Warsaw School of Economics
Institute of Econometrics
Department of Applied Econometrics

Department of Applied Econometrics Working Papers
Warsaw School of Economics
Al. Niepodleglosci 164
02-554 Warszawa, Poland

Working Paper No. 2-08

Forecasting inflation with dynamic factor model – the case of Poland

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Abstract

The purpose of the article is to evaluate the forecasting performance of dynamic factor models in forecasting inflation in the Polish economy. The factor models are based on the assumption that the behavior of most macroeconomic variables can be well described by several unobservable factors, which are often interpreted as the driving factors in the economy. Such models are very often successfully used for forecasting. Employing several factors instead of a large number of explanatory variables may increase the number of degrees of freedom with the same information content. In the article we compare forecast accuracy of dynamic factor models with the forecast accuracy of three competitive models: univariate autoregressive model, VAR model and the model with leading indicator from the business survey. We have used 92 monthly time series from the Polish and world economy to conduct the out-of-sample real time forecasts of inflation (consumer price index). The results are encouraging. The dynamic factor model outperforms other models for both 1-step ahead and 3-step ahead forecast. The advantage of factor models is more straightforward for 1-month than for 3-month horizon.

Keywords: inflation, forecasting, factor models
JEL codes: C22, C53, E31, E37

Introduction

The purpose of the article is to evaluate the forecasting performance of dynamic factor models in forecasting inflation in the Polish economy. The concept of factor models bases on the assumption that the behaviour of most macroeconomic variables may be well described using a small number of unobserved common factors. These factors are often interpreted as the driving forces in the economy. The particular variables may be then expressed as linear combinations of up-to-twenty common factors which usually make it possible to explain a major part of the variability of those variables. Similar approach is applied, among others, in DSGE models, where the endogenous variables are influenced by relatively small number of unobserved shocks with a clear economic interpretation.

Dynamic factor models are believed to have been pioneered by Geweke [1977] and Sims & Sargent [1977], who applied this type of models to the analysis of small sets of variables in frequency domain. The research in this area was continued by Engle & Watson [1981] and Stock & Watson [1991], who estimated factor models using the maximum likelihood method. One of the most important contributions in the field of factor models was the study by Stock & Watson [1998], in which the principal components method was applied both for the estimation of factor model parameters and unobserved factors. This approach is nowadays one of the most popular methods for estimating factor models and has also been used in the present study.

Dynamic factor models have a very wide field of applications. Such models are widely used for forecasting (Stock & Watson [2002a], Artis et al. [2003]), constructing leading indicators of business climate (Altissimo et al. [2001], monetary policy analysis (Bernanke, Boivin & Eliasz [2005]) or the analysis of international business cycles (Eickmeier [2004]). Their main advantage is the fact that they allow including in the model the information derived from a large set of explanatory variables without the need to include all those variables, which would cause a loss of a considerable number of degrees of freedom and in many case would be simply impossible. Moreover, a factor model in its basic form is a atheoretical model, which means that while constructing such model we avoid many assumptions on the exact form of economic relationships and structure of the model.

The present study is focused on the first of the listed applications of dynamic factor models, i.e. on forecasting. The inflation forecast was prepared, based on the set of monthly data from of period between January 1999 and April 2007 comprising 92 selected time series, and then its results were compared for forecast accuracy with competitive models, including a small VAR model, a model with leading indicator and a univariate autoregressive model.

The first part of the article presents a concept of a dynamic factor model. The second part discusses the approach to estimating model parameters and common factors. The third part presents the methods of specifying the number of factors in the model. The data used in the study have been described in the fourth part, while the fifth part expounds on the methods of evaluating forecasting performance of a factor model. The sixth part is devoted to the analysis of achieved empirical results and the seventh, final part summarises the whole study.

1. Dynamic factor model

Let y_t stand for a variable to be forecast and let X_t express the vector of N variables containing information that can be useful in forecasting the future values of y_t. In the dynamic factor model we assume that all variables x_{it} contained in vector X_t may be expressed as a linear combination of current and lagged unobserved factors f_{it}

$$x_{it} = \lambda_i(L) f_t + e_{it}, \text{ for } i = 1, 2, \ldots, N, \tag{1}$$

where $f_t = [f_{1t}, f_{2t}, \ldots, f_{\bar{r}t}]'$ stands for vector $\bar{r}$ of unobserved common factors at moment t, $\lambda_i(L) = \lambda_{i0} + \lambda_{i1}L + \lambda_{i2}L^2 + \ldots + \lambda_{iq}L^q$ represent a lag polynomials in non-negative power of L, and e_{it} express an idiosyncratic errors for variable x_{it} (Stock & Watson [1998], see also Armah & Swanson [2007]).

In turn, future values of variable y_t may be noted as the function of current and lagged common factors contained in vector f_t and the past values of variable y_t, in line with the following formula

$$y_{t+h} = \beta(L) f_t + \gamma(L) y_t + e_{t+h}. \tag{2}$$

In (2) y_{t+h} expresses the value of variable y_t in period $t + h$, $\beta(L)$ and $\gamma(L)$ stand for lag polynomials and e_{t+h} stands for the forecast error in period h.

The model described with equations (1) and (2) is a dynamic factor model. There are both current and lagged variables on the right-hand side of the equations. However, if polynomials $\lambda_i(L)$, $\beta(L)$ and $\gamma(L)$ are polynomials of finite order, then the model can also be expressed in the static form.

Let $F_t = \left[f_t', f_{t-1}', ..., f_{t=q}'\right]'$ stand for a static factors vector of dimensions $r \times 1$, where $r = (q + 1) \times \bar{r}$. Analogically, $\Lambda_i = \left[\lambda_{i0}', \lambda_{i1}', ..., \lambda_{iq}'\right]'$ shall be expressed by vector of dimensions of $r \times 1$, containing coefficients (factor loadings) present in equation (1) at the factors included in vector F_t. Equation (1) may be now noted in the static form according to the following formula

$$x_{it} = \Lambda_i' F_t + e_{it} \tag{3}$$

The system of equations (2) and (3) shall be called a dynamic factor model in the static form.

From the perspective of forecasting applications of the factor model, the selection of the dynamic or static form is not very important. However, the static notation of the model makes it possible to estimate both the values of factors included in vector F_t and the parameters of equation (3) using a relatively simple principal components method (see Stock & Watson [1998]).

If the idiosyncratic errors in equation (3) are mutually uncorrelated at all leads and lags, i.e. when the following condition is fulfilled:

$$E(e_{it} e_{js}) = 0 \text{, for all } i, j, t, s \text{ such that } i \neq j, \tag{4}$$

then we call the model (3) the *strict* or *exact factor model*.

If condition (4) is not fulfilled and the errors are weakly cross-correlated, then such model is called an *approximate factor model* (Stock & Watson [1998], [2005]).

Bai & Ng [2002] and Bai [2003] show that if $N,T \to \infty$, then even if the idiosyncratic errors e_{it} are weakly autocorrelated or cross-correlated in the sense of Bai & Ng [2002] then the estimates of factors and factors loadings in (3) are still consistent.

Introducing the following notation:

$$X_i = \left[x_{i1}, x_{i2}, ..., x_{iT}\right]', \qquad X = \left[X_1, X_2, ..., X_N\right]$$

$$F = \left[F_1, F_2, ..., F_T\right]', \qquad \Lambda = \left[\Lambda_1, \Lambda_2, ..., \Lambda_N\right]'$$

$$e_i = \left[e_{i1}, e_{i2}, ..., e_{iT}\right]' \qquad e = \left[e_1, e_2, ..., e_N\right]$$

equation (3) may be also written as follows

$$X_i = F\Lambda_i + e_i, \tag{5}$$

while the dynamic factor model for every N as

$$X = F\Lambda' + e. \tag{6}$$

2. Factor model estimation

Nowadays, one of the most widely used methods of parameter and factor estimation in a factor model is the method of principal components, first applied for this purpose by Stock & Watson [1998]. Let us emphasise that both the factor matrix F and the coefficient matrix Λ are unknown in equation (6). Model (6) is thus equivalent to the model in the form of

$$X = F\mathrm{H}\mathrm{H}^{-1}\Lambda' + e,$$

where matrix H is any non-singular matrix of dimension $r \times r$. In view of the above, in order to have a unique factor matrix F, it is necessary to carry out the appropriate normalisation of matrix H. Stock & Watson [1998] propose that for this purpose a condition in the form of $(\Lambda'\Lambda/N) = \mathrm{I}_r$ may be imposed on the parameters of model (6), which would render matrix H orthonormal.

The estimation of matrices F and Λ using the method of principal components consists in finding such estimates of matrices $\hat{F}$ and $\hat{\Lambda}$ that would minimise the residual sum of squares in equation (6) as expressed with the following formula

$$V(F,\Lambda) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \Lambda_i' F_t)^2 \ . \tag{7}$$

In order to obtain an estimate of an unknown matrix Λ it is necessary, in the first step, to perform a minimisation of function (7) in respect to factor matrix F, with the assumption that matrix Λ is known and fixed. Then, we obtain estimate $\hat{F}$ (as function Λ), which is subsequently substituted in equation (7) for the true value of F. This way the only remaining unknown matrix in equation (7) is matrix Λ. In the second step, we minimise the concentrated function (7) in respect to matrix Λ with a normalisation condition $(\Lambda'\Lambda/N) = \mathrm{I}_r$, thus directly obtaining estimate $\hat{\Lambda}$. It should be emphasised that the minimisation of concentrated function (7) is equivalent to maximisation of expression $tr[\Lambda'(X'X)\Lambda]$ subject to $(\Lambda'\Lambda/N) = \mathrm{I}_r$.

Matrix $\hat{\Lambda}$, which is a solution to problem (7) is a matrix whose subsequent columns are eigenvectors of matrix $X'X$ (multiplied by $\sqrt{N}$) corresponding to r highest eigenvalues of the same matrix. In turn, the estimate of matrix F is expressed by the formula

$$\hat{F} = (X\hat{\Lambda})/N \ . \tag{8}$$

It is worth emphasising that the normalisation condition $(\Lambda'\Lambda/N) = \mathrm{I}_r$ is a statistical condition and so the factors determined on basis of formula (9) do not have an economic interpretation.

Stock & Watson [1998] emphasise that if the number of variables is higher than the number of observations, i.e. $N > T$, then from the computational point of view it is easier to apply an opposite procedure, namely first to concentrate out matrix Λ from function (7) and then to determine estimate $\tilde{F}$ by minimising concentrated function (7) in respect to matrix F with the condition $F'F/T = I_r$. Matrix $\tilde{F}$ will then contain eigenvectors of matrix XX' corresponding to r highest eigenvalues of this matrix and multiplied by $\sqrt{T}$. In turn, the estimate of matrix $\tilde{\Lambda}$ will assume the following form

$$\tilde{\Lambda}' = (\tilde{F}'X)/T. \tag{9}$$

Both $\hat{F}$ and $\tilde{F}$ estimates span the same space and so if we use a factor model for forecasting purposes, it does not matter which estimation method we actually chose. If $T > N$, then it will be easier to determine the eigenvalues of matrix $X'X$, while if $N > T$, then the lower calculating cost will be connected with the search for the eigenvalues of matrix XX'. As in the present article, the values of T and N are close, we will use the former method to estimate the factor model[1].

3. Selection of the number of factors

It should be pointed out that both the estimates and the minimal value of function (7) are directly dependent on the number of factors r. Stock & Watson [2002b] and Artis et al. [2003] emphasise that if the estimate of factor matrix F is to be consistent, then the number of factors used in the model cannot be lower than their true number.

There are several methods to determine the number of factors in the model. The first one consists in the analysis of the eigenvalues of the matrix of correlations R of explanatory variables x_{it}. We know that for any square matrix the sum of eigenvalues is equal to the trace of matrix. In case of the matrix of correlations this means that the sum of eigenvalues of this matrix is equal to the number of variables, i.e. $tr(R) = \sum_{i=1}^{N} \mu_i = N$, where μ_i are subsequent eigenvalues of matrix R in descending order. In this case the ratio $\tau(k) = \sum_{i=1}^{k} \mu_i / N$ determines the share of the variance of the set of explanatory variables explained by k common factors.

[1] The method proposed by Stock & Watson [1998] is not the only method of estimating factor model parameters. Forni et al. [2005] propose an approach being a modification of the principal components method with spectral analysis elements. In turn, Kapetanios and Marcellino [2004] estimate a factor model based on the methodology of state space models.

Unfortunately, there are no common accepted norms as to what percentage of the explained variance may be deemed satisfactory. Breitung & Eickmeier [2006] assume 40% here, though to a large extent this value depends on the type and size of the set of data used in the model.

The second method of identifying the number of factors in a factor model is based on the indications of the information criteria proposed by Bai & Ng [2002]. Those authors propose three different criteria

$$IC_1(k) = \ln(\hat{V}(k)) + k\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right), \tag{10a}$$

$$IC_2(k) = \ln(\hat{V}(k)) + k\left(\frac{N+T}{NT}\right)\ln C_{NT}^2 , \tag{10b}$$

$$IC_3(k) = \ln(\hat{V}(k)) + k\left(\frac{\ln(C_{NT}^2)}{C_{NT}^2}\right), \tag{10c}$$

where $C_{NT} = \min\{\sqrt{N}, \sqrt{T}\}$.

The composition of all the three criteria is similar. Each of them represents the sum of two values: the logarithm of the residual sum of squares determined by formula (7) and the penalty for overfitting the model. The residual sum of squares is a decreasing function of the number of factors in the model, while the value of the penalty function increases together with k. The selection of the number of factors in the model is carried out by comparing the value of a give criterion for various k. As the true number of factors r in the model we assume such value of k for which a given criterion reaches its minimum.

Bai & Ng [2002] demonstrate that all the three criteria are consistent, i.e. for T, $N \to \infty$ they show the true number of factors with probability 1.

4. Description of data

The data used in the study are monthly data and encompass the period from February 1999 to April 2007 (99 observations). In total, 92 time series were considered, representing of the basic macroeconomic categories: output and sales, construction, foreign trade, labour market, prices, wages, interest rates, monetary aggregates, exchange rates, stock exchange indices and indicators of economic climate in industry, construction and retail trade. The full list of the variables with the source of the obtained data is presented in Appendix A.

Before embarking on the work on factor model specification the data had to be appropriately modified. First, all variables were logarithmised, apart from these which contained negative values or were already expressed in the form of fractions (e.g. interest rates). In the next step, the variables which displayed a clear pattern of seasonality were adjusted for the impact of seasonal fluctuations using the ARIMAX12 procedure. At this stage outliers were also removed.

In line with the factor model assumptions (see Stock & Watson [1998]), all the explanatory variables should be stationary. That's why variables integrated of order one were made stationary by taking first differences. It was arbitrarily assumed that all variables expressing prices and monetary aggregates are $I(1)$. Therefore, they will be featuring in the model in the form of first differences. Unit root test was preformed for the remaining variables and appropriate transformation was carried out according to test results. Detailed information on how each variable was transformed can be found in Appendix A.

In the final step, all variables were standardised to have zero mean and unit standard deviation.

5. Forecasting from the factor model

The purpose of the present study is to evaluate the applicability of the factor model to forecasting future values of inflation (CPI). A forecasting horizon of h=1 and h=3 periods was considered in the study. The forecast applies to a variable constructed in line with the following formula

$$y_{t+h}^{h} = \frac{\ln(CPI_{t+h}/CPI_{t})}{h},$$

where CPI_t stands for the seasonally adjusted consumer price index with a constant base. Thus variable y_{t+h}^{h} expresses an average monthly relative change in period h.

Forecasts in the dynamic factor model were based on equation (2), which after estimating common factors and parameters included in polynomials $\beta(L)$ and $\gamma(L)$ has the following from

$$\hat{y}_{t+h}^{h} = \hat{\alpha}_h + \sum_{k=1}^{K} \hat{\beta}_{h,k} \hat{F}_{t-k+1} + \sum_{p=1}^{P} \hat{\gamma}_{h,p} y_{t-p+1}, \qquad (11)$$

where $\hat{y}_{t+h}^{h}$ stands for the forecast of variable y_{t+h}^{h}, $y_t = \ln(CPI_t/CPI_{t-1})$ represents monthly rate of inflation and $\hat{F}_t$ expresses the estimate of the factors vector obtained using the principal components method as described in point 3. The maximum lags K and P in model (11) were determined on the basis of indications of the Bayesian information criterion (BIC).

The forecasts at moment t+h obtained from equation (11) are determined directly on the basis of information available in period t. This is a different approach than the iterative method which in practice is used more often. This method involves determining forecasts for one period ahead, substituting the obtained forecasts of period t+1 to the model in place of unknown actual values of explanatory variables in period t+1, re-determining one-period forecasts for period t+2, substituting the obtained forecasts to the model and so on until the forecast values for period t+h are obtained.

Direct forecasting for h periods ahead has an advantage over such iterative one-period forecasting in that it does not require the knowledge of the values of explanatory variables in the forecasting period and so does not necessitate additional model equation to be constructed with a view to forecast future values of factors $\hat{F}_t$. This is obviously just the question of forecasts prepared for 3 periods ahead, as for h=1 both the forecasting methods are identical.

The forecasting performance of the factor model were evaluated by comparing the accuracy of inflation forecasts y_{t+h}^h obtained on the basis of the factor model with the accuracy of inflation forecasts derived from other competitive models. Three competitive models have been taken into consideration: a univariate autoregressive model, a model with a leading indicator and a VAR model with three variables. Brief characteristics of each of these models are presented below.

Autoregressive model (AR model)

A univariate autoregressive model was adopted as the main benchmark model for evaluating the forecasting performance of the factor model. In this model the forecast of variable y_{t+h}^h are determined according to the formula

$$\hat{y}_{t+h}^h = \hat{\alpha}_h + \sum_{p=1}^{P} \hat{\gamma}_{h,p} y_{t-p+1}\,, \tag{12}$$

where the value of the maximum lag P is set on the basis of the indication of the BIC. Analogically as in the factor model, forecasts derived from the autoregressive model are determined directly for h periods ahead.

Autoregressive model with leading indicator (AR-IND)

The second competitive model is a univariate model which apart from current and lagged values of variable y_t as an explanatory variable also contains an leading indicator taken from GUS (Polish CSO) monthly survey studies of enterprises involved in retail trade. The indicator has the form of the balance of responses to the question on the change of current prices of goods sold by enterprises in retail trade sector[2]. In our opinion, out of all the business climate indicators expressing the response of enterprises to the question of current and future price level, the selected indicator best corresponds to those price categories which are covered by the forecast variable, i.e. the Consumer Price Index.

The forecasts from the autoregressive model with the leading indicator are determined according to the following formula

$$\hat{y}_{t+h}^{h} = \hat{\alpha}_h + \sum_{k=1}^{K} \delta_{h,k} RETP_{t-k+1} + \sum_{p=1}^{P} \hat{\gamma}_{h,p} y_{t-p+1} , \tag{13}$$

where variable $RETP_t$ expresses a seasonally adjusted value of the balance of responses to the question on the level of prices in retail trade. In order to establish the lag orders K and P, we once again make use of the information criterion, the BIC. The forecasts of variable y_{t+h}^{h}, just like in the two previous models, are prepared directly for h periods ahead.

Vector autoregressive model (VAR)

The last model used in this study to compare the accuracy of inflation forecasts obtained from the factor model is a small model VAR model. The model features three variables expressing: the Consumer Price Index, industrial production and yields on two-year Treasury bonds[3]. All the three variables were expressed in the form of first differences and so they assumed the same form as in the factor model. The time series of production and prices had been previously seasonally adjusted.

The equation describing price changes in the VAR model may be noted in the following form

$$\hat{y}_{t+1} = \hat{\alpha} + \sum_{k=1}^{K} \hat{\beta}_k y_{t-k+1} + \sum_{k=1}^{K} \hat{\gamma}_k \Delta ip_{t-k+1} + \sum_{k=1}^{K} \hat{\delta}_k \Delta yield_{t-k+1} , \tag{14}$$

where variables Δip_t and $\Delta yield_t$ represent monthly changes in industrial production and yields on two-year bonds, respectively. For each equation and each variables in the VAR model the same lag was assumed, which was determined on the basis of BIC indications.

In contrast to other models, the forecasts of variable y_t in the VAR model are derived as one-step ahead forecasts. Thus, for the forecast horizon h=3 periods we make forecasts of all the three variables in the model for one period ahead and then the forecasts are substituted

[2] A detailed description of the indicator's structure and the actual survey sent to enterprises can be found in *Business tendency survey in manufacturing, construction, retail trade, and services* – a material cyclically published by the GUS.

[3] Analogical set of variables for a VAR model was proposed by Artis et al. [2005] and Stock & Watson [2002a].

in place of unknown actual values of those variables and once again determine one-period forecast for the next period. By reiterating this procedure we arrive at a sequence of one-period forecasts of variable y_t, which we subsequently sum up to obtain values comparable with the forecast made directly for *h* periods ahead, as it is the case in the remaining models.

The forecasts computed from the four models were constructed in such a way as to best simulate the real-time forecasting process. The sample on which the study was based was divided into two sub-samples. Preliminary specification of all the models was made for data encompassing the period from February 1999 to March 2005 (for h=3) or to May 2005 (for h=1), in particular the Bayesian information criterion, BIC was used to determine the dynamic structure of the models (the lag order) and their parameters were estimated. Observations from the second part of the sample were used to evaluate the forecasts accuracy. The forecasts were derived for one and for three months ahead, while after each forecast computation the sample was lengthened with another observation, the dynamic structure of models was established using the BIC, data were standardised (for the factor model) and model parameters and factors were re-estimated. In total, 24 forecasts for each forecast horizon were determined.

Two different criteria were applied to evaluate the forecasting performance of the discussed models. The first criterion is the value of the mean square error. For each of the three competitive models this error was determined in the relative form, i.e. as the ratio of the mean square error for a given model and the mean square error for the factor model. Values above one point to better forecasting performance of the factor model. The values of relative mean square errors are supplemented with the results of West test [2005], which verifies the hypothesis assuming that the mean square error for a given competitive model is the same as for the factor model.

The second criterion for evaluating forecast accuracy is based on the results of a test proposed by Chong & Hendry [1986]. The test involves an estimation of the parameters of the following regression equation

$$y_{t+h}^{h} = \alpha \hat{y}_{t+h}^{DFM,h} + (1-\alpha)\hat{y}_{t+h}^{BENCH,h} + v_{t+h}^{h}, \tag{15}$$

and subsequent verification of relevant hypotheses against the values of coefficient α. In equation (15) y_{t+h}^{h} stands for the actual rate of inflation (change in prices of consumer goods and services) in period $t+h$, $\hat{y}_{t+h}^{DFM,h}$ expresses an inflation forecast based on the factor model, while $\hat{y}_{t+h}^{BENCH,h}$ stands for a forecast based on a competitive model, both forecasts being made at moment t for h periods ahead. If coefficient α equals 1, then we say that the inflation forecast based on the factor model encompasses the forecast from the competitive model. In contrast, if α is equal to 0, then the forecast based on the competitive model encompasses the forecast obtained from the factor model. Thus, the verification will test two hypotheses

(1) H_0: $\alpha = 1$ vs H_0: $\alpha \neq 1$,

and

(2) H_0: $\alpha = 0$ vs H_0: $\alpha \neq 0$,

The failure to reject the first null-hypothesis (α = 1) and the rejection of the second null-hypothesis (α = 0) allow concluding that forecasts obtained from the factor model are closer to the actual values of the forecast variable than those obtained from the competitive model.

6. Empirical results

The first stage of the study involved the determination of the actual number of factors in the considered factor model. On the basis of the full sample encompassing the period from February 1999 to April 2007 the eigenvalues of the matrix of correlations for the whole data set were determined. Analysis of the eigenvalues presented in Table 1 leads to the conclusion that the model is relatively well fitted to actual data. The first 2 factors explain almost 22% of the total variance, the first 6 factors approx. 40% and the first 12 factors – almost 58% of the variance.

The differences between the first and second eigenvalue and between the second and third eigenvalue amount to 0.051 and 0.028, respectively and are markedly higher than the differences between subsequent eigenvalues (the difference between the third and fourth eigenvalue is only 0.007), which would suggest that the number of factors in the model may be equal to 2 or 3.

The values of information criteria defined by formulas (10a) – (10c) do not yield unequivocal results. The first two criteria reach minimum for the number of factors equal to 2, while the third criteria assumes its lowest value for 12 factors. Due to the fact that two out of three criteria display the same value, we arbitrarily assume that the number of factors in the model is 2. This value remains consistent with previous observations on the behaviour of subsequent eigenvalues of the correlation matrix.

Table 1. Selection of the number of factors in the model.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of factors	Eigenvalues	Contribution to variance	Cumulative contribution to variance	IC1	IC2	IC3
1	12.537	0.133		-0.065	-0.052	-0.097
2	7.765	0.083	0.216	**-0.087**	**-0.060**	-0.151
3	5.151	0.055	0.271	-0.081	-0.039	-0.176
4	4.474	0.048	0.318	-0.069	-0.014	-0.197
5	4.061	0.043	0.362	-0.056	0.013	-0.215
6	3.572	0.038	0.400	-0.038	0.044	-0.230
7	3.247	0.035	0.434	-0.019	0.078	-0.242
8	3.117	0.033	0.467	-0.001	0.110	-0.256
9	2.932	0.031	0.498	0.017	0.141	-0.270
10	2.671	0.028	0.527	0.038	0.175	-0.281
11	2.465	0.026	0.553	0.059	0.210	-0.292
12	2.248	0.024	0.577	0.082	0.247	**-0.301**

Column (2) presents, in descending order, 12 greatest eigenvalues of the correlation matrix. Column (3) contains contributions of particular factors in total variance, while column (4) shows cumulative contributions. The last three columns of the tables express values of information criteria defined by formulas (10a) –(10c). The minimum values of the criteria are highlighted in bold type.
Source: Own calculations.

As it was mentioned before, factors estimated using the principal components method do not have an economic interpretation. However, they span the same space as the structural factors. For this reason, it is possible to carry out a regression of particular variables against each of the estimated factors and check which factor explains the behaviour of a given variable to the greatest extent.

Charts 1a – 1f present the R-squared on the regression of particular variables grouped in specific economic categories (according to the description in Appendix B) against each of the first six factors.

The values indicated in the chart suggest that the first factor primarily affects the variability of prices and domestic interest rates. The second factor determines the development of the values of industrial production, retail sales, business climate indicators (mainly from the sector of retails trade) and, once again, domestic interest rates. The third factor to the greatest extent influences the values of foreign interest rates, the exchange rate, foreign trade turnover (exports and imports), stock exchange indices and some indicators of business climate in industry. The fourth of the estimated factors is primarily responsible for the behaviour of monetary aggregates and, similarly to the third factor, for foreign trade turnover. The impact of the fifth factor is mostly visible in the case of business climate indicators in construction and in labour market variables (particularly employment). Finally, the sixth factor loads the variable expressing wages in the enterprises sector and some indicators of business climate in industry and retail trade.

The interpretation of the first factor as “the driving force” behind price processes in the economy is to a large extent the result of a relatively strong representation of the price category in the entire variable set (as many as 27 series). In turn, variables expressing production are connected with as many as three factors (from the second to the fourth). The connection of some categories (e.g. construction) with the first six factors is rather weak, which indicates that a greater impact on the behaviour of these categories is exerted by the remaining factors, not featured in the charts.

In the further stage of the study the forecasting performance of the factor model were evaluated. The accuracy of inflation forecasts obtained from the factor model and three competitive models was compared using two different criteria described in point 5 above. The forecasts were determined recursively. In the first step, a specification was performed for all the four models for the sample encompassing the period from February 1999 to March 2005 (for h=3) or to May 2005 (for h=1), in particular the BIC was used to determine the dynamic structure of each of the models. In the case of the factor model the following general form of the model was used, which was corresponding to equation (11):

$$\hat{y}^{h}_{t+h} = \hat{\alpha}_h + \sum_{k=1}^{3} \hat{\beta}^{(1)}_{h,k} \hat{F}^{(1)}_{t-k+1} + \sum_{m=1}^{3} \hat{\beta}^{(2)}_{h,m} \hat{F}^{(2)}_{t-m+1} + \sum_{n=1}^{3} \hat{\beta}^{(3)}_{h,n} \hat{F}^{(3)}_{t-n+1} + \sum_{p=1}^{4} \hat{\gamma}_{h,j} y_{t-p+1} \,, \tag{16}$$

where $\hat{F}^{(i)}_t$ expresses the estimate of i-th factor in period t. It follows from formula (16) that in model specification only the first three factors, each one with three lags, and the values of monthly inflation with a maximum lag of 4 were considered. Artis et al. [2005] emphasise that forecasting performance of factor models are better if they contain an autoregressive component and so it was assumed that the model includes at least on lag of variable y_t.

Based on the BIC the specification of three competitive models, defined by formulas (12) – (14), was also carried out. Estimation results of all the models for the last iteration, i.e. based on the entire sample, are presented in Table 2 below.

Table 2. Model estimation results for entire sample.

Forecast horizon	h=1		h=3
Sample	02.1999 – 04.2007		02.1999 – 02.2007
DFM model		**DFM model**	
Constant	0.0040	*Constant*	0.0040
	[8.853]		[10.916]
y_{t-1}	-0.3319	y_{t-3}	-0.3650
	-[2.539]		[-3.415]
$\hat{F}_{t-1}^{(1)}$	0.00105	$\hat{F}_{t-3}^{(1)}$	0.00097
	[8.085]		[9.017]
$\hat{F}_{t-1}^{(2)}$	0.00024	$\hat{F}_{t-3}^{(2)}$	0.00018
	[3.127]		[2.804]
R^2	0.650	R^2	0.678
AR model		**AR model**	
Constant	0.0012	*Constant*	0.0007
	[3.094]		[2.046]
y_{t-1}	0.6020	y_{t-3}	0.3021
	[7.452]		[3.692]
		y_{t-4}	0.1058
			[1.189]
		y_{t-5}	0.0810
			[0.910]
		y_{t-6}	0.2345
			[2.903]
R^2	0.353	R^2	0.490
AR-IND model		**AR-IND model**	
Constant	0.0012	*Constant*	0.0007
	[3.330]		[2.099]
y_{t-1}	0.5851	y_{t-3}	0.2803
	[7.443]		[3.526]
$RETP_{t-1}$	0.0007	y_{t-4}	0.0709
	[2.657]		[0.815]
		y_{t-5}	0.1353
			[1.531]
		y_{t-6}	0.2358
			[3.022]
		$RETP_{t-3}$	0.0006
			[2.668]
R^2	0.410	R^2	0.529
VAR model		**VAR model**	
Constant	0.0013	*Constant*	0.0013
	[3.448]		[3.427]
y_{t-1}	0.5554	y_{t-1}	0.5556
	[6.593]		[6.526]
Δip_{t-1}	0.0004	Δip_{t-1}	0.0004
	[1.288]		[1.288]
$\Delta yield_{t-1}$	0.0007	$\Delta yield_{t-1}$	0.0007
	[2.239]		[2.219]
R^2	0.415	R^2	0.415

In the above table, $\hat{F}_t^{(i)}$ expresses the estimate of *i*-th factor in period *t*, variable y_t represents monthly rate of inflation, $RETP_t$ stands for seasonally adjusted balance of responses to the question on the level of prices in retail trade, while variables Δip_t and $\Delta yield_t$ correspond to monthly changes in industrial production and yields on 2-year bonds, respectively. Square brackets show the values of *t* statistics.
Source: Own calculations.

It should be noted that in the case of the factor model the BIC revealed the same form of the model for both considered forecast horizons, i.e. for h=1 and for h=3, which features only current values of the first two factors (and as h>0 they are in fact lagged by 1 and 3 periods, respectively) and the current value of monthly inflation (in fact lagged by 1 and 3 periods).

On the basis of the obtained models the forecast were produced for h=1 and h=3 periods ahead, on each occasion extending the sample by one observations, once again specifying the structure of the models and re-estimating factors and parameters of the models. In total, 24 forecasts of inflation were produced for each forecast horizon, encompassing the period from June 2005 to May 2007. Table 3 presents the values of relative mean square errors for each of the models together with West test [2005] results and the results of verification of two hypothesis assuming that coefficient α in equation (15) is equal to 0 and 1, respectively. The rejection of the first hypothesis and the failure to reject the second one means that the factor model has better forecasting performance than the competitive model.

For h=1 the values of mean square errors for all three competitive models expressed in relation to the mean square error for the factor model are significantly higher than 1. For each of the considered competitive models the results of West test [2005] confirm that, at the 10% significance level, we should reject the hypothesis that the values of mean square errors for this model and the factor model are identical. This means that the factor model has better forecast accuracy than the remaining models. Moreover, the best of the competitive models generates forecasts whose mean square error is 67% larger than the error of the factor model, which may be assessed as a rather high value.

Results of verification of hypotheses for equation (15) indicate that in the case of all three competitive models at the significance level of 5% we can not reject the hypothesis that the value of coefficient α equal one, while the hypothesis that this coefficient is equal to zero should be rejected. Such a result attests to better forecasting performance of the factor model in comparison to the other models.

Table 3. Measures for evaluating forecast accuracy.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Forecast horizon	h=1			h=3		
Model	MSE	α estimate	H_0: $\alpha = 1$	MSE	α estimate	H_0: $\alpha = 1$
AR	1.726 (0.0288)	1.1261 [5.330] (0.00002)	0.3562 (0.5564)	1.357 (0.1804)	0.8286 [3.106] (0.00497)	0.4126 (0.5270)
AR-IND	1.955 (0.0583)	1.2482 [5.613] (0.00001)	1.2452 (0.2760)	1.703 (0.1019)	1.0911 [3.760] (0.00102)	0.0986 (0.7564)
VAR	1.675 (0.0652)	1.0290 [4.723] (0.00009)	0.0177 (0.8952)	2.382 (0.0693)	0.8966 [4.955] (0.00005)	0.3264 (0.5733)

Mean square error was expressed in the relative form as the ratio of the mean square error as obtained on the basis of a given model and the mean square error for the factor model. Columns (2) and (5) apart from the values of mean square errors also present p-values of West test [2005] verifying the hypothesis of equal mean square error values for a given model and the factor model. Rejecting the null-hypothesis in West test means that the factor model generates forecasts with a smaller mean square error than the competitive model.
Columns (3) and (6) present estimates of coefficient α in equation (15) together with t statistics and p-values. Columns (4) and (7) contain the values of F statistics and their corresponding p-values in the test verifying whether coefficient α is equal to 1. In both cases we used the Newey-West estimator (HAC).
Source: Own calculations.

With a three-month forecast horizon (h=3), the mean square error for forecasts obtained from the factor model is once again smaller than the error for the three remaining models. The best of the competitive models yields forecasts with a mean square error that is 36% higher than the error for the factor model. For the VAR model this error is almost 2.5 times higher. This time, however, in the case of the autoregressive model West test allows the rejection of the hypothesis of equal mean square error values for this model and the factor model only at the significance level of 20%.

Verification of hypotheses concerning the values of coefficient α in equation (15) renders results that are similar to those obtained for one-period forecasts. Again for none of the three competitive models null-hypothesis of $\alpha = 1$ can be rejected, while test results unequivocally allow rejecting the hypothesis of $\alpha = 0$. Thus the indications of the test confirm that the factor model has better accuracy of forecasts for three periods ahead than the other models.

Out of the remaining models for h=1 the VAR model yields the smallest forecast error, while for h=3 the most accurate forecast can be obtained from the autoregressive (AR) model.

Summary

This study presents the results of evaluation the forecasting performance of dynamic factor models in forecasting inflation in the Polish economy. The model was specified on monthly data encompassing the period from February 1998 to April 2007, while model parameters and factors were estimated using the principal components method, firstly proposed by Stock & Watson [1998].

The results confirm that for a one- and three- month horizon the forecasts obtained from the factor model have smaller mean square error than forecasts based on the competitive models: an autoregressive model, a model with a leading indicator and a small VAR model. The advantage of the factor model is more conspicuous in the case of one-month ahead forecasts, which is also indicated by the results of West test [2005]. With a one-month forecast horizon, the mean square error in the best-performing competitive model is 67% higher than in the factor model, while for a three-month horizon this discrepancy is equal to 36%.

Good forecasting performance of the factor model were also confirmed through verifying hypotheses concerning the coefficients of a regression equation where the actual values of a forecast variable were described by forecasts based on the factor model and one of the competitive models. For both forecast horizons and all considered competitive models the results of statistical tests indicated that we can not reject the hypothesis that coefficient value for a factor model forecast equals 1. At the same time we should reject the hypothesis of a zero value of this coefficient.

In the study we tried to associate the estimated factors with particular variables grouped in appropriate economic categories. Based on the analysis of eigenvalues of a matrix of correlation of the entire data set and indications of information criteria it was established that the number of unobserved factors in the model was equal to 2. The first of the factors is primarily responsible for the behaviour of prices and domestic interest rates. In turn, the second factor loads mostly production, money and some business climate indicators. However, it has to be borne in mind that factors determined using the principal components method are not the structural factors but are only their linear combination and so the estimated factors should be interpreted with proper caution.

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APPENDIX A. Set of variables featured in the study.

No.	Name of variable	Description of variable	Transformation performed	Source of data
Output & Sales				
1	PSPM	Industrial production in constant prices (Jan-1999=100), SA	Δln	GUS
2	PSPP	Industrial production in manufacturing in constant prices (Jan-1999=100), SA	Δln	GUS
3	PSGRN	Production in mining in constant prices (Jan-1999=100), SA	Δln	GUS
4	PZAOP	Supply of electricity, gas and water in constant prices (Jan-1999=100), SA	Δln	GUS
5	SPDET	Retail sales in constant prices (Jan-1999=100), SA	Δln	GUS
Construction				
6	PBUD_SA	Construction and assembly production in constant prices (Jan-1999=100), SA	Δln	GUS
7	L_MIESZK_SA	Number of completed dwellings, SA	Δln	GUS
Foreign Trade				
8	EKS_SA	Exports in constant prices (Jan-1999=100), SA	Δln	GUS
9	IMP_SA	Imports in constant prices (Jan-1999=100), SA	Δln	GUS
10	IMP_ROPA	Oil imports	Δln	GUS
Labour market				
11	ZAT_SA	Average employment in enterprise sector, SA	Δln	GUS
12	L_BEZ_SA	Number of unemployed, SA	Δln	GUS
13	NOWI_BEZ_SA	Number of new unemployed, SA	Δln	GUS
14	OFERTY_PRACY_SA	Number of vacancies, SA	Δln	GUS
Prices				
15	CPI_SA	Consumer Price Index (Jan-1999=100), SA	Δln	GUS
16	CENY_ZM_SA	CPI net of most volatile prices (Jan-1999=100), SA	Δln	NBP
17	CENY_ZMPAL_SA	CPI net of most volatile prices and fuels (Jan-1999=100), SA	Δln	NBP
18	CENY_KONTR_SA	CPI net of regulated prices (Jan-1999=100), SA	Δln	NBP
19	CENY_15_SA	15% trimmed mean (Jan-1999=100), SA	Δln	NBP
20	CENY_NETTO_SA	Net inflation (Jan-1999=100), SA	Δln	NBP
21	CENY_ZYWN_SA	Food prices in CPI basket (Jan-1999=100), SA	Δln	GUS
22	CENY_ALK_SA	Alcohol prices in CPI basket (Jan-1999=100), SA	Δln	GUS
23	CENY_TYTON_SA	Tobacco prices in CPI basket (Jan-1999=100), SA	Δln	GUS
24	CENY_ODZIEZ_SA	Clothes prices in CPI basket (Jan-1999=100), SA	Δln	GUS
25	CENY_OBUWIE_SA	Footwear prices in CPI basket (Jan-1999=100), SA	Δln	GUS
26	CENY_MIESZUZ_SA	Housing maintenance prices in CPI basket (Jan-1999=100), SA	Δln	GUS
27	CENY_MIESZWYP_SA	Home furnishing prices in CPI basket (Jan-1999=100), SA	Δln	GUS
28	CENY_ZDROWIE_SA	Health-related prices in CPI basket (Jan-1999=100), SA	Δln	GUS
29	CENY_TRANSP_SA	Transport prices in CPI basket (Jan-1999=100), SA	Δln	GUS
30	CENY_LACZN_SA	Telecommunications prices in CPI basket (Jan-1999=100), SA	Δln	GUS
31	CENY_KULT_SA	Culture-related prices in CPI basket (Jan-1999=100), SA	Δln	GUS
32	CENY_EDUK_SA	Education-related prices in CPI basket (Jan-1999=100), SA	Δln	GUS
33	CENY_REST_SA	Prices in ‘Hotels and restaurants’ category in CPI basket (Jan-1999=100), SA	Δln	GUS
34	CENY_PPI_SA	Producer prices in industry (Jan-1999=100), SA	Δln	GUS
35	CENY_PRZET_SA	Producer prices in manufacturing (Jan-1999=100), SA	Δln	GUS

36	CENY_PALIWA_SA	Prices in manufacture of coke and refined petroleum products (Jan-1999=100), SA	Δln	GUS
37	CENY_GRN_SA	Prices in mining (Jan-1999=100), SA	Δln	GUS
38	CENY_ZAOP_SA	Prices in supply of electricity, gas and water (Jan-1999=100), SA	Δln	GUS
39	CENY_EKS_SA	Export prices (Jan-1999=100), SA	Δln	GUS
40	CENY_IMP_SA	Import prices (Jan-1999=100), SA	Δln	GUS
41	CENY_BUD_SA	Prices of construction and assembly production (Jan-1999=100), SA	Δln	GUS
Wages				
42	PLACA_SA	Average wage in enterprise sector, SA	Δln	GUS
43	PLACE_HAND_SA	Average wage in enterprise sector, in retail trade, SA	Δln	GUS
Interest Rates				
44	WIBOR1M	1-month WIBOR rate	Δ	Reuters
45	WIBOR3M	3-month WIBOR rate	Δ	Reuters
46	PL2Y	Average yields on 2-year Polish Treasury bonds	Δ	Reuters
47	PL5Y	Average yields on 5-year Polish Treasury bonds	Δ	Reuters
48	BUND5Y	Average yields on 5-year German Treasury bonds	Δ	Reuters
49	USD5Y	Average yields on 5-year US Treasury bonds	Δ	Reuters
Money & Credit				
50	GOTOWKA_SA	Currency in circulation (in million zloty), SA	Δln	NBP
51	DEP_GD_SA	Deposits of households (in million zloty), SA	Δln	NBP
52	DEP_P_SA	Deposits of enterprises (in million zloty), SA	Δln	NBP
53	M1_SA	M1 aggregate (in million zloty), SA	Δln	NBP
54	M3_SA	M3 aggregate (in million zloty), SA	Δln	NBP
55	KRED_GD_SA	Loans to households (in million zloty), SA	Δln	NBP
56	KRED_P_SA	Loans to enterprises (in million zloty), SA	Δln	NBP
57	AKT_ZAG_SA	Net foreign assets (in million zloty), SA	Δln	NBP
Exchange Rates				
58	EURPLN	EUR/PLN exchange rate at month-end	Δln	NBP
59	EURUSD	EUR/USD exchange rate at month-end	Δln	Reuters
60	EURGBP	EUR/GBP exchange rate at month-end	Δln	Reuters
61	USDJPY	USD/JPY exchange rate at month-end	Δln	Reuters
Stock Exchange Indices				
62	WIG	Warsaw Stock Exchange Index WIG	Δln	Reuters
63	DJI	Dow Jones Index	Δln	Reuters
Business climate indicators in industry (Surv Ind)				
64	P_OGOL_SA	Overall economic situation (net balance), SA	Δ	GUS
65	P_PRTF_SA	Domestic and foreign order book (net balance), SA	Δ	GUS
66	P_PRTFZAG_SA	Foreign order book (net balance), SA	Δ	GUS
67	P_PROD_SA	Output level (net balance), SA	Δ	GUS
68	P_ZAP_SA	Stocks of finished products (net balance), SA	Δ	GUS
69	P_FIN_SA	Ability to pay current debts (net balance), SA	Δ	GUS
70	P_NALEZ_SA	Volume of total liabilities (net balance), SA	Δ	GUS
71	P_OGOL_OCZ_SA	Expected overall economic situation (net balance), SA	Δ	GUS
72	P_PRTF_OCZ_SA	Expected domestic and foreign order book (net balance), SA	Δ	GUS
73	P_PRTFZG_OCZ_SA	Expected foreign order book (net balance), SA	Δ	GUS
74	P_PROD_OCZ_SA	Expected output level (net balance), SA	Δ	GUS
75	P_CENY_OCZ_SA	Expected price level (net balance), SA	Δ	GUS

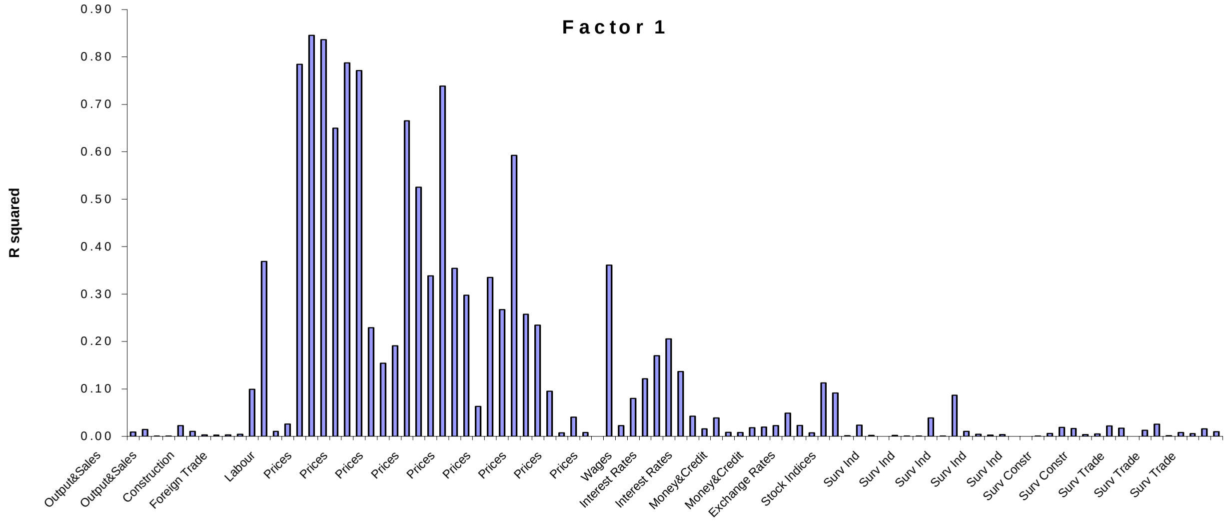
76	P_ZAT_SA	Expected employment (net balance), SA	Δ	GUS
77	P_FIN_OCZ_SA	Expected ability to pay current debts (net balance), SA	Δ	GUS
Business climate indicators in construction (Surv Constr)				
78	B_OGOL_SA	Overall economic situation (net balance), SA	Δ	GUS
79	B_PRTFKR_SA	Domestic order book (net balance), SA	Δ	GUS
80	B_MOCE_SA	Production capacity utilisation in enterprises (in %), SA	Δ	GUS
81	B_PROD_SA	Construction and assembly production in domestic market (net balance), SA	Δ	GUS
82	B_SYTFIN_SA	Financial situation of enterprise (net balance), SA	Δ	GUS
Economic climate indicators in retail trade (Surv Trade)				
83	S_OGOL_SA	Overall economic situation (net balance), SA	Δ	GUS
84	S_SPRZ_SA	Amount of goods sold (net balance), SA	Δ	GUS
85	S_ZAP_SA	Stocks of goods (net balance), SA	Δ	GUS
86	S_CENY_SA	Prices of goods sold (net balance), SA	Δ	GUS
87	S_CNZYW_SA	Prices in food section (net balance), SA	Δ	GUS
88	S_SPRZ_OCZ_SA	Expected amount of goods sold (net balance), SA	Δ	GUS
89	S_ZAT_OCZ_SA	Expected employment (net balance), SA	Δ	GUS
90	S_CENY_OCZ_SA	Expected prices of goods sold (net balance), SA	Δ	GUS
91	S_CNZYW_OCZ_SA	Expected prices in food section (net balance), SA	Δ	GUS
92	S_ZAM_OCZ_SA	Expected orders placed with suppliers (net balance), SA	Δ	GUS

Symbol Δ stands for first differences and Δln for first difference of logs. SA stands for ‘seasonally adjusted’.
Source: GUS, NBP, Reuters.

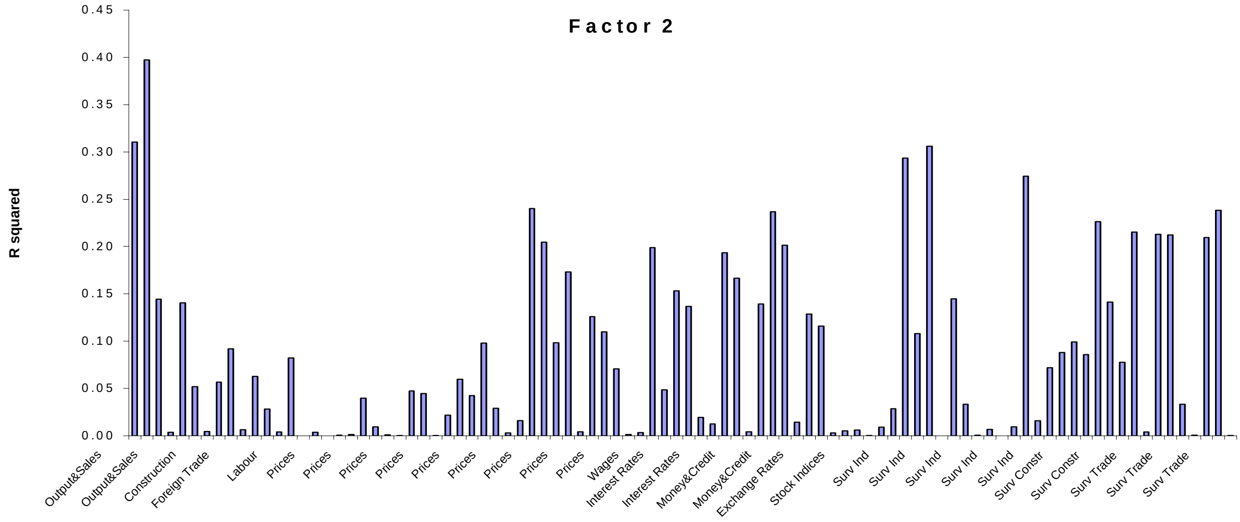
APPENDIX B

Figure 1. R-squared from the regression of particular variables on each of the first six factors.

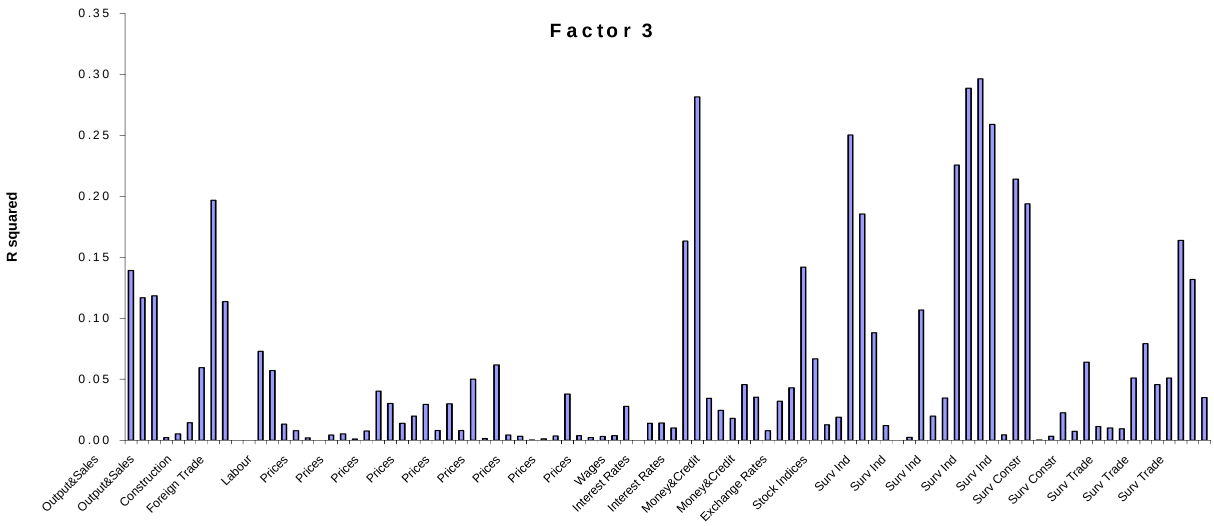
a)



b)



c)



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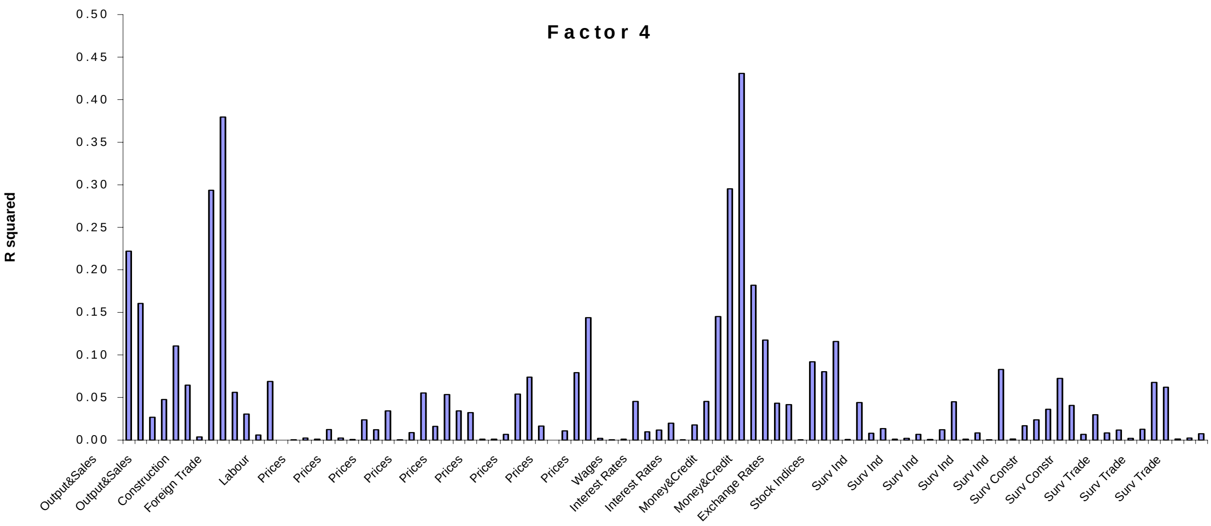
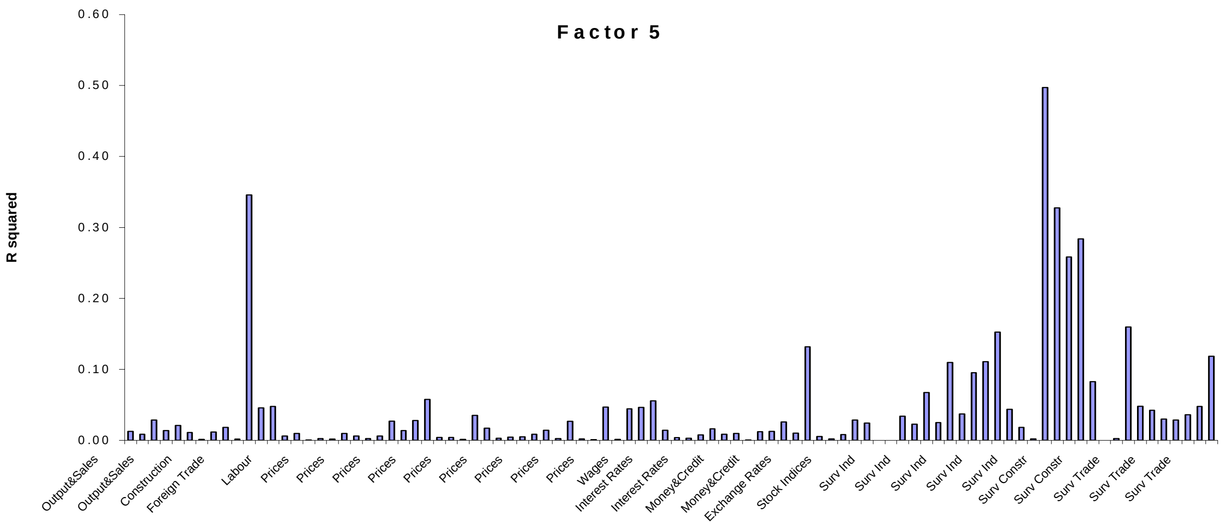
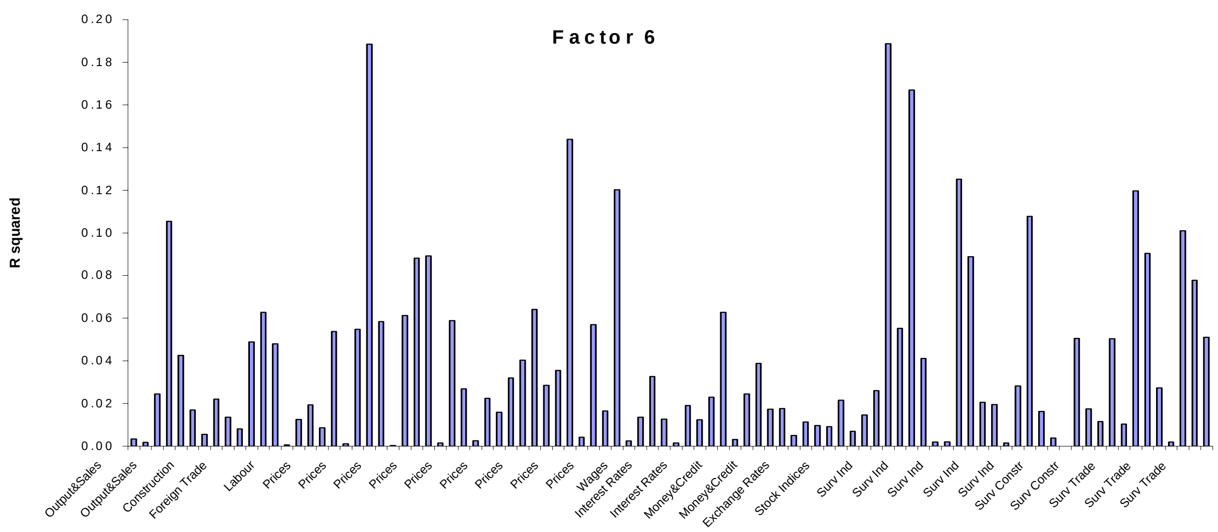


e)



f)



Source: Own calculations.