Factor forecasts for the UK [*]

Michael Artis
Department of Economics, European University Institute and CEPR

Anindya Banerjee
Department of Economics, European University Institute

Massimiliano Marcellino
Istituto di Economia Politica, Universita' Bocconi and IGIER

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Abstract

Time series models are often adopted for forecasting because of their simplicity and good performance. The number of parameters in these models increases quickly with the number of variables modelled, so that usually only univariate or small-scale multivariate models are considered. Yet, data are now readily available for a very large number of macroeconomic variables that are potentially useful when forecasting. We argue that recent developments in the theory of dynamic factor models enable such large data sets to be summarized by relatively few estimated factors, which can then be used to improve forecast accuracy. In this paper we construct a large macroeconomic data-set for the UK, with about 80 variables, model it using a dynamic factor model, and compare the resulting forecasts with those from a set of standard time series models. We find that just six factors are sufficient to explain 50% of the variability of all the variables in the data set. Moreover, these factors, which can be considered as the main driving forces of the economy, are related to key variables such as interest rates, monetary aggregates, prices, housing and labour market variables, and stock prices. Finally, the factor-based forecasts are shown to improve upon standard time series benchmarks for prices, real aggregates, and financial variables, at virtually no additional modelling or computational costs.

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1. Introduction

Dynamic factor-models have recently been successfully applied in a number of papers to forecasting US and Euro area macroeconomic variables, including Stock and Watson (1999, 2002a, 2002b) and Marcellino, Stock and Watson (2001, 2003)). Forni *et al.*(1999, 2000) have used factor methods to analyse business cycles, while Bernanke and Boivin (2003), by using factor-augmented vector autoregressions, have argued for their use in estimating policy reaction functions for the Federal Reserve Board in a data rich environment. Earlier applications of factor models include Geweke (1977), Sargent and Sims (1977), Engle and Watson (1981) and Stock and Watson (1991) who estimated small-N dynamic factor models in the time domain, where N denotes the number of variables in the data set on which information is available.

The primary justification for the use of factor models in large data sets (where both the number of series N and time dimension T are large and where N may approach or even exceed T) is their usefulness as a particularly efficient means of extracting information from a large number of data series, so that the usual imperative to reduce to a minimum the number of series involved is eliminated.

Recent econometric analyses (for example Stock and Watson (2002a)) have confirmed the view that the use of a large number of data series may improve the forecasts of key macroeconomic variables significantly, not least because in a rapidly changing economy (subject to irregular shocks) the ranking of variables as good leading indicators or forecasting devices for, say, inflation or GDP growth, is not at all clear *a priori*. Therefore, as described by Bernanke and Boivin (2003), factor models provide a methodology that allows us to remain 'agnostic' about the structure of the economy, by employing as much information as possible in the construction of the forecasting exercise.

This methodology also permits the incorporation of data at different vintages, at different frequencies and different time spans, thereby providing a clearly specified and statistically rigorous but economical framework for the use of multiple data sets.

Our paper focuses on forecasting key macroeconomic variables for the UK. We have collected 81 macroeconomic time-series that provide an exhaustive description of the UK economy, represented them with a factor model, and used the estimated factors for forecasting various real, nominal and financial variables. To our knowledge, this is the first systematic application of factor models to the UK economy.[1]

The factor forecasts are compared with alternative methods derived from using standard time series modelling techniques. We also evaluate the empirical performance of two methods for robustifying the forecasts in the presence of structural breaks, namely second-differencing and intercept correction, see e.g. Clements and Hendry (1999).

We show that factor models fit the data rather well. With only 6 factors we can explain about 50% of the variability of all the 81 variables. Moreover, the estimated factors appear to be related to relevant subsets of the variables, which justifies their interpretation as the major driving forces of the UK economy. By using a mean square forecast error criterion, we show that factor forecasts often yield improvements with respect to standard methods, with large and significant gains in a few cases. The gains are reduced when the forecasts are compared on the basis of a directional accuracy measure, but the factor models still outperform their competitors. There appear to be some small gains from the use of second-differencing and intercept corrections, except in the case of price series, where a combination of factor models and intercept corrections produces the best forecasts.

The paper is organized as follows. Having already motivated above the use of factor models, we describe them in more formal detail in section 2 and provide further intuition for their use in forecasting. Section 3 presents the data set employed and provides preliminary results for the estimated factors. In Section 4 we discuss the range of forecasting techniques and the evaluation criteria. Section 5 presents the forecast comparison based first on the relative mean square forecast error criterion and then using directional accuracy. Finally, in Section 6 we offer some suggestions for extensions and draw some general conclusions.

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[1] We are, however, aware of partial applications to the problem of inflation forecasting under way at

2. A large scale factor model

In the following sub-section we briefly introduce the representation and estimation theory for the dynamic factor model.

2.1 The factor model

Let X_t be the N-macroeconomic variables to be modelled, observed for $t=1,...,T$. As described in more detail in subsection 2 below, the object of the exercise is to derive h-period ahead forecasts of variables of interest using factor methods and to compare these forecasts with more standard approaches.

X_t admits an approximate linear dynamic factor representation with $\bar{r}$ common factors, f_t, if:

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

for i=$1,...,N$, where e_{it} is an idiosyncratic disturbance with limited cross-sectional and temporal dependence, and $\lambda_i(L)$ are lag polynomials in non-negative powers of L (and represent the vector of dynamic factor loadings); see for example Geweke (1977), Sargent and Sims (1977), Forni, Hallin, Lippi, and Reichlin (1999, 2000) and, in particular, Stock and Watson (2002b). If $\lambda_i(L)$ have finite orders of at most q, equation (1) can be rewritten as,

$$X_t = \Lambda F_t + e_t \quad (2)$$

where $F_t = (f_t^{'},\ldots,f_{t-q}^{'})'$ is $r\times1$, where $r \leq (q+1)\bar{r}$, and the i-th row of Λ in (2) is $(\lambda_{i0},\ldots,\lambda_{iq})$.

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the Bank of England.

The factors provide a summary of the information in the data set, and can therefore be expected to be useful for forecasting. From a more structural point of view, the factors can be considered as the driving forces of the economy. In both cases, it is extremely important to have accurate estimators of the factors.

Stock and Watson (2002b) show that, under some technical assumptions (restrictions on moments and stationarity conditions), the column space spanned by the dynamic factors f_t can be estimated consistently by the principal components of the $T \times T$ covariance matrix of the X's. A condition that is worth mentioning for the latter result to hold is that the number of factors included in the estimated model has to be equal or larger than the true number. In what follows we apply the Bai and Ng (2002) selection criteria to determine the number of factors to be included in the model. These criteria add penalty terms to the minimised objective function. The penalty depends on N and T and the number of factors included in the model in such a way as to ensure consistency, *i.e.*, the true number of factors is selected with probability one when N and T diverge. The criteria are asymptotically equivalent, but can differ in finite samples for different specifications of the penalty term.

The principal component estimator of the factors is computationally convenient, even for very large N. Moreover, it can be generalised to handle data irregularities such as missing observations using the EM algorithm. In practice, the estimated factors from the balanced panel are used to provide an estimate of the missing observations, the factors are then extracted from the completed data set, the missing observations are re-estimated using the new set of estimated factors, and the process is iterated until the estimates of the missing observations and of the factors do not change substantially.

It should be stressed that the estimator is consistent for the space spanned by the factors, *not* for the factors themselves. This follows from the lack of identification of the factors, since the representation in equation (2) is identical to

$$X_t = \Lambda P^{-1} P F_t + e_t = \Theta G_t + e_t, \tag{3}$$

where P is any square matrix of full rank r and G_t is an alternative set of r factors. While this lack of identification is not problematic for forecasting, it should be taken into consideration when interpreting the factors in a structural way.

Finally, it is worth noting that, under additional mild restrictions on the model, the principal component based estimator remains consistent even in the presence of changes in the factor loadings, i.e. $\Lambda = \Lambda_t$. In particular, Stock and Watson (2002b) allow either for a few abrupt changes, or for a smooth evolution as modelled by a multivariate random walk for Λ_t.

2.2 Forecasting with factor models

In order to provide some further intuition on the use of factor models for forecasting, we follow Bai and Ng (2003) and consider a single forecasting equation for a one-step ahead forecast of a variable of interest generated by

$$y_{t+1} = \alpha f_t + \varepsilon_t$$

where ε_t are i.i.d $(0, \sigma_\varepsilon^2)$. Since it is necessary to impose some dynamic consideration on the evolution of the factors, suppose further that,

$$f_t = \rho f_{t-1} + u_t,$$

where u_t are i.i.d $(0, \sigma_u^2)$ and the errors are assumed to be independent for all t and s. If α, ρ are known and f_t is observable, then the one-step ahead forecast error (conditional on the past history of y_t observable at time t) is easily seen to be given by σ_ε^2. If f_t is not observable (while the parameters of the model remain known), y_t may be written as an ARMA (1,1) process

$$y_{t+1} = \rho y_t + z_{t+1} + \theta z_t$$

where $z_t = g(\varepsilon_{t+1}, u_t)$, and the forecast error variance is now given by $\sigma_z^2 = E(z_{t+1}^2)$ and it may be shown that $\sigma_z^2 > \sigma_\varepsilon^2$. The differential between the forecast errors (between when f_t is observable and when it is not) goes to zero in the limit as $N \to \infty$, so that forecasts based on factor methods are the same whether or not the factors are known or have to be estimated, see Stock and Watson (2002b).

Yet, in practice both the parameters of the model and the factor are unknown and must be estimated – the latter by extraction from a factor model given by (2) above and the former by a regression of y_{t+1} on the estimated factor – the variance of the resulting forecast error is of importance. Bai and Ng (2003) show that, even in more general models, estimation of the parameters adds $O(T^{-1})$ uncertainty to the forecast while as stated earlier, estimation of the factor adds $O(N^{-1})$ uncertainty. In other words, the forecast error variance for the case where both the factor and the parameters of the model have to be estimated is given by $\sigma_\varepsilon^2 + O(T^{-1}) + O(N^{-1})$ which is less than σ_z^2 when N and T are large.

This is a remarkable result since one can then expect factor forecasts to yield better forecasts even when the factors are unobservable and must be estimated. Moreover, when N increases faster than T, such that the ratio T/N tends to zero in the limit, the uncertainty about the factors is dominated by paramter uncertainty and the factors can be treated as if they were known. Confidence intervals for the forecasts that are root-T consistent can then be constructed and the formulas are the same regardless of whether the factors are stationary or integrated of order one (in the framework of the example above whether $|\rho < 1|$ or $\rho = 1$, see Bai and Ng (2003) for details.

To summarize the arguments presented for the use of factor models in large data sets, first, they provide a useful means of extracting information. Second, the space spanned by the factors can be consistently estimated under weak regularity assumptions that include within their scope structural breaks, different orders of integration, different frequencies of measurement and different vintages of data. Finally, the estimate factors are useful for forecasting and in general the variance of the resulting forecast error can be expected to be smaller than with standard ARMA models since they enable the empirical investigator to allow as much data as possible to be fed into the forecasting exercise.

Before turning to the estimation of the factor model for our UK data set, we describe the data and derive some results for the estimated factors.

3. The data

The data set for the UK, our X_t, contains 81 monthly series, over the period 1970:1-1998:3, extracted from the OECD database and from Datastream. To have a balanced and as exhaustive as possible representation of the UK economy, we include output variables (industrial production and sales, disaggregated by main sectors); labour market variables (employment, unemployment, wages and unit labour costs); prices (consumer, producer, and retail prices, disaggregated by type of goods); monetary aggregates (M2, M0); interest rates (different maturities, spreads); stock prices; exchange rates (effective and nominal); imports, exports and net trade; and other miscellaneous series. A complete list of the variables is reported in the Appendix.

Following Marcellino, Stock and Watson (2003), the data are pre-processed in three stages before being modelled with a factor representation. First, the series are transformed to account for stochastic or deterministic trends, and logarithms are taken of all nonnegative series that are not already in rates or percentage units. We apply the same transformations to all variables of the same type. The main choice is whether prices and nominal variables are *I(1)* or *I(2)*. The *I(1)* case is our baseline model. Results for the *I(2)* case are worse from a forecasting point of view, and are available upon request.

Second, we pass all the series through a seasonal adjustment procedure, even though most of them are originally reported as seasonally adjusted. The monthly series are regressed against eleven monthly indicator variables and, if the HAC F-test on these eleven coefficients is significant at the 10% level, the series are seasonally adjusted using Wallis' (1974) linear approximation to X-11 ARIMA.

Finally, the transformed seasonally adjusted series are screened for large outliers (outliers exceeding six times the interquartile range). Each outlying observation is recoded as missing data, and the EM algorithm is used to estimate the factor model for the resulting unbalanced panel.

3.1 Results from estimating the factor model for the UK

We start by noting from Table 1 that the factor model appears to fit the data well. With 4 factors we are able to explain about 40% of the variability of all the 81 variables, a figure that increases to 50% with 6 factors and to 68% with 12. According to the Bai and Ng (2002) selection criteria, in their more robust log version, only 2 to 4 factors should be included in the model. Slightly lower values for the trace R^2 are obtained using the balanced panel, and in this case just one factor is selected by the Bai and Ng (2002) criteria. Given that the balanced panel includes only 34 series, versus the 81 in the unbalanced panel, we will concentrate on the latter.

We also report the R^2 in the regression of each variable to be forecast on the factors. We consider three groups of series: real variables, including industrial production (IP), the volume of retail sales (RTVOL) and the unemployment rate (LURAT); prices, including the consumer price index (CPI), the retail price index excluding mortgage interest payments (RPIX), and consumer prices less food (CPNF); and financial variables, including the treasury bill rate (FYTB), the Financial Times share price index for non-financial assets (FS), and the exchange rate against the US dollar (ESPO). All variables are transformed into growth rates, except LURAT and FYTB that are analysed instead in first differences in accordance with standard practice.

The factor model works best for prices. The lowest R^2 for this group is .67 with 4 factors for CPNF, which becomes .81 with 6 factors. Good results are also obtained for financial variables. The values of R^2 with 4 factors are .66 for FYTB, .51 for FS, but only .09 for ESPO (that rises to .37 with 6 factors). For real variables, the worst performance is for RTVOL, where R^2 is only .10 with 4 factors, but increases to .46 with 6 factors. In this case, the values of R^2 for IP and LURAT are, respectively, .59 and .54.

Although the factor model is agnostic about the structure of the economy, it is nevertheless worth addressing the question of the interpretation of the estimated factors. It is difficult to provide a structural interpretation because of identification issues. However, the estimated factors span the same space as the true factors so that, even if the estimated factors do not coincide with the driving forces of the economy, linear combinations of them do coincide. To gain further information on the composition of the factors, we regress each variable in the data set on each factor. A high value of R^2 in the resulting regression indicates that the factor under analysis explains well that particular variable. Also, as noted by Stock and Watson (2002b), a high value of R^2 indicates that the variable is a relevant component of the factor under analysis.

The results are summarised in Figures 1 and 2. The numbers on the x-axis relate to the coding of the variables in the data set, while the y-axis gives the value of the R^2 of the factor loaded on to the particular variable. Referring to the data appendix, the most important components of factors 1 to 3 are interest rates and price series; monetary aggregates are also relevant for factor 1 and exchange rates for factor 2. Housing variables and stock prices are particularly significant for factor 4, employment series for factor 5, and other stock variables for factor 6. The values of R^2 are very low for all variables in the case of factors 6 to 12, which is coherent with the outcome of the selection criteria that indicated at most 4 factors as being normally relevant.

The extracted factors from our data set are thus interesting, informative and interpretable from an economic point of view, although it is worth re-stressing that the driving trends of the UK economy do not necessarily coincide with the variables indicated above, but could be linear combinations of them. We next turn to describing the methodology for the forecast comparison exercise, in order to establish further the value of factor forecasting methods.

4. Forecast comparison framework

In this section we present the competing forecasting methods we consider, and the criteria we use to evaluate their relative merits.

4.1 Forecasting Models

All forecasting models are specified and estimated as a linear projection of an *h*-step ahead variable, y_{t+h}^{h}, onto t-dated predictors, which at a minimum include lagged transformed values of y_t, the variable of interest. More precisely, the forecasting models all have the form,

$$y_{t+h}^{h} = \mu + \alpha(L)y_t + \beta(L)'Z_t + \varepsilon_{t+h}^{h} \quad (4)$$

where $\alpha(L)$ is a scalar lag polynomial, $\beta(L)$ is a vector lag polynomial, μ is a constant, and Z_t is a vector of predictor variables. The forecast horizon, h for the reported results in section 5 below is 12 months (h = 12), although analogous results for h = 6 or 24 are available from us upon request.

The "*h*-step ahead projection" approach in (4), also called dynamic estimation (e.g. Clements and Hendry (1996)), differs from the standard approach of estimating a one-step ahead model, then iterating that model forward to obtain *h*-step ahead predictions. The *h*-step-ahead projection approach has two main advantages. First, additional equations for simultaneously forecasting Z_t, e.g. by a VAR, are not needed. Second, the potential impact of specification error in the one-step ahead model (including the equations for Z_t) can be reduced by using the same horizon for estimation as for forecasting.

The construction of y_{t+h}^{h} depends on whether the series is modelled as I(0), I(1) or I(2). Recall that series integrated or order *d*, denoted I(*d*) are those for which the *d-th* difference (Δ^{d}) is stationary. Denoting by *x* the series of interest (usually in logs), in the I(0) case it is $y_{t+h}^{h} = x_{t+h}$ and $y_{t} = x_{t}$. In the I(1) case, it is $y_{t+h}^{h} = \sum_{t+1}^{t+h} \Delta x_{s}$ so that $y_{t+h}^{h} = x_{t+h} - x_{t}$, while $y_{t} = x_{t} - x_{t-1}$. In words, the forecasts are for the growth in the series *x* between time period *t* and *t+h*. In the I(2) case, it is $y_{t+h}^{h} = \sum_{t+1}^{t+h} \Delta x_{s} - h\Delta x_{t}$ or $y_{t+h}^{h} = x_{t+h} - x_{t} - h\Delta x_{t}$, i.e., the difference of the growth of *x* between time periods *t* and *t+h* and *h* times its growth between periods *t-1* and *t*, and $y_{t} = \Delta^{2} x_{t}$. This is a convenient formulation because, given that x_{t} and its lags are known when forecasting, the unknown component of y_{t+h}^{h} conditional on the available information is equal to x_{t+h} independently of the choice of the order of integration. This makes the mean square forecast error (MSFE) from models for second-differenced variables directly comparable with, for example, that from models for first differences only.

The various forecasting models we compare differ in their choice of Z_t. Let us list the forecasting models and briefly discuss their main characteristics.

Autoregressive forecast (bse0). Our benchmark forecast is a univariate autoregressive forecast based on (4) excluding Z_t. In common with the literature, we choose the lag length using an information criterion, the BIC, starting with a maximum of 6 lags.

Autoregressive forecast with second-differencing (bse0_i2). Clements and Hendry (1999) showed that second-differencing the dependent variable can improve the forecasting performance of autoregressive models in the presence of structural breaks, even in the case of over-differencing. Hence, this model corresponds to (4), excluding Z_t and treating the variable of interest as I(2).

Autoregressive forecast with intercept correction (bse0_ic). An alternative remedy in the presence of structural breaks over the forecasting period is to put the forecast back on track by adding past forecast errors to the forecast, see *e.g.* Clements and Hendry (1999) and Artis and Marcellino (2001). They showed that the simple addition of the *h*-period ahead forecast error could be useful. Hence, the forecast is given by $\hat{y}_{t+h}^{h} + \varepsilon_t^h$, where $\hat{y}_{t+h}^{h}$ is the *bse0* forecast and ε_t^h is the forecast error made when forecasting y_t in period *t-h*. Note that both second-differencing and intercept correction increase the MSFE, when not needed, by adding a moving average component to the forecast error, and thus are not costless.

VAR forecasts (varf). . VAR forecasts are constructed using equation (4) with different regressors Z_t. In particular, Z_t includes the CPI and the treasury bill rate (FYTB) for real variables; IP, and FYTB for the price series; IP and FYTB for FS and ESPO, and the CPI and IP for FYTB. Intercept corrected versions of the forecasts are also computed (*varf_ic*).

Factor-based forecasts. These forecasts are based on setting Z_t in (4) to be the estimated factors from model (2). Stock and Watson (2002b) provide conditions under which these estimated factors yield asymptotically efficient forecasts, in the sense that the MSFE converges to the value that is obtained with known factors. We have already provided an illustration in section 2.2. above of the usefulness of factor models in this context.

We consider three different factor based forecasts. First, in addition to the lagged dependent variable, up to 4 factors and 3 lags of each of them are included in the model (*fdiarlag*), and the variable selection is again based on BIC. Second, up to 12 factors are included, but not their lags (*fdiar*). Third, only up to 12 factors appear as regressors in (4), but no lagged dependent variable (*fdi*). For each of these 3 forecasts, the factors can be extracted from the unbalanced panel (prefix *fac*), or from the balanced panel (prefix *fbp*). The former contains more variables than the latter, and therefore more information. The only drawback is that missing observations have to be estimated in a first stage, which could introduce noise in the factor estimation.

In order to evaluate the forecasting role of each factor, for the unbalanced panel we also consider forecasts using a fixed number of factors, from 1 to 4 (*fdiar_01* to *fdiar_04* and *fdi_01* to *fdi_04*). For each of the 14 factor based forecasts, we also consider the intercept corrected version (prefix *ic*).

Overall therefore we have 33 different versions of the forecasting model (4).

4.2 Forecast Comparison

The forecast comparison is conducted using three different methodologies and is performed in a simulated out-of-sample framework where all statistical calculations are done using a fully recursive methodology. The models are first estimated on data from 1970:1 to 1984:12. h-step ahead forecasts are then computed. The estimation sample is then augmented by one month and the corresponding h-step ahead forecast is computed. The forecast period is 1985:1 - 1998:3, for a total of 159 months, and the final estimation sample for 12-month ahead forecasts is therefore 1985:1-1987:3. Every month, (*i.e.* for every augmentation of the sample) all model estimation, standardisation of the data, calculation of the estimated factors, etc., are repeated. The simulated out of sample MSFE is then computed as the average of the sum of squares of all the comparisons between the actual value of the variable and its forecast (under any of the methods given in section 4.1 above.)

The forecasting performance of the various methods described is initially examined by comparing their simulated out-of-sample MSFE relative to the benchmark AR forecast (*bse0*). West (1996) standard errors are computed around the relative MSFE.

We then consider a pooling regression where the actual values are regressed on the benchmark forecast and, in turn, on each of the competing forecasts. We report the coefficient of the latter, with robust standard errors. This coefficient should be equal to one for the benchmark forecast to be redundant, assuming that the two coefficients have to sum to one. Such a condition is also sufficient for the alternative forecast to MSFE-encompass the benchmark forecast, under the additional hypothesis of unbiasedness of the former, see Marcellino (2000).

Finally, we also include an evaluation of relative directional forecasting accuracy. There are several situations in which directional forecasting accuracy has an importance of its own. The particular significance in macroeconomic analysis attaching to the identification of cyclical turning points is an example.

Let us denote by z_{t+h} the difference between y^h_{t+h} and y^h_t, and by $\hat{z}_{t+h}$ that between $\hat{y}^h_{t+h}$ and y^h_t. Next, let us introduce the indicator variables i_{t+h} and $\hat{i}_{t+h}$. i_{t+h} (respectively $\hat{i}_{t+h}$) is assigned the value one if z_{t+h} (respectively $\hat{z}_{t+h}$) is positive, and is zero otherwise. Thus, when the variable x is measured in logarithms (levels), i_{t+h} is equal to one if the growth rate (change) of x over the period t to t+h exceeds that over the previous period (t-h to t).[2]

To compare i_{t+h} with $\hat{i}_{t+h}$ we use the "concordance" index proposed by Harding and Pagan (1999) to measure the synchronicity of business cycles between pairs of countries. In their case the time series to be compared are sequences of binary (boom, recession) states for each of two economies. In our case the binary states are simply those of increase or decrease in the underlying series of interest (*e.g*. the increase or decrease in the inflation rate or IP growth), whilst the analogue to the two economies is provided by the status of "forecast" and "actual".

The concordance index for the two series i and $\hat{i}$ over a sample of T observations then has the form:

$$C = \frac{1}{T}\left\{\sum_{t=1}^{T} i_t \hat{i}_t + \sum_{t=1}^{T}(1-i_t)(1-\hat{i}_t)\right\}.$$

The concordance index lies between 0 and 1, with unity indicating maximum concordance. Put simply, the index measures the proportion of observations of a given series of interest in which the forecast *direction of change* is correct. If z_{t+h} and $\hat{z}_{t+h}$ were i.i.d., we could apply a chi-square test for independence to the concordance index values, as Harding and Pagan (1999) have shown in related work, but this is not the case in our application. For this reason, the concordance indices should be read as descriptive statistics only.

[2] Alternative definitions could have been chosen. For example, we might want to ask what directional change is implied by the forecast compared to the most recent (one-month) change. We computed the results also for this alternative definition, but they do not differ substantially from the basic case.

5. Forecasting Results

In this section we report the results of the forecast comparison for the UK macroeconomic variables for h=12. Tables 2 - 4 present the MSFE and the pooling regression tests, whilst Table 5 reports the directional accuracy measures. In each case, we deal first with real variables; then with prices; and finally with financial series.

5.1 Real variables

The MSFE of the competing methods relative to the benchmark AR model are reported in Table 2. Four general results emerge: first, the factor models often outperform the other methods, with an average gain in the range 10-20% with respect to the benchmark AR model. Second, using a fixed number of factors is often equivalent or better than BIC selection, and including an AR component in the forecasting model is usually beneficial. Third, the factors extracted from the unbalanced panel perform better than those from the balanced panel, i.e., the additional information in the unbalanced panel is useful for forecasting. Fourth, in general, both methods to deal with structural breaks, i.e. second-differencing and intercept correction, increase the MSFE.

In more detail, for IP the best model is fac_fdi_02 with a relative MSFE of 0.87, i.e., a model where the first two estimated factors are used as regressors. For RTVOL, the best models is fac_fdi_04 with a relative MSFE 0.77. For LURAT the VAR is best with relative MSFE of 0.73. The latter result is in line with what Marcellino, Stock and Watson (2001) found in other European countries. The two factor models fac_fdiar_02 and fac_fdiarlag_bic perform well for all the three real variables and systematically beat the AR benchmark.

When the forecasts from these models are inserted in a pooling regression with the benchmark AR, their coefficients are also not statistically different from one. Yet, both the standard errors around these estimated coefficients and the West (1996) standard errors around the relative MSFE are rather large.

5.2 Prices

Results of the forecast comparison for the price series are presented in Table 3. Three main comments are in order. First, overall the factor models perform well also in this case with respect to the AR benchmark, with average gains of about 10-20%, with peaks for the best model. Second, the best model for all three price series is fac_ic_fdi_01 (MSFE of 0.43 for CPI and RPIX and 0.49 for CPNF), *i.e.*, a model with one factor only, extracted from the unbalanced panel, and whose forecasts are intercept corrected. It is worth recalling that this factor is mainly a linear combination of exchange rates, interest rates and monetary aggregates (see Figure 1). The gains with respect to the benchmark AR are therefore in the region of 50% to 60% depending on the series considered. The West (1996) standard errors are rather small compared to the relative MSFE, and the benchmark forecast is not statistically significant in a pooling regression with the best model. Finally, for CPI and RPIX the second best model is a simple AR with second-differencing of the dependent variable. More generally, second-differencing and intercept corrections appear to be quite useful for price series, in accordance with the results of Clements and Hendry (1998), where such series are expected to have structural breaks and/or order of integration up to order 2.

In Figure 3 we report, for each price series, the actual values and the 12-step ahead forecasts from the best non-factor and factor model.

XX Why do we have only a figure for prices and not also for real and financial variables? The best factor model performs very poorly, either the figure or the table are wrong, this should be checked.

5.3 Financial variables

The forecasting results for the financial variables are reported in Table 4. Three comments are worth making. First, for the FS it is never possible to beat the benchmark AR, which is in line with efficiency of stock markets. Second, for FYTB and ESPO the best models are factor based, but the gains are small and in the order of 5-10%. Finally, second-differencing and intercept corrections are not useful.

Results for other forecast horizons

The working paper version of this paper contains detailed results for forecast horizons h=6 and h=24. For the sake of concision we provide only a summary of these results and refer the interested reader to the working paper for more information.

For real variables, the results are qualitatively similar to those reported for h = 12. Except for LURAT (where the VAR is again dominant, although not by much) the best forecasting models are those provided by the inclusion of factors. This is also true for the price variables where the gains with respect to the benchmark AR increase with the forecast horizon h, and range from 40% to 59% for CPI, from 39% to 59% for RPIX and from 28% to 61% for CPNF. These results highlight the striking efficacy of factor models in forecasting price variables. Finally, for financial variables, the gains derived from using factors for forecasting are muted for h = 6 while for the longest horizon (h = 24) gains of up to nearly 50% are recorded from the use of factors for FYTB and of up to nearly 25% for ESPO (more specifically by using fbp_bic).

5.4 Directional Accuracy

The directional accuracy indexes are reported in Table 5. Four points are worth making. First, concordance index values are nearly always above 50%, and for factor-based models without intercept correction, comfortably so. Second, the resulting ranking of the forecasting methods is similar to that based on relative MSFE. Third, the gains of the factor based forecasts for improving concordance are on average rather small, except for RTVOL when they are in the range 10-20%. Finally, intercept correction and second-differencing are not particularly useful, also in the case of price series.

6. Conclusions

In this paper we have evaluated how good a dynamic factor model is for representing a large data set for the UK, and for forecasting a set of key macroeconomic variables. The results are extremely encouraging, and in line with those from previous studies for the US (Stock and Watson (2002b)), and for the Euro area (Marcellino, Stock and Watson (2001, 2003)).

With only 6 factors we can explain about 50% of the variability of 81 variables, and the factors are related to groups of key variables, such as interest rates, price series, monetary aggregates, labour market variables and exchange rates.

Moreover, factor-based forecasts usually outperform standard time series methods, with gains of about 20% for real variables and with even higher gains for prices. The gains are lower for financial variables at shorter horizons but improve significantly at longer horizons and for particular models. For price series, second-differencing and intercept corrections of the forecasts are also very useful, less so for the other variables. Directional accuracy checks revealed the factor-based forecasts to be no worse, and sometimes better than the standard alternatives.

In summary, the theoretical advantages highlighted in the paper are amply verified by the subsequent estimation, and lend considerable justification for the use of factor methods. Further improvements could be obtained by enlarging even more the data set and extending the theory to allow for non-stationary variables, possibly related by long run relationships. These extensions are left for future research.

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Appendix. The data set

real output and income

ip	Industrial production, Total s.a.
ipi	Investment goods s.a.
ipint	Intermediate goods
ipman	Manufacturing s.a.

employment and hours

lureg	unemployment, registered unemployed s.a.
lurat	unemployment, rate s.a.
luinds	uk unemployment index - detrended (discontinued)
lvac	unfilled vacancies s.a.
lvacds	uk vacancies: job centres, volume, s.a.

retail, manufacturing and trade sales

rtval	retail sales, total: value s.a.
rtvol	retail sales, total: volume s.a.
rtvolds	retail sales, volume, s.a.
cars	new passenger car registrations s.a.
mst	manufacturing, engineering: total s.a.
msd	manufacturing, engineering: domestic s.a.
mse	manufacturing, engineering: export s.a.

housing

hno	construction, new orders: total s.a.
hnores	construction, new orders: residential s.a.
housepu	uk housebuilding starts, public sector
housepr	uk housebuilding starts, private sector

stock prices

fsres	uk-ds resources - price index
fsbas	uk-ds basic industries - price index
fsgen	uk-ds gen. industrials - price index
fscyco	uk-ds cyc. cons. goods - price index
fsncco	uk-ds non cyc cons gds - price index
fscysv	uk-ds cyclical service - price index
fsncsv	uk-ds non cyc.services - price index
fsinf	uk-ds information tech - price index
fsfin	uk-ds financials - price index
fstot	uk-ds market - price index
fs	share prices, ft-se-a: non-financials

<u>exchange rates</u>

ereff	uk real effective exchange rate
efrancs	uk french francs to uk pound
elire	uk italian lire to uk pound
emarks	uk german marks to uk pound
espo	us $ exchange rate: spot
efor	us $ exchange rate: forward

<u>interest rates</u>

abbey	uk abbey national - mortgage rate
fy1int	uk interbank 1 month - middle rate
fy1st	uk sterling certs. 1 month - middle rate
fy3st	uk sterling certs. 3 month - middle rate
fy6st	uk sterling certs. 6 month - middle rate
fy1yst	uk sterling certs. 1 year - middle rate
fyon	overnight interbank rate
fylocl	London clearing banks' base rate
fy3int	3-month interbank loans
fy10gov	yield of 10 year gvt. bonds
fytb	treasury bill rate

<u>money aggregates</u>

mnot	uk money supply m0, current prices, s.a.
m2	monetary aggregate (m2) s.a.

<u>price indices</u>

cpi	all items
cpns	all items excl. seasonal items
pir	input: raw materials
pif	input: fuel
cpnf	all items less food
cpf	food
cpdrink	beverages and tobacco
cpfuel	fuel and electricity
cphouse	housing
rpix	uk retail price index, excl. mortgage interest payments
pimpf	uk import price indices - fuels, current prices
pimpno	uk import price index - less oil & erratics
puvds	uk import unit value - food, beverages & tobacco
poiluk	uk market price index - uk brent
poilwd	wd petroleum spot price, current prices
pwdall	wd export price index - all exports, excl. fuels

<u>wages</u>

ww	weekly earnings
wc	unit labour cost s.a.

<u>miscellaneous</u>

finp	imports c.i.f. s.a.
fexp	exports f.o.b. s.a.
fnet	net trade (f.o.b. - c.i.f.) s.a.

Tables

Table 1 – Cumulative R^2 from regression of variables on factors

Factor	Trace	ip	rtvol	lurat	cpi	rpix	cpnf	fytb	fs	espo
1	0.121	0.03	0.00	0.04	0.02	0.02	0.02	0.37	0.10	0.00
2	0.232	0.13	0.07	0.41	0.32	0.34	0.37	0.47	0.14	0.00
3	0.312	0.20	0.08	0.41	0.63	0.64	0.56	0.58	0.34	0.02
4	0.395	0.29	0.10	0.41	0.75	0.76	0.67	0.66	0.51	0.09
5	0.444	0.38	0.42	0.50	0.76	0.77	0.68	0.67	0.52	0.14
6	0.495	0.59	0.46	0.54	0.89	0.90	0.81	0.68	0.53	0.37
7	0.538	0.66	0.59	0.54	0.91	0.91	0.81	0.77	0.53	0.42
8	0.573	0.77	0.65	0.58	0.93	0.93	0.85	0.79	0.55	0.43
9	0.605	0.77	0.66	0.59	0.94	0.94	0.86	0.79	0.55	0.43
10	0.633	0.78	0.66	0.59	0.96	0.95	0.88	0.79	0.55	0.43
11	0.657	0.87	0.66	0.60	0.97	0.95	0.89	0.79	0.55	0.46
12	0.68	0.88	0.66	0.62	0.97	0.95	0.90	0.79	0.55	0.84

Notes:

Estimation period is 1970:1-1998:3. Factors are extracted from unbalanced panel.
Trace R^2 is referred to a regression of all the 81 variables on the factors.
ip - industrial production
rtvol - retail sales volume
lurat - unemployment rate
cpi - consumer price index, all items
rpix - retail price index excluding MIPs
cpnf - consumer price index, all items less food
fytb - treasury bill rate
fs - share prices, non-financials
espo - US $ exchange rate: spot

Table 2 Results for real variables, h = 12

---- Series ---

Forecast Method	ip		rtvol		lurat	
_bse0_01	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2_01	7.97 (14.35)	0.04 (0.03)	5.06 (2.99)	0.10 (0.04)	0.95 (0.20)	0.56 (0.21)
_bse0ic_01	1.58 (0.47)	0.28 (0.10)	0.93 (0.31)	0.54 (0.17)	1.23 (0.33)	0.37 (0.15)
_varf_01	1.52 (0.75)	0.22 (0.21)	1.19 (0.42)	0.38 (0.22)	0.73 (0.13)	1.23 (0.36)
_varfic_01	1.69 (0.39)	0.17 (0.12)	0.86 (0.28)	0.57 (0.14)	0.97 (0.20)	0.52 (0.15)
a_fac__fdiarlag_bic_f_01	0.90 (0.17)	0.62 (0.20)	0.80 (0.21)	0.72 (0.22)	0.78 (0.10)	1.52 (0.40)
a_fac__fdiar_bic_f_01	1.14 (0.21)	0.38 (0.17)	0.94 (0.24)	0.56 (0.24)	1.04 (0.14)	0.34 (0.48)
a_fac__fdi_bic_f_01	1.14 (0.21)	0.38 (0.17)	0.85 (0.22)	0.66 (0.23)	1.39 (0.25)	-0.01 (0.20)
a_fbp__fdiarlag_bic_f_01	1.24 (0.23)	0.26 (0.19)	1.00 (0.33)	0.50 (0.27)	0.84 (0.09)	1.29 (0.49)
a_fbp__fdiar_bic_f_01	1.42 (0.46)	0.28 (0.19)	1.04 (0.32)	0.48 (0.22)	1.19 (0.20)	-0.06 (0.43)
a_fbp__fdi_bic_f_01	1.43 (0.46)	0.28 (0.19)	1.02 (0.29)	0.48 (0.26)	1.32 (0.24)	-0.03 (0.30)
a_fac__fdiar_01	1.01 (0.02)	-0.64 (1.64)	1.01 (0.02)	-1.01 (2.15)	1.01 (0.01)	-3.60 (3.53)
a_fac__fdiar_02	0.90 (0.18)	0.63 (0.21)	0.79 (0.17)	0.88 (0.28)	0.77 (0.10)	1.61 (0.38)
a_fac__fdiar_03	0.95 (0.16)	0.56 (0.21)	0.80 (0.21)	0.72 (0.22)	0.79 (0.10)	1.41 (0.42)
a_fac__fdiar_04	0.93 (0.14)	0.61 (0.20)	0.82 (0.21)	0.69 (0.21)	0.81 (0.10)	1.30 (0.40)
a_fac__fdi_01	1.01 (0.02)	-0.64 (1.64)	1.00 (0.02)	0.55 (0.43)	2.19 (0.78)	-0.32 (0.17)
a_fac__fdi_02	0.87 (0.14)	0.78 (0.26)	0.79 (0.15)	0.98 (0.28)	1.27 (0.26)	0.22 (0.19)
a_fac__fdi_03	0.91 (0.13)	0.68 (0.27)	0.78 (0.18)	0.82 (0.22)	1.32 (0.29)	0.20 (0.18)
a_fac__fdi_04	0.87 (0.14)	0.73 (0.23)	0.77 (0.18)	0.84 (0.23)	1.34 (0.29)	0.15 (0.17)
a_fac_ic_fdiarlag_bic_f_01	1.60 (0.63)	0.31 (0.12)	0.85 (0.26)	0.57 (0.11)	0.99 (0.19)	0.51 (0.14)
a_fac_ic_fdiar_bic_f_01	2.10 (0.87)	0.21 (0.10)	0.99 (0.32)	0.50 (0.13)	1.02 (0.21)	0.49 (0.13)
a_fac_ic_fdi_bic_f_01	2.10 (0.87)	0.21 (0.10)	1.04 (0.32)	0.48 (0.12)	1.20 (0.29)	0.35 (0.20)
a_fbp_ic_fdiarlag_bic_f_01	2.11 (0.83)	0.21 (0.11)	0.95 (0.34)	0.52 (0.14)	1.08 (0.23)	0.45 (0.14)
a_fbp_ic_fdiar_bic_f_01	2.29 (0.73)	0.18 (0.08)	1.13 (0.40)	0.45 (0.14)	1.19 (0.29)	0.40 (0.14)
a_fbp_ic_fdi_bic_f_01	2.30 (0.73)	0.17 (0.08)	1.20 (0.38)	0.43 (0.12)	1.05 (0.19)	0.46 (0.14)
a_fac_ic_fdiar_01	1.59 (0.49)	0.27 (0.11)	0.92 (0.31)	0.54 (0.17)	1.23 (0.33)	0.37 (0.15)
a_fac_ic_fdiar_02	1.60 (0.63)	0.31 (0.12)	0.94 (0.30)	0.53 (0.13)	0.99 (0.19)	0.51 (0.14)
a_fac_ic_fdiar_03	1.71 (0.63)	0.29 (0.11)	0.85 (0.26)	0.57 (0.11)	1.01 (0.18)	0.49 (0.14)
a_fac_ic_fdiar_04	1.69 (0.60)	0.29 (0.11)	0.87 (0.25)	0.55 (0.11)	1.01 (0.19)	0.49 (0.14)
a_fac_ic_fdi_01	1.59 (0.49)	0.27 (0.11)	1.00 (0.30)	0.50 (0.15)	1.48 (0.47)	0.11 (0.24)
a_fac_ic_fdi_02	1.69 (0.61)	0.28 (0.11)	1.06 (0.30)	0.48 (0.11)	1.13 (0.19)	0.39 (0.16)
a_fac_ic_fdi_03	1.72 (0.63)	0.27 (0.11)	0.96 (0.25)	0.52 (0.10)	1.19 (0.24)	0.33 (0.18)
a_fac_ic_fdi_04	1.56 (0.56)	0.32 (0.12)	0.96 (0.25)	0.51 (0.10)	1.21 (0.26)	0.32 (0.19)

RMSE for AR Model 0.027 0.026 1.051

Notes:

The estimation period is 1970:1-1984:12. The forecast period is 1985:1-1998:3.
For each variable, the four columns report the MSFE relative to the benchmark AR model, with West (1996) standard error in parentheses, and the coefficient of the forecast under analysis in a pooling regression with the benchmark forecast, with robust standard error in parentheses. The last line reports the root MSFE for the AR benchmark.
The forecasts in the rows of table 2 are (see section 3.1 for details):

_bse0	AR model, benchamrk
_bse0_i2	AR model for second-differenced variable
_bse0ic	AR model with intercept correction
_varf	VAR model
_varfic	VAR model with intercept correction
a_fac__fdiarlag_bic	Factors from unbalanced panel (BIC selection), their lags, and AR terms
a_fac__fdiar_bic	Factors from unbalanced panel (BIC selection), and AR terms
a_fac__fdi_bic	Factors from unbalanced panel (BIC selection)
a_fbp__fdiarlag_bic	Factors from balanced panel (BIC selection), their lags, and AR terms
a_fbp__fdiar_bic	Factors from balanced panel (BIC selection), and AR terms
a_fbp__fdi_bic	Factors from balanced panel (BIC selection)
a_fac__fdiar_01	n factors from unbalanced panel, n=1,2,3,4, and AR terms
a_fac__fdiar_02	
a_fac__fdiar_03	
a_fac__fdiar_04	
a_fac__fdi_01	n factors from unbalanced panel, n=1,2,3,4
a_fac__fdi_02	
a_fac__fdi_03	
a_fac__fdi_04	
a_fac_ic_fdiarlag_bic	As factor models above, but with intercept correction
a_fac_ic_fdiar_bic	
a_fac_ic_fdi_bic	
a_fbp_ic_fdiarlag_bic	
a_fbp_ic_fdiar_bic	
a_fbp_ic_fdi_bic	
a_fac_ic_fdiar_01	
a_fac_ic_fdiar_02	
a_fac_ic_fdiar_03	
a_fac_ic_fdiar_04	
a_fac_ic_fdi_01	
a_fac_ic_fdi_02	
a_fac_ic_fdi_03	
a_fac_ic_fdi_04	

Table 3 Results for price series, h = 12

---- Series ---

Forecast Method	cpi		rpix		cpnf	
_bse0_01	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2_01	0.67 (0.17)	0.70 (0.10)	0.66 (0.17)	0.71 (0.10)	0.82 (0.19)	0.60 (0.12)
_bse0ic_01	0.83 (0.19)	0.58 (0.10)	0.83 (0.19)	0.58 (0.10)	0.92 (0.20)	0.54 (0.10)
_varf_01	1.05 (0.10)	0.34 (0.31)	1.06 (0.10)	0.29 (0.31)	0.81 (0.08)	1.09 (0.20)
_varfic_01	0.80 (0.18)	0.59 (0.09)	0.80 (0.18)	0.59 (0.09)	0.80 (0.18)	0.59 (0.09)
a_fac__fdiarlag_bic_f_01	0.97 (0.06)	0.82 (0.49)	0.96 (0.06)	0.84 (0.46)	0.90 (0.06)	0.90 (0.23)
a_fac__fdiar_bic_f_01	0.98 (0.10)	0.55 (0.24)	0.95 (0.10)	0.63 (0.25)	0.97 (0.12)	0.54 (0.15)
a_fac__fdi_bic_f_01	1.13 (0.15)	0.29 (0.22)	1.12 (0.13)	0.30 (0.21)	0.96 (0.09)	0.58 (0.18)
a_fbp__fdiarlag_bic_f_01	0.97 (0.11)	0.58 (0.26)	0.99 (0.11)	0.54 (0.30)	0.83 (0.12)	0.78 (0.22)
a_fbp__fdiar_bic_f_01	0.86 (0.14)	0.72 (0.23)	0.88 (0.14)	0.68 (0.22)	0.77 (0.12)	0.93 (0.23)
a_fbp__fdi_bic_f_01	0.94 (0.15)	0.59 (0.23)	0.95 (0.15)	0.57 (0.22)	0.78 (0.12)	0.90 (0.23)
a_fac__fdiar_01	0.97 (0.06)	0.82 (0.49)	0.96 (0.06)	0.84 (0.46)	0.95 (0.05)	1.10 (0.53)
a_fac__fdiar_02	0.99 (0.04)	0.57 (0.37)	0.98 (0.05)	0.63 (0.37)	0.97 (0.05)	0.67 (0.29)
a_fac__fdiar_03	0.97 (0.05)	0.73 (0.35)	0.98 (0.04)	0.67 (0.36)	0.86 (0.07)	1.02 (0.21)
a_fac__fdiar_04	0.97 (0.05)	0.71 (0.35)	0.98 (0.04)	0.64 (0.36)	0.88 (0.06)	0.99 (0.23)
a_fac__fdi_01	3.01 (1.18)	-0.62 (0.11)	3.05 (1.22)	-0.61 (0.11)	2.28 (0.68)	-0.73 (0.16)
a_fac__fdi_02	1.92 (0.49)	-0.89 (0.15)	1.95 (0.50)	-0.88 (0.15)	1.44 (0.24)	-0.56 (0.26)
a_fac__fdi_03	1.24 (0.13)	-0.14 (0.26)	1.26 (0.14)	-0.20 (0.27)	0.96 (0.08)	0.60 (0.21)
a_fac__fdi_04	1.24 (0.12)	-0.16 (0.26)	1.26 (0.13)	-0.22 (0.26)	0.97 (0.07)	0.61 (0.21)
a_fac_ic_fdiarlag_bic_f_01	0.89 (0.20)	0.55 (0.09)	0.90 (0.20)	0.55 (0.09)	0.97 (0.20)	0.51 (0.08)
a_fac_ic_fdiar_bic_f_01	1.19 (0.31)	0.43 (0.10)	0.96 (0.18)	0.52 (0.08)	1.70 (0.58)	0.31 (0.07)
a_fac_ic_fdi_bic_f_01	1.51 (0.40)	0.35 (0.07)	1.43 (0.36)	0.37 (0.07)	1.44 (0.40)	0.37 (0.07)
a_fbp_ic_fdiarlag_bic_f_01	1.16 (0.30)	0.44 (0.09)	1.09 (0.24)	0.47 (0.08)	1.12 (0.30)	0.46 (0.10)
a_fbp_ic_fdiar_bic_f_01	1.08 (0.23)	0.47 (0.08)	1.07 (0.22)	0.47 (0.08)	1.02 (0.22)	0.49 (0.09)
a_fbp_ic_fdi_bic_f_01	1.15 (0.26)	0.45 (0.08)	1.16 (0.26)	0.44 (0.08)	1.03 (0.22)	0.49 (0.09)
a_fac_ic_fdiar_01	0.89 (0.20)	0.55 (0.09)	0.90 (0.20)	0.55 (0.09)	0.96 (0.20)	0.52 (0.10)
a_fac_ic_fdiar_02	0.96 (0.21)	0.51 (0.09)	0.96 (0.21)	0.52 (0.09)	1.07 (0.24)	0.47 (0.09)
a_fac_ic_fdiar_03	0.92 (0.20)	0.53 (0.09)	0.93 (0.20)	0.53 (0.09)	0.93 (0.22)	0.53 (0.09)
a_fac_ic_fdiar_04	0.93 (0.20)	0.53 (0.09)	0.94 (0.20)	0.53 (0.09)	0.96 (0.21)	0.52 (0.08)
a_fac_ic_fdi_01	0.43 (0.19)	0.83 (0.11)	0.43 (0.19)	0.83 (0.11)	0.49 (0.18)	0.81 (0.11)
a_fac_ic_fdi_02	1.09 (0.25)	0.47 (0.08)	1.09 (0.25)	0.47 (0.08)	1.07 (0.24)	0.47 (0.08)
a_fac_ic_fdi_03	0.92 (0.21)	0.53 (0.08)	0.93 (0.22)	0.53 (0.08)	0.91 (0.21)	0.53 (0.08)
a_fac_ic_fdi_04	0.91 (0.21)	0.53 (0.08)	0.92 (0.21)	0.53 (0.08)	0.91 (0.21)	0.54 (0.08)

RMSE for AR Model 0.032 0.032 0.036

Notes: See notes to Table 2

Table 4 Results for financial series, h = 12

---- Series ---

Forecast Method	fytb		fs		espo	
_bse0_01	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2_01	4.56 (5.55)	0.10 (0.05)	11.24 (36.79)	-0.05 (0.03)	8.30 (15.44)	0.01 (0.04)
_bse0ic_01	1.69 (0.51)	0.18 (0.16)	2.82 (2.16)	-0.38 (0.19)	2.41 (1.01)	-0.11 (0.16)
_varf_01	1.23 (0.19)	-0.64 (0.55)	1.27 (0.19)	-0.19 (0.24)	1.03 (0.13)	0.36 (0.55)
_varfic_01	1.60 (0.49)	0.18 (0.17)	3.30 (2.57)	-0.26 (0.17)	2.83 (1.47)	-0.11 (0.14)
a_fac__fdiarlag_bic_f_01	1.01 (0.14)	0.45 (0.50)	1.20 (0.22)	0.02 (0.43)	0.94 (0.06)	1.10 (0.61)
a_fac__fdiar_bic_f_01	0.93 (0.15)	0.68 (0.35)	1.34 (0.29)	0.12 (0.25)	0.97 (0.07)	0.70 (0.59)
a_fac__fdi_bic_f_01	0.95 (0.14)	0.66 (0.43)	1.34 (0.29)	0.12 (0.25)	0.97 (0.07)	0.70 (0.59)
a_fbp__fdiarlag_bic_f_01	1.15 (0.13)	-0.21 (0.41)	1.26 (0.20)	-0.60 (0.43)	1.00 (0.11)	0.49 (0.53)
a_fbp__fdiar_bic_f_01	0.97 (0.22)	0.56 (0.37)	1.66 (0.54)	0.02 (0.24)	1.02 (0.12)	0.41 (0.52)
a_fbp__fdi_bic_f_01	0.97 (0.22)	0.56 (0.37)	1.66 (0.54)	0.02 (0.24)	1.02 (0.12)	0.41 (0.52)
a_fac__fdiar_01	0.94 (0.04)	4.44 (0.98)	1.11 (0.07)	-0.48 (0.39)	1.02 (0.02)	0.11 (0.51)
a_fac__fdiar_02	1.01 (0.14)	0.45 (0.50)	1.15 (0.21)	-0.00 (0.58)	0.94 (0.06)	1.04 (0.61)
a_fac__fdiar_03	1.08 (0.16)	0.21 (0.50)	1.19 (0.24)	-0.09 (0.60)	0.90 (0.08)	1.33 (0.65)
a_fac__fdiar_04	1.04 (0.14)	0.37 (0.51)	1.22 (0.24)	0.02 (0.40)	0.92 (0.08)	1.06 (0.57)
a_fac__fdi_01	0.94 (0.04)	4.44 (0.98)	1.11 (0.07)	-0.48 (0.39)	1.01 (0.03)	0.38 (0.55)
a_fac__fdi_02	1.01 (0.14)	0.45 (0.50)	1.15 (0.21)	-0.00 (0.58)	0.92 (0.07)	1.21 (0.62)
a_fac__fdi_03	1.08 (0.16)	0.21 (0.50)	1.19 (0.24)	-0.09 (0.60)	0.93 (0.07)	1.11 (0.65)
a_fac__fdi_04	1.04 (0.14)	0.37 (0.51)	1.22 (0.24)	0.02 (0.40)	0.95 (0.07)	0.87 (0.55)
a_fac_ic_fdiarlag_bic_f_01	1.51 (0.43)	0.22 (0.17)	2.93 (2.38)	-0.34 (0.17)	2.47 (1.08)	-0.10 (0.18)
a_fac_ic_fdiar_bic_f_01	1.66 (0.46)	0.17 (0.15)	3.09 (2.51)	-0.23 (0.15)	2.57 (1.19)	-0.12 (0.18)
a_fac_ic_fdi_bic_f_01	1.58 (0.48)	0.20 (0.17)	3.09 (2.51)	-0.23 (0.15)	2.57 (1.19)	-0.12 (0.18)
a_fbp_ic_fdiarlag_bic_f_01	1.76 (0.61)	0.17 (0.15)	3.39 (3.36)	-0.39 (0.15)	2.64 (1.26)	-0.09 (0.16)
a_fbp_ic_fdiar_bic_f_01	1.62 (0.57)	0.12 (0.21)	3.28 (2.76)	-0.23 (0.14)	2.74 (1.31)	-0.10 (0.16)
a_fbp_ic_fdi_bic_f_01	1.62 (0.57)	0.12 (0.21)	3.28 (2.76)	-0.23 (0.14)	2.74 (1.31)	-0.10 (0.16)
a_fac_ic_fdiar_01	1.66 (0.47)	0.20 (0.14)	3.17 (2.71)	-0.33 (0.15)	2.51 (1.10)	-0.12 (0.16)
a_fac_ic_fdiar_02	1.51 (0.43)	0.22 (0.17)	2.96 (2.42)	-0.39 (0.17)	2.53 (1.16)	-0.11 (0.17)
a_fac_ic_fdiar_03	1.57 (0.47)	0.20 (0.17)	2.96 (2.45)	-0.40 (0.17)	2.45 (1.04)	-0.09 (0.16)
a_fac_ic_fdiar_04	1.53 (0.45)	0.22 (0.17)	2.94 (2.42)	-0.33 (0.17)	2.52 (1.10)	-0.09 (0.15)
a_fac_ic_fdi_01	1.66 (0.47)	0.20 (0.14)	3.17 (2.71)	-0.33 (0.15)	2.50 (1.09)	-0.12 (0.16)
a_fac_ic_fdi_02	1.51 (0.43)	0.22 (0.17)	2.96 (2.42)	-0.39 (0.17)	2.49 (1.10)	-0.11 (0.17)
a_fac_ic_fdi_03	1.57 (0.47)	0.20 (0.17)	2.96 (2.45)	-0.40 (0.17)	2.51 (1.12)	-0.11 (0.17)
a_fac_ic_fdi_04	1.53 (0.45)	0.22 (0.17)	2.94 (2.42)	-0.33 (0.17)	2.57 (1.17)	-0.10 (0.16)

RMSE for AR Model 2.282 0.128 0.117

Notes: See notes to Table 2

Table 5 Directional forecasting accuracy

Concordance Index for each series $h = 12$

---- Series --- Forecast Method	ip	rtvol	lurat	cpi	rpix	cpnf	fytb	fs	espo
_bse0_01	0.70	0.63	0.65	0.59	0.62	0.62	0.78	0.80	0.80
_bse0_i2_01	0.47	0.52	0.70	0.59	0.59	0.59	0.61	0.53	0.52
_bse0ic_01	0.39	0.55	0.68	0.56	0.54	0.48	0.27	0.44	0.34
_varf_01	0.70	0.70	0.86	0.59	0.61	0.65	0.77	0.76	0.78
_varfic_01	0.56	0.58	0.70	0.56	0.57	0.53	0.48	0.44	0.38
a_fac__fdiarlag_bic_f_01	0.73	0.73	0.78	0.58	0.61	0.60	0.80	0.71	0.81
a_fac__fdiar_bic_f_01	0.67	0.73	0.69	0.56	0.61	0.60	0.82	0.70	0.80
a_fac__fdi_bic_f_01	0.68	0.73	0.60	0.56	0.59	0.58	0.81	0.70	0.80
a_fbp__fdiarlag_bic_f_01	0.69	0.72	0.75	0.56	0.59	0.57	0.78	0.69	0.82
a_fbp__fdiar_bic_f_01	0.72	0.68	0.64	0.54	0.55	0.59	0.82	0.68	0.80
a_fbp__fdi_bic_f_01	0.71	0.67	0.59	0.52	0.56	0.59	0.82	0.68	0.80
a_fac__fdiar_01	0.71	0.63	0.65	0.58	0.61	0.63	0.80	0.78	0.80
a_fac__fdiar_02	0.73	0.71	0.78	0.58	0.61	0.62	0.80	0.70	0.82
a_fac__fdiar_03	0.70	0.73	0.78	0.58	0.61	0.61	0.78	0.70	0.82
a_fac__fdiar_04	0.69	0.73	0.80	0.58	0.61	0.60	0.78	0.72	0.80
a_fac__fdi_01	0.71	0.61	0.56	0.56	0.59	0.63	0.80	0.78	0.80
a_fac__fdi_02	0.70	0.68	0.66	0.54	0.56	0.59	0.80	0.70	0.82
a_fac__fdi_03	0.70	0.73	0.68	0.58	0.59	0.60	0.78	0.70	0.82
a_fac__fdi_04	0.70	0.73	0.67	0.58	0.59	0.59	0.78	0.72	0.80
a_fac_ic_fdiarlag_bic_f_01	0.57	0.65	0.71	0.61	0.61	0.50	0.65	0.47	0.50
a_fac_ic_fdiar_bic_f_01	0.58	0.64	0.69	0.50	0.52	0.48	0.59	0.51	0.47
a_fac_ic_fdi_bic_f_01	0.57	0.67	0.67	0.57	0.59	0.51	0.61	0.51	0.47
a_fbp_ic_fdiarlag_bic_f_01	0.60	0.62	0.67	0.56	0.57	0.51	0.52	0.44	0.47
a_fbp_ic_fdiar_bic_f_01	0.63	0.59	0.66	0.56	0.54	0.56	0.60	0.48	0.42
a_fbp_ic_fdi_bic_f_01	0.63	0.59	0.68	0.52	0.51	0.56	0.60	0.48	0.42
a_fac_ic_fdiar_01	0.49	0.60	0.68	0.61	0.61	0.58	0.52	0.44	0.45
a_fac_ic_fdiar_02	0.59	0.65	0.71	0.60	0.59	0.52	0.65	0.42	0.48
a_fac_ic_fdiar_03	0.59	0.65	0.71	0.61	0.59	0.51	0.61	0.41	0.48
a_fac_ic_fdiar_04	0.62	0.65	0.70	0.61	0.59	0.54	0.61	0.47	0.49
a_fac_ic_fdi_01	0.49	0.50	0.54	0.54	0.53	0.50	0.52	0.44	0.45
a_fac_ic_fdi_02	0.53	0.59	0.65	0.50	0.50	0.45	0.65	0.42	0.48
a_fac_ic_fdi_03	0.55	0.65	0.69	0.59	0.58	0.52	0.61	0.41	0.46
a_fac_ic_fdi_04	0.62	0.69	0.70	0.59	0.57	0.52	0.61	0.47	0.46

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ip - industrial production
rtvol - retail sales volume
lurat - unemployment rate
fytb - treasury bill rate
fs - share prices, non-financials
espo - US $ exchange rate: spot
cpi - consumer price index, all items
rpix - retail price index excluding MIPs
cpnf - consumer price indec, all items less food

Figures

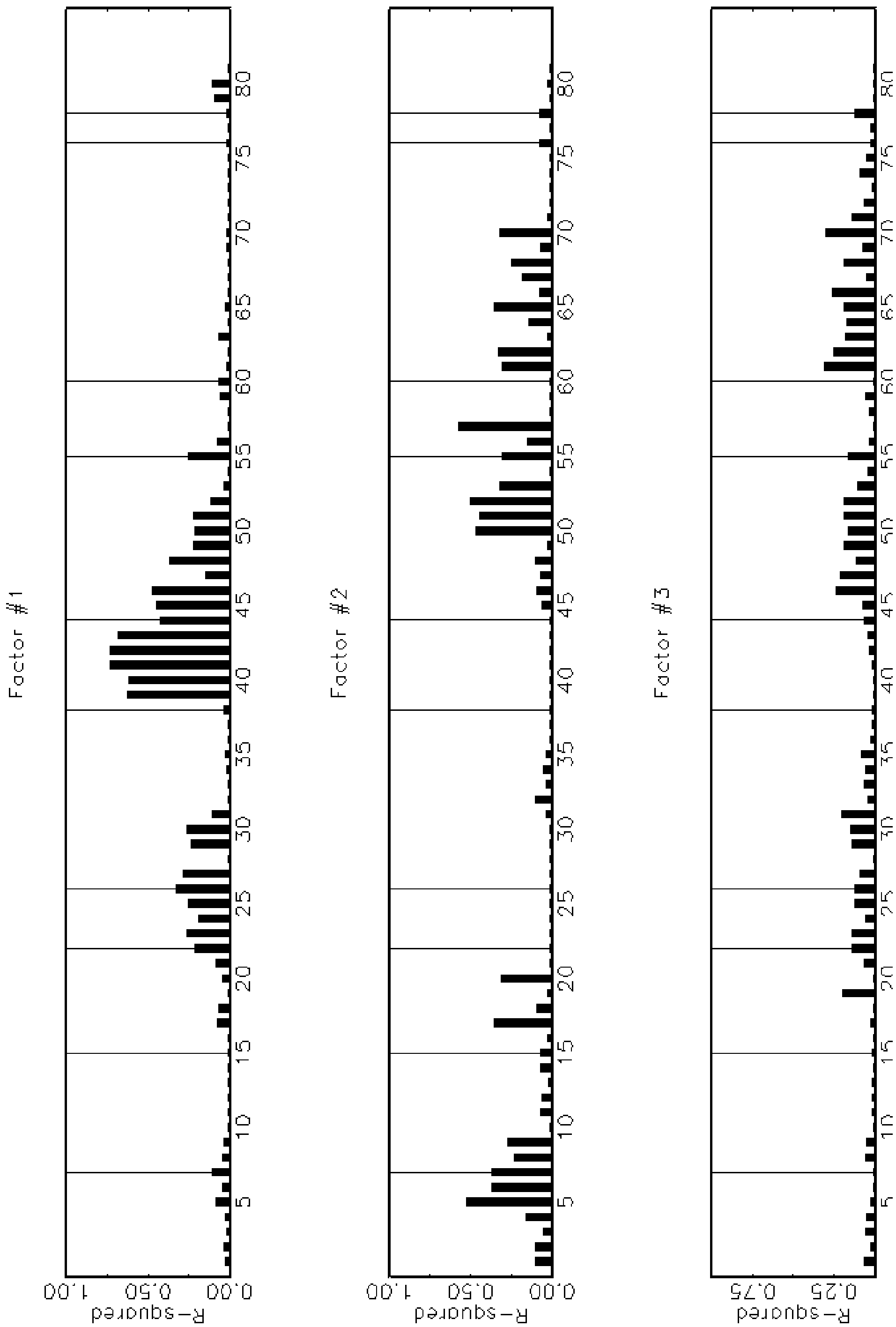

Figure 1 – R^2 from regression of factors 1 to 3 on variables

Notes: The vertical lines divide the variables into groups, as in the Appendix

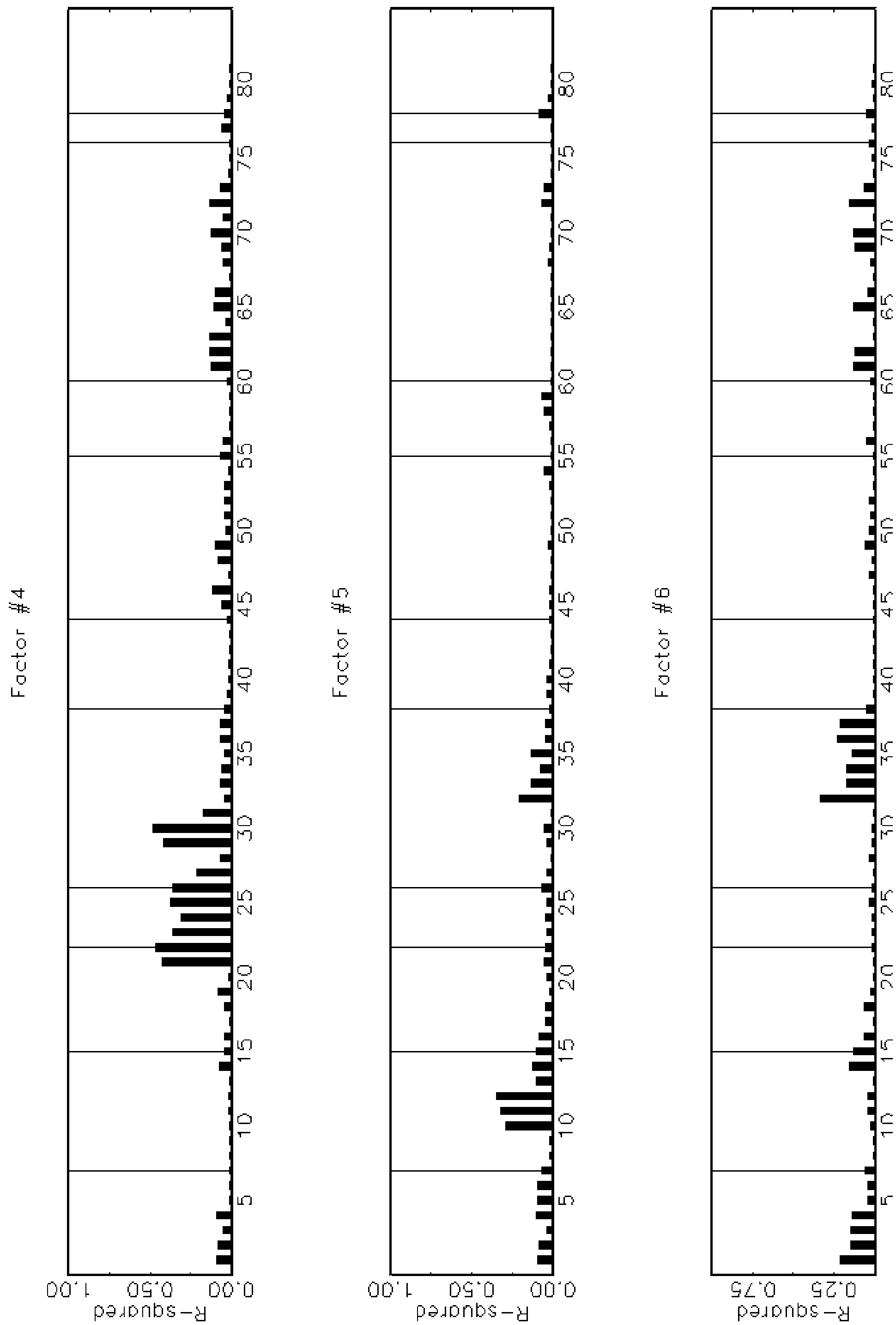

Figure 2 – R^2 from regression of factors 4 to 6 on variables

Notes: The vertical lines divide the variables into groups, as in the Appendix

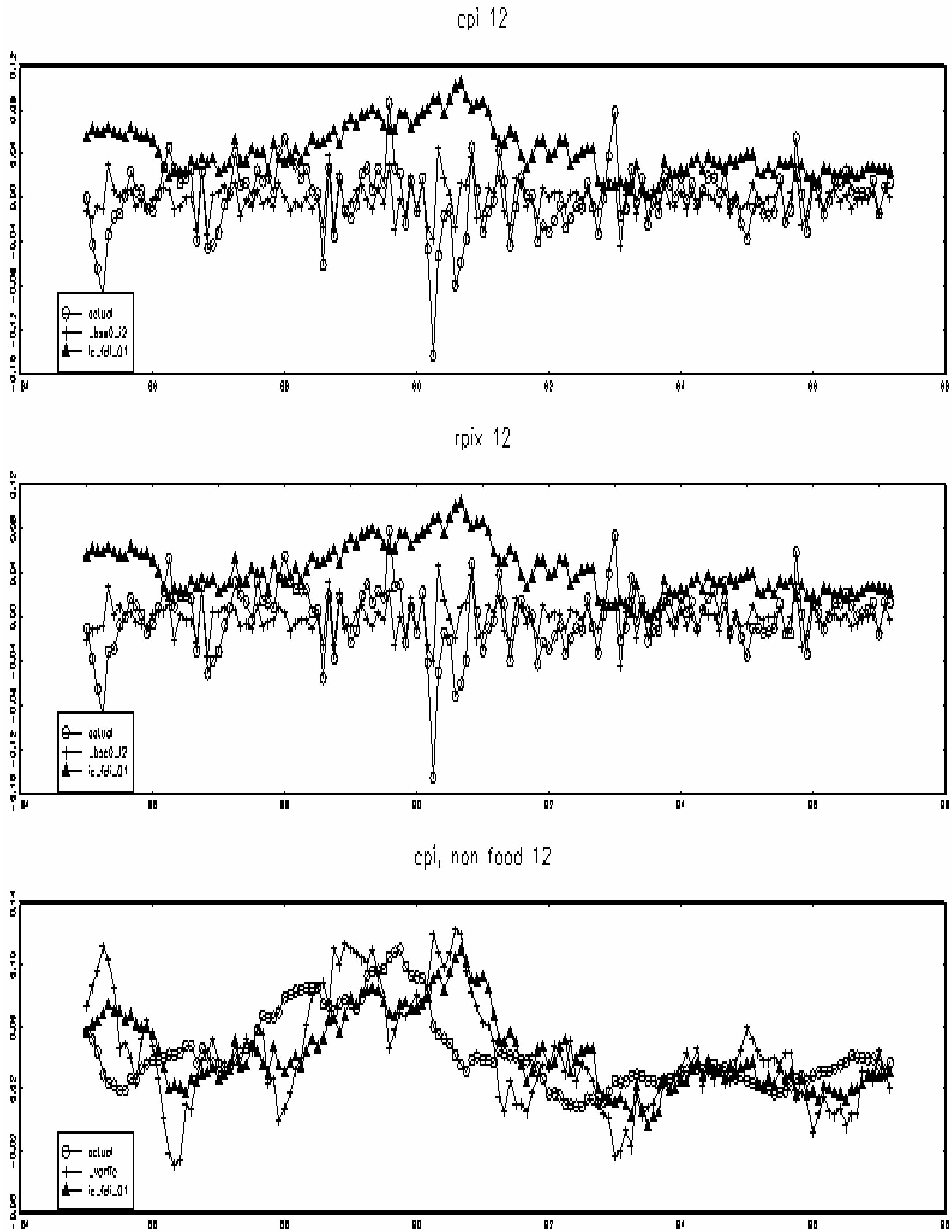

Figure 3 – 12-step ahead forecasts, prices

Note: The figure reports the actual values of the series, the best non factor-based forecast and the best factor-based forecast