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Factor forecasts for the UK *

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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. Hence, 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 benchmarks for prices, real aggregates, and financial variables, at virtually no additional modelling or computational costs.

Key Words: Factor models, forecasts, time series models

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1. Introduction

Dynamic factor-models have recently been successfully applied to forecasting US and Euro area macroeconomic variables (Stock and Watson (1998), Marcellino, Stock and Watson (2000, 2001)), and to business cycle analysis (Forni *et al.*, (1999, 2000)). 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. The extensions of this technique to large *N* can therefore be viewed 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 reversed.

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.

From a forecasting point of view, using a mean square forecast error criterion, the 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.

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

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. In the next section we describe in some detail the factor model, the data set employed and the estimated factors. In Section 3 we discuss the forecasting techniques and the evaluation criteria. Section 4 presents the forecast comparison based first on the relative mean square forecast error and then on the directional accuracy. Finally, in Section 5 we offer some suggestions for extensions and draw some general conclusions.

2. A large scale factor model for the UK

In this section we briefly introduce the representation and estimation theory for the dynamic factor model. We next discuss the UK data set. Finally, we present the results from modelling such a data set with a dynamic factor model.

2.1 The factor model

Let X_t be the N-macroeconomic variables to be modelled, observed for $t=1,...,T$. X_t admits an approximate linear dynamic factor representation with $\bar{r}$ common factors, f_t, if:

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

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; see for example Geweke (1977), Sargent and Sims (1977), Forni, Hallin, Lippi, and Reichlin (1999, 2000) and, in particular, Stock and Watson (1998). If $\lambda_i(L)$ have finite orders of at most q, equation (1) can be rewritten as,

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

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 $(\lambda_{i0}, \ldots, \lambda_{iq})$.

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 (1998) 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 (2000) 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 reestimated 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

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

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 (1998) allow either for a few abrupt changes, or for a smooth evolution as modelled by a multivariate random walk for Λ_t.

2.2 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 (2000), 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.

2.3 Results

The factor model appears to fit the data rather well. From Table 1, with 4 factors we already 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 (2000) 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 (2000) criteria. Given that the balanced panel includes only 34 series, versus the 81 in the unbalanced panel, we will concentrate on the latter.

In Table 1 we then 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.

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.

The final question we address in this section is that of the interpretation of the estimated factors. As discussed earlier, it is difficult to provide a structural interpretation because of identification issues. Yet, 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 (1998), 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 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 relevant.

Overall, these results are interesting and sensible from an economic point of view, even though we stress once again that the driving forces of the UK economy do not necessarily coincide with the variables indicated above, but could be linear combinations of them.

3. Forecasting

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

3.1 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,

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

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*, is 6, 12 and 24 months.

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^h_{t+h} depends on whether the series is modelled as *I(1)* or *I(2)*. In the *I(1)* case, it is $y^h_{t+h} = \sum_{t+1}^{t+h} \Delta x_s$, where *x* is the series of interest (usually in logs), so that $y^h_{t+h} = x_{t+h} - x_t$. 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 $y^h_{t+h} = \sum_{t+1}^{t+h} \Delta x_s - h\Delta x_t$, 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*. This is a convenient formulation because, given that Δx_t is known when forecasting, the mean square forecast error (msfe) from models for second differenced variables is directly comparable with that from models for first differences only.

The various forecasting models we compare differ in their choice of Z_t. Let us list them 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 cost less.

VAR forecasts (varf). . VAR forecasts are constructed using three-variable VARs. For real variables, the VARs include the real variable under analysis, the CPI, and the treasury bill rate (FYTB). Forecasts for prices are constructed using VARs for the price series under analysis, IP, and FYTB. For the financial variables, VARs for FS and ESPO include IP and FYTB, while for FYTB the CPI and IP are included. 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 (1998) 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 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. Yet, the 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 we have 33 different versions of the forecasting model (4).

3.2 Forecast Comparison

The forecast comparison is performed in a simulated out-of-sample framework where all statistical calculations are done using a fully recursive methodology. The forecast period is 1985:1 - 1998:3, for a total of 159 months. Every month, all model estimation, standardisation of the data, calculation of the estimated factors, etc., are repeated.

The forecasting performance of the various methods described in section 3.1 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 also 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).

In addition, we 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_{t+h}^{h} and y_{t}^{h}, and by $\hat{z}_{t+h}$ that between $\hat{y}_{t+h}^{h}$ and y_{t}^{h}. 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.

4. Forecasting Results

In this section we report the results of the forecast comparison for the UK macroeconomic variables. Tables 2-7 present the msfe and the pooling regression tests, whilst Tables 8 –10 report the directional accuracy measures. In each case, we deal first with real variables; then with prices; and finally with financial series.

4.1 Real variables

The msfe of the competing methods relative to the benchmark AR model are reported in Table 2 for h=12 and in Table 3 for h=6 and h=24. Four general results emerge: first, the factor models outperform the other methods, with an average gain of about 15-20% 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, both methods to deal with structural breaks, i.e. second-differencing and intercept correction, increase the msfe.

[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.

In more detail, for IP the best models are fac_fdiar_02 for h=6, fac_fdi_02 for h=12, and the var for h=24. The relative msfe are, respectively, .84, .87, and .90. For RTVOL, the best models are fac_diar_02 for h=6 and h=24, and fac_fdi_04 for h=12. The relative msfe are, respectively .81, .90 and .77. For LURAT the var is best for all forecast horizons, with relative msfe of .81 (h=6), .70 (h=12) , and .63 (h=24). The latter result is in line with what Marcellino, Stock and Watson (2001) found in other European countries.

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.

The best forecasts are graphed in Figure 3. More specifically, Figure 3 reports, for each real variable, the actual values and the 12-step-ahead forecasts from the best non-factor and factor model.

4.2 Prices

Results of the forecast comparison for the price series are presented in Table 4 for h=12, and in Table 5 for h=6 and h=24. Four comments are in order. First, the factor models perform well also in this case, with average gains of about 10-20%, with peaks for the best model and for h=24. Next, second-differencing and intercept corrections are quite useful, the more so the longer the forecast horizon. Third, the best model is always fac_ic_fdi_01, 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 increase with h, and range from 40% to 59% for CPI, from 39% to 59% for RPIX, and from 28% to 61% for CPNF. 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 often a simple AR with second-differencing of the dependent variable.

In Figure 4 we report, for each price series, the actual values and the 12-step ahead forecasts from the best non-factor and factor model.

4.3 Financial variables

The forecasting results for the financial variables are reported in Tables 6 for h=12 and Table 7 for h=6 and h=24. Three comments are worth making. First, for the FS it is never possible to beat the benchmark AR. Second, for FYTB and ESPO the best models are factor based, but the gains are small, about 5-10% for h=6 and h=12. For h=24 instead the best models are, respectively, fbp_bic and fac_fdiar_02, with gains of 48% and 24% with respect to the benchmark AR. Finally, second-differencing and intercept corrections are not useful.

Figure 5 presents, for each financial variable, the actual values and the 12-step ahead forecasts from the best non -factor and factor model.

4.4 Directional Accuracy

The directional accuracy indexes are reported in Tables 8 to 10 for different forecast horizons. 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 mse. Third, the gains of the factor based forecasts are rather small, except for price variables when h=24 and for RTVOL when h=6 and 12, 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.

5. 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 encouraging, and in line with those from previous studies for the US (Stock and Watson (1998)), and for the Euro area (Marcellino, Stock and Watson (2000, 2001)).

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 prices, lower for financial variables, but even larger for longer horizons and 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.

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

exchange rates

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

interest rates

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

money aggregates

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

price indices

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

wages

ww	weekly earnings
wc	unit labour cost s.a.

miscellaneous

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

Forecast Method	ip		rtvol		lurat	
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	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	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	1.02 (0.29)	0.48 (0.21)	1.09 (0.36)	0.43 (0.26)	0.70 (0.13)	1.37 (0.36)
_varfic	1.13 (0.35)	0.44 (0.15)	0.80 (0.26)	0.62 (0.16)	0.96 (0.20)	0.53 (0.15)
a_fac__fdiarlag_bic	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	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	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	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	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	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	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	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	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	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	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	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	

---- Series ---

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 real variables, h=6 and h=24

Horizon = 6.000

Forecast Method	ip		rtvol		lurat	
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	5.75 (6.32)	-0.02 (0.05)	4.08 (1.73)	0.10 (0.04)	0.87 (0.15)	0.69 (0.22)
_bse0ic	2.09 (1.22)	0.12 (0.14)	1.02 (0.14)	0.49 (0.07)	1.46 (0.44)	0.27 (0.14)
_varf	1.00 (0.16)	0.50 (0.18)	1.28 (0.38)	0.34 (0.17)	0.81 (0.09)	1.12 (0.31)
_varfic	1.56 (0.76)	0.22 (0.18)	0.88 (0.16)	0.57 (0.09)	1.29 (0.36)	0.34 (0.15)
a_fac__fdiarlag_bic	0.84 (0.11)	0.78 (0.18)	0.98 (0.18)	0.51 (0.13)	0.85 (0.07)	1.34 (0.37)
a_fac__fdiar_bic	0.84 (0.11)	0.78 (0.18)	0.98 (0.18)	0.51 (0.13)	0.98 (0.08)	0.60 (0.38)
a_fac__fdi_bic	1.01 (0.06)	0.48 (0.24)	0.99 (0.19)	0.51 (0.15)	1.88 (0.42)	-0.10 (0.12)
a_fbp__fdiarlag_bic	1.00 (0.10)	0.49 (0.22)	1.10 (0.27)	0.44 (0.16)	0.92 (0.07)	1.02 (0.49)
a_fbp__fdiar_bic	1.00 (0.10)	0.49 (0.22)	1.03 (0.25)	0.48 (0.15)	1.07 (0.09)	0.16 (0.39)
a_fbp__fdi_bic	1.03 (0.01)	-0.10 (0.15)	1.02 (0.20)	0.48 (0.17)	1.57 (0.30)	-0.09 (0.17)
a_fac__fdiar_01	0.96 (0.03)	1.03 (0.41)	0.99 (0.01)	2.19 (2.07)	1.03 (0.02)	-1.80 (0.98)
a_fac__fdiar_02	0.84 (0.11)	0.78 (0.18)	0.81 (0.14)	0.80 (0.21)	0.85 (0.07)	1.34 (0.37)
a_fac__fdiar_03	0.88 (0.10)	0.71 (0.18)	0.98 (0.18)	0.51 (0.13)	0.87 (0.07)	1.21 (0.40)
a_fac__fdiar_04	0.91 (0.09)	0.68 (0.19)	0.99 (0.19)	0.51 (0.12)	0.89 (0.07)	1.15 (0.40)
a_fac__fdi_01	0.97 (0.03)	1.36 (0.83)	1.00 (0.03)	0.47 (0.24)	3.32 (1.67)	-0.17 (0.09)
a_fac__fdi_02	0.90 (0.08)	0.92 (0.34)	0.83 (0.11)	0.86 (0.20)	2.05 (0.71)	0.03 (0.11)
a_fac__fdi_03	0.96 (0.09)	0.62 (0.25)	0.92 (0.15)	0.57 (0.13)	2.11 (0.77)	0.01 (0.11)
a_fac__fdi_04	0.88 (0.09)	0.79 (0.21)	0.90 (0.15)	0.60 (0.13)	2.12 (0.75)	-0.03 (0.11)
a_fac_ic_fdiarlag_bic	1.72 (0.87)	0.21 (0.16)	1.18 (0.19)	0.43 (0.07)	1.20 (0.30)	0.37 (0.16)
a_fac_ic_fdiar_bic	1.72 (0.87)	0.21 (0.16)	1.18 (0.19)	0.43 (0.07)	1.20 (0.30)	0.38 (0.15)
a_fac_ic_fdi_bic	2.06 (1.20)	0.13 (0.14)	1.29 (0.21)	0.39 (0.07)	1.11 (0.22)	0.42 (0.14)
a_fbp_ic_fdiarlag_bic	1.95 (1.15)	0.17 (0.14)	1.01 (0.18)	0.49 (0.08)	1.36 (0.39)	0.30 (0.15)
a_fbp_ic_fdiar_bic	1.95 (1.15)	0.17 (0.14)	1.11 (0.21)	0.45 (0.09)	1.21 (0.32)	0.38 (0.15)
a_fbp_ic_fdi_bic	2.10 (1.23)	0.12 (0.13)	1.45 (0.20)	0.36 (0.06)	1.13 (0.22)	0.41 (0.13)
a_fac_ic_fdiar_01	1.98 (1.16)	0.16 (0.14)	1.02 (0.14)	0.49 (0.07)	1.44 (0.45)	0.28 (0.14)
a_fac_ic_fdiar_02	1.72 (0.87)	0.21 (0.16)	1.07 (0.17)	0.47 (0.07)	1.20 (0.30)	0.37 (0.16)
a_fac_ic_fdiar_03	1.79 (0.97)	0.19 (0.16)	1.18 (0.19)	0.43 (0.07)	1.22 (0.30)	0.36 (0.16)
a_fac_ic_fdiar_04	1.94 (1.08)	0.14 (0.14)	1.21 (0.20)	0.42 (0.07)	1.22 (0.31)	0.36 (0.16)
a_fac_ic_fdi_01	2.10 (1.23)	0.13 (0.13)	1.29 (0.16)	0.39 (0.06)	1.24 (0.21)	0.31 (0.13)
a_fac_ic_fdi_02	2.14 (1.20)	0.13 (0.13)	1.39 (0.18)	0.37 (0.06)	1.11 (0.15)	0.41 (0.11)
a_fac_ic_fdi_03	2.21 (1.38)	0.10 (0.13)	1.53 (0.23)	0.33 (0.05)	1.12 (0.16)	0.40 (0.12)
a_fac_ic_fdi_04	1.91 (1.07)	0.15 (0.15)	1.51 (0.23)	0.34 (0.05)	1.20 (0.21)	0.35 (0.13)
RMSE for AR Model	0.017		0.015		0.418	

---- Series ---

Horizon = 24.000

Forecast Method	ip		rtvol		lurat	
	---- Series ---					
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	11.63 (34.87)	0.03 (0.02)	6.94 (6.36)	0.08 (0.03)	1.10 (0.42)	0.44 (0.26)
_bse0ic	2.28 (1.32)	-0.03 (0.22)	1.64 (1.00)	0.22 (0.28)	1.76 (1.07)	0.08 (0.29)
_varf	0.90 (0.16)	0.68 (0.31)	1.13 (0.46)	0.42 (0.28)	0.63 (0.16)	1.66 (0.46)
_varfic	1.70 (0.57)	0.11 (0.27)	1.09 (0.39)	0.45 (0.21)	1.27 (0.58)	0.29 (0.37)
a_fac__fdiarlag_bic	1.05 (0.08)	0.37 (0.25)	0.94 (0.30)	0.56 (0.30)	0.78 (0.09)	1.67 (0.53)
a_fac__fdiar_bic	1.19 (0.20)	0.29 (0.18)	1.19 (0.45)	0.35 (0.33)	0.89 (0.08)	1.01 (0.41)
a_fac__fdi_bic	1.19 (0.20)	0.29 (0.18)	1.23 (0.49)	0.31 (0.34)	0.98 (0.10)	0.57 (0.32)
a_fbp__fdiarlag_bic	1.04 (0.10)	0.41 (0.24)	1.16 (0.58)	0.37 (0.42)	0.86 (0.09)	1.49 (0.66)
a_fbp__fdiar_bic	1.71 (0.99)	-0.08 (0.34)	1.25 (0.59)	0.32 (0.37)	1.15 (0.28)	-0.01 (0.73)
a_fbp__fdi_bic	1.72 (0.99)	-0.08 (0.34)	1.14 (0.48)	0.37 (0.40)	1.20 (0.29)	-0.14 (0.66)
a_fac__fdiar_01	1.01 (0.06)	0.38 (0.55)	1.00 (0.02)	0.44 (0.54)	0.98 (0.02)	4.80 (3.23)
a_fac__fdiar_02	0.96 (0.07)	0.72 (0.40)	0.90 (0.20)	0.75 (0.48)	0.78 (0.08)	2.09 (0.47)
a_fac__fdiar_03	0.98 (0.09)	0.61 (0.48)	0.92 (0.29)	0.59 (0.31)	0.77 (0.10)	1.79 (0.59)
a_fac__fdiar_04	1.01 (0.09)	0.47 (0.21)	0.94 (0.30)	0.56 (0.30)	0.77 (0.09)	1.67 (0.51)
a_fac__fdi_01	1.01 (0.06)	0.38 (0.55)	0.99 (0.03)	0.62 (0.50)	1.26 (0.19)	-0.46 (0.59)
a_fac__fdi_02	0.96 (0.07)	0.72 (0.40)	0.89 (0.17)	0.84 (0.46)	0.83 (0.10)	1.08 (0.46)
a_fac__fdi_03	0.98 (0.09)	0.61 (0.48)	0.88 (0.26)	0.65 (0.31)	0.83 (0.12)	0.98 (0.49)
a_fac__fdi_04	0.99 (0.09)	0.52 (0.26)	0.89 (0.25)	0.65 (0.31)	0.85 (0.11)	0.94 (0.47)
a_fac_ic_fdiarlag_bic	2.24 (1.21)	-0.02 (0.21)	1.31 (0.55)	0.38 (0.20)	1.51 (0.82)	0.10 (0.38)
a_fac_ic_fdiar_bic	2.28 (1.08)	-0.05 (0.22)	1.51 (0.68)	0.30 (0.22)	1.54 (0.80)	0.15 (0.34)
a_fac_ic_fdi_bic	2.28 (1.08)	-0.05 (0.22)	1.52 (0.63)	0.30 (0.21)	1.58 (0.76)	0.10 (0.36)
a_fbp_ic_fdiarlag_bic	2.26 (1.15)	-0.04 (0.22)	1.48 (0.78)	0.32 (0.22)	1.68 (0.99)	0.06 (0.33)
a_fbp_ic_fdiar_bic	2.68 (1.84)	-0.23 (0.21)	1.40 (0.68)	0.33 (0.25)	1.84 (1.08)	0.05 (0.30)
a_fbp_ic_fdi_bic	2.69 (1.84)	-0.23 (0.20)	1.43 (0.67)	0.32 (0.24)	1.79 (0.99)	0.03 (0.32)
a_fac_ic_fdiar_01	2.24 (1.26)	-0.09 (0.25)	1.59 (0.93)	0.22 (0.29)	1.76 (1.07)	0.09 (0.29)
a_fac_ic_fdiar_02	2.18 (1.10)	-0.01 (0.22)	1.53 (0.76)	0.30 (0.21)	1.50 (0.80)	0.12 (0.37)
a_fac_ic_fdiar_03	2.16 (1.09)	-0.03 (0.24)	1.32 (0.56)	0.38 (0.20)	1.49 (0.79)	0.10 (0.39)
a_fac_ic_fdiar_04	2.10 (0.97)	0.01 (0.22)	1.32 (0.56)	0.38 (0.20)	1.46 (0.77)	0.12 (0.40)
a_fac_ic_fdi_01	2.24 (1.26)	-0.09 (0.25)	1.60 (0.91)	0.22 (0.28)	1.90 (1.16)	-0.12 (0.33)
a_fac_ic_fdi_02	2.18 (1.10)	-0.01 (0.22)	1.56 (0.75)	0.29 (0.21)	1.46 (0.68)	0.11 (0.39)
a_fac_ic_fdi_03	2.16 (1.09)	-0.03 (0.24)	1.35 (0.56)	0.36 (0.20)	1.49 (0.71)	0.08 (0.40)
a_fac_ic_fdi_04	2.08 (0.98)	0.00 (0.23)	1.35 (0.56)	0.36 (0.20)	1.49 (0.72)	0.08 (0.40)
RMSE for AR Model	0.046		0.044		2.694	

Notes: See notes to Table 2

Table 4 - Results for price series, h=12

Forecast Method	cpi		rpix		cpnf	
	---- Series ---					
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	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	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	0.85 (0.08)	1.46 (0.52)	0.86 (0.08)	1.44 (0.54)	0.86 (0.07)	1.51 (0.45)
_varfic	0.98 (0.18)	0.51 (0.08)	0.97 (0.18)	0.51 (0.08)	1.06 (0.20)	0.47 (0.08)
a_fac__fdiarlag_bic	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	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	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	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	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	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	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	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	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	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	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	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 5 - Results for price series, h=6 and h=24

Horizon = 6.000

Forecast Method	cpi		rpix		cpnf	
	---- Series ---					
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	0.77 (0.13)	0.68 (0.11)	0.77 (0.13)	0.69 (0.11)	0.88 (0.15)	0.59 (0.12)
_bse0ic	1.06 (0.16)	0.47 (0.08)	1.08 (0.17)	0.46 (0.08)	1.13 (0.21)	0.44 (0.10)
_varf	0.81 (0.07)	1.37 (0.29)	0.82 (0.07)	1.37 (0.30)	0.81 (0.06)	1.52 (0.23)
_varfic	1.19 (0.20)	0.42 (0.07)	1.18 (0.20)	0.42 (0.07)	1.19 (0.23)	0.42 (0.09)
a_fac__fdiarlag_bic	0.94 (0.05)	0.77 (0.23)	0.97 (0.04)	0.81 (0.32)	0.82 (0.10)	0.85 (0.17)
a_fac__fdiar_bic	1.05 (0.11)	0.41 (0.17)	1.00 (0.07)	0.49 (0.30)	0.93 (0.13)	0.57 (0.15)
a_fac__fdi_bic	1.13 (0.13)	0.31 (0.16)	1.17 (0.14)	0.25 (0.16)	1.02 (0.12)	0.48 (0.17)
a_fbp__fdiarlag_bic	0.91 (0.10)	0.69 (0.21)	0.92 (0.09)	0.85 (0.38)	0.80 (0.13)	0.75 (0.18)
a_fbp__fdiar_bic	0.87 (0.11)	0.72 (0.19)	0.90 (0.10)	0.70 (0.21)	0.78 (0.13)	0.79 (0.17)
a_fbp__fdi_bic	0.92 (0.14)	0.60 (0.19)	0.95 (0.14)	0.57 (0.19)	0.85 (0.13)	0.68 (0.16)
a_fac__fdiar_01	0.97 (0.04)	1.05 (0.52)	0.96 (0.04)	1.07 (0.48)	0.96 (0.03)	1.89 (0.72)
a_fac__fdiar_02	0.99 (0.04)	0.58 (0.40)	0.98 (0.04)	0.70 (0.39)	0.98 (0.05)	0.64 (0.36)
a_fac__fdiar_03	0.91 (0.07)	0.88 (0.26)	0.91 (0.06)	0.92 (0.29)	0.82 (0.10)	0.85 (0.17)
a_fac__fdiar_04	0.91 (0.06)	0.89 (0.25)	0.92 (0.06)	0.93 (0.28)	0.82 (0.09)	0.87 (0.17)
a_fac__fdi_01	3.96 (1.63)	-0.41 (0.07)	4.09 (1.75)	-0.40 (0.07)	2.87 (0.92)	-0.49 (0.10)
a_fac__fdi_02	2.21 (0.64)	-0.59 (0.11)	2.28 (0.69)	-0.58 (0.11)	1.60 (0.33)	-0.36 (0.19)
a_fac__fdi_03	1.24 (0.15)	0.16 (0.19)	1.28 (0.17)	0.11 (0.20)	0.95 (0.11)	0.57 (0.17)
a_fac__fdi_04	1.24 (0.15)	0.15 (0.19)	1.28 (0.16)	0.10 (0.20)	0.95 (0.11)	0.58 (0.16)
a_fac_ic_fdiarlag_bic	1.17 (0.21)	0.43 (0.08)	1.11 (0.16)	0.45 (0.07)	1.19 (0.26)	0.42 (0.09)
a_fac_ic_fdiar_bic	1.75 (0.64)	0.27 (0.09)	1.38 (0.36)	0.35 (0.09)	1.69 (0.53)	0.29 (0.09)
a_fac_ic_fdi_bic	1.64 (0.44)	0.31 (0.07)	1.67 (0.46)	0.30 (0.07)	1.39 (0.40)	0.36 (0.09)
a_fbp_ic_fdiarlag_bic	1.07 (0.19)	0.47 (0.08)	1.04 (0.18)	0.48 (0.08)	1.02 (0.19)	0.49 (0.09)
a_fbp_ic_fdiar_bic	1.03 (0.17)	0.49 (0.08)	1.04 (0.17)	0.48 (0.08)	1.01 (0.21)	0.49 (0.10)
a_fbp_ic_fdi_bic	1.04 (0.17)	0.48 (0.07)	1.05 (0.17)	0.48 (0.07)	1.01 (0.20)	0.49 (0.10)
a_fac_ic_fdiar_01	1.11 (0.16)	0.45 (0.07)	1.13 (0.17)	0.44 (0.07)	1.13 (0.21)	0.44 (0.09)
a_fac_ic_fdiar_02	1.20 (0.19)	0.41 (0.07)	1.20 (0.19)	0.41 (0.07)	1.25 (0.24)	0.39 (0.08)
a_fac_ic_fdiar_03	1.17 (0.20)	0.43 (0.08)	1.17 (0.20)	0.43 (0.07)	1.19 (0.26)	0.42 (0.09)
a_fac_ic_fdiar_04	1.16 (0.20)	0.43 (0.07)	1.16 (0.19)	0.43 (0.07)	1.17 (0.25)	0.43 (0.09)
a_fac_ic_fdi_01	0.60 (0.15)	0.79 (0.11)	0.61 (0.15)	0.78 (0.11)	0.72 (0.15)	0.69 (0.12)
a_fac_ic_fdi_02	1.34 (0.24)	0.38 (0.06)	1.35 (0.25)	0.38 (0.06)	1.26 (0.25)	0.40 (0.08)
a_fac_ic_fdi_03	1.32 (0.30)	0.39 (0.07)	1.34 (0.31)	0.38 (0.07)	1.18 (0.26)	0.43 (0.09)
a_fac_ic_fdi_04	1.30 (0.29)	0.39 (0.08)	1.33 (0.31)	0.39 (0.08)	1.16 (0.25)	0.44 (0.09)
RMSE for AR Model	0.014		0.014		0.016	

Horizon = 24.000

Forecast Method	cpi		rpix		cpnf	
	---- Series ---					
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	0.55 (0.23)	0.72 (0.10)	0.55 (0.23)	0.72 (0.10)	0.66 (0.24)	0.65 (0.11)
_bse0ic	0.57 (0.27)	0.69 (0.15)	0.57 (0.28)	0.69 (0.15)	0.52 (0.26)	0.72 (0.15)
_varf	0.88 (0.09)	1.51 (0.63)	0.88 (0.09)	1.46 (0.63)	0.89 (0.09)	1.37 (0.66)
_varfic	0.61 (0.28)	0.66 (0.15)	0.61 (0.28)	0.66 (0.15)	0.57 (0.27)	0.68 (0.15)
a_fac__fdiarlag_bic	0.93 (0.09)	1.16 (0.65)	0.92 (0.09)	1.19 (0.61)	0.88 (0.09)	1.47 (0.52)
a_fac__fdiar_bic	0.76 (0.22)	0.77 (0.21)	0.79 (0.22)	0.69 (0.17)	0.65 (0.20)	0.91 (0.16)
a_fac__fdi_bic	0.82 (0.23)	0.72 (0.26)	0.83 (0.23)	0.71 (0.27)	0.70 (0.20)	0.92 (0.21)
a_fbp__fdiarlag_bic	0.93 (0.14)	0.72 (0.41)	0.94 (0.14)	0.67 (0.41)	0.75 (0.14)	1.14 (0.28)
a_fbp__fdiar_bic	0.73 (0.23)	0.78 (0.23)	0.74 (0.23)	0.76 (0.22)	0.66 (0.21)	0.97 (0.26)
a_fbp__fdi_bic	0.77 (0.23)	0.74 (0.24)	0.79 (0.24)	0.73 (0.24)	0.66 (0.21)	0.97 (0.26)
a_fac__fdiar_01	0.93 (0.09)	1.16 (0.65)	0.92 (0.09)	1.20 (0.61)	0.91 (0.09)	1.31 (0.64)
a_fac__fdiar_02	0.93 (0.10)	1.16 (0.72)	0.91 (0.10)	1.22 (0.68)	0.93 (0.08)	1.21 (0.61)
a_fac__fdiar_03	0.96 (0.09)	0.93 (0.77)	0.95 (0.09)	0.93 (0.73)	0.88 (0.09)	1.44 (0.53)
a_fac__fdiar_04	0.91 (0.10)	1.22 (0.66)	0.91 (0.10)	1.19 (0.64)	0.84 (0.10)	1.53 (0.43)
a_fac__fdi_01	2.21 (0.68)	-1.00 (0.19)	2.24 (0.70)	-0.98 (0.19)	1.79 (0.43)	-1.23 (0.26)
a_fac__fdi_02	1.71 (0.36)	-1.39 (0.23)	1.73 (0.37)	-1.35 (0.24)	1.38 (0.19)	-1.27 (0.35)
a_fac__fdi_03	1.22 (0.10)	-0.58 (0.41)	1.24 (0.10)	-0.60 (0.41)	0.99 (0.07)	0.55 (0.38)
a_fac__fdi_04	1.17 (0.08)	-0.32 (0.37)	1.18 (0.08)	-0.34 (0.37)	0.95 (0.07)	0.77 (0.31)
a_fac_ic_fdiarlag_bic	0.50 (0.26)	0.73 (0.13)	0.50 (0.26)	0.73 (0.13)	0.46 (0.25)	0.75 (0.13)
a_fac_ic_fdiar_bic	0.75 (0.24)	0.60 (0.09)	0.86 (0.23)	0.55 (0.08)	0.69 (0.24)	0.63 (0.10)
a_fac_ic_fdi_bic	0.71 (0.24)	0.62 (0.09)	0.71 (0.24)	0.62 (0.09)	0.60 (0.24)	0.67 (0.11)
a_fbp_ic_fdiarlag_bic	0.66 (0.23)	0.64 (0.09)	0.68 (0.23)	0.63 (0.09)	0.77 (0.26)	0.60 (0.12)
a_fbp_ic_fdiar_bic	0.86 (0.29)	0.56 (0.13)	0.87 (0.29)	0.55 (0.13)	0.73 (0.26)	0.63 (0.14)
a_fbp_ic_fdi_bic	0.89 (0.30)	0.54 (0.13)	0.90 (0.30)	0.54 (0.13)	0.73 (0.26)	0.63 (0.14)
a_fac_ic_fdiar_01	0.50 (0.26)	0.73 (0.13)	0.50 (0.26)	0.73 (0.13)	0.45 (0.25)	0.76 (0.14)
a_fac_ic_fdiar_02	0.46 (0.25)	0.75 (0.13)	0.45 (0.26)	0.76 (0.13)	0.47 (0.25)	0.75 (0.14)
a_fac_ic_fdiar_03	0.47 (0.26)	0.75 (0.13)	0.46 (0.26)	0.76 (0.13)	0.48 (0.26)	0.74 (0.15)
a_fac_ic_fdiar_04	0.47 (0.26)	0.74 (0.13)	0.46 (0.26)	0.75 (0.13)	0.49 (0.26)	0.73 (0.14)
a_fac_ic_fdi_01	0.41 (0.26)	0.82 (0.19)	0.41 (0.26)	0.82 (0.19)	0.39 (0.25)	0.84 (0.19)
a_fac_ic_fdi_02	0.70 (0.28)	0.63 (0.14)	0.70 (0.29)	0.63 (0.14)	0.66 (0.27)	0.65 (0.14)
a_fac_ic_fdi_03	0.61 (0.29)	0.66 (0.15)	0.62 (0.29)	0.66 (0.15)	0.58 (0.28)	0.68 (0.15)
a_fac_ic_fdi_04	0.63 (0.29)	0.65 (0.15)	0.63 (0.29)	0.65 (0.15)	0.59 (0.28)	0.67 (0.15)
RMSE for AR Model	0.077		0.076		0.083	

Notes: See notes to Table 2

Table 6 - Results for financial variables, h=12

	---- Series ---					
Forecast Method	fytb		fs		espo	
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	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	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	1.23 (0.18)	-0.59 (0.54)	1.17 (0.16)	0.01 (0.30)	1.03 (0.14)	0.38 (0.57)
_varfic	1.61 (0.49)	0.18 (0.17)	3.08 (2.39)	-0.27 (0.19)	2.82 (1.48)	-0.12 (0.14)
a_fac__fdiarlag_bic	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	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	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	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	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	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	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	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	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	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	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	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 7 - Results for financial variables, h=6 and h=24

Horizon = 6.000

Forecast Method	fytb		fs		espo	
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	4.06 (4.45)	0.00 (0.07)	5.94 (9.47)	-0.02 (0.05)	4.31 (3.87)	-0.04 (0.06)
_bse0ic	1.76 (0.60)	0.17 (0.13)	2.21 (1.25)	-0.08 (0.16)	2.31 (0.98)	-0.12 (0.13)
_varf	1.17 (0.12)	-0.82 (0.57)	1.07 (0.07)	0.15 (0.28)	1.01 (0.07)	0.40 (0.56)
_varfic	1.81 (0.64)	0.15 (0.12)	2.36 (1.37)	-0.01 (0.12)	2.54 (1.24)	-0.07 (0.10)
a_fac__fdiarlag_bic	1.05 (0.11)	0.32 (0.36)	1.11 (0.07)	-0.07 (0.32)	0.98 (0.02)	1.17 (0.77)
a_fac__fdiar_bic	1.00 (0.09)	0.51 (0.32)	1.19 (0.10)	-0.21 (0.22)	0.98 (0.02)	1.17 (0.77)
a_fac__fdi_bic	1.03 (0.10)	0.41 (0.35)	1.19 (0.10)	-0.21 (0.22)	0.98 (0.02)	1.17 (0.77)
a_fbp__fdiarlag_bic	1.16 (0.11)	-0.26 (0.29)	1.00 (0.00)	. (.)	1.04 (0.02)	-1.11 (0.62)
a_fbp__fdiar_bic	0.99 (0.10)	0.53 (0.36)	1.00 (0.00)	. (.)	1.04 (0.02)	-1.11 (0.62)
a_fbp__fdi_bic	1.00 (0.11)	0.49 (0.32)	0.99 (0.03)	2.00 (2.58)	1.04 (0.02)	-1.11 (0.62)
a_fac__fdiar_01	0.97 (0.04)	1.01 (0.51)	1.04 (0.04)	0.08 (0.55)	0.98 (0.02)	1.17 (0.77)
a_fac__fdiar_02	1.05 (0.11)	0.34 (0.35)	1.05 (0.10)	0.24 (0.61)	0.97 (0.03)	1.47 (0.76)
a_fac__fdiar_03	1.00 (0.09)	0.52 (0.41)	1.07 (0.11)	0.14 (0.61)	0.97 (0.03)	1.29 (0.79)
a_fac__fdiar_04	0.94 (0.09)	0.77 (0.43)	1.10 (0.11)	0.09 (0.45)	0.99 (0.03)	0.73 (0.63)
a_fac__fdi_01	0.97 (0.04)	1.01 (0.51)	1.04 (0.04)	0.08 (0.55)	0.98 (0.02)	1.17 (0.77)
a_fac__fdi_02	1.05 (0.11)	0.34 (0.35)	1.05 (0.10)	0.24 (0.61)	0.97 (0.03)	1.47 (0.76)
a_fac__fdi_03	1.00 (0.09)	0.52 (0.41)	1.07 (0.11)	0.14 (0.61)	0.97 (0.03)	1.29 (0.79)
a_fac__fdi_04	0.94 (0.09)	0.77 (0.43)	1.10 (0.11)	0.09 (0.45)	0.99 (0.03)	0.73 (0.63)
a_fac_ic_fdiarlag_bic	1.53 (0.43)	0.21 (0.14)	2.24 (1.18)	-0.04 (0.13)	2.27 (0.99)	-0.10 (0.13)
a_fac_ic_fdiar_bic	1.51 (0.42)	0.24 (0.13)	2.40 (1.48)	-0.07 (0.14)	2.27 (0.99)	-0.10 (0.13)
a_fac_ic_fdi_bic	1.53 (0.44)	0.22 (0.13)	2.40 (1.48)	-0.07 (0.14)	2.27 (0.99)	-0.10 (0.13)
a_fbp_ic_fdiarlag_bic	1.60 (0.45)	0.23 (0.12)	2.21 (1.25)	-0.08 (0.16)	2.41 (1.06)	-0.12 (0.12)
a_fbp_ic_fdiar_bic	1.55 (0.42)	0.24 (0.12)	2.21 (1.25)	-0.08 (0.16)	2.41 (1.06)	-0.12 (0.12)
a_fbp_ic_fdi_bic	1.65 (0.51)	0.21 (0.13)	2.17 (1.17)	-0.08 (0.15)	2.41 (1.06)	-0.12 (0.12)
a_fac_ic_fdiar_01	1.70 (0.53)	0.18 (0.12)	2.30 (1.21)	-0.05 (0.12)	2.27 (0.99)	-0.10 (0.13)
a_fac_ic_fdiar_02	1.52 (0.43)	0.21 (0.14)	2.13 (1.03)	-0.04 (0.13)	2.26 (0.97)	-0.10 (0.13)
a_fac_ic_fdiar_03	1.54 (0.44)	0.22 (0.13)	2.14 (1.03)	-0.04 (0.13)	2.29 (0.99)	-0.10 (0.13)
a_fac_ic_fdiar_04	1.52 (0.41)	0.22 (0.13)	2.19 (1.05)	-0.03 (0.12)	2.36 (1.07)	-0.10 (0.12)
a_fac_ic_fdi_01	1.70 (0.53)	0.18 (0.12)	2.30 (1.21)	-0.05 (0.12)	2.27 (0.99)	-0.10 (0.13)
a_fac_ic_fdi_02	1.52 (0.43)	0.21 (0.14)	2.13 (1.03)	-0.04 (0.13)	2.26 (0.97)	-0.10 (0.13)
a_fac_ic_fdi_03	1.54 (0.44)	0.22 (0.13)	2.14 (1.03)	-0.04 (0.13)	2.29 (0.99)	-0.10 (0.13)
a_fac_ic_fdi_04	1.52 (0.41)	0.22 (0.13)	2.19 (1.05)	-0.03 (0.12)	2.36 (1.07)	-0.10 (0.12)
RMSE for AR Model	1.282		0.094		0.090	

Horizon = 24.000

Forecast Method	fytb		fs		espo	
_bse0	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)	1.00 (0.00)	. (.)
_bse0_i2	7.38 (16.06)	0.05 (0.06)	37.98 (435.9)	-0.03 (0.01)	16.66 (64.55)	0.02 (0.04)
_bse0ic	2.35 (1.21)	-0.16 (0.31)	2.37 (2.34)	0.01 (0.25)	1.98 (0.69)	0.07 (0.21)
_varf	1.24 (0.28)	-0.49 (0.76)	1.33 (0.50)	-0.16 (0.41)	0.89 (0.18)	0.89 (0.56)
_varfic	2.28 (0.98)	-0.26 (0.32)	2.75 (3.36)	-0.02 (0.19)	1.83 (0.63)	0.19 (0.18)
a_fac__fdiarlag_bic	1.10 (0.17)	0.11 (0.56)	1.46 (0.60)	0.11 (0.27)	0.76 (0.18)	1.27 (0.36)
a_fac__fdiar_bic	0.62 (0.26)	1.43 (0.40)	1.68 (0.90)	0.08 (0.28)	1.27 (0.46)	-0.14 (0.52)
a_fac__fdi_bic	0.60 (0.25)	1.63 (0.43)	1.68 (0.90)	0.08 (0.28)	1.26 (0.46)	-0.13 (0.52)
a_fbp__fdiarlag_bic	1.07 (0.14)	0.17 (0.64)	1.26 (0.50)	0.29 (0.26)	0.92 (0.10)	0.70 (0.21)
a_fbp__fdiar_bic	0.52 (0.33)	1.18 (0.29)	2.33 (1.62)	0.04 (0.18)	1.05 (0.10)	0.39 (0.20)
a_fbp__fdi_bic	0.54 (0.33)	1.13 (0.30)	2.33 (1.62)	0.04 (0.18)	1.05 (0.10)	0.39 (0.20)
a_fac__fdiar_01	0.96 (0.04)	5.53 (2.18)	1.25 (0.19)	-0.00 (0.20)	0.97 (0.03)	1.20 (0.53)
a_fac__fdiar_02	0.98 (0.11)	0.58 (0.55)	1.29 (0.45)	0.23 (0.25)	0.76 (0.18)	1.27 (0.36)
a_fac__fdiar_03	1.11 (0.19)	0.10 (0.59)	1.41 (0.67)	0.14 (0.31)	0.78 (0.18)	1.23 (0.39)
a_fac__fdiar_04	1.08 (0.16)	0.18 (0.60)	1.44 (0.56)	0.13 (0.25)	0.81 (0.16)	1.17 (0.37)
a_fac__fdi_01	0.96 (0.04)	5.53 (2.18)	1.13 (0.07)	-0.08 (0.28)	0.97 (0.03)	1.20 (0.53)
a_fac__fdi_02	0.98 (0.11)	0.58 (0.55)	1.29 (0.45)	0.23 (0.25)	0.77 (0.17)	1.29 (0.39)
a_fac__fdi_03	1.11 (0.19)	0.10 (0.59)	1.41 (0.67)	0.14 (0.31)	0.79 (0.17)	1.24 (0.42)
a_fac__fdi_04	1.08 (0.16)	0.18 (0.60)	1.44 (0.56)	0.13 (0.25)	0.82 (0.15)	1.18 (0.41)
a_fac_ic_fdiarlag_bic	2.08 (0.86)	-0.14 (0.34)	2.64 (1.74)	-0.00 (0.21)	2.08 (0.84)	0.08 (0.18)
a_fac_ic_fdiar_bic	1.27 (0.33)	0.23 (0.35)	2.43 (1.46)	0.04 (0.20)	2.94 (2.41)	0.00 (0.12)
a_fac_ic_fdi_bic	1.21 (0.34)	0.31 (0.32)	2.43 (1.46)	0.04 (0.20)	2.94 (2.42)	0.00 (0.12)
a_fbp_ic_fdiarlag_bic	2.07 (0.85)	-0.04 (0.29)	2.40 (1.64)	0.05 (0.20)	2.33 (1.17)	0.09 (0.14)
a_fbp_ic_fdiar_bic	1.23 (0.35)	0.21 (0.44)	3.52 (2.40)	0.03 (0.12)	2.59 (1.61)	0.08 (0.12)
a_fbp_ic_fdi_bic	1.32 (0.42)	0.13 (0.45)	3.52 (2.40)	0.03 (0.12)	2.59 (1.61)	0.08 (0.12)
a_fac_ic_fdiar_01	2.25 (1.11)	-0.12 (0.31)	2.72 (2.74)	0.03 (0.20)	1.99 (0.71)	0.08 (0.19)
a_fac_ic_fdiar_02	1.87 (0.72)	-0.07 (0.35)	2.27 (1.47)	0.06 (0.24)	2.08 (0.84)	0.08 (0.18)
a_fac_ic_fdiar_03	2.02 (0.78)	-0.13 (0.34)	2.38 (1.69)	0.02 (0.24)	2.13 (0.86)	0.07 (0.18)
a_fac_ic_fdiar_04	2.01 (0.78)	-0.12 (0.33)	2.55 (1.60)	0.02 (0.22)	2.19 (0.90)	0.08 (0.17)
a_fac_ic_fdi_01	2.25 (1.11)	-0.12 (0.31)	2.67 (2.59)	-0.00 (0.21)	1.99 (0.71)	0.08 (0.19)
a_fac_ic_fdi_02	1.87 (0.72)	-0.07 (0.35)	2.27 (1.47)	0.06 (0.24)	2.13 (0.91)	0.07 (0.18)
a_fac_ic_fdi_03	2.02 (0.78)	-0.13 (0.34)	2.38 (1.69)	0.02 (0.24)	2.18 (0.94)	0.06 (0.19)
a_fac_ic_fdi_04	2.01 (0.78)	-0.12 (0.33)	2.55 (1.60)	0.02 (0.22)	2.25 (0.99)	0.05 (0.18)
RMSE for AR Model	3.766		0.137		0.163	

---- Series ---

Notes: See notes to Table 2

Table 8: Directional forecasting accuracy

Concordance Index for each series

Horizon = 12.00

	---- 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	0.35
_varf_01	0.72	0.72	0.86	0.59	0.61	0.63	0.76	0.76	0.78
_varfic_01	0.64	0.57	0.71	0.57	0.54	0.50	0.50	0.50	0.40
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

Note: The Concordance Index is defined, as in Harding and Pagan (1999),
as the fraction of cases where the direction is forecast correctly.

Table 9 Directional forecasting accuracy

Horizon = 6.00

Forecast Method	ip	rtvol	lurat	cpi	rpix	cpnf	fytb	fs	espo
	---- Series ---								
_bse0_01	0.75	0.70	0.60	0.57	0.57	0.59	0.72	0.78	0.75
_bse0_i2_01	0.46	0.50	0.69	0.55	0.58	0.57	0.69	0.75	0.51
_bse0ic_01	0.46	0.56	0.63	0.42	0.46	0.51	0.48	0.34	0.32
_varf_01	0.69	0.73	0.74	0.56	0.54	0.58	0.72	0.76	0.76
_varfic_01	0.72	0.62	0.63	0.47	0.48	0.46	0.49	0.46	0.49
a_fac__fdiarlag_bic_f_01	0.73	0.75	0.71	0.54	0.55	0.59	0.73	0.71	0.76
a_fac__fdiar_bic_f_01	0.73	0.75	0.64	0.56	0.55	0.59	0.76	0.70	0.76
a_fac__fdi_bic_f_01	0.68	0.78	0.52	0.58	0.58	0.60	0.75	0.70	0.76
a_fbp__fdiarlag_bic_f_01	0.72	0.73	0.70	0.61	0.61	0.61	0.73	0.78	0.73
a_fbp__fdiar_bic_f_01	0.72	0.75	0.59	0.62	0.61	0.61	0.77	0.78	0.73
a_fbp__fdi_bic_f_01	0.73	0.70	0.56	0.60	0.61	0.61	0.76	0.78	0.73
a_fac__fdiar_01	0.76	0.70	0.59	0.55	0.56	0.60	0.75	0.76	0.76
a_fac__fdiar_02	0.73	0.76	0.71	0.56	0.55	0.61	0.75	0.71	0.76
a_fac__fdiar_03	0.71	0.75	0.69	0.54	0.55	0.59	0.74	0.71	0.76
a_fac__fdiar_04	0.73	0.75	0.70	0.54	0.55	0.59	0.76	0.69	0.77
a_fac__fdi_01	0.76	0.67	0.54	0.52	0.52	0.56	0.75	0.76	0.76
a_fac__fdi_02	0.73	0.72	0.59	0.53	0.53	0.59	0.75	0.71	0.76
a_fac__fdi_03	0.73	0.73	0.59	0.55	0.55	0.59	0.74	0.71	0.76
a_fac__fdi_04	0.72	0.77	0.59	0.55	0.55	0.59	0.76	0.69	0.77
a_fac_ic_fdiarlag_bic_f_01	0.61	0.62	0.67	0.46	0.45	0.52	0.66	0.49	0.53
a_fac_ic_fdiar_bic_f_01	0.61	0.62	0.67	0.49	0.46	0.52	0.65	0.48	0.53
a_fac_ic_fdi_bic_f_01	0.47	0.57	0.66	0.52	0.52	0.54	0.62	0.48	0.53
a_fbp_ic_fdiarlag_bic_f_01	0.59	0.64	0.63	0.46	0.50	0.52	0.61	0.34	0.29
a_fbp_ic_fdiar_bic_f_01	0.59	0.61	0.65	0.48	0.48	0.53	0.65	0.34	0.29
a_fbp_ic_fdi_bic_f_01	0.47	0.49	0.63	0.54	0.54	0.50	0.64	0.32	0.29
a_fac_ic_fdiar_01	0.59	0.61	0.65	0.46	0.48	0.48	0.51	0.42	0.53
a_fac_ic_fdiar_02	0.61	0.63	0.67	0.47	0.48	0.50	0.69	0.53	0.50
a_fac_ic_fdiar_03	0.61	0.62	0.67	0.46	0.47	0.52	0.62	0.52	0.51
a_fac_ic_fdiar_04	0.56	0.63	0.66	0.48	0.49	0.52	0.65	0.48	0.46
a_fac_ic_fdi_01	0.54	0.44	0.57	0.57	0.57	0.44	0.51	0.42	0.53
a_fac_ic_fdi_02	0.48	0.48	0.58	0.44	0.44	0.45	0.69	0.53	0.50
a_fac_ic_fdi_03	0.50	0.52	0.61	0.50	0.50	0.51	0.62	0.52	0.51
a_fac_ic_fdi_04	0.57	0.52	0.57	0.52	0.52	0.51	0.65	0.48	0.46

Table 10 Directional forecasting accuracy

Horizon = 24.00

	---- Series ---								
Forecast Method	ip	rtvol	lurat	cpi	rpix	cpnf	fytb	fs	espo
_bse0_01	0.79	0.74	0.56	0.54	0.54	0.59	0.81	0.78	0.77
_bse0_i2_01	0.52	0.47	0.69	0.65	0.62	0.65	0.61	0.61	0.51
_bse0ic_01	0.19	0.46	0.64	0.50	0.52	0.46	0.38	0.43	0.27
_varf_01	0.84	0.73	0.76	0.57	0.57	0.62	0.77	0.76	0.79
_varfic_01	0.67	0.64	0.72	0.56	0.56	0.49	0.52	0.58	0.53
a_fac__fdiarlag_bic_f_01	0.78	0.79	0.67	0.58	0.58	0.64	0.76	0.70	0.81
a_fac__fdiar_bic_f_01	0.81	0.76	0.59	0.70	0.72	0.75	0.79	0.68	0.80
a_fac__fdi_bic_f_01	0.81	0.73	0.58	0.64	0.64	0.71	0.79	0.68	0.80
a_fbp__fdiarlag_bic_f_01	0.79	0.75	0.67	0.60	0.60	0.62	0.79	0.73	0.79
a_fbp__fdiar_bic_f_01	0.78	0.71	0.59	0.65	0.66	0.68	0.82	0.67	0.80
a_fbp__fdi_bic_f_01	0.79	0.73	0.56	0.64	0.64	0.68	0.81	0.67	0.80
a_fac__fdiar_01	0.79	0.73	0.56	0.58	0.58	0.64	0.83	0.73	0.79
a_fac__fdiar_02	0.79	0.76	0.69	0.59	0.59	0.64	0.80	0.72	0.81
a_fac__fdiar_03	0.80	0.79	0.67	0.58	0.59	0.64	0.76	0.70	0.81
a_fac__fdiar_04	0.79	0.79	0.66	0.59	0.59	0.65	0.77	0.70	0.82
a_fac__fdi_01	0.79	0.73	0.50	0.49	0.49	0.56	0.83	0.74	0.79
a_fac__fdi_02	0.79	0.76	0.64	0.50	0.50	0.56	0.80	0.72	0.81
a_fac__fdi_03	0.80	0.79	0.65	0.55	0.55	0.61	0.76	0.70	0.81
a_fac__fdi_04	0.81	0.77	0.64	0.55	0.55	0.62	0.77	0.70	0.81
a_fac_ic_fdiarlag_bic_f_01	0.53	0.64	0.68	0.61	0.60	0.61	0.53	0.53	0.50
a_fac_ic_fdiar_bic_f_01	0.63	0.59	0.64	0.65	0.66	0.68	0.76	0.64	0.44
a_fac_ic_fdi_bic_f_01	0.63	0.58	0.62	0.70	0.70	0.68	0.74	0.64	0.44
a_fbp_ic_fdiarlag_bic_f_01	0.59	0.56	0.62	0.67	0.68	0.55	0.64	0.61	0.48
a_fbp_ic_fdiar_bic_f_01	0.56	0.60	0.52	0.56	0.57	0.57	0.79	0.63	0.41
a_fbp_ic_fdi_bic_f_01	0.56	0.61	0.53	0.57	0.58	0.57	0.75	0.63	0.41
a_fac_ic_fdiar_01	0.53	0.48	0.61	0.61	0.60	0.59	0.50	0.50	0.50
a_fac_ic_fdiar_02	0.55	0.50	0.67	0.64	0.62	0.58	0.61	0.61	0.50
a_fac_ic_fdiar_03	0.56	0.62	0.67	0.63	0.64	0.59	0.54	0.61	0.49
a_fac_ic_fdiar_04	0.56	0.63	0.64	0.64	0.64	0.58	0.57	0.58	0.47
a_fac_ic_fdi_01	0.53	0.43	0.42	0.61	0.61	0.60	0.50	0.44	0.50
a_fac_ic_fdi_02	0.55	0.53	0.66	0.49	0.49	0.48	0.61	0.61	0.49
a_fac_ic_fdi_03	0.56	0.57	0.64	0.57	0.57	0.54	0.54	0.61	0.47
a_fac_ic_fdi_04	0.56	0.56	0.62	0.57	0.57	0.57	0.57	0.58	0.42

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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

Figures

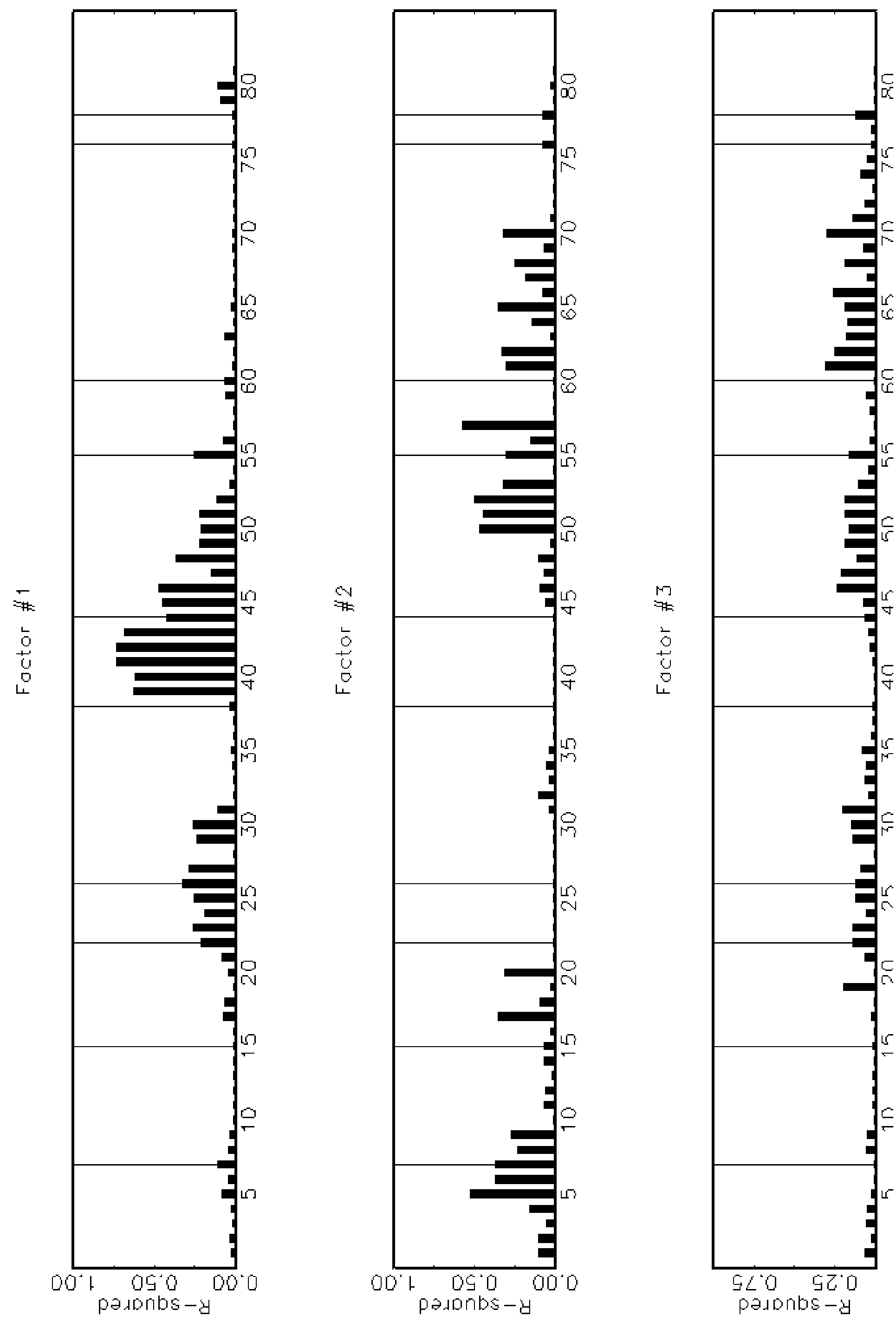

Figure 1 – R^2 from regression of factors 1 to 3 on variables

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

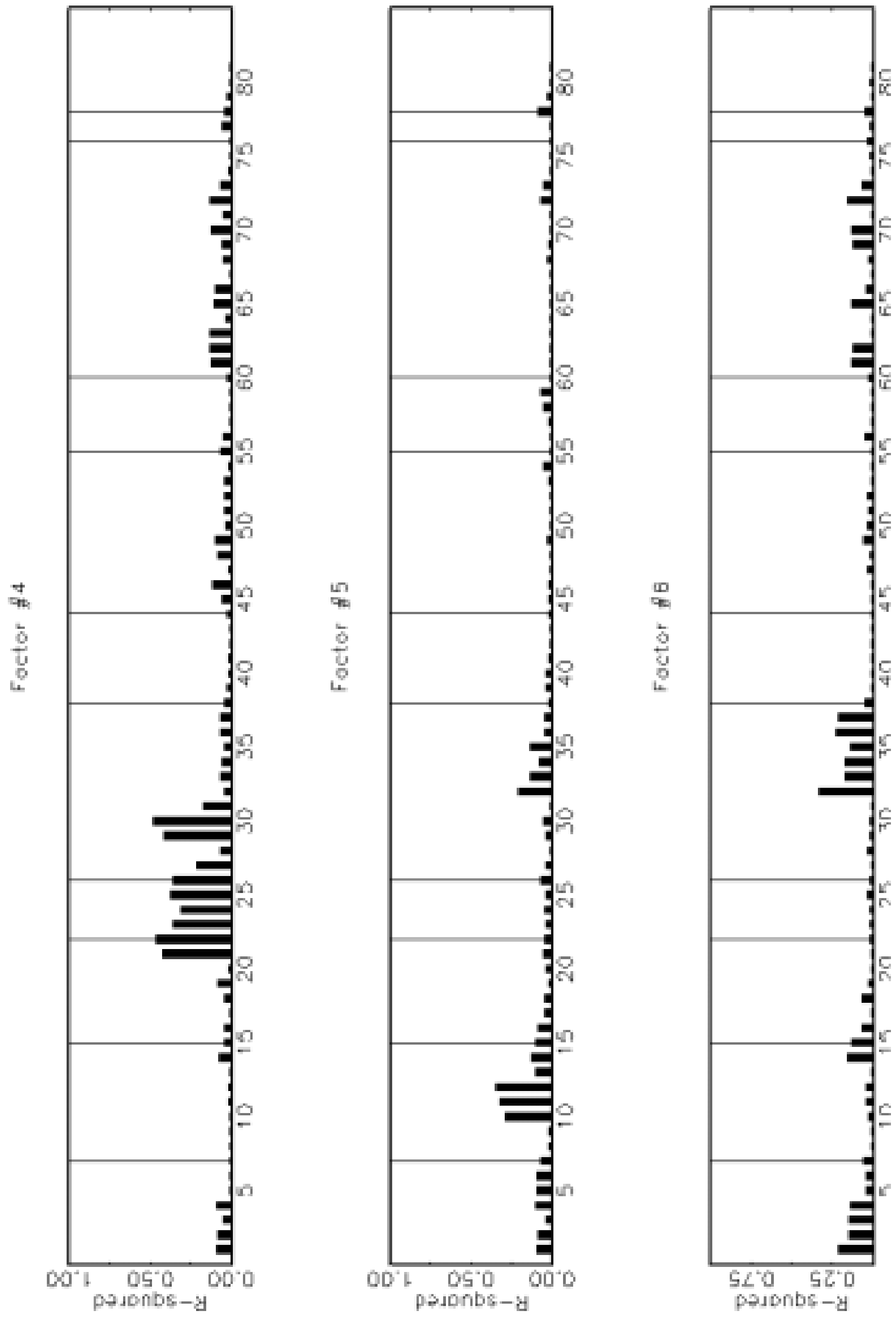

Figure 2 – R^2 from regression of factors 4 to 6 on variables

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

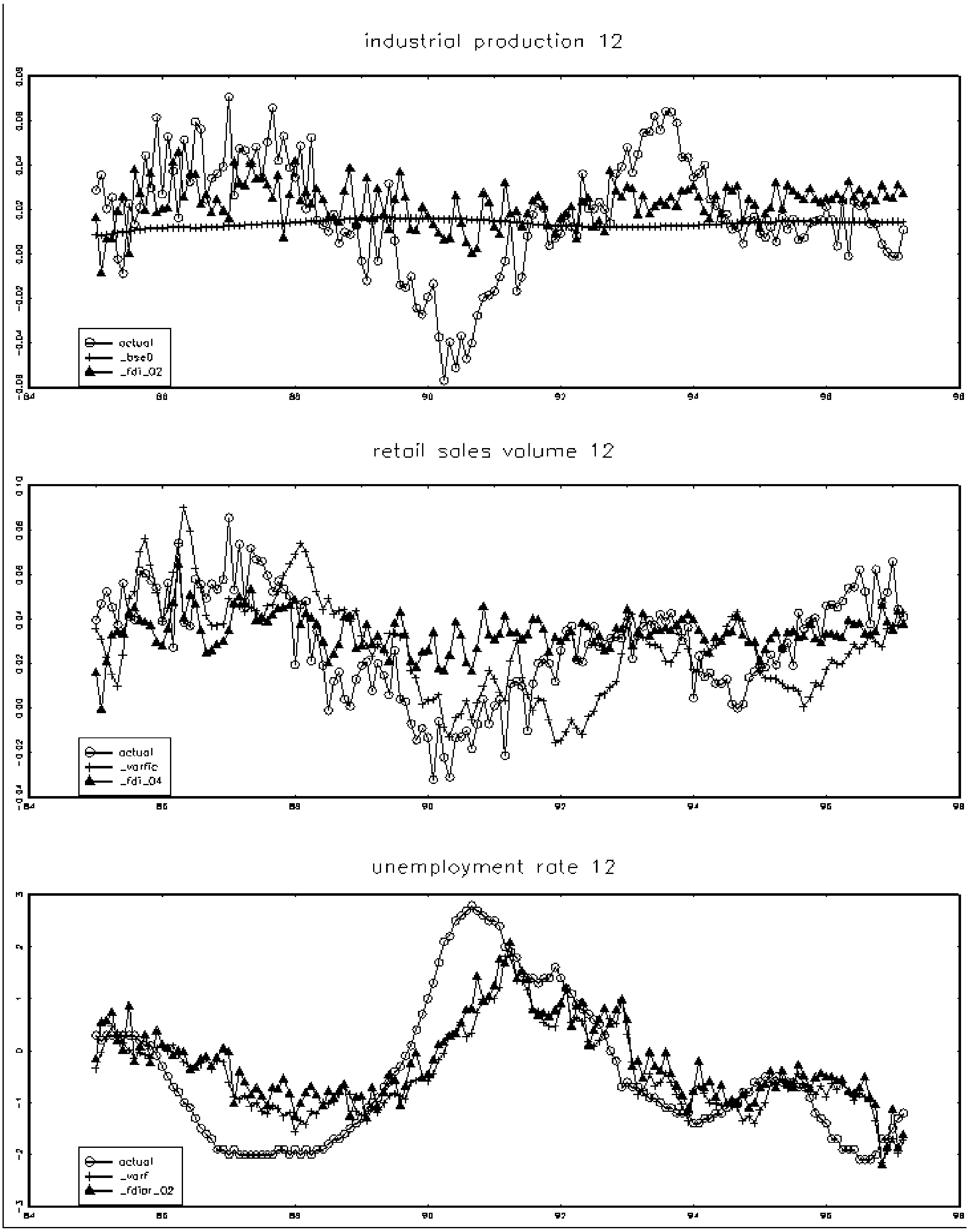

Figure 3 – 12-step-ahead forecasts, real variables

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

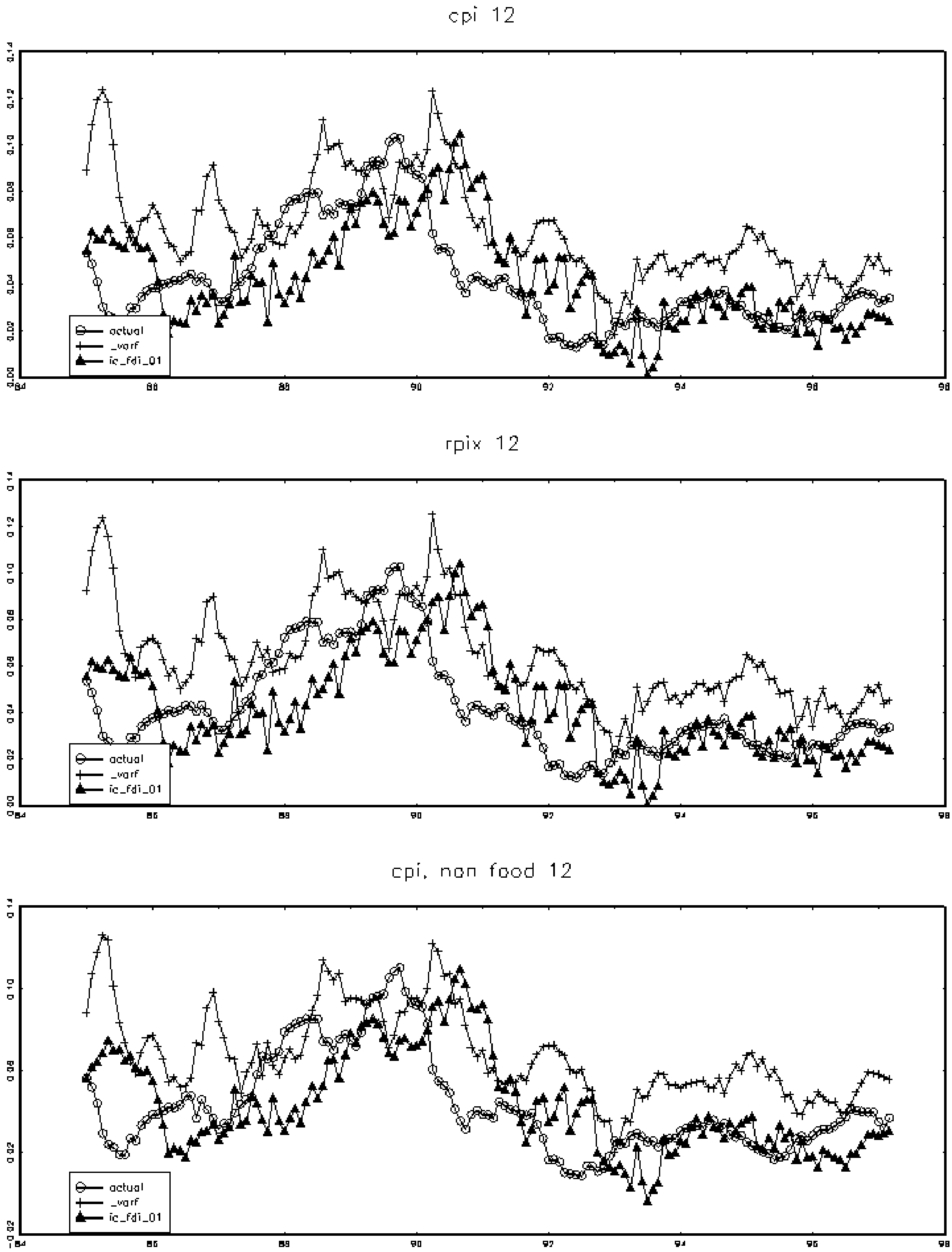

Figure 4 – 12-step ahead forecasts, prices

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

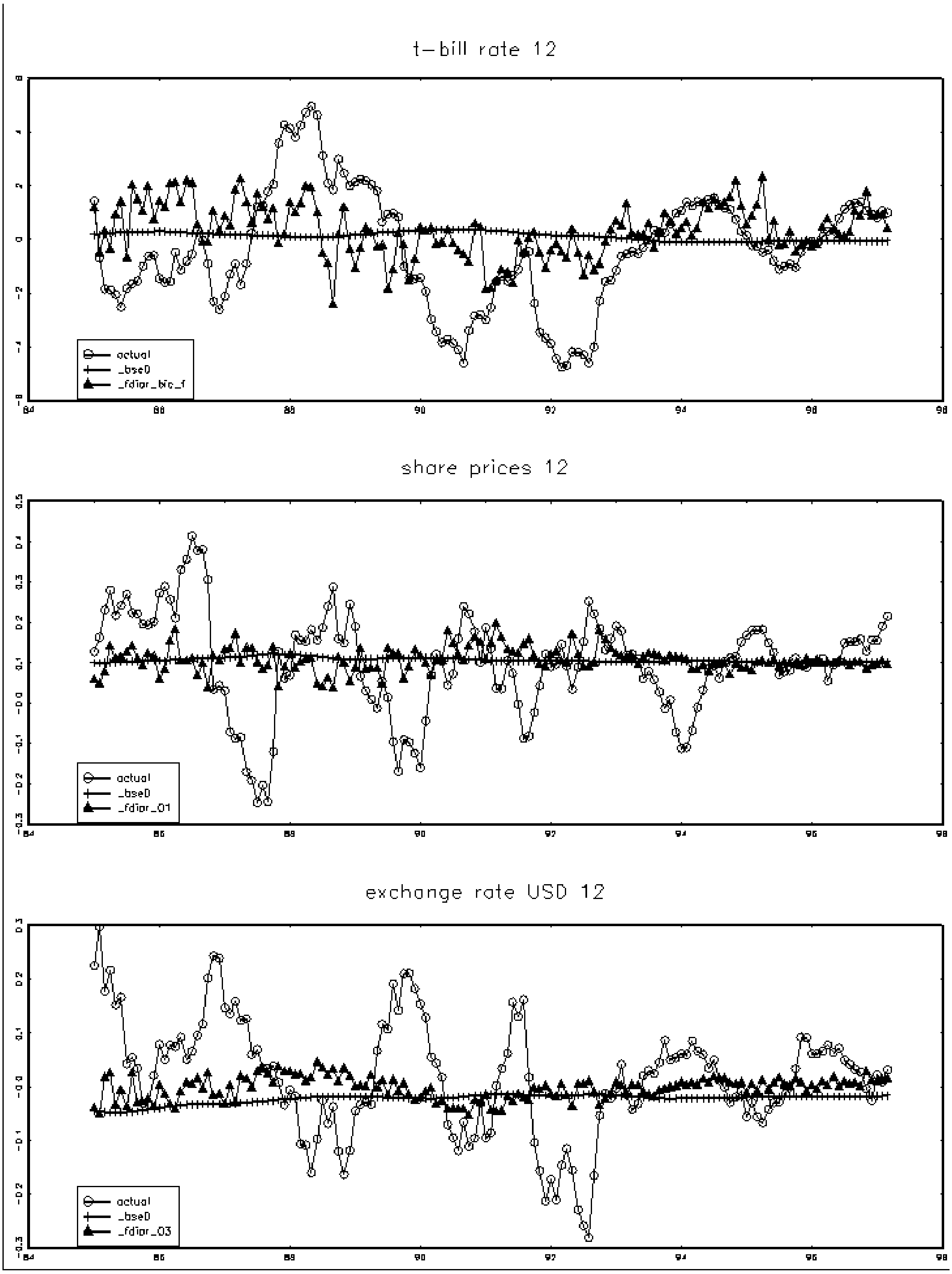

Figure 5 – 12-step ahead forecasts, financial variables

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