the use of factor analysis as a tool to extract the common information to produce a consensus forecast and to reveal the degree of disagreement

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amongst the different forecasters. The one factor model has previously been used in forecast combination by Figlewski (1983) and Figlewski and Urich (1983), who focused on forecast errors, and by Chan et al. (1999) who used an approximated factor model for the forecasts from different time series approaches. In this paper we compare the forecast accuracy of one and two factor models to combine forecasts of US inflation. Our endogenous variables in the factor model will be the predictions provided by different panelists. The first factor is usually a weighted mean of the observations (in this case, the individual forecasts), so with this factor we expect similar results to the equal weights approach. The second factor generally provides the differences among the variables and, since our observations are forecasts, our conjecture is that it may be related with the dispersion in forecasting expectations. We will analyze the potential usefulness of the second factor as a proxy of uncertainty in inflation, and check its relationship with the level of inflation and its ability to improve forecasting performance. In this sense, we would revisit Friedman's (1977) hypothesis.

The paper is organized as follows. In section 2 we describe the data. In section 3 we present the factor model and the forecasting combination rule. In section 4 we report the estimation and initial forecasting results of the one and two factor models. In section 5 we explore the capabilities of the second factor as a measure of uncertainty and check its forecasting performance with the previous models. Finally, in section 6 we conclude.

2   The data

This paper considers the individual forecasts for US inflation from the Survey of Professional Forecasters, provided since 1990 by the Federal Reserve Bank of Philadelphia. This Survey gives

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regular inflation forecasts from private sector economists (Wall Street financial firms, banks, economic consulting and other private firms). It is distributed free of charge and its forecasts are widely watched as they are reported in major newspapers like the Wall Street Journal and on financial newswires. The forecasts are anonymous and do not reflect the ideas of the institutions they belong to. It is conducted quarterly and, at each moment in time, it provides the last observed value and forecasts for one to five quarters ahead of the annualized growth rate, that allows us to have real one period ahead forecasts. Other surveys like the Livingston Survey, the Blue Chip Economic Indicators, the National Association of Business Economists (NABE) or the Consensus Forecast do not fill our requirements because of their periodicity or because they provide the forecasts for the mean of the year and, in that case, the forecasts are updated for the same time period but with different information sets.

The Survey of Professional Forecasters was thoroughly analyzed by Zarnowitz and Braun (1993) who found that the forecast combination of many of these individuals provided a consensus forecast with lower average errors than most individual forecasts. Also, the survey performed favorably in forecast accuracy in comparison with a variety of econometric and time series models. For instance, Batchelor and Dua (1996) analyses a variety of proxies for inflation uncertainty based on survey and time-series approaches and they find that survey-based proxies for inflation seem less misleading than the time series proxies. Dutt and Ghosh (2000) have also assessed the rationality of inflation expectations from this survey, though in a weak form. Engsted (1991) and Berk (1999) have found the same conclusion using data from surveys in the UK and the Netherlands, respectively. Most recently, Baghestani (2005) has found that the multiperiod forecasts of the corporate bond yield spread from the Survey of Professional Forecasters are generally unbiased and consistently outperform the comparable ARIMA forecasts.

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3   The model

Let $y_{t+1|t,i}$ be the one period ahead forecast, with information up to time t, given by individual forecaster i, $i = 1, 2, ..., I$. Let $\mathbf{y}_{t+1|t} = (y_{t+1|t,1}, ..., y_{t+1|t,I})'$ be an I-dimensional vector of inflation forecasts. We use a factor model to separate the common information contained across the I forecasts, from the specific one to each forecaster. Consider the $r-$dimensional vector of common factors $\mathbf{m}_t = (m_{t,1}, ..., m_{t,r})', r < I$. Then, it can be assumed that the forecasts can be generated by a linear combination of the common information plus the specific components or error terms, such that

$$\mathbf{y}_{t+1|t} = \Lambda \mathbf{m}_t + \mathbf{e}_t, \tag{1}$$

where Λ is an $I \times r$ factor loading matrix, and $\mathbf{e}_t = (e_{t,1}, ..., e_{t,I})'$ is the vector of **specific errors**. Therefore, all the common correlated information comes through the common factors, $\mathbf{m}_t$, and the vector $\mathbf{e}_t$ contains information specific to each time series forecast. The error terms are assumed to have a diagonal variance-covariance matrix, since if there were any information correlated among two terms in $\mathbf{e}_t$, it should be captured by the term $\Lambda \mathbf{m}_t$. We assume, furthermore, that $\text{cov}(\mathbf{m}_t, \mathbf{e}_t)=0$. As it is explained in Chan et al. (1999), this assumption is not restrictive if joint normality is assumed.

We will follow Forni et al. (2000) and Stock and Watson (2002a) who use the principal components to consistently estimate the dynamic factors. In this case, the factor models are known as *approximate factor models* and the procedure consists in estimating the r common factors through the first r principal components of the variance-covariance matrix of $\mathbf{y}_{t+1|t}$. Approximate factor models have been proven useful in forecasting macroeconomic variables (see Stock and Watson, 2002b and Favero et al., 2004).

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Let $\mathbf{v}_i$ be the eigenvector associated to the i- th largest eigenvalue of the variance-covariance matrix of $\mathbf{y}_{t+1|t}$. Then, the i-th principal component (which is a consistent estimate of the $i-$th common factor) is estimated as $\widehat{m}_{it} = \mathbf{v}_i' \mathbf{y}_{t+1|t}$. Let $\widehat{\mathbf{m}}_t = (\widehat{m}_{1t}, ..., \widehat{m}_{rt})'$ be the first estimated r principal components.

The factor combining rule to produce a single one step ahead forecast $\widehat{y}^*_{t+1|t}$ from all the sources of information is given by

$$\widehat{y}^*_{t+1|t} = \widehat{\beta}_0 + \widehat{\beta}_1 \widehat{m}_{1t} + \cdots + \widehat{\beta}_r \widehat{m}_{rt}, \tag{2}$$

where $\widehat{\beta} = (\widehat{\beta}_0, ..., \widehat{\beta}_r)'$ is the ordinary least squares estimate from the regression

$$\pi_t = \beta_0 + \beta_1 \widehat{m}_{1t-1} + \cdots + \beta_r \widehat{m}_{rt-1} + error_t,$$

with π_t the observed inflation at time t. Notice that $\widehat{y}^*_{t+1|t}$ are true ex-ante forecasts since the coefficients β_i are estimated only with information up to time t and do not include any information of the forecasting sample.

4   Estimation and initial forecasting results

We consider one period ahead forecasts from the first quarter of 1991 until the last quarter of 2002. The initial number of panelists was approximately 30 but it had to be reduced to 14 as we had to choose those individuals who systematically collaborate, that is, they have been in the panel for a minimum of seven years and did not miss more than four consecutive forecasts. This might introduce some selection bias, but it is done in this way in order to treat the missing data and obtain a balanced panel of forecasts. This has been done previously in the literature since it avoids biases due to changes in panel composition. See, for instance, Batchelor and Dua (1996),

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who restrict their analysis to the 21, from 60 original respondents, forecasters who contributed consistently over the sample period they analysed.

As regards missing data, in this setup, they are one step ahead inflation forecasts that were not given by some individuals in a particular period of time. As every individual provides one to four periods ahead forecasts, we can substitute the missing data by the forecast that the same individual provided for that period in the previous quarter, that is, the two period ahead forecast. If this datum were also unavailable, we would consider the three period ahead forecast and so forth. This is the reason why we can only consider panelists that do not miss more than four consecutive forecasts. This procedure is intended to preserve the special features of each forecaster. As an alternative to this option we could take the average of the remaining forecasts at that point of time. But this would annihilate the panelists own characteristics and would provide a downwards bias in the estimation of the forecast dispersion. With these considerations in mind, the final sample considered goes from 1991-III to 2002-IV and for this period both inflation and one period ahead inflation forecasts might be considered as stationary.

The model is estimated with one and two common factors. It is common practice in the literature to take as benchmark, for comparison purposes, the average of forecasts (see, for instance, Batchelor, 2001) and this is the approach we have taken. Our benchmark forecast will be the average forecast of the 14 panelists. Therefore, the procedure to analyze the different forecast combinations is as follows:

1. We use the data, 1991-III to 1999-IV to fit one and two factor models, as well as the benchmark forecast.

2. Then, the fitted models will be used to generate one-step-ahead forecasts for the years in our forecasting sample, 2000-I to 2002-IV. In order to obtain one step-ahead forecasts, *models will*

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be reestimated adding one data point at the time, using all previous data prior to each forecast period.

3. Forecast errors will be computed for each forecast period. The root mean squared errors (RMSEs) by model will be computed to verify the forecasting performance of alternative forecast combinations.

Trying to verify the robustness of our forecasting exercise, a similar procedure is also repeated later, for different estimation and forecasting samples.

To illustrate the estimation results, figure 1 shows the factor loadings for the 1st and 2nd common factors using the whole sample. It can be seen that the first factor is a weighted mean of the observations. The interpretation of the second factor is as follows: in figure 1 it is shown that the second eigenvector gives positive weights to some individuals and negative to others, so this second factor opposes the expectations in forecasting inflation of the different panelists. As our observations as forecasts, a measure of the magnitude of this second factor might be related to the expectations uncertainty on the future of inflation.

To decide on the number of common factors we follow Stock and Watson (2002b) who considered factor models until they account for more than 50% of the total variance. In our case, the first factor accounts for 45% of the variance and the second one adds 13%, so with these two common factors together more than 50% of the total variance is explained.

Figure 1 goes around here.

Table 1 compares the forecasting results in terms of the ratio of the RMSE of the different factor models over the RMSE of the average forecast (benchmark forecast) for different samples. So, a ratio less than one means that the factor model improves the benchmark forecast. The first and second columns show the estimation and forecasting samples while the third and fourth

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show the RMSE ratios of the 1 and 2 common factors forecast combination methods respectively. The fifth column will be analyzed in the next section.

Table 1 should be around here

These results point out that just one factor is not enough to beat the mean, and that the second factor seems necessary to improve forecast accuracy. Nevertheless, in the next section we will explore in more detail the potential contribution of the second factor.

5   Uncertainty in inflation expectations

Friedman (1977) remarks the importance of uncertainty in inflation expectations, suggesting a positive correlation between the level of inflation and inflation uncertainty. Since then, many articles have attempted to measure inflation uncertainty. Engle (1983), Capporale and McKiernan (1997), Belton et al. (2002), or more recently Kontonikas (2004) employ ARCH and GARCH techniques to estimate this uncertainty with mixed results. Bomberger and Frazer (1981), Bomberger (1996) and Shoesmith (2000) interpret inflation uncertainty in terms of the intramarket price variability and Cukierman and Wachtel (1979) and Zarnowitz and Lambros (1987) take the variance of inflationary expectations from survey data as a proxy for the variance of the inflationary process. We proceed as in Cukierman and Wachtel (1979) and Zarnowitz and Lambros (1987) relating the dispersion in the survey data with uncertainty in inflation in the context of our two factors model.

We have seen that the first factor is a weighted mean of the forecasts. The contemporaneous correlation between the first factor and the mean of the forecasts is 0.96. Given such a high correlation between the first factor and the mean it explains why there should not be much

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gain in using just one factor models. The second factor opposes the expectations in forecasting

inflation of different panelists, so a measure of the magnitude of this second factor might be

related to the uncertainty in forecasting. The contemporaneous correlation between the squared

second factor and the variance of the inflationary expectations forecasts is 0.71 which gives and

idea of the strong relationship between both measures; and it is a little smaller between the

absolute value of the second factor and the standard deviation of the inflationary expectations.

During most of the nineties, US inflation rates have become lower and less variable, but rele-

vant events have occurred in our forecasting sample (years 2000, 2001 and 2002) that could have

introduced a higher level of uncertainty in inflation expectations. We propose to test Friedman's

hypothesis introducing the absolute value of the second common factor as an additional regressor

to explain the level of inflation

$$\pi_{t+1} = \beta_0 + \beta_1 \widehat{m}_{1t} + \beta_2 \widehat{m}_{2t} + \beta_3 |\widehat{m}_{2t}| + error_{t+1}. \tag{3}$$

We expect β_3 to be positive if the level of inflation is positively correlated with the level of

uncertainty.

The fifth column of table 1 shows the ratios of the RMSE of the factor model accounting for

uncertainty over the RMSE of the benchmark forecast. The big improvement -the ratio is 0.54-

obtained in the last part of the sample might be seen in the context of greater uncertainty of the

economy during the period analyzed.

For a better understanding of this improvement in forecasting, we present the estimation

results by OLS of the model with the whole sample

$$\widehat{\pi}_{t+1} = \underset{(14.18)}{2.32} + \underset{(5.56)}{0.36}\,\widehat{m}_{1t} - \underset{(2.11)}{0.25}\,\widehat{m}_{2t} + \underset{(1.66)}{0.30}\,|\widehat{m}_{2t}|$$

where t-values are given in parenthesis. The highest correlation coefficient between the estimated

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parameters is negligible (less than 0.1), so $|\widehat{m}_{2t}|$ adds valuable additional orthogonal information when trying to explain inflation. The positive value of the coefficient related to $|m_{2t}|$ might be interpreted in the sense of Friedman's hypothesis meaning the relationship between uncertainty and higher inflation rates. The coefficient for $|m_{2t}|$ is not highly significant, the reduction of the estimated residual standard error goes from 0.754 to 0.738, and the R^2 increases only from 43% to 47% after its inclusion. However, this might be due to the characteristics of the sample period analyzed where inflation during the nineties has been most of the time under control, except perhaps for the last two years, where the forecasting improvement is clear as we have seen previously.

6　Concluding Remarks

Factor analysis seems a reasonable alternative to combine US inflation forecasts, but as it has been seen just one factor may not be enough to beat the forecasts average. A second factor seems necessary to improve forecast accuracy, measured in terms of the RMSE. This second factor is interpreted as a measure of dispersion in inflationary expectations since it gives positive weights to some panelists and negative to others, pointing out the differences amongst them. The magnitude of this dispersion, measured as the absolute value of the second factor is also helpful when forecasting the level of inflation.

Inflation during the nineties became lower and more stable with the absence of economic recessions (except for the one in 1991), but the beginning of the 21st century was shocked by relevant social events, like September 11th terrorist attacks, that introduced higher levels of uncertainty in the whole economy and, therefore, in US inflation. In this sense, we revisited

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Friedman's hypothesis to check if the uncertainty in inflation expectations is nowadays still related to the level of inflation. We have found that including a measure of uncertainty resulted in more accurate forecasts.

Further work should include the extension of our results to forecast other macroeconomic aggregates and check wether factor analysis still appears as a reasonable alternative to combine expectations. Also, it would be desirable to analyse deeper the interpretation of the two first common factors, both, from a theoretical and an empirical points of view.

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8   Table

Table 1

Ratios of the RMSE of the different factor models over the RMSE of the average forecast (benchmark forecast).

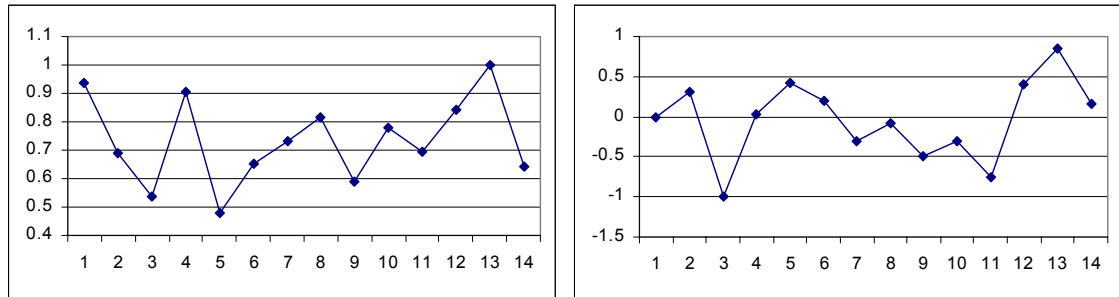| Initial Estimation Sample	Forecasting Sample	1 Factor	2 Factor	2 Factor + Uncert.
1991-III to 1999-IV	2000-I to 2002-IV	1.00	1.00	0.99
1991-III to 2000-IV	2001-I to 2002-IV	0.96	0.94	0.92
1991-III to 2001-IV	2002-I to 2002-IV	1.28	0.89	0.54

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9 Figures

Figure 1: Factor loadings for the 1st and 2nd common factors (left and right panels respectively).

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