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SHORT TERM INFLATION PROJECTIONS FOR SLOVENIJA: COMPARING FACTOR MODELS WITH AR AND VAR MODELS

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Abstract

This paper builds factor forecasts for the overall inflation and the subcomponents (energy inflation, industrial goods inflation, services inflation, processed food and the non-processed food inflation) for Slovenia. The forecasts of the factor model are compared to autoregressive (AR) and vector autoregressive (VAR) models in terms of the Root Mean Squared Error (RMSE). In addition, the factors were identified so as to give interpretation to the forecasts. Results show that the factor model is significantly better than the AR benchmark forecasts and is not worse from the VAR forecasts for all subcomponents and the headline inflation, which renders it a good tool for forecasting inflation in Slovenia.

JEL codes: C32, F3.
Keywords: forecasts, factor model, inflation, AR, VAR.

Povzetek

Ta članek ocenjuje napovedno moč faktorskih modelov na primeru inflacije in njenih podkomponent (energije, industrijskih dobrin, storitev, predelane in nepredelane hrane) za Slovenijo. Napovedi faktorskih modelov se primerjajo z napovedmi avtoregresivnih (AR) in vektorskih avtoregresivnih (VAR) modelov s pomočjo kriterija "Root mean squared error" (RMSE). Poleg tega so bili identifcirani tudi faktorji, tako da se jim lahko dodeli ekonomska interpretacija. Rezultati kažejo, da je faktorski model statistično značilno boljši od AR modelov za večino podkomponent, prav tako pa ni slabši od VAR modelov in je zaradi tega ustrezno orodje za napovedovanje inflacije v Sloveniji.

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1. INTRODUCTION

Forecasting macroeconomic aggregates has played an important role in the Bank of Slovenia policy conduct. Also, the accession of Slovenia to the European Union in 2004 and especially to the Eurosystem in January 2007 makes the forecasting of inflation additionally important, since inflation has to be forecasted four times per year. The forecasts have to be reported to the European Central Bank (ECB) and included as a part of the euro area forecasts, which are known as the Short Term Projections (STIP) and are a part of the broader Narrow Inflation Projection Exercise (NIPE).[1] This paper examines how one particular forecasting device, namely the factor models can deal with this task.

Since the introduction of the approximate dynamic factor models in forecasting by Stock and Watson [34], [35], [36], [37] and their claim that they outperform autoregressive (AR) and vector autoregressive (VAR) models, considerable amount of research was made in order to test this claim for a wide variety of countries and a wide variety of economic indicators. For euro zone the literature comparing the forecast performance of factor models is e.g. Camba-Mendez and Kapetanios [9], Espasa et al. [13], Forni et al. [14], [15], [16], Marcellino [26] and Marcellino, Stock and Watson [25] among others. A good survey on this literature is available in Hendry and Hubrich [18]. Factor models were also evaluated for several individual euro area countries, for UK such comparison was done by Artis et al. [1], for Holland by den Reijer and Vlaar [31] and by den Reijer [30], for Germany by Schumacher [33] and for Austria by Schneider and Spitzer [32].

Most of these studies find similar conclusions. First, factor models perform well in out-of-sample forecast exercises and better than AR and VAR models and other multivariate models (notably non-linear models, Stock and Watson [34]), although not always by significant amount (e.g. Schneider and Spitzer [32]). Second, usually the best forecasting performance can be achieved with relatively small dataset which includes a limited number of variables only (typically from 30 to 80 variables). Factor models on these smaller datasets perform significantly better than large factor models with all available variables included (their number can exceed 400).

The source of a good forecast performance of dynamic and approximate dynamic factor models is their ability to reduce large datasets into small number of orthogonal indicators which are then used in forecasting. This is a very desirable feature, especially since often researchers do not have good indications on which series to include in the forecasting model. In addition, as Clements and Hendry [10] notice, the choice of variables based on economic theory is many times not efficient for forecasting purposes.

By extracting common components from a large number of series, factor models are also helpful in cases where the time series are short, which is a prominent feature of the data from the new EU member states, as shown in the work by Banerjee et al. [4]. In such cases they showed that factor models are preferred to VAR models since the use of particular variables as good forecasting devices in the economy undergoing a transition is not clear a priori. On the other hand, factor models provide a methodology that allows us to remain agnostic about the structure of the economy. Banerjee et al [4] also showed that in forecasting economic activity and prices for the new EU members, factor models give good forecasts, in some cases beating the AR and VAR forecasts.

In this paper we build an approximate dynamic factor model for Slovenia, proposed by Stock and Watson [35], [36], and compare its forecast performance to AR and VAR forecasts for

[1] Both STIP and NIPE projection exercises are under supervision of the European Central Bank.

HICP and five HICP-based series: overall inflation, energy inflation, unprocessed food inflation, processed food inflation, non-energy industrial goods inflation and services inflation.[2]

While the choice of variables to forecast in this paper reflects the interest for the Bank's economic analysis, it can be further motivated by Slovenia's entry into the European Monetary Union. Since after the euro adoption, Slovenia has to produce forecasts in the framework of the STIP, for each of the subcomponents and the headline inflation for several months ahead, this paper is a test on whether for these series factor models would be a good forecasting device in fulfilling the STIP requirements. In addition, this paper identifies the different factors by performing a correlation exercise between the factors and different series in the way as Stock and Watson [35] proposed. The purpose of such identification is to give qualitative interpretation to the forecasts, as commonly deemed necessary when forecasting in the central bank.

Our study differs in three ways from by now the only available forecasting horse-race of factor models for the new EU members by Banerjee et al. [4]. First, in our study the forecast differences between the AR, VAR and the factor models are evaluated by the statistical test (we use the Diebold Mariano [12]). This test, although based on a non-parametric test statistic, is a frequent and reasonable indicator on whether the difference between two models is significant. Secondly, the factors are identified, i.e. they are related to a qualitative interpretation of the role they may play in the economy. This is of particular value for the central bankers who want to attach reasoning and interpretation to the driving forces of the forecasts. Thirdly, the HICP based inflation series were not included in the Banerjee et al. [4] forecast comparison. Instead, in their study they used CPI data to produce forecasts at the quarterly frequency, while here we are interested in the monthly forecasts of the HICP and its subcomponents, which is in line with the already mentioned NIPE and STIP projects of the ECB.

Our results show that when forecasting the headline inflation as well as most subcomponents (exceptions are the processed food and industrial goods subcomponents, where the difference is insignificant and the energy subcomponent, where VAR seems to perform better), the factor model outperforms the AR and VAR forecasts for all horizons investigated (from one month ahead up to 12 months ahead), whereby the difference between the VAR and the factor model was not explicitly tested with the Diebold-Mariano test.[3] In addition, reasonable interpretations in terms of wage pressures, inflation expectations, external pressures and business cycle pressures can be attributed to extracted factors.

This paper is organized as follows: in Section 2 different models compared in our paper are presented, Section 3 outlines the data used in different models, Section 4 identifies the factors used and calculates how much of the variance of the variables forecasted different factors explain, while Section 5 performs the horse-race between the AR, VAR and the factor models. Section 6 concludes.

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[2] Strictly speaking, the factor model employed in this paper is a static factor model (Forni et al. [16]), since the factors are extracted in a static way (with static principal component analysis). However, the factors extracted enter into the forecasting equation in a dynamic fashion,. Therefore the model can also be called an approximate dynamic factor model.

[3] Note that, however, the factor model has a lower RMSE compared to the VAR models, which suffices as a statement about better models in a lot of the factor model literature (e.g. Benalal et al. [6]).

2. FORECAST MODELS USED IN THE PAPER

In this paper forecasts of three statistical models are compared: the AR, VAR and the approximate dynamic factor models. All three models' forecasts and the expert forecasts are compared on the basis of the root mean squared error (RMSFE), which is a standard criterion used in the forecast comparison literature (Stock and Watson [35]). The RMSE is defined as

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{t+h+i}-\hat{x}_{t+h+i})} \qquad (1)$$

where N denotes the number of forecasts used, x_{t+h} denotes the forecast h periods ahead and i denotes the i^{th} forecast used in the calculation. The relative performance of various models is compared in terms of the relative RMSE, where AR models are taken as the baseline. This is standard in the forecasting models, as models are judged to be good if their RMSE is lower than that of the AR process, since they are easy to compute and in many cases very hard to be beaten even by very sophisticated methods (e.g. non-linear, structural models). In that respect AR forecast serves as the benchmark forecast.

The first models in comparison undertaken were the AR models. They are standard in the forecasting literature and their form is

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + Dt + e_t \qquad (2)$$

where y_t is the stationary variable forecasted, A_p denotes the AR coefficients and the D term contains the deterministic terms included in the model. In our forecasting exercises the constant was always included, while the trend was included only if it was significant. The lag length p was determined by the lag selection criterion, whereby two different criteria were used, the first is the Akaike Information Criterion (AIC) and the second is the Bayesian information criterion (BIC). Among the two criteria, the AR model with the lower RMSE was used as the benchmark forecast for the subsequent analysis, and most of the time AIC gave lower RMSE. The stationarity of the variables was achieved with the differencing after the ADF test for the unit root in the period under investigation was performed (the lags included in the ADF regression were determined by the AIC).[4] The models' parameters were estimated with the ordinary least squares method (OLS).

The second group of models in the comparison were the vector autoregressive (VAR) models. They were of the form

$$X_t = B_1 X_{t-1} + ... + B_p X_{t-p} + Dt + e_t \qquad (3)$$

where X_t is now the (N×1) vector of stationary variables used in the analysis and the first variable in this vector is our y_t variable of interest. The B_p matrix is the (N×N) matrix of the coefficients corresponding to the lagged variables of the p^{th} lag, D is the (N×1) matrix of the coefficients of the deterministic terms included. The variables selected for the VAR models are described in Section 3.

The choice of the lag length was again performed according to the lag selection criteria AIC and BIC. In the VAR the variables taken were tested for stationarity with the ADF test and

[4] The results on the ADF tests are available from the author.

then if the variables have a unit root, they were differenced. No cointegration terms were included in the VAR models. A procedure for exclusion of insignificant lags was also applied in order to allow for more exact estimation of the parameters, which improves the forecasts, as shown by Brüggemann et al. [8]. The procedure used for exclusion of insignificant lags is called Sequential Elimination of Regressors (SER) and is available in their paper. Again, the criterion for determining the number of lags excluded was the AIC criterion.

The final statistical model was the approximate dynamic factor model suggested by Stock and Watson [35] and Bai and Ng [2]. The static principal component method is used to extract the factors. The method uses the correlation matrix of the data, which has to be transformed, so as to be stationary and standardized. The differencing of variables forecasted was made (as in the case of the AR and VAR models) after performing the ADF test. The representation of the approximate dynamic factor model is as following. Let the y_t be the series of interest to be forecasted. By assuming that the series allows for the factor representation, we decomposed it in a common component f_t and a idiosyncratic component e_t such as to get the following expression

$$y_t = \omega_1 f_{1,t} + ... + \omega_k f_{k,t} + Dt + e_t \qquad (4)$$

where y_t denotes the series of interest in period t, $f_{k,t}$ denotes the factor k in the period t and ω_k denotes the loading of the factor k into the series. The factors follow an autoregressive process $A(L)f_t = u_t$ with L being the lag operator and the residuals u_t and e_t are orthogonal. The factors are obtained by the eigenvalue-eigenvector decomposition. By applying the eigenvalue-eigenvector decomposition to the correlation matrix of the data included in the model we obtain the factors and the shares of the variance. The orthonormal eigenvectors represent the factors while the eigenvalues represent the amount of variance explained by the corresponding factor. In other words, the factors are obtained by solving the eigenvalue problem of the correlation matrix $C = P'P$ (where P denotes the lower triangular matrix), so that the problem reduces to solving the following equation

$$C = \Lambda L \Lambda' \qquad (5)$$

where $x_{i,t}$ is the series i included in the factor model, Λ contains the first q eigenvectors and L is the diagonal matrix with the eigenvalues on the diagonal.

The number of factors chosen in forecasting model for each subcomponent in our paper was determined by the Bai and Ng [2], [3] information criteria IC_1 and IC_3. These two criteria seek to minimize the idiosyncratic variance of the dataset by adding factors to the models. Each additional factor presents, however, also a penalty in the information criteria. Note that these two criteria are determining the number of static factors, meaning that the number of factors they suggest is the sum of either the factors or their lags (Stock and Watson [35]). The number of lags in such factor models was determined with the AIC criterion, where the maximum number of lags allowed for was set to 4. The insignificant lags were excluded from the models with the sequential elimination procedure by Brüggemann et al. [8], which is analogue to the one used for the VAR models. The code for all models is available from the author; the forecast horse-races were programmed in the Gauss 6.0 software.

3. DATA USED IN THE FORECAST COMPARISON

In all models used in the horse-race the series forecasted were the six inflation series of interest (headline HICP inflation for Slovenia and the five sub-components), all on the monthly frequency. These sub-components are: the processed food inflation, the unprocessed food inflation, the services prices, the energy prices and the non-energy industrial goods inflation. The inflation series were computed as the year-on-year percentage change of the HICP index from the year 1997 to the year 2001, while the out-of sample forecasts were made until May 2006. Details on the horse-races are given in Section 5 below. The series used are available from the author.

The variables taken in the VAR models were the inflation rate series of interest, the average gross real wage in Slovenia, the nominal effective exchange rate, the short term nominal interest rate on the money market, the industrial production index and the oil price of the North Sea Brent per barrel. The data sources were from the Bank of Slovenia databases. The variables were chosen on the basis of the open economy models of monetary policy like e.g. Monacelli [29] whereby the industrial production variable was taken instead of GDP due to its unavailability at the monthly frequency. The source of the oil prices was the Reuters database.

In the factor model 30 variables were used. They are all listed in *Appendix 1* and can be classified into the following categories:

- The inflation series to be forecasted – 1 series,
- Employment and real wage index - 2 series,
- Monetary aggregates in Slovenia (M1, M2 and M3) - 3 series,
- Survey based indices (prices, employment, consumption) - 5 series,
- Short and long term interest rates and CPI indices in the euro area and the US - 6 series,
- Slovenian short and long term nominal interest rates - 2 series,
- Producer price indices in four sectors - 4 series,
- Nominal exchange rates of SIT to US$, British pound and to euro – 3 series,
- Real trade in goods and services (imports and exports) – 4 series.

This selection is similar in terms of the number of categories of variables to the selection of Stock and Watson [35] and Forni et al. [14], however, it uses less indicators per category. More indicators per category were not chosen for two reasons: first, since factor models which include several hundred variables do not perform significantly better than those with "only" around 70 variables included (Boivin and Ng [7]), we limited the number of included variables to 30. Second, for Slovenia less indicators of a certain category are available compared to the US or the euro area.

4. SELECTION AND IDENTIFICATION OF FACTORS

In this paper four factors were included in the forecasting model for each series to be forecasted. Such selection was proposed by the Bai and Ng [3] selection criteria. The decision on which four factors to include ($f_{i,t}$ where $i=1,..,4$) was obtained by examining which out of the first twelve factors explain most of the variance of the forecasted series. Hence the factors chosen in this paper were not those that explain the most of the common variance of the whole dataset, but those that explain the most of the variance of forecasted series. The intuition for such choice is that although a certain factor captures little of common covariance, it still can be very useful for forecasting the series of interest if it captures a lot if its variance.

In this Section we therefore examine how much of the variance of forecasted inflation series is explained by the individual factor. The explained share of variance is calculated as the explained sum of squared residuals of the individual factors divided by the total variance of the inflation series. This is because we hope to include those series that are the best leading indicators for the inflation indices forecasted. In symbols, the formula for such calculation is given as

$$R^2 = \frac{\omega_k f'_{k,t} \omega_k f_{k,t}}{y'_t y_t} \qquad (6)$$

where y_t is one of the inflation series forecasted, once again $f_{k,t}$ is the factor k *(k=1,….,12)* and ω_k is the loading of this factor.[5] The R^2 is the obtained coefficient of determination. *Table 1* below shows the obtained share of variance explanation of the series due to those four factors, which explain most of it. In parentheses the rank of these factors in explaining the overall variance of the whole data is also displayed. These four factors are finally used in the out-of-sample factor model.

Table 1: Explained variance of the forecasted series

Factors	HICP	Energy	Un.food	Pr.food	Services	Ind.goods
1st	0.36 (5)	0.16 (1)	0.35 (5)	0.18 (3)	0.23 (7)	0.19 (8)
2nd	0.09 (2)	0.13 (6)	0.08 (9)	0.10 (4)	0.07 (8)	0.18 (19)
3rd	0.07 (7)	0.13 (7)	0.08 (4)	0.08 (6)	0.08 (10)	0.14 (7)
4th	0.07 (6)	0.16 (3)	0.07 (6)	0.05 (9)	0.06 (2)	0.08 (5)
All	0.59	0.58	0.58	0.41	0.44	0.59

Notes: In the brackets is the rank of the factor in explaining the overall variance of all series.

We find that the most important factor explains from 16% to 36% of the variance of the forecasted series for all subcomponents as well as for the headline inflation. The other factors explain from 5% to 18% of the variance of forecasted series. Overall, the first four factors are able to explain from 41% to 57% of the variance of the series of interest.

The next question is which series out of the 30 load well into particular factors and which are less important? This was examined by attributing a qualitative interpretation to a particular factor, in other words, by attaching economic sense to it. For this purpose, we regressed the factor k ($f_{k,t}$, $k=1,\ldots,4$) on the constant c and the individual series x_t included in the factor model. Hence 30 regressions were made for each factor, using OLS. The regressions were performed of the form

$$f_{k,t} = c + bx_t + \varepsilon_{k,t} \qquad (7)$$

where $\varepsilon_{k,t}$ denotes the obtained residual of the regression. Then the coefficient of determination R^2 for each regression was computed in the form

$$R_i^2 = \frac{f'_{k,t} f_{k,t} - e'_{k,t} e_{k,t}}{f'_{k,t} f_{k,t}} \qquad (8)$$

[5] Note the different subscript *k*, which denotes all the twelve factors analysed, and *i*, which denotes the four factors chosen in the forecasts.

which can be interpreted as the explained variance of the factor divided by the total variance in the factors. The coefficients of determination of such regressions are plotted as bars in *Appendix 2*.

The figures for the headline inflation as well as for all its subcomponents in *Appendix 2* can be interpreted in the following way. For the headline inflation the first factor, which explains the bulk of the inflation variance, is connected to the survey information on consumer sentiments and exports as well as to monetary and external movements, therefore it can be named as the common trend in both domestic and foreign market expectations. The second is the domestic expectations common trend, since it captures the movements only in domestic surveys. The third factor is related to information about foreign monetary conditions, therefore it may be capturing the foreign price pressures well. The final (fourth) factor combines domestic monetary conditions with price expectations, since it captures the movements of domestic money, surveys and exchange rates.

As for the services subcomponent, the first factor, which explains 23% of the services series' variance, is related to the price movements in the euro area and the export and import of services. The second factor, capturing 7% of the variance in the services inflation can be named the domestic conditions factor, since it captures well the comovement of employment and domestic interest rates. Both of these are related to the services prices and therefore also to inflation in this sector. The third and fourth factors are related to the consumer sentiment trends, since they are related to the trade flows of services, and to the survey information, respectively.

Regarding the unprocessed food sub-component, the first factor, explaining 35% of the inflation variance, captures well movements in the consumer sentiment and exports, since it is related to these survey information. The second and the third factors are related to the producer sentiment, since they capture the producer prices and the exchange rate, respectively, while the fourth factor relates to the foreign activity expectations, since it captures well the comovement between surveys and the exchange rate movements.

The processed food inflation factor decomposition shows that the first factor (which explains 18% of the sub-components' variance) captures well movements in the monetary trends, while the second relates to the producer price movements. The third factor is related to the domestic as well as foreign monetary conditions, since it captures well the movements in the exchange rate and the interest rates. The fourth factor relates to the nominal trends at home and abroad.

With regards to the energy prices, the first factor resembles international price conditions and exchange rate movements, while the second relates to the domestic monetary conditions, especially the interest rate movements. The third and the fourth factors are connected to the domestic and the monetary conditions in the EU and the U.S., since they capture well movements in the domestic money growth and foreign monetary movements, respectively.

Finally, as for the non-energy industrial goods inflation, the analysis shows that most of the first factor is related to the export of services and exchange rates, while the second is related to the import of services. The third factor is related to the domestic monetary conditions, since it is well correlated with the domestic short-term interest rate, wages, monetary aggregate M1 and euro area inflation. The fourth captures movements in the consumer expectations and expected exports.

5. FORECAST COMPARISON

In this study out-of-sample monthly forecasts were made for the horizons from one to up to twelve months ahead. The forecasts for more than one month ahead were made in the indirect way. In particular, in order to obtain the two months ahead forecast the model was forecasted one month ahead with the one month ahead forecast included in the data estimated. This forecasting procedure was showed to perform favourably to the direct forecasts (Marcellino, Stock and Watson [25]). The same procedure was used to compute other many-months-ahead forecasts.

The forecasts were made in the out-of-sample recursive way. This includes recursive parameter estimation, model selection, and so forth. The first simulated out of sample forecast was made for January 2001. To construct this forecast, the parameters of the AR, VAR and factor models were estimated by using only data available from the start of the sample, which is from January 1997 through to December 2000. Then the out-of-sample forecasts were made for one to twelve months ahead. All parameters and factors were then re-estimated, information criteria were recomputed, and models were selected using data from January 1997 to January 2001, and forecasts from these models were then computed for this new period. The final simulated out of sample forecast was made in April 2006 for May 2006. Of course for this period only the one month ahead forecast could be made.
The baseline specification of the VAR and factor models includes series as mentioned in Section 3. In terms of the lags included, they were chosen with the AIC criterion, with the Sequential Exclusion Restriction used to exclude the insignificant lags out of the system (from Brüggemann et al. [8]).

The forecasting performance for individual series is shown in *Table 2* below. The forecasts were compared for the horizons one, two, three, six and twelve months ahead. For the headline inflation the factor model significantly outperforms the AR benchmark, since the relative RMSE is lower than 1 for all horizons and the difference is statistically significant. On the other hand, the VAR model does not significantly outperform the AR benchmark and is for some horizons even worse (relative RMSE higher than one).

As for the subcomponents, the factor model proves to beat the AR benchmark, except for the processed food *(Table 2*). For the unprocessed food, industrial goods and services forecasts, it outperforms the AR benchmark at all horizons investigated, since the difference is statistically significant. On the other hand, the VAR model proves to be better than the AR benchmark for industrial goods, energy and unprocessed food subcomponents, while for the services subcomponent it is not significantly better (except for 1 and 12 months ahead). From this it follows that factor model is preferred to the VAR model for forecasting purposes.

Table 2: Relative RMSE of factor and VAR models

Horizon	1		2		3		6		12	
	VAR	Fact.	VAR	Fact.	VAR	Fact.	VAR	Fact.	VAR	Fact.
HICP	0.95	0.91*	0.97	0.92*	0.93	0.91*	1.05	0.95*	1.03	0.96*
Ener.	0.94*	0.98	1	1.03	1.01	1.03	0.91	0.96	0.81*	0.76*
Fdpr	1.05	1.01	1.04	1	1.06	0.99	1.05	0.98	1.02	0.98
Unpr	0.87*	0.81*	0.85*	0.82*	0.82*	0.81*	0.82*	0.80*	0.79*	0.74*
Indg	0.94*	0.95*	0.87*	0.89*	0.87*	0.88*	0.90*	0.92*	0.88*	0.88*
Serv.	0.98*	0.91*	0.96	0.92*	0.97	0.89*	0.96	0.85*	0.98	0.79*

Notes: The * denotes that the forecast is significantly better than the autoregressive (AR) benchmark, tested with the Diebold-Mariano test. HICP - headline inflation, Ener. - energy inflation, Fpdr - processed food inflation, Unpr - unprocessed food inflation, Indg - industrial goods inflation, Serv. - services inflation. The number of lags in all models was chosen with the AIC criterion.

Additionally, alternative specifications for the AR and VAR models were examined. The lags in the AR, VAR and factor models were determined by the BIC and not by the AIC. Then, the insignificant lags were excluded according to BIC and not AIC criterion from the models and insignificantly different results were obtained. The results of these robustness checks are available from the author.

6. CONCLUSIONS

In this paper we have evaluated the performance of factor models with respect to more traditional small-scale time-series models, such as the AR and VAR models for forecasting the HICP inflation and its subcomponents in Slovenia. The advantage of factor models is in using many time series and thereby hindering the small sample problem. In addition, no a priori knowledge is needed on which variables to include, which increases the likelihood of a good forecasting performance.

The models were compared one, two, three, six and twelve months ahead forecasts in terms of the RMSE. The forecasts were compared from January 2001 to May 2006. The significance of the difference of the forecasts was measured with the Diebold-Mariano tests. The series were differenced if needed and models of I(1) series at most were considered in the paper. There were 30 series included in the factor models, the data ranging from producer prices, to wages, exchange rates, trade flows, interest rates, inflation in the Euro area and the U.S., survey data, money indicators and unemployment indicators. The factors were chosen based on their ability to explain the variance of the series of interest in the forecasting exercise.

In this paper an attempt is made to also identify the factors. Most of the time, they are identified as being related to the relative price movements, domestic producer price indices, consumer sentiments, wage movements, external movements in nominal variables or the trade trends. Hence, the identified common driving trends are not far from those expected to lead inflation variables in Slovenia.

The results can be summarized as follows. Factor models are beating the AR forecasts for the headline inflation as well as for the four out of five subcomponent series. As for comparison to the VAR forecasts, the results are less clear-cut, since the VAR model used in this paper also beats AR benchmark for the three subcomponents significantly, while for the services subcomponent it is not significantly better (except for 1 and 12 months ahead). From this and the other advantages (easier selection of the relevant information set, and model configuration) it follows that factor model is preferred to the VAR model for forecasting purposes of inflation in Slovenia.

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APPENDIX 1:

SERIES INCLUDED IN THE FACTOR MODEL

No.	*Abbreviation*	*Name of the series*
1.	*x*	inflation series *x* used in the forecast
2.	ZAPRSM	employment in the real sector
3.	BTWM	gross wages total
4.	M1	M1
5.	M2	M2
6.	M3	M3
7.	KZIND_95M	expected consumption in retail production
8.	KZPOT_95M	consumption sentiment
9.	PTV6_95M	expected price in next 3-4 months
10.	PTV7_95M	expected employment in next 3-4 months
11.	PTV9_95M	expected export in next 3-4 months
12.	LIBEU1LM	1-year LIBOR on euro currency
13.	LIBEU3MM	3-months LIBOR on euro currency
14.	LIBUS1LM	1-year LIBOR on US$
15.	LIBUS3MM	3-months LIBOR on US$
16.	TEUR64M	CPI for euro area countries
17.	T84064M	CPI for the US
18.	UTRBLTM	real imports of goods
19.	ITRBLTM	real exports of goods
20.	ITRSTTM	real exports of services
21.	UTRSTTM	real imports of services
22.	PCDSKM	producer price index for all goods
23.	PCINVM	producer price index of investment goods
24.	PCPOTM	producer price index of consumption goods
25.	PCREPM	producer price index of materials
26.	EURPM	exchange rate SIT/€
27.	USDPM	exchange rate US$/€
28.	GBPPM	exchange rate pound/€
29.	OMDTSNM	nominal short term interest rate
30.	OMDTSRM	nominal long term interest rate

APPENDIX 2:

IDENTIFICATION OF THE FACTOR

HICP

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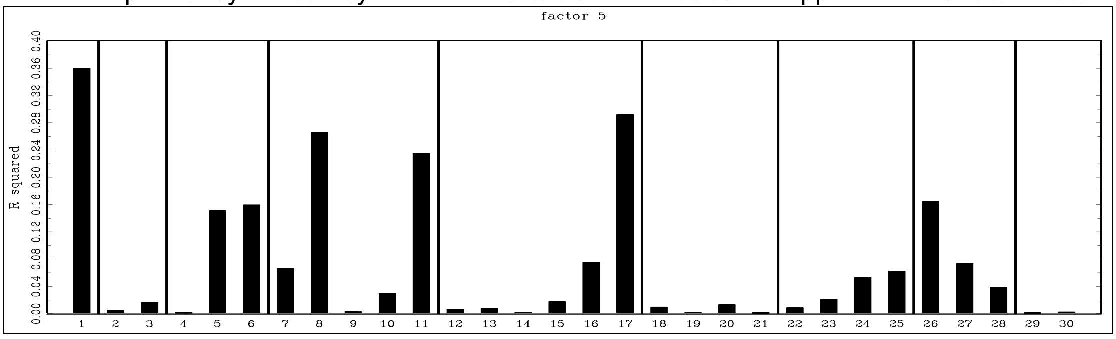

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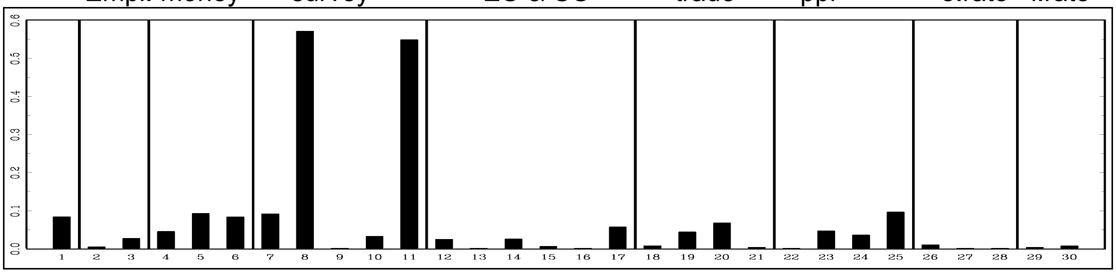

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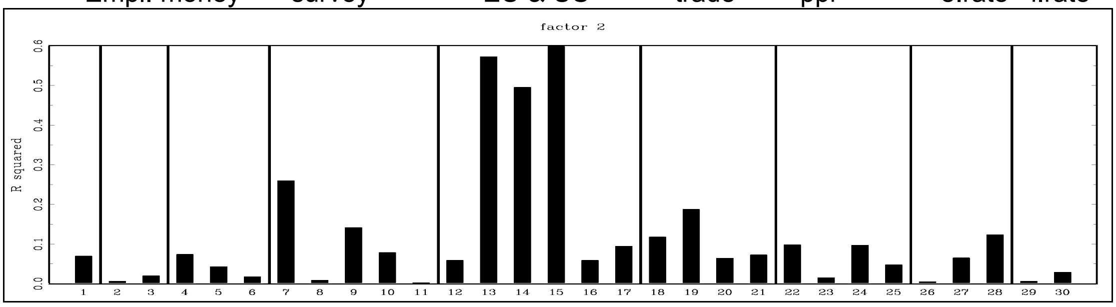

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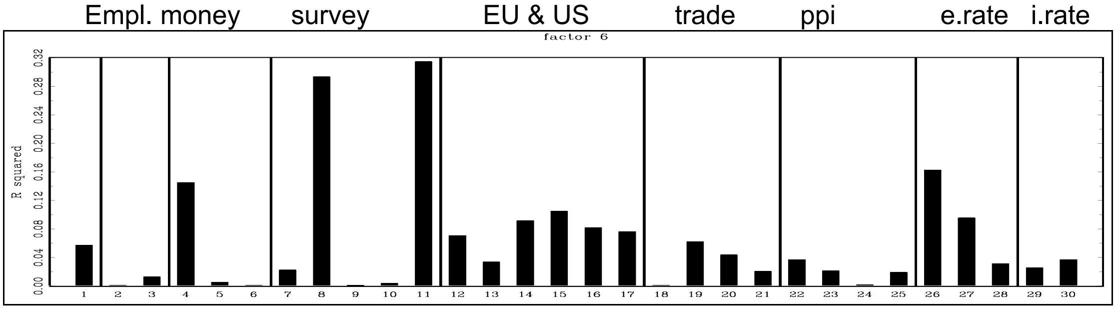
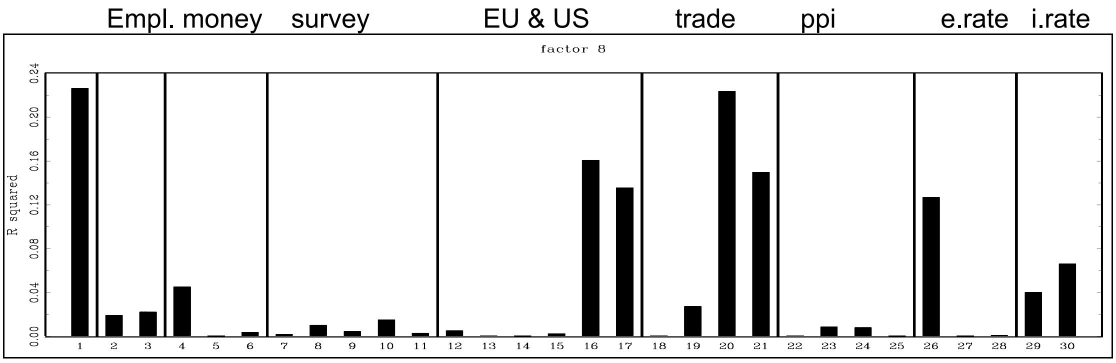
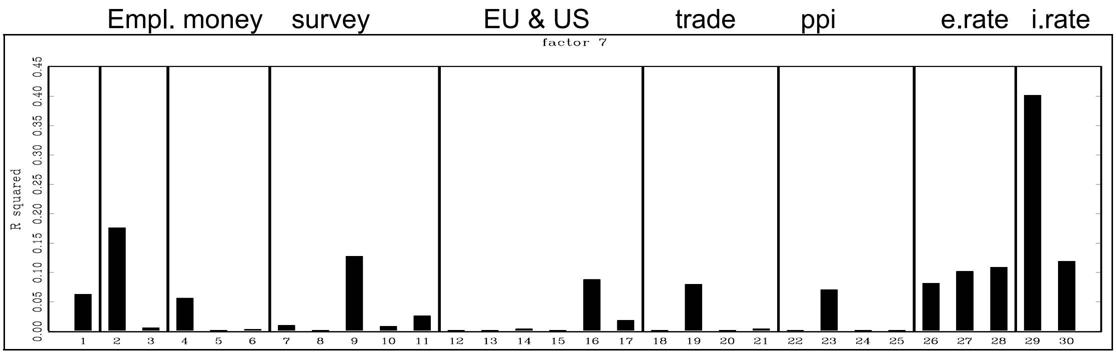
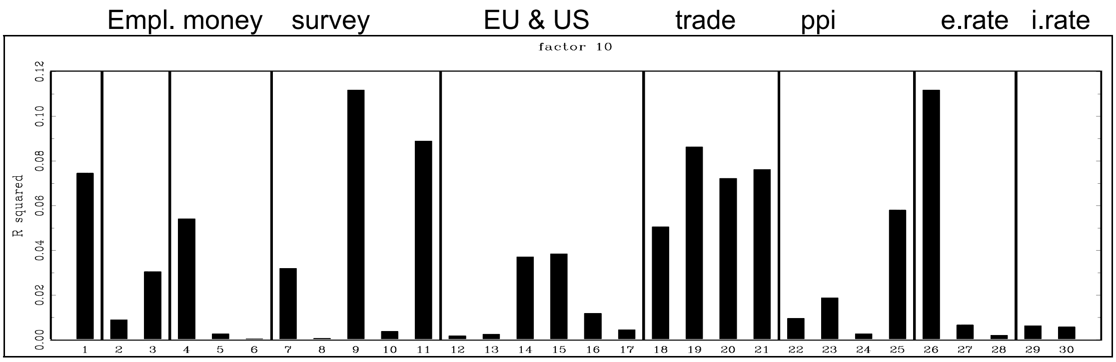
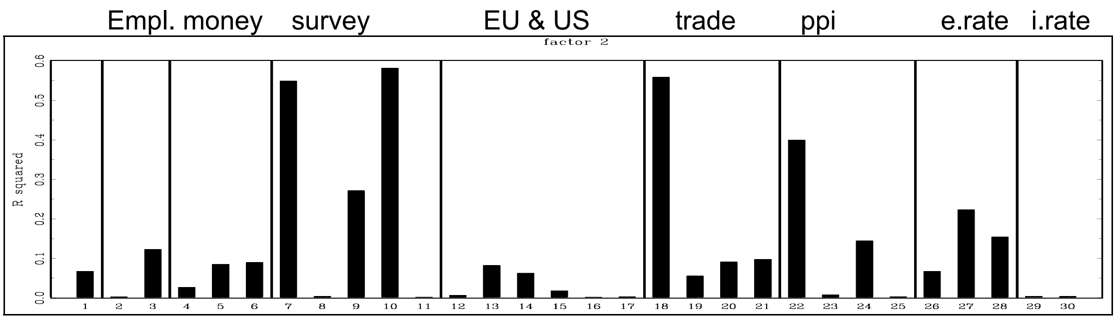


Services subcomponent

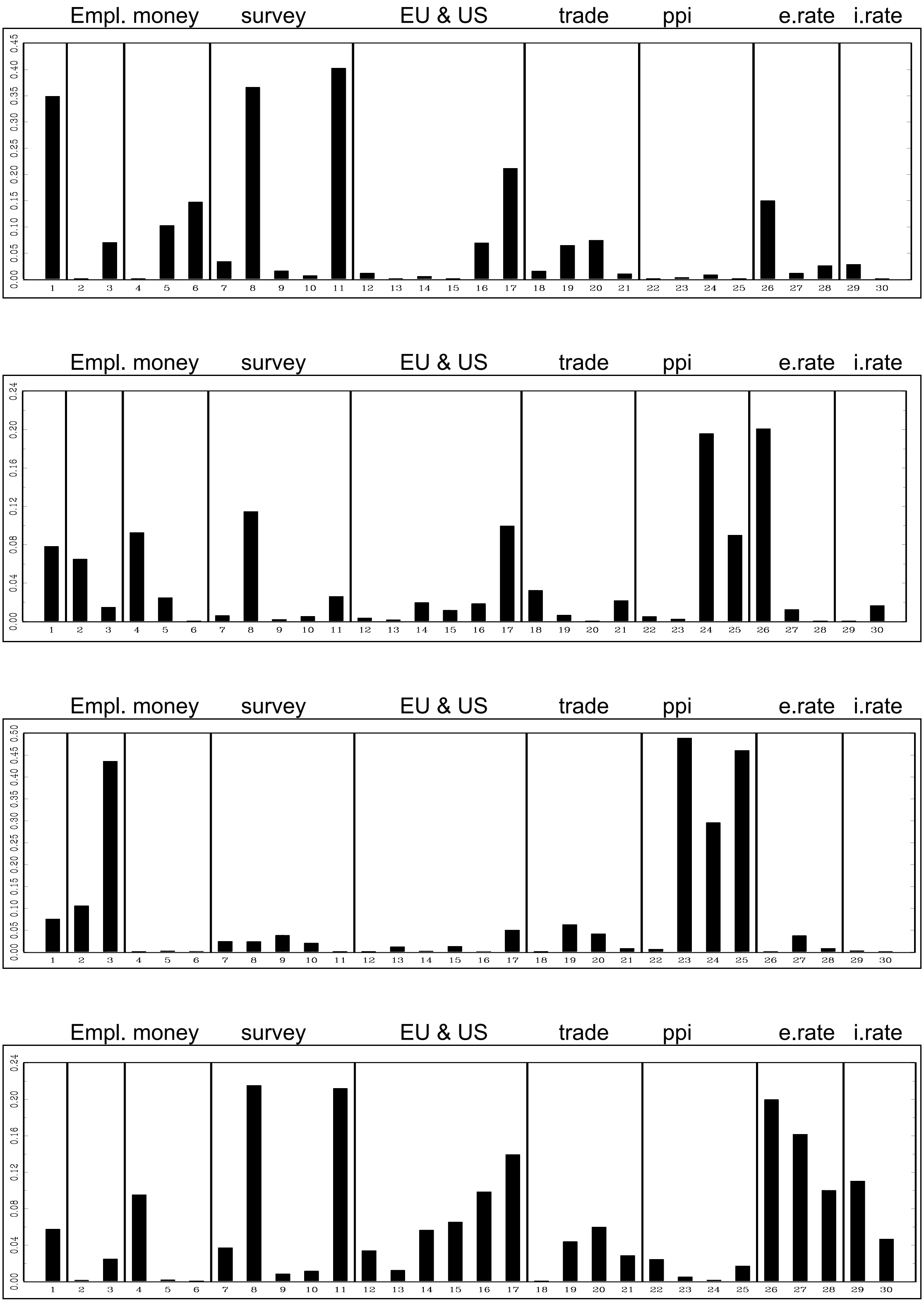




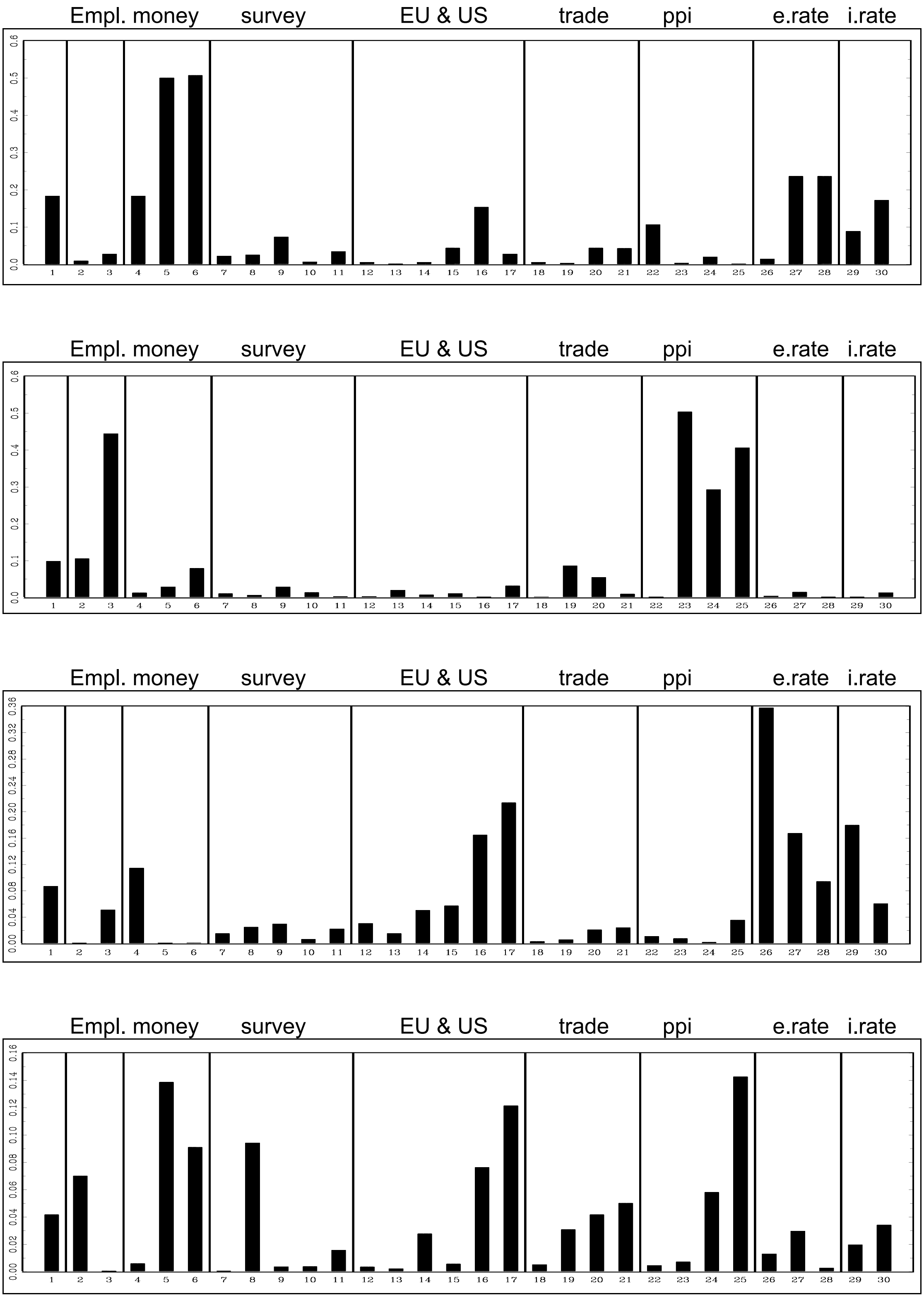




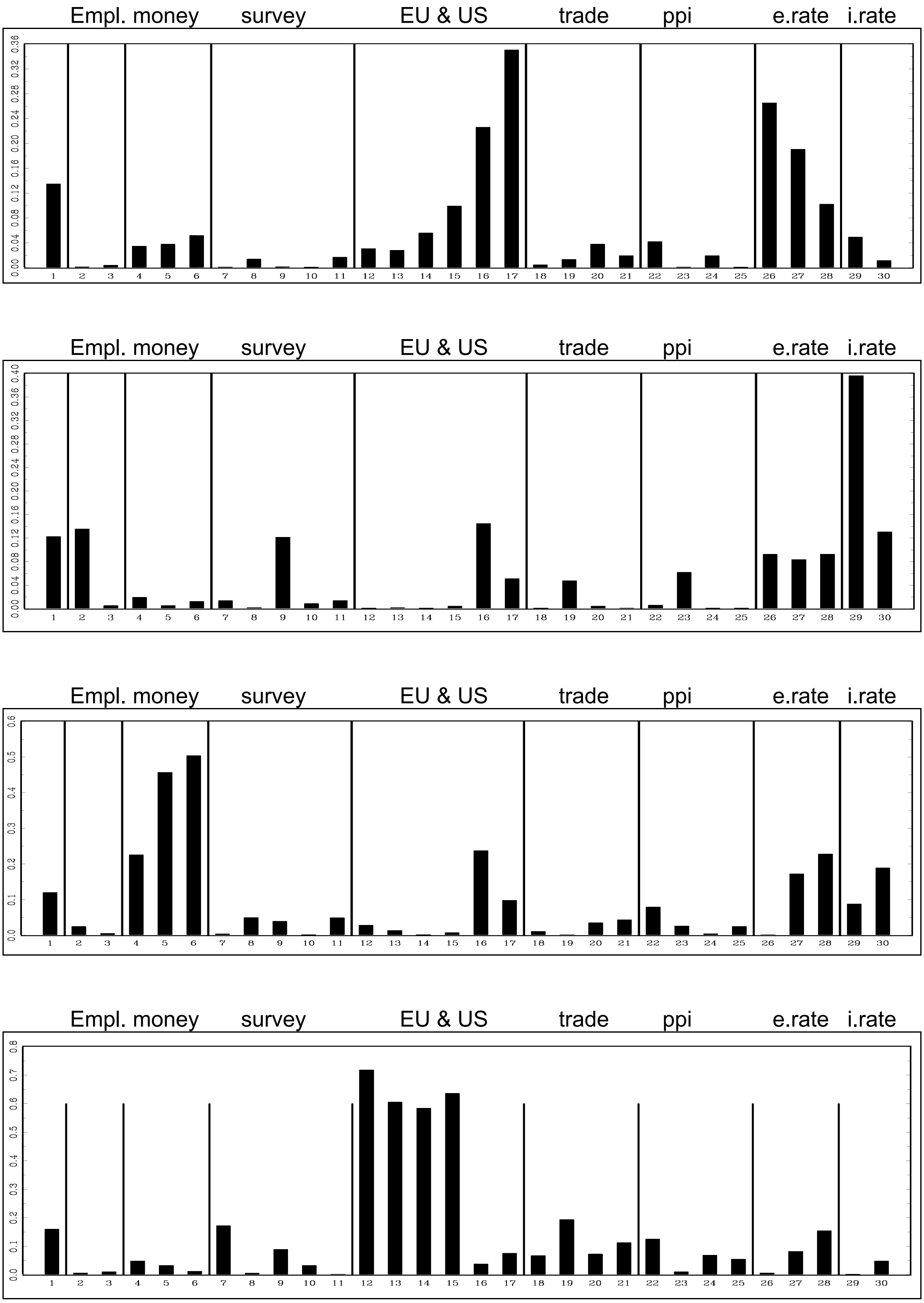
Unprocessed food subcomponent



Processed food subcomponent



Energy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Non-energy industrial goods