ЕРЕВАНСКИЙ ГОСУДАРСТВЕННЫЙ УНИВЕРСИТЕТ

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YEREVAN STATE UNIVERSITY

ЕРЕВАНСКИЙ ГОСУДАРСТВЕННЫЙ УНИВЕРСИТЕТ
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ON APPLICABILITY OF DYNAMIC FACTOR MODELS FOR ECONOMIC FORECASTING IN ARMENIA

In the recent applied time series of econometrics, dynamic factor models have become quite popular. The idea underlying these models is that given a large number of initial variables, only a small number of factors can be extracted, which summarize the information contained in the whole dataset. There are many applications of dynamic factor models to forecast economic variables [9, 10]. The main achievement of these applications is that the forecasts generated from dynamic factor models are superior to traditional univariate and multivariate time-series models. Indeed, these results are informative but it does not mean that we can successfully apply dynamic factor models to other countries, since all previous results are based on the country specific dataset. The work aims at examining the applicability of the dynamic factor models to developing countries and, in particular, to the Armenian economic variables. For that, we put in competition the small-scale univariate autoregression, vector autoregression and Bayesian vector autoregression (hereafter AR, VAR and BVAR) models with their factor-augmented counterpart models, such as factor-augmented autoregression, factor-augmented vector autoregression and factor-augmented Bayesian vector autoregression models (hereafter FAAR, FAVAR and BFAVAR). We use three small-scale models (AR, VAR and BVAR) in order to evaluate the out of-sample forecast performances of the three large-scale factor-augmented models (FAAR, FAVAR and BFAVAR).

The AR model can be estimated with using the following linear regression model: $y_t = c + \sum_{j=1}^{p} \rho_j y_{t-j} + \varepsilon_t$, where t is the time ($t = 1,2,...,T$). All unknown parameters (constant term c and ρ_j, $j = 1,2,..,p$) can be consistently estimated by using traditional OLS method. The unrestricted VAR model can be estimated by using the following model: $y_t = A_0 + A(L)y_t + \varepsilon_t$, where y_t is a $(n \times 1)$ vector of constant terms, $A(L)$ is a $(n \times n)$ polynomial matrix in the backshift operator L with the lag length p, ε_t is a $(n \times 1)$ vector of error terms. We assume that $\varepsilon_t \sim N\left(0, \sigma^2 I_n\right)$, where I_n is $(n \times n)$ identity matrix. All unknown parameters of the VAR model can be consistently estimated by using traditional OLS method [8]. In this work, we also consider the small-scale BVAR model. To estimate BVAR model we uses the 'Minnesota' type priors, according to which, the prior mean and standard deviation of the BVAR model can be set as follows:

1. The parameters of the first lag of the dependent variables follow an AR(1) process, while the parameters of other lags are set to be equal to zeros.

2. The variances of the priors are specified as follows:

$$\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \text{ if } i=j,\ \left(\frac{\sigma_i\lambda_1\lambda_2}{\sigma_j l^{\lambda_3}}\right)^2 \text{ if } i\neq j,\ \left(\sigma_1\lambda_4\right)^2 \text{ for the constant term}$$

Where, i refers to the dependent variable in the j-th equation and j to the independent variables in that equation, σ_i and σ_j are standard errors from AR regression estimated via OLS method. The ratio of σ_i and σ_j controls for the possibility that variable i and j may have different scale (l is the lag length). As a rule, the values for λ's are set by researchers, which control of the tightness of the prior. For example, [3] reports the following values for these parameters: $\lambda_1=0.2,\ \lambda_2=0.5,\ \lambda_3=1 \text{ or } 2,\ \lambda_4=10^5$. Thus having calibrated 'Minnesota' type priors it is already possible to calculate the posterior parameters by using Bayesian estimation approach [8].

$$\beta^*=\left(H^{-1}+\Sigma^{-1}\otimes X_t^{'}X_t\right)^{-1}\left(H^{-1}\tilde{b}_0+\Sigma^{-1}\otimes X_t^{'}X_t\hat{b}\right)$$

$$\operatorname{var}\left(\beta^*\right)=\left(H^{-1}+\Sigma^{-1}\otimes X_t^{'}X_t\right)^{-1}$$

Where, β^* is the vector of the posterior parameters, $\tilde{b}_0$ is the vector of the prior parameters (calibrated by using 'Minnesota' type rule), H is the diagonal matrix with the prior variances on the main diagonal (calibrated by using 'Minnesota' type rule), X is the $(T\times k)$ matrix of the initial time series, Σ - is the $(k\times k)$ identity matrix.

Unlike the small-scale models, the large-scale FAAR, FAVAR and BFAVAR models include static or dynamic factors. The factor-augmented models are estimated in two steps, particularly in the first step, we estimate the dynamics of the unobservable factors and then in the second step, we estimate the models and producing forecasts. The question that we need to consider is how it is possible to estimate the unobservable factors.

There are three main algorithms for extracting factors, namely 1. The static principal components as in [11] 2. The dynamic principal component (frequency domain) approach as in [7] and 3. The dynamic principal component approach (time domain) as in [5] and [6]. There are a number of works, where computational steps of the mentioned factor models are presented in detail [1][1]. The Stock and Watson [11] approach consists of deriving the static principal components using variance-covariance matrix of the additional vector

[1] The best way to understand the computational steps for extracting unobservable static and dynamic factors is to examine the MATLAB codes. The corresponding MATLAB codes for factor model proposed by Doz, Gianonne & Reichlin [5, 6] can be found here https://www.newyorkfed.org/research/economists/giannone/pub, MATLAB codes for factor model proposed by Forni, Hallin, Lippi & Reichlin [7] can be found here: http://www.barigozzi.eu/Codes.html

of time series. The Doz, Gianonne & Reichlin [5] and [6] uses state-space model and Kalman filter to extract the dynamic principal components. The Forni, Hallin, Lippi & Reichlin [7] approach estimate the dynamic principal components using spectral density matrix of the data. Having extracted factors, the FAVAR (BFAVAR) model can be presented as follows:

$$\begin{vmatrix} Y_t \\ F_t \end{vmatrix} = A_0 + A_1 \begin{vmatrix} Y_{t-1} \\ F_{t-1} \end{vmatrix} + A_2 \begin{vmatrix} Y_{t-2} \\ F_{t-2} \end{vmatrix} + \dots + A_p \begin{vmatrix} Y_{t-p} \\ F_{t-p} \end{vmatrix} + \begin{vmatrix} v_t \\ u_t \end{vmatrix}$$

Where, Y_t is the vector of observable variables (for example real GDP growth or inflation), F_t is the vector of extracted factors, A_0 is a $(n \times 1)$ vector of constant terms, $A_1, A_2, \dots, A_p$ are $(n \times n)$ matrices of the estimated parameters. These parameters can be estimated with using OLS or Bayesian estimation method. The errors v_t and u_t are independent and identically distributed with zero mean and diagonal variance-covariance matrices, Q and V.

Now let us present the actual time series that we uses for estimation the models. To estimate the small-scale models we have to select four key economic times series, particularly real GDP growth, inflation, short-term nominal interest rate and unemployment rate. Apart from these four key economic time series, our dataset also includes 40 additional economic time series, which we use to estimate the dynamics of unobservable factors. Our dataset is balanced and it starts with 1996Q1 until 2018Q4, quarterly time series. Each variable in our dataset includes 92 observations. The dynamics of the four key economic time series is presented in the Figures 1 to 4.

The first important variable is the real GDP growth. To obtain real GDP growth rates with respect to the previous quarter, the following preliminary calculations have been done. First, absolute values of real GDP calculated at average prices of 2005 have been logged and then seasonally adjusted (using X12ARIMA seasonal adjustment algorithm). Then, using seasonally adjusted values, we have calculated the first differences. In Figure 2, we present the dynamics of CPI inflation. The CPI has been calculated since 1993 on a monthly basis. The CPI in the Republic of Armenia is the only indicator characterizing the inflation dynamics. The third important variable is the short-term nominal interest rate for time deposits in national currency. The preliminary treatment for this variable includes only first differences (in percentage points). The next variable is the total unemployment rate. The official values for unemployment (in persons) have been taken in yearly terms from the World Bank development indicators. Then, using temporal decomposition method, particularly Boot Faibes and Lisman, mechanical projection algorithm of the yearly unemployment data has been decomposed to quarterly data[2]. After that, the unemployment data have been logged, and first differences have been calculated.

Figure 1. Real GDP growth, %-th to the previous quarter

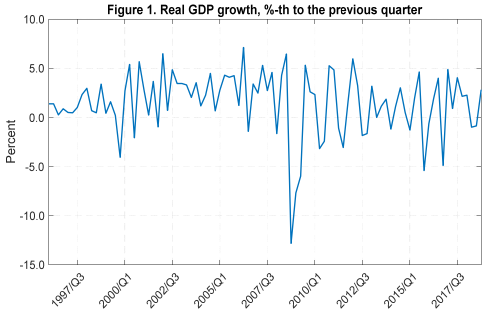


Figure 2. CPI inflation, %-th to the previous quarter

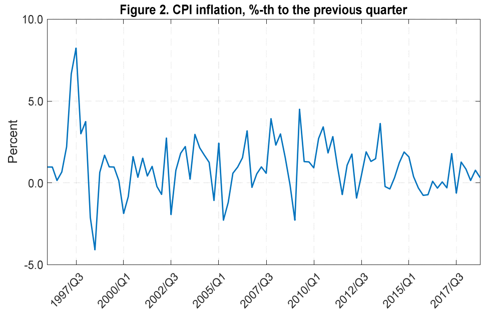


Figure 3. Short-term nominal interest rate, pp with respect to previous querter

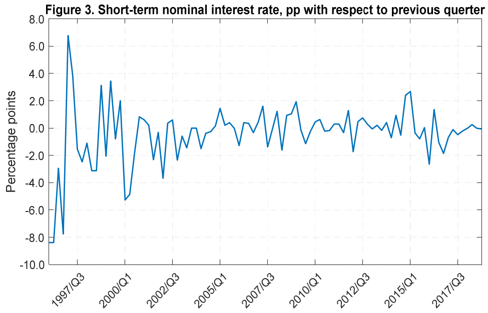
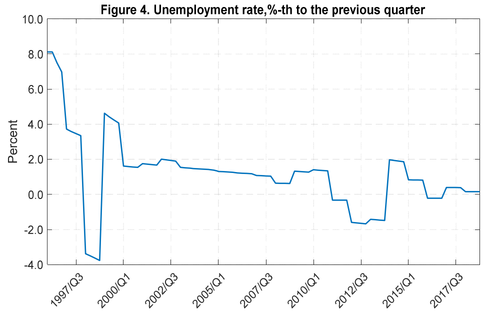


Figure 4. Unemployment rate,%-th to the previous quarter



As it has been mentioned above, in order to extract the dynamics of unobservable factors, we use 40 additional economic variables. We have to select 40 additional economic time series to extract unobservable factors, because some studies have shown that smaller dataset with about 40 series outperform larger datasets with more than 100 time series [1, 2]. The additional dataset comprises information on national accounts (production and expenditure components) consumer and producer price indices, employment and labor force variables, monetary and interest rates, as well as international indicators on growth rates and prices. The additional set of variables were selected from different sources, particularly from *https://stats.oecd.org/* and *https://www.indexmundi.com/*. For some of the additional variables, seasonal adjustment procedures have been applied. All no stationary time series are made stationary through the first differencing. All calculations and forecasts experiments have been done using the MATLAB (r2018b) codes. Some of the MATLAB codes are taken from the internet sources, for example, codes for extracting dynamic factors in frequency and time domain have been taken from the Internet[3]. Some part of MATLAB codes are written by the authors. In addition, we have C# codes for time domain factor model, as well as recursive and rolling regressions, which can be used directly from

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[2] The corresponding MATLAB codes for Boot Faibes and Lisman mechanical projection algorithm can be found here: https://www.spatial-econometrics.com/

[3] MATLAB codes for time domain factor model can be found https://www.newyorkfed.org/research/economists/giannone/pub, while MATLAB codes for frequency domain factor model can be found http://www.barigozzi.eu/Codes.html

MS Excel spreadsheet. To run the models from MS Excel, we have to create a specific interface using VBA.

As it has been mentioned above, we want to put large-scale factor-augmented models in competition with their small-scale counterpart models to examine the forecast performances of the large-scale models. To do that, we need to conduct an out-of-sample forecast experiments. In this work, we use the recursive regression scheme. For out-of-sample forecast evaluations, we divide the whole sample on the two part, particularly in-sample and out-of-sample periods. In our experiments, in-sample periods include 70 % of observations, while out-of-sample periods - 30 % of observations. This means that if the whole sample includes data from 1996Q1 to 2018Q4 (92 observations), then in sample period includes 1996Q1 to 2012Q1 (65 observations), while out-of-sample period includes observations from 2012Q2 to 2018Q4 (27 observations).

The recursive simulation scheme proceeds as follows: first, we estimate the models using subsample 1996Q1 – 2012Q1 (65 observations) and generate 1 to 4 steps-ahead forecasts. Then we increase the sample size by one (66 observations, 1996Q1 – 2012Q2) and generate again 1 to 4 steps-ahead forecasts. We continue increasing the sample size by one and generating 1 to 4 steps-ahead forecast until the sample size 84 (1996Q1 – 2017Q4). Then we increase the sample size by one but only generate 1 to 3 steps-ahead forecasts (since we only have 88 observations in total). We continue increasing the sample size until we have 87 observations in the sample, in which case we can only compute the one step-ahead forecast. In such way, we obtain 27 one-step-ahead forecasts, 26 forecasts for 2-steps-ahead, 25 for 3-steps – ahead and finally 24 forecast for 4-steps-ahead.

Next, we use the out-of-sample forecasts from recursive regressions to compute the corresponding root mean squared forecast error (RMSFE) indices for each of the fourth forecasting horizons. More formally let us denote the out-of-sample period by T^* (in our case, $T^* = 27$) and forecast horizons $h = 1,2,3,4$. Then the RMSFE index is calculated by the following formula:

$$RMSFE_{ih} = \sqrt{\frac{1}{T^*-(h-1)} \sum_{t=1}^{T^*-(h-1)} \left(\hat{y}_{it} - y_{it}\right)^2},$$

Where y_{it} denotes the actual value of the i-th dependent variable (in our case we have four core variables and therefore $i = 1,2,3,4$), $\hat{y}_{it}$ is the forecasted value of the i-th dependent variable, and $RMSFE_{ih}$ is the root mean squared error calculated for the i-th dependent variable and the h-th forecast horizon.

Now we can present the out-of-sample forecast evaluation results for 15 competing models. However, let us first explain how we can select the number of lags and the number of unobservable factors in the forecasting models. First, in order to keep robustness of our results we have to estimate models with different lags length and different combinations of static and dynamic factors. Then we choose the one model that yields the best forecasting performance in the sense of minimization of the RMSFE indices. We vary the number of lags in the models from 1 up to 4 lags. In addition, we vary the number of static and dynamic factors in the factor-augmented models. Thus, varying both number of lags and number of static and dynamic factors we comparing estimated models to each other and select only one model, which provides a minimum value of RMSFE index. In Tables 1 and 2, we present the results of out-of-sample forecast evaluation for 15 competing models.

Real GDP growth: as we can see from Tables 1, the factor-augmented models are outperforms small-scale models for all forecast horizons. For one-step ahead forecast horizon FAAR_TS model, outperform all small-scale benchmark models producing the minimum value of RMSFE's. In the case of two, three and four steps ahead forecast horizons the FAVAR_QML, FAVAR_SW and BFAVAR_TS are outperform all small-scale benchmark models.

Inflation: from Table 2 we can see that again factor augmented models are outperform small-scale benchmark models for all forecast horizons with exception only two steps ahead forecast horizon. For one-step ahead forecast horizon the FAVAR_TS is outperform all small-scale models producing the lowest RMSFE's value. For two steps ahead forecast horizon the small-scale BVAR model outperforms all factor-augmented models. For three and four steps, ahead forecast horizons the FAVAR_TS and BFAVAR_SW are outperformed all small-scale models producing lowest RMSFE's values.

Table 1. RMSFE indices for the real GDP growth (recursive regression scheme)[4]

Forecasting models	Forecast horizons			
	1	2	3	4
AR (p = 4)[5]	2.588	2.539	2.512	2.452
VAR (p = 1)	2.544	2.566	2.518	2.481
BVAR (p = 2, w = 0.3, d = 1)[6]	2.639	2.546	2.510	2.482

[4] FAAR_SW is a FAAR model with static factors, FAAR_FHLR is a FAAR model with factors estimated in the frequency domain, FAAR_TS is a FAAR model estimated in the time domain with using two steps Kalman filter approach, FAAR_QML is a FAAR model estimated in the time domain with using quasi-maximum likelihood algorithm. In the same way, we can explain the abbreviations for the FAVAR and BFAVAR models.

[5] The number in the brackets means that the minimum RMSFE indices for AR model has been achieved in case of four lags. For all other models in the brackets are presented the number of lags where the particular model achieved its minimum RMSFE.

[6] w = 0.3 and d = 1, the coefficients that we use for BVAR and BFAVAR models estimation. The first coefficient (overall tightness) is implementing to the diagonal matrix of the standard errors, while the second coefficient (decay) is implemented to the lags. In this paper, we set the overall tightness equal to 0.1, 0.2 and 0.3 and lag decay equal to 1 and 2. Thus we vary the coefficients of the overall tightness and decay parameters and estimate the BVAR models for different lags lengths. Then we select the one model that yields the best ex post forecast performance in the sense of the minimization of RMSFE.

FAAR_SW (p = 3, r = 2)[7]	2.051	2.556	2.422	2.489
FAAR_FHLR (p = 3, q = 1, r = 2)[8]	2.039	2.593	2.420	2.452
FAAR_TS (p = 3, q = 1, r = 2)	***<u>2.036</u>***	2.501	2.485	2.462
FAAR_QML (p = 3, q= 2, r = 2)	2.181	2.474	2.433	2.504
FAVAR_SW (p = 1, r = 2)	2.375	2.627	***<u>2.298</u>***	2.404
FAVAR_FHLR (p = 1, q = 2, r = 2)	2.327	2.562	2.333	2.420
FAVAR_TS (p = 1, q = 2, r = 2)	2.338	2.555	2.317	2.394
FAVAR_QML (p = 1, q = 2, r = 2)	2.329	***<u>2.453</u>***	2.399	2.423
BFAVAR_SW (p = 1, r = 2, w = 0.3, d = 1)	2.406	2.609	2.356	2.402
BFAVAR_FHLR (p = 1, q = 2, r = 2, w = 0.3, d = 1)	2.392	2.551	2.367	2.456
BFAVAR_TS (p = 1, q = 2, r = 2, w = 0.3, d = 1)	2.326	2.554	2.319	***<u>2.390</u>***
BFAVAR_QML (p = 1, q = 2, r = 2, w = 0.3, d = 1)	2.328	2.458	2.400	2.413

Table 2. RMSFE indices for inflation (recursive regression scheme)

Forecasting models	Forecast horizons			
	1	2	3	4
AR (p = 1)	1.146	1.135	1.165	1.189
VAR (p = 1)	1.118	1.110	1.137	1.131
BVAR (p = 1, w = 0.2, d = 1)	1.150	***<u>1.059</u>***	1.096	1.108
FAAR_SW (p = 4, r = 1)	1.154	1.131	1.122	1.120
FAAR_FHLR (p = 4, q = 1, r = 1)	1.188	1.175	1.169	1.179
FAAR_TS (p = 4, q = 1, r= 1)	1.194	1.166	1.160	1.170
FAAR_QML (p = 4, q = 1, r = 1)	1.297	1.249	1.253	1.274
FAVAR_SW (p = 3, r = 2)	1.140	1.139	1.149	1.083
FAVAR_FHLR (p = 3, q = 2, r = 2)	1.147	1.150	1.156	1.110
FAVAR_TS (p = 3, q = 1, r = 2)	***<u>1.117</u>***	1.154	***<u>1.064</u>***	1.081
FAVAR_QML (p = 3, q = 2, r = 2)	1.124	1.167	1.191	1.207
BFAVAR_SW (p = 3, r = 2, w = 0.3, d = 2)	1.184	1.169	1.100	***<u>1.075</u>***
BFAVAR_FHLR (p = 3, q = 2, r = 2, w = 0.3, d = 1)	1.162	1.195	1.146	1.174
BFAVAR_TS (p = 3, q = 1, r = 2, w = 0.3, d = 1)	1.160	1.163	1.113	1.101
BFAVAR_QML (p = 3, q = 1, r = 2, w = 0.3, d = 1)	1.172	1.205	1.136	1.143

[7] The numbers in the brackets p = 3, r = 2 means that FAAR model with number of lags equal to 3 and number of static factors equal to 2 yields the best out of sample forecast performance, in the sense of minimum RMSFE.

[8] Comparing with the FAAR_SW numbers in the brackets we see that here we have one additional parameter, q = 1, which says that FAAR_FHLR model yields the minimum value of RMSFE when we apply three lags, one dynamic and two static factors

The next question that we need to consider is whether the obtained results for RMSFE are significantly different among of different models. To answer this question, we also perform across models tests. The across model test is based on a statistics proposed by Diebold and Mariano [3]. In this work, we calculate the Diebold-Mariano statistics by regressing the loss differential on an intercept, using heteroscedasticity autocorrelation robust (HAC) standard errors. The time-t loss differential between forecast 1 and 2 can be calculated as $l_t = \left(\varepsilon_t^{AR}\right)^2 - \left(\varepsilon_t^i\right)^2$, where, ε_t^{AR} is the forecast error from AR model at time t $\left(t = 1, 2, ..., T*\right)$, ε_t^i denote the forecast error from the alternative factor augmented counterpart model $\left(i = FAAR\_SW, FAAR\_FHLR, FAAR\_TS, FAAR\_QML\right)$. In the same way we can calculate the loss differentials for VAR and BVAR models errors. Thus, we regress the loss differential on an intercept using HAC standard errors.

In the Tables 3 and 4 presented relative RMSFE's for real GDP growth and inflation. To calculate the relative RMSFE's we use the following ratio.

$$RRMSFE_{i,h}^{M} = \frac{RMSFE_{i,h}^{M}}{RMSFE_{i,h}^{M_0}}$$

where $RRMSFE_{i,h}^{M}$ is the relative RMSFE for i-th variable (real GDP growth, inflation) calculated at h forecast horizon with model M-th, $RMSFE_{i,h}^{M}$ is the RMSFE value for i-th variable calculated at h forecast horizon with model M-th, $RMSFE_{i,h}^{M_0}$ is the RMSFE value for i-th variable calculated at h forecast horizon with using M_0 small-scale benchmark model ($M_0 = AR,\ VAR,\ BVAR$). The relative RMSFE should be below 1 to outperform the benchmark counterpart model.

Table 3. Relative RMSFE's for real GDP growth models

Models	Forecast horizons			
	1	2	3	4
FAAR_SW versus AR	**0.792**	1.007	**0.964**	1.015
FAAR_FHLR versus AR	**0.788***	1.021	**0.963**	1.000
FAAR_TS versus AR	**0.787***	**0.985**	**0.989**	1.004
FAAR_QML versus AR	**0.843**	**0.974**	**0.969**	1.021
FAVAR_SW versus VAR	**0.934**	1.024	**0.913**	**0.969**
FAVAR_FHLR versus VAR	**0.915**	**0.999**	**0.926**	**0.975**
FAVAR_TS versus VAR	**0.919**	**0.996**	**0.920**	**0.965**
FAVAR_QML versus VAR	**0.915**	**0.956**	**0.953**	**0.977**
BFAVAR_SW versus BVAR	**0.912**	**1.025**	**0.938**	**0.968**
BFAVAR_FHLR versus BVAR	**0.907**	**1.002**	**0.943**	**0.990**
BFAVAR_TS versus BVAR	**0.881**	**1.003**	**0.924**	**0.963**

BFAVAR_QML versus BVAR	**0.882**	**0.965**	**0.956**	**0.972**

Note: Diebold Mariano t-statistics that are statistically significant at the confidence levels of 90 %, 95 % and 99 % respectively are denoted by *, **, ***.

Table 4. Relative RMSFE's for Inflation models

Models	Forecast horizons			
	1	2	3	4
FAAR_SW versus AR	1.007	**0.997**	**0.964**	**0.942**
FAAR_FHLR versus AR	1.037	1.036	1.003	**0.991**
FAAR_TS versus AR	1.042	1.028	**0.996**	**0.984**
FAAR_QML versus AR	1.132	1.101	1.075	1.071
FAVAR_SW versus VAR	1.020	1.026	1.010	**0.957**
FAVAR_FHLR versus VAR	1.026	1.037	1.016	**0.981**
FAVAR_TS versus VAR	**0.975**	1.017	**0.913**	**0.909**
FAVAR_QML versus VAR	**0.981**	1.028	1.023	1.015
BFAVAR_SW versus BVAR	1.030	1.104	1.004	**0.970**
BFAVAR_FHLR versus BVAR	1.010	1.129	1.046	1.060
BFAVAR_TS versus BVAR	1.008	1.098	1.016	**0.994**
BFAVAR_QML versus BVAR	1.019	1.138	1.037	1.032

Now let us explain the relative RMSFE indices first for real GDP growth and then for inflation. As we see from Table 3, when we compare the FAAR models with its counterpart model, we see that relative RMSFE values are below 1 in 10 cases out of 16. However, when we use Diebold – Mariano test we see that only in two cases the relative RMSFE values are significantly differ. When we compare FAVAR with its counterpart model, we see that relative RMSFE values are below 1 in 15 cases out of 16. However, when we apply Diebold-Mariano test, we see that the differences between RMSFE values are not statistically significant. In the case of comparing BFAVAR with the small-scale BVAR, we see that in all cases we have RMSFE values below 1, but when we apply Diebold-Mariano test, we see that the differences are not statistically significant.

In Table 4 presented relative RMSFE values are calculated for inflation models. From this table we see that there are no significant differences between RMSFE values when we apply Diebold-Mariano test. In addition, we see that the number of cases where relative RMSFE values below 1 is relatively less comparing with the real GDP growth results (Table 3). For example, when comparing FAAR models with its counterpart model, we see that the relative RMSFE values are below 1 only in 6 cases out of 16, while in the case of real GDP growth, this combination is 10/16. We also observe the same picture in case of FAVAR models, where we have the same combinations 6/16. Finally, when we compare the BFAVAR with the BVAR we see that only in two cases the RMSFE values are below 1, while in the prevailing cases we have the opposite situation.

Thus, based on the used dataset and results of calculations we can see that when we apply factor-augmented models to real GDP growth, in the prevailing part of total cases the factor-augmented models outperform their counterpart small-scale models (41 out of 48). Even in two cases, the differences between RMSFE values are statistically significant. When we apply factor augmented models to inflation, we see that the number of outperforming cases are radically decreasing (14 out of 48). Therefore, for the Armenian dataset the large-scale factor-augmented models outperform small-scale models only for the real GDP growth forecasts, even applying these methods we can significantly improve forecast accuracy.

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ON APPLICABILITY OF DYNAMIC FACTOR MODELS FOR ECONOMIC FORECASTING IN ARMENIA

Key words: factor-augmented models, static and dynamic factors, recursive regression, forecasting, time series analysis.

In this work, we are trying to find out whether advanced forecasting techniques can be successfully employed to a developing country to forecast key economic variables. We compare the forecasting performance of large-scale FAAR, FAVAR and BFAVAR with their small-scale benchmark counterpart models, namely AR, VAR and BVAR. Using Armenian quarterly economic time series from 1996Q1 – 2018Q4, we estimate parameters for all alternative models. Based on the calculated RMSFE's values, we conclude that when we apply advanced forecasting techniques to real GDP growth then in the prevailing part of experiments the factor-augmented models outperform small-scale benchmark models, but when we apply to inflation then we conclude that factor-augmented models outperform small-scale benchmark models only in a few cases. Therefore, advanced forecasting techniques can be more successfully applied for forecasting real GDP growth, and applying these methods we can significantly improve forecast accuracy.

Պողոսյան Ռուբեն

ԴԻՆԱՄԻԿ ԳՈՐԾՈՆԱՅԻՆ ՄՈԴԵԼՆԵՐԻ ԿԻՐԱՌԵԼԻՈՒԹՅՈՒՆԸ ՀԱՅԱՍՏԱՆԻ ՏՆՏԵՍՈՒԹՅԱՆ ԿԱՆԽԱՏԵՍՄԱՆ ՀԱՄԱՐ

Բանալի բառեր՝ գործոններով ընդլայնված մոդելներ, ստատիկ և դինամիկ գործոններ, ռեկուրսիվ ռեգրեսիա, կանխատեսում, ժամանակային շարքերի վերլուծություն:

Սույն աշխատանքում փորձ է կատարվել բացահայտելու, թե հնարավոր է արդյոք կանխատեսման ժամանակակից մեթոդաբանությունն արդյունավետորեն կիրառել զարգացող երկրների տնտեսական ցուցանիշների կանխատեսման համար: Դրա համար իրականացնում ենք գործոններով ընդլայնված (FAAR, FAVAR, BFAVAR) և նմուշային մոդելներով (AR, VAR, BVAR) կանխատեսումների համեմատական վերլուծություններ: Հետազոտության այլընտրանքային մոդելների պարամետրերի գնահատումն իրականացվել է՝ կիրառելով Հայաստանի տնտեսական ժամանակային շարքերը 1996Q1-2018Q4 ժամանակահատվածի համար: Հիմնվելով RMSFE հաշվարկված արժեքների վրա՝ եզրակացնում ենք, որ երբ ժամանակակից կանխատեսման մեթոդաբանությունը կիրառվում է ՀՆԱ-ի իրական աճի համար, ապա փորձերի գերակշռող դեպքերում գործոններով ընդլայնված մոդելներն ավելի ճշգրիտ են կանխատեսում, քան նմուշային մոդելները, իսկ գնաճի համար կիրառելիս գործոններով ընդլայնված մոդելների կանխատեսումները փորձերի բավականին սակավաթիվ դեպքերում են գերազանցում նմուշային մոդելների արդյունքները: Արդյունքում եզրահանգում ենք, որ կանխատեսման ժամանակակից մեթոդաբանությունն արդյունավետորեն հնարավոր է կիրառել ՀՆԱ-ի իրական աճը կանխատեսելու համար, ընդ որում, այդ մոդելները կարող են նշանակալիորեն բարելավել կանխատեսման ճշգրտությունը:

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О ПРИМЕНИМОСТИ ДИНАМИЧЕСКИХ ФАКТОРНЫХ МОДЕЛЕЙ ДЛЯ ПРОГНОЗИРОВАНИЯ ЭКОНОМИКИ АРМЕНИИ

Ключевые слова: факторно-расширенные модели, статические и динамические факторы, рекурсивная регрессия, прогнозирование, анализ временных рядов.

В данной работе вы пытаемся выявить возможность эффективности применения современных методов прогнозирования в развивающихся странах для прогнозирования основных экономических показателей. Для этого мы осуществили сравнительный анализ прогнозов, полученных с помощью факторно-расширенных моделей (FAAR, FAVAR, BFAVAR) с прогнозами по моделям (AR, VAR, BVAR). Оценивание параметров альтернативных моделей, включенных в исследование, было осуществлено на основе экономических временных рядов Армении для периода с 1996Q1 по 2018Q4. Основываясь на рассчитанных значениях показателей RMSFE, мы заключаем, что когда современные методы прогнозирования применяются для реального роста ВВП, то для большинства случаев эксперимента факторно-расширенные модели дают более точные прогнозы, чем эталонные модели, тогда как если эти методы применяются для показателя инфляции, то факторно-расширенные модели опережают эталонные модели только в некоторых случаях. В результате можно заключить, что продвинутые методы прогнозирования могут эффективно применяться для прогнозирования динамики реального роста ВВП, причем эти модели могут существенно повысить точность прогнозов.