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Do Financial Variables Help Forecasting Inflation and real Activity in the Euro Area?

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Abstract

The paper uses a large data set, consisting of 447 monthly macroeconomic time series concerning the main countries of the Euro area to simulate out-of-sample predictions of the Euro area industrial production and the harmonized inflation index and to evaluate the role of financial variables in forecasting. We considered two models which allow forecasting based on large panels of time series : Forni, Hallin, Lippi, and Reichlin (2000, 2001b) and Stock and Watson (1999). Performance of both models were compared to that of a simple univariate AR model. Results show that multivariate methods outperform univariate methods for forecasting inflation at one, three, six, and twelve months and industrial production at one and three months. We find that financial variables do help forecasting inflation, but do not help forecasting industrial production.

Key words : Dynamic Factor Models, Principal Components, Business Cycle, Forecasting, Financial Variables
JEL Classification : C13; C33; C43

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1 Introduction

There is a large literature in finance and macroeconomics suggesting that financial variables are good predictors of inflation and real economic activity. Empirical evidence, however, is mixed and results are not robust with respect to model specification, sample choice, and forecast horizons (for an excellent review of the empirical literature, see Stock and Watson, 2000). This is clearly a puzzle for economic theory and one that is worth investigating.

Our paper exploits the information from a large panel of monthly time series for the six main economies of the Euro area. The panel contains industrial production data (by sectors and nations), prices (by sectors and nations), money aggregates (by nations), a variety of potentially leading variables (survey data and others), and financial variables such as interest rates (nominal and real, for different countries and maturities), spreads, and exchange rates.

The key idea of the paper is to evaluate whether by pooling information from a broad group of financial variables we can obtain good predictions for the Euro-area industrial production and consumer price indexes. In other words, instead of evaluating the predictive contents of single financial variables, we evaluate the predictive contents of suitably selected averages of many of such variables. Forecasting performances at different time horizons are evaluated through an out-of-sample simulation exercise.

The motivation of our strategy is not far from Stock and Watson (2000), who have recently suggested that, by combining forecasts from poorly performing bivariate models, the predictive power of financial variables is rescued. Here, instead of combining bivariate forecasts obtained with different financial variables as predictors, we directly combine information. By pooling forecasts, poor performances are averaged out; by pooling predictors, as we do, noisy informations are averaged out.

Our reference model is the generalized dynamic factor model proposed and discussed in Forni, Hallin, Lippi, and Reichlin (2000, 2001a, 2001b, 2002) and Forni and Lippi (2001), which is specifically designed to handle large panels of dynamically related time series.

In this model, each time series in the panel is represented as the sum of two components : a component which captures most of the multivariate correlation (the *common component*) and a component which is poorly cross-sectionally correlated (the *idiosyncratic component*). The common components in the cross section have, so to speak, 'reduced rank', meaning they are all driven by a few common shocks. Such low dimensionality implies that common components can be consistently estimated and forecasted on the basis of few regressors, i.e. the present and the past of the common shocks, or linear combinations of them.

Unfortunately, the common shocks are not observable. Here we try to capture the relevant information by constructing 'aggregates' of the variables in the panel. The key idea behind this procedure is simply that suitable aggregation kills the idiosyncratic components, which are almost uncorrelated, because of an obvious large-number effect. A similar idea is what motivates the forecasting strategy suggested by Stock and Watson (1999) (SW). The latter method and ours differ by the way the aggregates to be used in the projection are constructed.

In Stock and Watson (1999), the averages used in prediction are simply the static principal components of the variables in the panel. In Forni, Hallin, Lippi, and Reichlin (2001b) (FHLR), forecasting is in two steps. In the first, we estimate the covariance structure of the common and the idiosyncratic components using the procedure suggested in Forni, Hallin, Lippi, and Reichlin (2000). In the second step, we exploit the additional information obtained in the first step about the variance of the common and idiosyncratic components to construct averages which, loosely speaking, place larger weights on the variables having larger 'commonality'.

To evaluate the role of financial variables, we use both FHLR's and SW's methods on a data set which contains different blocks of variables, and evaluate changes in forecasting performance when financial variables are excluded. The performances of the two multivariate methods (FHLR and SW) are also compared with those of simple univariate autoregressive models.

The paper is organized as follows. In Section 2 we introduce the model and provide an illustrative example. In Section 3 we briefly illustrate the data set and the data treatment. Section 4 reports detail of the forecasting exercise and the empirical results. Section 5 concludes.

2 Theory

2.1 The model

We assume that the i-th time series in the panel, possibly after suitable transformation, is a realization from a zero mean, wide-sense stationary process $\{x_{it}; t \in \mathbb{Z}\}$. Each process in the panel is thought of as an element from an infinite sequence of processes, indexed by $i \in \mathbb{N}$. Moreover, all of the x's are co-stationary, i.e. stationarity holds for any of the n-dimensional vector processes $\{\mathbf{x}_{nt} = (x_{1t}, ..., x_{nt})'; t \in \mathbb{Z}\}$, $n \in \mathbb{N}$.

Each variable in the panel decomposes into

$$x_{it} = \chi_{it} + \xi_{jt} = \mathbf{b}_i(L)\mathbf{u}_t + \xi_{it} = \sum_{h=1}^{q} b_{ih}(L)u_{ht} + \xi_{it}, \tag{2.1}$$

where χ_{it} is the *common component*, $\mathbf{u}_t = (u_{1t}, \dots, u_{qt})'$ is a q-dimensional vector of *common shocks*, $\mathbf{b}_i(L) = b_{i1}(L), \dots, b_{iq}(L)$ is a row vector of polynomials of order not larger than s in the lag operator, and the *idiosyncratic component* ξ_{it} is orthogonal to $\mathbf{u}_{t-k}$ for any k and i. The q processes $\{u_{jt}; t \in \mathbb{Z}\}$, $j = 1, \dots, q$ are assumed to be mutually orthogonal (at all leads and lags) white noise processes, with unit variance.

Moreover, we assume that (a) the q non-zero eigenvalues $\lambda_1^{\chi}(\theta), \dots, \lambda_q^{\chi}(\theta)$ of the spectral density matrix of $\boldsymbol{\chi}_{nt} = (\chi_{1t}, \dots, \chi_{nt})'$ go to infinity as $n \to \infty$, a.e. on $[-\pi, \pi)$; (b) the largest eigenvalue $\lambda_1^{\xi}(\theta)$ of the spectral density matrix of $\boldsymbol{\xi}_{nt} = (\xi_{1t}, \dots, \xi_{nt})'$, say is bounded by some real number $\lambda > 0$, a.e. on $[-\pi, \pi)$ for any n.

Finally, in order to ensure consistency of the predictors that we use in the sequel, we need the additional technical assumptions listed in Forni, Hallin, Lippi, and Reichlin (2001b).

For detailed comments on the model we refer to Forni, Hallin, Lippi, and Reichlin (2000, 2001b, 2002). Here we shall limit ourselves to a few remarks.

First, the model generalizes the traditional dynamic factor model of Sargent and Sims (1977) and Geweke (1977), in that the idiosyncratic components are not necessarily orthogonal to each other. This feature is shared with the static approximate factor model of Chamberlain and Rothschild (1983), of which our model provides a dynamic generalization.

Second, the orthogonality assumption is replaced here by assumptions (a) and (b), which, loosely speaking, impose a minimal amount of cross-correlation for the common components and a maximal amount of cross-correlation among the idiosyncratic components. Condition (b), in particular, includes the classic mutual orthogonality as a specific case and guarantees that suitable linear combinations of the idiosyncratic components, like simple unweighted averages, vanish as n goes to infinity. This property will be used below.

Finally, note that the distributed lag operators $\mathbf{b}_i(L)$ acting on the common shocks u_{kt} are quite general. Different variables in the cross-section may react to the same shock with different signs and time delays, giving rise to a wide range of dynamic behaviors. In particular, variables may be 'leading' or 'lagging' in a sense that will be clarified in the sequel.

2.2 A stylized example

To convey the intuition of our forecasting procedure we introduce the highly stylized example

$$x_{it} = \chi_{it} + \xi_{it} = u_{t-s_i} + \xi_{it},$$

where the spectral density matrix of the vector $(\xi_{1t}\ \xi_{2t}\ \cdots\ \xi_{nt})$ is equal to $\mathbf{I}_n$. This corresponds to the case in which the variables ξ are strictly idiosyncratic (i.e. mutually orthogonal). We also assume that s_i is equal to zero, one, or two, this being a stylization of real situations in which some of the variables are lagging ($s_i = 2$), and some others are leading ($s_i = 0$), with respect to a central group of variables ($s_i = 1$), let us call them coincident.

Let us see what happens in this example when taking a simple cross-sectional average of a subset $\mathcal{S}$ of the x_{it}'s. We get

$$X_t = a_0 u_t + a_1 u_{t-1} + a_2 u_{t-2} + \sum_{i \in \mathcal{S}} \xi_{it}/n_{\mathcal{S}},$$

where a_0, a_1 and a_2 are respectively the percentages of leading, coincident and lagging variables in $\mathcal{S}$ (so that $a_1 + a_2 + a_3 = 1$), and $n_{\mathcal{S}}$ denotes the total number of variables in the set.

The first thing to stress is that the variance of the averaged idiosyncratic component $\sum_{i \in \mathcal{S}} \xi_{it}/n_{\mathcal{S}}$ is $n_{\mathcal{S}}/n_{\mathcal{S}}^2 = 1/n_{\mathcal{S}}$, so that this component itself vanishes as $n_{\mathcal{S}} \to \infty$. Other linear combinations, such as weighted averages, would have the same effect.

Now assume that $n_{\mathcal{S}}$ is large, so that the idiosyncratic term is negligible, and that we want to use $X_t = a_0 u_t + a_1 u_{t-1} + a_2 u_{t-2}$ in order to predict, x_{1t+1}, say, which we assume to be coincident. Moreover, let us concentrate on the prediction of the common component χ_{1t+1} of x_{1t+1}; since x_{1t} is coincident, we have $\chi_{1t+1} = u_t$ (we shall come back to the prediction of the idiosyncratic part). Finally, let us assume for illustrative purposes that we do not make use of the lagged values of X_t in prediction, and use instead the static projection

$$\chi_{1t+1} = u_t = AX_t + e_t.$$

Obviously,

$$A = \frac{a_0}{a_0^2 + a_1^2 + a_2^2},$$

while the variance of the residual has a maximum for $a_0 = 0$ and a minimum of zero when $a_1 = a_2 = 0$. In other words, considering the common components $\chi_{it} = u_{t-s_i}$, none of them has any power to predict itself or the common component of leading variables. However, the common components of the leading variables help predicting the common components of the coincident (and lagging) variables.

This example shows that by taking appropriate leading averages we can get rid of idiosyncratic components and successfully predict the common components of the observed series (particularly the non-leading ones).

Our procedure will then be able to obtain suitable aggregates predicting the common components of the European CPI and IP indexes. Clearly, however, our final aim is to forecast the variables themselves, not just their common components. The idiosyncratic term is white noise in the example, but in general is autocorrelated and therefore can be predicted. Accordingly, our ith forecasting equation includes a linear combination of the contemporaneous values of the aggregates (which takes care of the prediction of the common component), along with a linear combination of lagged values of the ith idiosyncratic (accounting for the predictibility of the idiosyncratic component); see Section 4 for details.

2.3 The estimation procedure

In our empirical exercise we shall consider two different methods to obtain the aggregates to be use as predictors. Both methods provide consistent forecasts as the number of observations over time and over the cross-section go to infinity at appropriate rates, as shown in Stock and Watson (1999) and Forni, Hallin, Lippi, and Reichlin (2002). The relative performance of the two methods in small samples are studied in Forni, Hallin, Lippi, and Reichlin (2001b).

- *Stock and Watson (1999) (SW)*

In the first method, recently discussed by Stock and Watson (1999), the averages used in prediction are simply the static principal components of the variables in the panel. In the example above, the principal components (suitably standardized) are $u_{t-k} + \tilde{\xi}_k / a_{kN}$, $k = 0, 1, 2$, where $\tilde{\xi}_k$ is the sum of the idiosyncratic components of the variables lagging k periods and N is the total number of variables in the panel. Since the first principal components are ordered according to the percentages a_j, the first principal component is not necessarily leading, so that three aggregates could be needed in order to obtain good forecasts. In general, we could need a number of principal components equal to the (static) dimension of the common factor space.

- *Forni, Hallin, Lippi, and Reichlin (2001b) (FHLR)*

With the second method, forecasting is in two steps. In the first one we estimate the covariance structure of the common and the idiosyncratic components. More precisely, we estimate the spectral density matrix of the common and the idiosyncratic components by means of a dynamic principal component procedure explained in detail in the Appendix. The theoretical basis of such a procedure is found in Forni, Hallin, Lippi, and Reichlin (2000). Consistency results for the entries of this matrix as both n and T (the number of time series in the panel and the length of the observation period) go to infinity follow from the results in that paper*.

From the estimated spectral density matrices we can obtain all the autocovariances and cross-covariances at all leads and lags by applying the inverse Fourier transform.

In the second step, we compute the generalized principal components of the x's, a construction which involves the (contemporaneous) variance-covariance matrices of the common and the idiosyncratic components estimated in the first step (see the Appendix). We do this because the generalized principal components have an important "efficiency" property : they are the contemporaneous linear combinations of the x's with smallest idiosyncratic-common variance ratio.

The intuition behind this two-step procedure is then to exploit the additional information obtained in the first step about the variance of the common and the idiosyncratic components in order to construct averages which, loosely speaking, place larger weights on the variables having larger 'commonality'.

3 Dataset and data treatment

The database used in this paper has been constructed by the Banca d'Italia research department within a Bank of Italy-CEPR project. Here we used the 447 variables subset fully documented in Cristadoro et al. (2001). We are using monthly time series on key aggregate and sectoral variables for the six main economies in the Euro area—Germany, France, Italy, Spain, the Netherlands, Belgium—and, when available, for the Euro area as a whole. The time span is 1987 :2-2001 :3.

For the purpose of this paper we have organized the data into six blocks :

- block 1 : 118 financial variables (interest rates, nominal and real, spreads and exchange rates);
- block 2 : 42 money aggregates (money stocks for different countries);
- block 3 : 46 industrial production variables (indexes for different countries and industrial sectors);
- block 4 : 139 price variables (producer price indexes and consumer price indexes);
- block 5 : 62 European Commission surveys and price expectations;
- block 6 : 40 others.

*For results on consistency rates see Forni, Hallin, Lippi, and Reichlin (2001a).

We removed outliers from each series using Tramo, a procedure developed by Gomez and Maravall (1996); in particular we focused on transitory changes, level shifts and additive outliers. The same procedure allowed to adjust for working days effects, whenever requested. We did not remove seasonality. To induce stationarity we took first log differences for industrial productions, financial series, monetary aggregates, prices and nominal interest rates and first differences of survey responses; *real* interest rates and the spreads between long and short term nominal interest rates did not need any transformation.

The series were normalized subtracting their meansand then dividing for their standard deviations. This standardization is necessary to avoid overweighting series with large variances when estimating the spectral density.

It should be stressed that the selection of an appropriate set of statistics for monetary and financial markets is a more complex task given the multiplicity of alternative definitions of money and the rapidly evolving range of instruments created by financial operators. Given the central role played in the ECB monetary policy strategy we included the national components of M1, M2, and M3, as well as the corresponding European aggregates. We also constructed real measures of money, by deflating the nominal quantities with the national CPIs. We considered a relatively large collection of interest rates : our panel contains almost 80 nominal interest rates (on Government bills and bonds as well as on private loans); we also constructed interest rate spreads and real interest rates based on Government long and short term maturities. Other financial variables that might contain useful information for future price developments, like stock market prices and exchange rates were also included.

4 Empirical results

The forecasting exercise is a traditional simulated out-of-sample experiment. We first estimated the model using observations from 1987:2 to 1997:1 and we computed forecasts $h = 1, 3, 6, 12$ steps ahead. We then reestimated the model using an additional observation and computed again h step ahead forecasts. We repeated the exercise until all observations, from 1987:2 to 2001:3$-h$, are used in estimation and we averaged mean squared errors at corresponding horizons.

This exercise is carried out (i) for a pure univariate AR model (M0), (ii) for the AR model augmented by the factors of the FHLR method (FHLR), and (iii) for the AR model augmented by the static factors of the SW method (SW). Approaches (ii) and (iii) actually consist in computing the sum of the forecast of the common component as a regression on the factors and the forecast of the idiosyncratic component treated as a univariate autoregressive process. Note that, in the SW model, the observables autoregressive terms should help forecasting the idiosyncratic component while the aggregates help forecasting the common component. In the FHLR model, on the other hand, the forecast of the idiosyncratic is computed by exploiting the first step from which one obtains an estimate of the lagged covariances of the idiosyncratic component.

Our target variables are the harmonized consumer price index for the Euro area and the aggregate industrial production index (both in difference of logs). Denoting by

x_t these target variables, and by v_{rt} and v^*_{rt} the $r \times 1$ vectors of aggregates constructed via the FHLR and SW methods, respectively, the models for these three approaches take the following forms :

$$x_{t+h} = \alpha_0^h(L)x_t + \epsilon_{0t}^h, \tag{M0}$$

$$x_{t+h} = \sum_{r=1}^{g} \beta_{r1}^h v_{rt} + \sum_{j=1}^{m} \gamma_j \xi_{t-j}, \tag{FHLR}$$

$$x_{t+h} = \alpha_1^h(L)x_t + \sum_{r=1}^{d} \beta_{r2}^h v^*_{rt} + \epsilon_{2t}^h. \tag{SW}$$

Models (FHLR) and (SW) have been estimated considering six alternative data sets :

- D1 : all variables;
- D2 : all variables except those in the financial block;
- D3 : all variables except those in the money block;
- D4 : all variables except those in the price block;
- D5 : all variables except those in the IP block;
- D6 : all variables except those in the survey block.

Index k is used below for the results corresponding to each of these data sets ($k = D1, \dots, D6$).

(M0) The pure autoregressive model (M0) with maximum lags $l = 0, \dots, 30$, is estimated by OLS. We obtain the forecasts x_{0T+h}^{Tl}, $h = 1, 3, 6, 12$, $T = 120, \dots, 170 - h$ and compute the mean squared errors

$$MSE_{0h}^{l} = \sum_{T=120}^{170-h} (x_{T+h} - x_{0T+h}^{Tl})^2 / \sum_{T=120}^{170-h} (x_{T+h} - \bar{x}_T)^2,$$

where $\bar{x}_T = T^{-1} \sum_{t=1}^{T} x_t$. We retained the dynamic specification l^* minimizing the MSE.

(FHLR) We computed the forecast of the common component with static ranks $g = 1, \dots, 50$ and the forecast of the idiosyncratic component with lags $j = 1, \dots, m$ for $m = 1, \dots, 30$. For the latter we used the theoretical OLS coefficients based on the lagged covariances resulting from the first step. We computed the mean squared errors

$$MSE_{kh}^{g,m} = \sum_{T=121}^{170-h} (x_{T+h} - x_{k,T+h}^{Tgm})^2 / \sum_{T=120}^{170-h} (x_{T+h} - \bar{x}_T)^2$$

and retained the rank g^* and maximal lag m^* minimizing this MSE.

(SW) For this model we computed the forecasts for static ranks $g = 1, \dots, d$ and $p = 1, \dots, 30$ autoregressive terms. The corresponding mean squared errors are

$$MSE_{kh}^{dp} = \sum_{T=121}^{170-h} (x_{T+h} - x_{k,T+h}^{Tdp})^2 / \sum_{T=120}^{170-h} (x_{T+h} - \bar{x}_T)^2;$$

we retained the rank d^* and the lag p^* minimizing this MSE.

Those three models where estimated on the basis of the data sets $D1$-$D6$, yielding $h-$step ahead forecasts for horizons $h = 1, 3, 6, 12$, with $T = 121, \dots, 170 - h$ and $k = D1, \dots, D6$.

For the FHLR method, two more parameters need to be set for estimation : the number of common factors q and the window size M. Those were set to $q = 2$ and $M = 18$ on the basis of minimum mean squared errors from the whole sample.

Tables 5.1 and 5.2 below illustrate results. The numbers in squared brackets in the first column indicate the optimal lag length l^* for (M0); the numbers in round brackets in the other columns are the optimal static ranks ($g*$ for FHLR and d^* for SW), and the minimal lag length (s^* for FHLR and p^* for SW), respectively.

Table 5.1 : Results for the (M0) and (FHLR) methods

IP							
horizon	M0	D1	D2	D3	D4	D5	D6
h=1	0.721[11]	0.682(6,3)	0.663(10,3)	0.661(5,11)	0.660(5,5)	0.713(5,3)	0.672(16,3)
h=3	0.811[18]	0.772(3,3)	0.822(1,4)	0.745(18,3)	0.779(2,3)	0.777(3,2)	0.764(4,2)
h=6	0.935[18]	0.995(3,3)	0.943(4,3)	0.965(3,1)	0.937(2,3)	0.940(3,3)	0.946(3,3)
h=12	0.912[24]	0.959(6,6)	1.006(4,6)	1.008(1,6)	1.042(3,6)	0.891(12,6)	0.997(6,6)
HICP							
horizon	M0	D1	D2	D3	D4	D5	D6
1	0.659[9]	0.532(10,1)	0.550(25,1)	0.520(8,1)	0.549(10,1)	0.547(13,1)	0.518(15,1)
3	0.660[10]	0.655(5,2)	0.726(13,2)	0.671(4,2)	0.605(25,2)	0.658(5,2)	0.650(5,2)
6	0.678[10]	0.672(2,3)	0.708(1,3)	0.664(2,3)	0.612(3,3)	0.684(2,3)	0.675(1,3)
12	0.854[13]	0.887(5,1)	0.945(1,1)	0.887(4,1)	0.852(3,1)	0.887(5,1)	0.901(1,1)

Table 5.2 : Results for the (M0) and (SW) methods

IP							
horizon	M0	D1	D2	D3	D4	D5	D6
h=1	0.721[11]	0.728(4,11)	0.715(11,11)	0.656(11,11)	0.668(12,11)	0.715(4,3)	0.703(4,11)
h=3	0.811[18]	0.810(2,1)	0.751(6,1)	0.790(6,9)	0.858(2,1)	0.744(5,1)	0.798(1,1)
h=6	0.935[18]	0.960(1,3)	0.845(6,3)	0.940(4,1)	0.949(1,3)	0.942(1,3)	0.970(1,1)
h=12	0.912[24]	0.968(17,7)	0.990(1,7)	0.980(1,7)	1.022(1,7)	0.952(19,8)	0.978(2,7)
HICP							
horizon	M0	D1	D2	D3	D4	D5	D6
h=1	0.659[9]	0.670(10,9)	0.741(1,9)	0.684(50,1)	0.722(1,9)	0.641(14,9)	0.612(35,4)
h=3	0.660[10]	0.622(6,8)	0.632(4,8)	0.663(24,8)	0.642(5,7)	0.671(28,6)	0.647(1,8)
h=6	0.678[10]	0.667(1,6)	0.672(1,6)	0.616(2,6)	0.656(2,6)	0.623(3,6)	0.684(1,6)
h=12	0.854[13]	0.894(4,8)	0.921(5,1)	0.930(1,8)	0.940(1,8)	0.915(4,1)	0.900(7,1)

Careful inspection of the tables shows that in general the models (FHLR and SW) based on multivariate information do well in forecasting both variables at all horizons, and improve over the univariate AR model (M0) for one and three months ahead forecasts. At those horizons, the FHLR method outperfoms the SW one for forecasting inflation. For industrial production, the improvement over the SW method is limited to one month horizon while, at three months, the two methods yield similar performances. The best results, however, are not always obtained with the largest data set (D1).

The SW and FHLR methods lead to similar conclusions about the marginal predictive contents of different blocks of variables. Results about the role of financial variables are of particular interest. Excluding financial variables induces a deterioration of forecasting performance at all horizons (this is clear on the basis of both SW's and FHLR's methods). The same is not true however for industrial production, where results depend on the forecast horizon and are not so easily interpretable.

It is interesting to compare the performances of the financial block with those of the surveys. Both financial and survey data are available with minimal delay, and this is why they are widely used for short term forecasting. Moreover, they both should capture the expectations of consumers and those of business sectors. While, as we have seen, excluding the financial block deteriorates forecasting performance for inflation, this is not true for survey data : excluding them leaves mean squared errors basically unchanged. This indicates that, once financial variables are considered, the marginal role of surveys is nil.

5 Conclusions

We used a large data set, consisting of 447 monthly macroeconomic time series concerning the main countries of the Euro area to simulate out-of-sample predictions of the Euro area industrial production and consumer price indexes and to evaluate the role of financial variables in forecasting.

Our theoretical reference was the forecasting method recently proposed by Forni, Hallin, Lippi, and Reichlin (2001b). This method, which is based on dynamic principal components, allows for exploiting large numbers of time series in prediction problems. We also used an alternative method, based on static principal components, which was suggested by Stock and Watson (1999). Both methods have been used on the basis of the whole panel of time series and excluding, in turn, various blocks of variables. The performances of these two methods were also compared to that of a simple univariate AR model. Results show that (i) the multivariate methods outperform the univariate ones in forecasting inflation at all horizons, and industrial production at one and three months, and (ii) that financial variables do help forecasting inflation, at all horizons, but not industrial production.

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Appendix A : Technical details

In this appendix, we provide a brief outline of the technical details underlying the FHLR forcasting method; for details and a more rigorous presentation, the reader is referred to Forni, Hallin, Lippi, and Reichlin (2001b).

A.1 Estimating the covariances of the common components

The method proceeds in two steps. The first step consists in estimating the spectral density matrix and the covariances of the common components. We start by estimating the spectral density matrix $\mathbf{\Sigma}(\theta)$ of $\mathbf{x}_t = (x_{1t}, \dots, x_{nt})'$. The estimation $\widehat{\mathbf{\Sigma}}(\theta)$ is obtained by using a Bartlett lag-window of size $M = 18$, i.e. by computing the sample autocovariance matrices $\widehat{\mathbf{\Gamma}}_k$, multiplying them by the weights $w_k = 1 - \frac{|k|}{M+1}$ and applying the discrete Fourier transform :

$$\widehat{\mathbf{\Sigma}}_x(\theta) = \frac{1}{2\pi} \sum_{k=-M}^{M} w_k \cdot \widehat{\mathbf{\Gamma}}_k \cdot e^{-i\theta k}.$$

The spectra were evaluated at 101 equally spaced frequencies in the interval $[-\pi, \pi]$, namely, at a grid of frequencies $\theta_h = \frac{2\pi h}{100}$, $h = -50, \dots, 50$.

We then performed the dynamic principal component decomposition (see Brillinger, 1981). For each frequency of the grid, we computed the eigenvalues and eigenvectors of $\widehat{\mathbf{\Sigma}}(\theta)$. By ordering the eigenvalues in descending order for each frequency and collecting values corresponding to different frequencies, the eigenvalue and eigenvector functions $\hat{\lambda}_j(\,.\,)$ and $\hat{U}_j(\,.\,)$, $j = 1, \dots, n$, are obtained. The function $\hat{\lambda}_j(\theta)$ can be interpreted as the (sample) spectral density of the j-th principal component series and, in analogy with standard static principal component analysis, the ratio

$$p_j = \int_{-\pi}^{\pi} \hat{\lambda}_j(\theta) d\theta / \sum_{j=1}^{n} \int_{-\pi}^{\pi} \hat{\lambda}_j(\theta) d\theta$$

represents the contribution of the j-th principal component series to the total variance in the system. Denote by $\mathbf{\Lambda}_q(\theta)$ the diagonal matrix $\mathrm{Diag}(\hat{\lambda}_1(\theta), \dots, \hat{\lambda}_q(\theta))$ of spectral eigenvalues and by $\mathbf{U}_q(\theta)$ the corresponding $(n \times q)$ matrix $(\hat{U}_1(\theta), \dots, \hat{U}_q(\theta))$ of spectral eigenvectors. Then, our estimate of the spectral density matrix of the vector of common components $\boldsymbol{\chi}_t = (\chi_{1t}, \dots, \chi_{nt})'$ is

$$\widehat{\mathbf{\Sigma}}_\chi(\theta) = \mathbf{U}(\theta)\mathbf{\Lambda}(\theta)\tilde{\mathbf{U}}(\theta), \qquad (.2)$$

where tilde denotes complex conjugation. Given a correct choice of q, consistency results for the entries of this matrix as both n and T go to infinity follow from Forni, Hallin, Lippi, and Reichlin (2000); related results on consistency rates can be found in Forni, Hallin, Lippi, and Reichlin (2002). We identified $q = 2$ (as well as $M = 18$) by comparing the forecasting performances of different alternative choices.

An estimate of the spectral density matrix of the vector of idiosyncratic components $\boldsymbol{\xi}_t = (\xi_{1t}, \dots, \xi_{nt})'$ can be obtained as the difference $\widehat{\mathbf{\Sigma}}_\xi(\theta) = \widehat{\mathbf{\Sigma}}(\theta) - \widehat{\mathbf{\Sigma}}_\chi(\theta)$.

Starting from the estimated spectral density matrix we obtain estimates of the covariance matrices of $\boldsymbol{\chi}_t$ at different leads and lags by using the inverse discrete Fourier transform

$$\widehat{\mathbf{\Gamma}}_{\chi k} = \frac{2\pi}{101} \sum_{h=-50}^{50} \widehat{\mathbf{\Sigma}}_{\chi}(\theta_h) e^{i\theta_h k}.$$

A.2 Estimating the static factors

Starting from the covariances estimated in the first step, we estimate the static factors as linear combinations of (the present of) the observable variables x_{jt}, $j = 1, \dots, n$. Indeed, as observed in the main text, the static factors u_{ht-k}, $h = 1, \dots, q$, $k = 1, \dots, s$ appearing in representation (2.1) are not identified without imposing additional assumptions and therefore cannot be estimated. This however is not a problem, since we need only a set of $r = q(s+1)$ variables forming a basis for the linear space spanned by the u_{ht}'s and their lags. We then can obtain $\hat{\chi}_{jt}$ by projecting χ_{jt} on such factors.

Our strategy is to take the first r generalized principal components of $\widehat{\mathbf{\Gamma}}_{\chi 0}$ with respect to the diagonal matrix having on the diagonal the variances of the idiosyncratic components ξ_{jt}, $j{-}1, \dots, n$, denoted by $\widehat{\mathbf{\Gamma}}_{\xi 0}$. More precisely, we compute the generalized eigenvalues μ_j, i.e. the n complex numbers solving $\det(\mathbf{\Gamma}_{\chi 0}^T - z\widehat{\mathbf{\Gamma}}_{\xi 0}) = 0$, along with the corresponding generalized eigenvectors $\mathbf{V}_j$, $j = 1, \dots, n$, i.e. the vectors satisfying

$$\mathbf{V}_j \widehat{\mathbf{\Gamma}}_{\chi 0} = \mu_j \mathbf{V}_j \widehat{\mathbf{\Gamma}}_{\xi 0},$$

and the normalizing condition

$$\mathbf{V}_j \widehat{\mathbf{\Gamma}}_{\xi 0} \mathbf{V}_i' = \begin{cases} 0 & \text{for} \quad j \neq i, \\ 1 & \text{for} \quad j = i. \end{cases}$$

Ordering the eigenvalues μ_j in descending order and taking the eigenvectors corresponding to the r largest ones, our estimated static factors are the generalized principal components

$$\mathbf{v}_{jt} = \mathbf{V}_j' \mathbf{x}_t, \quad j = 1, \dots, r.$$

The motivation for this strategy is that, if $\widehat{\mathbf{\Gamma}}_{\xi 0}$ is the variance-covariance matrix of the idiosyncratic components, the generalized principal components are the linear combinations of the x_{jt}'s having smallest idiosyncratic-common variance ratio (see Forni, Hallin, Lippi, and Reichlin 2001b for a proof). We diagonalize the idiosyncratic variance-covariance matrix since, as shown in the paper cited above, this gives better results under simulation when n is large with respect to T as is the case here.