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Abstract

We build a small-scale factor model for the GDP of one of the hardest hit economies during the latest recession to study the exact dynamic versus static factor model performance along a business cycle, with an emphasis placing on nowcasting performance during a pronounced switch of business cycle phases due to the latest recession. We compare the factor models' nowcasting performance to a random walk, autoregressive and the best-performing nowcasting models at our hands, which are vector autoregressive (VAR) models. It is shown that a small-scale static factor-augmented VAR (FAVAR) model tends to improve upon the nowcasting performance of the VAR models when the model span and the nowcasting period stretch beyond a single business cycle phase, while exact dynamic factor models tend to fail to detect the timing and depth of the recession regardless of ARMA specifications. As regards the case when the model span and the nowcasting period are contained within a single business cycle phase, static and dynamic factor models appear to show similar performance with potentially slight superiority of dynamic factor models if the factor-forming set of variables and factor dynamics are carefully selected.

Keywords: nowcasting, business cycle, static versus dynamic factors, small-scale FAVAR, VAR, GDP
JEL code: C22, C32, C44, C52, C53

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1 Introduction

The choice between static and dynamic factors in now-/forecasting GDP is unresolved. Some papers find dynamic factors superior over the static ones (see, for example, den Reijer (2005)). Other papers find little or no advantage of dynamic over static factors. For example, Schumacher (2005) finds that dynamic factors only slightly outperform static factors. D'Agostino and Giannone (2007) find static and dynamic factors perform similarly. Marcellino and Schumacher (2008), among other results, report that information content of now- and forecasts hardly change if factors are estimated by static rather than dynamic principal components analysis. Ajevskis and Davidsons (2008) also find similar performance between static and dynamic factors. Finally, there are papers that argue for static over dynamic factors. For example, Boivin and Ng (2005) state that static factors are easier to construct than dynamic factors, and are favored on practical grounds. This paper contributes to the now-/forecasting literature by comparing GDP nowcasting performance of dynamic versus static factor models along a business cycle. For the fulfillment of the task, we had to choose the size of factor-forming set of variables, i.e., we had to decide whether to use a large-scale or a small-scale factor model, and what data to use.

Regarding the choice between large-scale and small-scale factor models, the following empirical evidence is observed. First, several papers on large-scale factor models compare the models only to simple benchmarks, instead of the best-performing models, and find large-scale factor models superior. For example, Siliverstovs and Kholodilin (2010) use a large-scale approximate dynamic factor model from 562 indicators and compare its now-/forecasting performance to, what they call, a naive constant-growth model, and find the factor model being superior. As another example, Ajevskis and Davidsons (2008) use large-scale static and approximate dynamic factor models from 126 indicators, compare them to a benchmark autoregressive model, and find factor models tending to be superior over the benchmark. There is another kind of papers that finds that large-scale factor models can not improve GDP now-/forecasting compared to non-factor models. For example, Banerjee, Marcellino and Masten (2010), inter alia, forecast the industrial production in Germany, and find that large-scale factor models extracted from 90 monthly series can not improve upon the forecasting performance of a simple autoregressive model, and conclude that factors per se may not increase the forecasting precision of models. Likewise, Gupta and Kabundi (2008, 2009) although have a misleading abstract, find that a large-scale factor model performs worse than a vector autoregressive model in forecasting South Africa's GDP. Finally, there are papers that argue for small-scale over the large-scale factor models (see, for example, Schneider and Spitzer (2004), Boivin and Ng (2003)). Given the lack of empirical evidence or rationale for clear advantage of large-scale over small-scale factor models in GDP now-/forecasting, our choice falls to using parsimonious, small-scale factor models.

Considering the choice of data, we choose Latvian data since it possesses a pronounced switch of business cycle phases - there is a period of high GDP growth that is followed by a rapid recession. Thus, we are able to compare nowcasting errors between two cases - when the model span and the nowcasting period are contained within a single business cycle phase versus the case when the model span and the nowcasting period stretch beyond a single business cycle phase. Although our choice falls to the Latvian data, the exercise described in the paper might be repeated on any data with a pronounced switch of business cycle phases, including generated data. Considerations of using other data are left for further research.

Note that this paper does not discuss the now-/forecasting performance of Markov-switching factor models (see, among others, Kim and Yoo (1995), Chauvet (1998), Kim and Nelson (1998), Chauvet and Hamilton (2005), and Camacho, Perez-Quiros and Poncela (2010)).

The paper is organized as follows. Section 2 describes the methodology of factor models and their estimation. Section 3 presents the results for the nowcasting performance of static, dynamic and mixed factor models versus a random walk (RW), autoregressive (AR), and vector autoregressive (VAR) models during a smooth growth phase as well as during a pronounced switch of business cycle phases. Finally, Section 4 concludes.

2 Methodology

This section discusses the estimation of static and exact dynamic factors, and is mainly in line with Doz and Lenglart (1999) and Dubois and Michaux (2010).

Consider an $(n+1)$-dimensional vector autoregressive model of order r, VAR(r):

$$\begin{bmatrix} y_t \\ x_{1t} \\ \vdots \\ x_{nt} \end{bmatrix} = \begin{bmatrix} a_0 + a_{01}y_{t-1} + \cdots + a_{0r}y_{t-r} + \cdots + a_{011}x_{1,t-1} + \cdots + a_{0nr}x_{n,t-r} + u_{0t} \\ a_1 + a_{11}y_{t-1} + \cdots + a_{1r}y_{t-r} + \cdots + a_{111}x_{1,t-1} + \cdots + a_{1nr}x_{n,t-r} + u_{1t} \\ \vdots \\ a_n + a_{n1}y_{t-1} + \cdots + a_{nr}y_{t-r} + \cdots + a_{n11}x_{1,t-1} + \cdots + a_{nnr}x_{n,t-r} + u_{nt} \end{bmatrix}, \tag{1}$$

where y_t is a scalar dependent variable at time $t = 1, \ldots, T$, $x_t = (x_{1t}, \ldots, x_{nt})'$ is an $n \times 1$ vector of endogenous explanatory variables at time t, $u_t = (u_{0t}, \ldots, u_{nt})'$ is an $(n+1) \times 1$ vector of innovation processes at time t with $E(u_t) = 0$, $E(u_t u_t') = \Sigma_u$, $E(u_t u_s') = 0$ for $s \neq t$ and $t = 1, 2, \ldots$. If n is large, model (1) incurs in a curse-of-dimensionality problem. A cure for this problem is to use a relatively small number of factors that are weighted averages of the predictors. We will consider two types of factor extractions - static and exact dynamic. Static factors are obtained *à la* Stock and Watson (1998) as follows. It is assumed that x_t can be represented as

$$x_t = \Lambda F_t + e_t, \tag{2}$$

where F_t is a $k \times 1$ vector of common factors at time t, Λ is an $n \times k$ matrix of factor loadings, and e_t is an $n \times 1$ vector of white noise processes at time t. It is assumed that

$$E(y_{t+1}|F_t, x_t, y_t, F_{t-1}, x_{t-1}, y_{t-1}, \ldots) = E(y_{t+1}|F_t, y_t, F_{t-1}, y_{t-1}, \ldots). \tag{3}$$

The assumption in (3) permits the dimension reduction of the matrix of explanatory variables from n to k. F_t is obtained by principal components analysis, i.e., by selecting k eigenvectors ν_j, $j = 1, 2, \ldots, k$ (that are of unit length) of $x'x$, where $x = (x_1, \ldots, x_T)'$, associated with the largest k eigenvalues of $x'x$ and projecting x on the eigenvectors, $F_j = x\nu_j$, $j = 1, 2, \ldots, k$; F_t then is the tth column of $(F_1, \ldots, F_k)'$.

The dynamic factor model is estimated as in Doz and Lenglart (1999), that develops an exact dynamic factor model, where factors are extracted from a relatively small number of variables. The procedure is described as follows. If n is the number of the variables under study, T the number of observations for each variable, x_{it} the value taken by the x_i variable at time t, and if $F_1, \ldots, F_k$, $k < n$ are the unobservable factors, the model has the following form:

$$x_{it} = \lambda_{i1} F_{1t} + \cdots + \lambda_{ik} F_{kt} + u_{it}$$

for $i = 1, \ldots, n$ and for all t. Each common factor F_j contributes to the explanation of the x_i variable with a loading equal to λ_{ij}. The idiosyncratic terms $(u_{it})_{t \in Z}$ are assumed to be independent of each other and independent of the common factors:

$$\begin{aligned} E(u_{it} u_{js}) &= 0 \; \forall i \neq j, \; \forall (t,s) \\ E(u_{it} F_{js}) &= 0 \; \forall (i,j), \; \forall (t,s). \end{aligned}$$

In the model designed for individual data, the common and idiosyncratic factors are assumed to be white noises, i.e.,

$$\begin{aligned} E(u_{it} u_{is}) &= 0 \; \forall i, \; \forall t \neq s \\ E(F_{it} F_{is}) &= 0. \end{aligned}$$

The model designed for individual data cannot be directly applied to time series, which generally show temporal autocorrelations. For this reason, it is called a static factor model. Using matrix notations

$$\begin{aligned} x_t &= (x_{1t}, \ldots, x_{nt})', \; F_t = (F_{1t}, \ldots, F_{kt})' \\ u_t &= (u_{1t}, \ldots, u_{nt})', \Lambda = (\lambda_{ij})_{\substack{1 \leq i \leq n \\ 1 \leq j \leq k}}, \end{aligned}$$

this model can be written as follows:

$$x_t = \Lambda F_t + u_t,$$

where

$$\begin{aligned} E(F_t) &= 0 \\ E(u_t) &= 0 \\ E(u_t u_t') &= D = diag(d_1, \ldots, d_n) \\ E(F_t u_s') &= 0, \; \forall (t,s), \; t \neq s \\ E(u_t u_s') &= 0, \; \forall (t,s), \; t \neq s. \end{aligned}$$

It is easy to see that the common factors are only defined up to a linear transformation, that is, it is always possible to premultiply F_t by any invertible matrix, as soon as Λ is postmultiplied by the inverse of the same matrix. Generally, it is assumed that $Var(F_t) = I_k$, so that F_t and Λ are defined up to a rotation matrix (at the estimation stage, they are fixed by imposing supplementary identifying constraints; see below). If it is imposed that $Var(F_t) = I_k$, then

$$Var(x_t) = \Lambda \Lambda' + D,$$

such that

$$Var(x_{it}) = \sum_{j=1}^{k} \lambda_{ij}^2 + d_i, \quad i = 1, \ldots, n.$$

Each λ_{ij}^2 represents the part of x_i's variance which is explained by F_j; thus, $h_i^2 = \sum_{j=1}^{k} \lambda_{ij}^2$ represents the total contribution of the factors to x_i's variance. On the other hand, $Var(u_i) = d_i$ is the part of x_i's variance which is not explained by the common factors.

There are two main methods to estimate the static model: principal components analysis (PCA) and the Maximum Likelihood (ML) under a Gaussian hypothesis. The first one does not need to make preliminary assumption about the number of factors, while this is necessary for the ML estimation. On the other hand, the ML gives efficient estimates of the parameters, which is not the case for PCA. Both methods are implemented as follows. At the first stage, the PCA is performed. Then, the ML estimation is run for the the appropriately chosen number of factors. Since we consider exact factor models, it is assumed that the processes (u_{it}) are uncorrelated with each other at all leads and lags. In this dynamic framework, the likelihood under the Gaussian assumption is not equal to the static model's likelihood. However, Doz and Lenglart (1999) show that, in a stationary framework, the estimators obtained by the maximization of the static model's likelihood are consistent estimators of the parameters. In brief, it is supposed that each of the real processes (F_{it}) and (u_{it}) is weakly stationary and can be autocorrelated, but that the model is estimated by a standard ML procedure as if those processes were Gaussian and were not autocorrelated. The stationarity of the processes (F_{it}) and (u_{it}) implies that the process (x_t) is stationary as well. The parameters of the model can be written in a vector $\mu = (\text{vec}\Lambda', d')'$,where $d = (d_1, \ldots, d_n)'$. The estimator $\hat{\mu}_T$, which is obtained this way is then an M-estimator of μ. Doz and Lenglart (1999) show that this estimator is consistent. Shortly, denote $z_{it} = x_{it} - \bar{x}_i$ and $z_t = (z_{1t}, \ldots, z_{nt})'$ for any t, $S = \frac{1}{T} \sum_t z_t z_t'$ the empirical covariance matrix of the observations and $\Sigma = \Lambda\Lambda' + D$ the theoretical covariance matrix. The quasi-likelihood of the model is computed under the Gaussian assumption as if neither the factors, nor the idiosyncratic components were autocorrelated. Up to a constant term, the quasi-likelihood can be written as

$$\begin{aligned}\mathcal{L}_T(z, \mu) &= \frac{1}{T} \sum_{t=1}^{T} \ln I_t(z, \mu) \\ &= -\frac{1}{2} \ln(\det(\Lambda\Lambda' + D)) - \frac{1}{2} \text{tr}((\Lambda\Lambda' + D)^{-1} S)\end{aligned}$$

Let μ_0 be the true value of the parameter μ. It is assumed that μ belongs to a set of the form $R^{nk} \times [\alpha, +\infty)^n$, $\alpha > 0$, which contains μ_0. Under this assumption, Σ is an invertible matrix, so the quasi-likelihood is well defined. The proof that the M-estimator $\hat{\mu}_T$, that maximizes $\mathcal{L}_T(z, \mu)$, is consistent, relies on several steps. First, Doz and Lenglart (1999) show that, in order to maximize the function on $R^{nk} \times [\alpha, +\infty)^n$, it is sufficient to maximize the function on a compact subset of $R^{np} \times [\alpha, +\infty)^n$. Then, they show that the function has properties which are sufficient to ensure the consistency.

Given the consistency of the factor loadings, a dynamic factor model with the common factors following an ARMA(p, q) process and the idiosyncratic components following an AR(l) process can be written as

$$\begin{aligned} x_{it} &= m_i + \lambda_{i1} F_{1t} + \ldots + \lambda_{ik} F_{kt} + u_{it} \\ (1 - \phi_{j1} L - \ldots - \phi_{jp} L^p) F_{jt} &= (1 - \theta_{j1} L - \ldots - \theta_{jq} L^q) \epsilon_{jt} \\ (1 - \rho_{i1} L - \ldots - \rho_{il} L^l) u_{it} &= \xi_{it} \end{aligned} \tag{4}$$

for $i = 1, \ldots, n$, $j = 1, \ldots, k$ and for all t, where ϵ_{jt} and ξ_{it} are the innovations of F_t and u_{it} at time t, l is the order of the AR process governing u_{it}, and the processes (ϵ_{jt}) and (ξ_{it}) are mutually independent. For identification purposes, the variance of the factor idiosyncratic components, ϵ_{jt}, is set to take the value 0.25.

Model (4) can be put into the state-space representation

$$x_t = Z\alpha_t + e_t \tag{5}$$

$$\alpha_t = A\alpha_{t-1} + R\eta_t, \tag{6}$$

where the processes (e_t) and (η_t) are serially uncorrelated and mutually uncorrelated at all leads and lags, and

$$\begin{aligned} E(e_t) &= 0 \\ Var(e_t) &= H \\ E(\eta_t) &= 0 \\ Var(\eta_t) &= Q. \end{aligned}$$

In our case, the state-space form of the model, (5) and (6), is the following:

$$x_t = \begin{bmatrix} \Lambda & 0_{n \times k(p+q-1)} & I_n & 0_{n \times n(l-1)} \end{bmatrix} \begin{bmatrix} F_t \\ \vdots \\ F_{t-p+1} \\ \epsilon_t \\ \vdots \\ \epsilon_{t-q+1} \\ u_t \\ \vdots \\ u_{t-l+1} \end{bmatrix}$$

$$
\begin{bmatrix} F_t \\ \vdots \\ F_{t-p+1} \\ \epsilon_t \\ \vdots \\ \epsilon_{t-q+1} \\ u_t \\ \vdots \\ u_{t-l+1} \end{bmatrix} = \begin{bmatrix} \phi & \theta & 0_{k\times nl} \\ I_{k(p-1)\times kp} & 0_{k(p-1)\times kq} & 0_{k(p-1)\times nl} \\ 0_{k\times kp} & 0_{k\times kq} & 0_{k\times nl} \\ 0_{k(q-1)\times kp} & I_{k(q-1)\times kq} & 0_{k(q-1)\times nl} \\ 0_{n\times kp} & 0_{n\times kq} & \rho \\ 0_{n(l-1)\times kp} & 0_{n(l-1)\times kq} & I_{n(l-1)\times nl} \end{bmatrix} \begin{bmatrix} F_{t-1} \\ \vdots \\ F_{t-p} \\ \epsilon_{t-1} \\ \vdots \\ \epsilon_{t-q} \\ u_{t-1} \\ \vdots \\ u_{t-l} \end{bmatrix}
$$

$$
+ \left[\begin{array}{c|c} \begin{matrix} I_k \\ 0_{k(p-1)\times k} \\ I_k \end{matrix} & 0_{k(p+1)\times n} \\ \hline 0_{[k(q-1)+nl]\times k} & \begin{matrix} 0_{k(q-1)\times n} \\ I_n \\ 0_{n(l-1)\times n} \end{matrix} \end{array}\right] \begin{bmatrix} \epsilon_t \\ \xi_t \end{bmatrix},
$$

where

$$
x_t = \begin{bmatrix} x_{1t} \\ \vdots \\ x_{nt} \end{bmatrix} \qquad \Lambda = \begin{bmatrix} \lambda_{11} & \cdots & \lambda_{1k} \\ \vdots & \vdots & \vdots \\ \lambda_{n1} & \cdots & \lambda_{nk} \end{bmatrix} \qquad F_t = \begin{bmatrix} F_{1t} \\ \vdots \\ F_{kt} \end{bmatrix} \qquad \epsilon_t = \begin{bmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{kt} \end{bmatrix}
$$

$$
u_t = \begin{bmatrix} u_{1t} \\ \vdots \\ u_{nt} \end{bmatrix} \qquad \xi_t = \begin{bmatrix} \xi_{1t} \\ \vdots \\ \xi_{nt} \end{bmatrix} \qquad \phi = \begin{bmatrix} \phi'_1 \\ \vdots \\ \phi'_p \end{bmatrix}' \qquad \phi_i = diag\left(\begin{bmatrix} \phi_{1i} \\ \vdots \\ \phi_{ki} \end{bmatrix}\right)
$$

$$
\theta = \begin{bmatrix} \theta'_1 \\ \vdots \\ \theta'_q \end{bmatrix}' \qquad \theta_j = diag\left(\begin{bmatrix} -\theta_{1j} \\ \vdots \\ -\theta_{kj} \end{bmatrix}\right) \qquad \rho = \begin{bmatrix} \rho'_1 \\ \vdots \\ \rho'_l \end{bmatrix}' \qquad \rho_s = diag\left(\begin{bmatrix} \rho_{1s} \\ \vdots \\ \rho_{ns} \end{bmatrix}\right)
$$

and is estimated by an ML using the Kalman filter. The initial values for F_t, Λ, and u_t are obtained from performing a static factor analysis, the initial values for ϕ and θ are obtained from running an ARMA(p, q) on F_t, and initial values for ρ and $Var(\xi_t)$ are obtained from running an AR process on u_t.

3 Results

The dependent variable in the model (1) is Latvia's quarterly GDP series from 1995$Q1$ till 2009$Q3$. The endogenous explanatory variables considered are i) an aggregate output in mining and quarrying, manufacturing, electricity, gas and water supply, and construction industries (*cp*), ii) imports, iii) exports, iv) a ratio of exports over imports (*nx*), and v) money supply M1 (m). All series are quarterly, expressed in logs, and once regularly and once seasonally differenced, except m, that is not seasonally differenced. Appendix contains a more detailed description of the data. We produce one-period ahead forecasts for GDP, given that all explanatory variables are known for the forecasting horizon (we call this exercise 'nowcasting'). All calculations are performed in Scilab with the aid of its econometrics toolbox Grocer (see Dubois and Michaux (2010)).

Figure 1 shows seasonally unadjusted as well as seasonally adjusted GDP series. The first five observations get lost to make the seasonally unadjusted series stationary. If the rest part is divided in halves, the first half contains a smooth growth (a matter to calculate within-a-business-cycle-phase RMSFEs), whereas the second half contains a pronounced switch of business cycle phases from growth to a deep recession (a matter to calculate between-business-cycle-phases RMSFEs). Table 1 to Table 5 show root mean squared forecast errors (RMSFE) for the full sample, the first half of the sample ($\mathrm{RMSFE}^{\mathrm{within}}_{\mathrm{phase}}$) and the second half of the sample ($\mathrm{RMSFE}^{\mathrm{between}}_{\mathrm{phases}}$) from pseudo real-time nowcasts beginning at sample size 19 from a random walk (RW), autoregressive (AR) and vector autoregressive (VAR) models versus static, dynamic and mixed factor-augmented VAR (FAVAR) models, where factors are formed from various combinations of variables *cp*, *imp*, *exp*, *nx* and *m*. In these tables, VAR models are specified by their endogenous variables (first parenthesis) and a lag order (second parenthesis). FAVAR models are specified by their endogenous variables (first parenthesis) and a lag order (second parenthesis). Static factors are specified by a combination of three symbols 'fsi', where the first symbol 'f' denotes that the variable is a factor, the second symbol 's' means that the factor is obtained in a static manner, and the third symbol 'i' denotes the order of the factor. In this paper, we will use only two kinds of static factors: 'fs1' and 'fs2', which are static first and second common factors, accordingly. Dynamic factors are specified by a symbol combination 'fdij(p,q)', where 'f' stands for being a factor, 'd' stands for being a dynamic one, 'ij' stands for being the i-th out of j simultaneously estimated factors, and the numbers '(p,q)' mean that the factor's dynamics in (4) are specified by an ARMA(p,q) process. Note that for simplicity, the indiosyncratic component in (4) is set to follow an AR(1) for all dynamic factors, regardless of their ARMA specifications. The least RMSFE for each sample space is framed.

Table 1 shows the results for the GDP nowcasting performance using endogenous explanatory variables *cp*, *nx*, and *m*. It is shown that it is better to use FAVAR with two static factors calculated from these three endogenous variables rather than VAR with the same three variables. It is also shown that the least nowcasting errors for a within-a-phase period are obtained by a parsimonious VAR model, whereas for the whole series and for a between-phases period - by a static FAVAR. Notably, none of the many dynamic and mixed factor FAVAR models specified by various ARMA dynamics is superior over the static FAVAR model. Table 2 shows the results for the GDP nowcasting performance using endogenous explanatory variables *cp*, *imp*, and *m*. One can see that a dynamic FAVAR with the two factors generated by ARMA(2,1) is the best nowcasting model for the whole sample as well as for the between-phases period, being slightly superior over the static FAVAR model with two factors. Table 3 shows the results for the GDP nowcasting performance using endogenous explanatory variables *cp*, *exp*, and *m*. It is shown that the best nowcasting performance for the whole series is obtained by a static one-factor FAVAR, for the between-phases period - by a static two-factor FAVAR, and for the within-a-phase period - by a dynamic FAVAR, where the only factor is the first common factor calculated from a two-factor model with the dynamics specified by ARMA(2,2). Table 4 shows the results for the GDP nowcasting performance using four endogenous explanatory variables, *cp*, *imp*, *exp*, and *m*.

It is shown that the best nowcasting performance for the within-a-phase period is obtained by a parsimonious VAR, while for the whole series as well as for the between-phases period - by a mixed FAVAR, where the first factor is taken from a dynamic two-factor model with ARMA(1,2), whereas the second factor is the second static common factor. Finally, Table 5 shows the results for the GDP nowcasting performance using four endogenous explanatory variables, *cp*, *imp*, *nx*, and *m*. This variable combination is interesting because (logged) *nx* is a difference between (logged) *exp* and *imp* and, thus, might resemble a case if one used a large number of both disaggregated and aggregated variables to form factors, since, in that case, some of the variables might be linear combinations of other variables. Thus, Table 5 shows the nowcasting results when the factor-forming variables are not carefully preselected. It is shown that the static two-factor FAVAR performs slightly better in this case compared to when static factors are formed only from a three-variable combination, $\{cp,nx,m\}$ or $\{cp,imp,m\}$ (see Table 1 or Table 2, respectively), giving the best nowcasting performance for the whole series as well as for the between-phases period. On the contrary, the best-performing dynamic factor model using a set of endogenous explanatory variables $\{cp,imp,m\}$ (see Table 2) now performs considerably worse, when adding *nx* to the set of variables for factor extraction. The latter observation might suggest that the performance of dynamic factors is less robust to a slight change of variables than that of static factors. To examine the issue, Table 6 to Table 10 show the ranking of the models reported in Table 1 to Table 5. The ranking for a static two-factor FAVAR (model 9) for the whole series, within-a-phase, and between-phases period is $\{1,10,1\}$ for variable set $\{cp,nx,m\}$, $\{5,15,4\}$ for variable set $\{cp,imp,m\}$, $\{2,22,1\}$ for variable set $\{cp,exp,m\}$, $\{5,9,4\}$ for variable set $\{cp,imp,exp,m\}$, and $\{1,11,1\}$ for variable set $\{cp,imp,nx,m\}$, out of overall 44 models. The ranking for a dynamic two-factor FAVAR(2,1) (model 33), the model which performs the best in Table 2, for the whole series, within-a-phase, and between-phases period is $\{18,5,19\}$ for variable set $\{cp,nx,m\}$, $\{1,8,1\}$ for variable set $\{cp,imp,m\}$, $\{19,26,20\}$ for variable set $\{cp,exp,m\}$, $\{10,4,14\}$ for variable set $\{cp,imp,exp,m\}$, and $\{44,44,40\}$ for variable set $\{cp,imp,nx,m\}$, out of overall 44 models. We can see that the ranking of the static FAVAR seems more stable with respect to change of variables than that of the dynamic FAVAR. Indeed, the dynamic factor model turns from the best-performing nowcasting model for the set of variables $\{cp,imp,m\}$, to the worst nowcasting model for the set of variables $\{cp,imp,nx,m\}$, where the only difference between the variable sets is an addition of a single variable to the former set. To take into account the changes in factor models' nowcasting performance with respect to a slight change of the set of variables, from which factors are extracted, Table 11 shows the models' ranking based on the mean rank calculated from the rankings reported in Table 6 to Table 10. It is shown that, although some of the mixed FAVAR perform decently, static FAVAR model appears to be the most precise and robust with respect to the change of the factor-forming set of variables for the whole series as well as for the between-phases period. Also, if one considers one-factor models, it is shown that one-factor static FAVAR outperforms one-factor dynamic FAVARs except for the within-a-phase period, where the performance is similar.

As an alternative to Table 11, Table 12 shows models ranking based on the root mean squared rank calculated from the rankings reported in Table 6 to Table 10 to penalize unstable nowcasting performance to a higher degree compared to the ranking in Table 11. With minor changes, Table 12 shows the same pattern as Table 11.

Finally, just for illustrative purposes, Figure 3 to Figure 11 show stationary GDP, static first common factor, and dynamic first common factor formed from the variable set $\{cp, nx, m\}$, where dynamic factors are generated by various ARMA specifications, starting from ARMA(0,1) and ending at ARMA(2,2). It is shown that, regardless of dynamics specification, dynamic factors fail to detect the timing and depth of the latest recession, the period of which is colored gray in the figures.

4 Conclusions

The choice between static and dynamic factors in now-/forecasting GDP is unresolved. Some papers find dynamic factors superior over the static ones. Other papers find little or no advantage of dynamic over static factors. On top of them, there are papers that argue for static over dynamic factors. Another debate is going on regarding large-scale versus small-scale factor models. Given the lack of empirical evidence or rationale for large-scale factor models in now-/forecasting GDP, we build a parsimonious, small-scale factor model for the GDP of one of the hardest hit economies during the latest recession to study the exact dynamic versus static factor model performance along a business cycle, with an emphasis placing on nowcasting performance during a pronounced switch of business cycle phases due to the latest recession. We compare the factor models' nowcasting performance to a random walk, autoregressive and the best-performing nowcasting models at our hands, which are VAR models. It is shown that a small-scale static FAVAR model tends to improve upon the nowcasting performance of the VAR models during the switch business cycle phases (between business cycle phases), while exact dynamic factor models tend to fail to detect the timing and depth of the recession regardless of ARMA specifications. As regards the period of smooth economic growth (within a business cycle phase), static and dynamic factor models appear to show similar performance with potentially slight superiority of dynamic factor models if the factor-forming set of variables and factor dynamics are carefully selected.

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Appendix

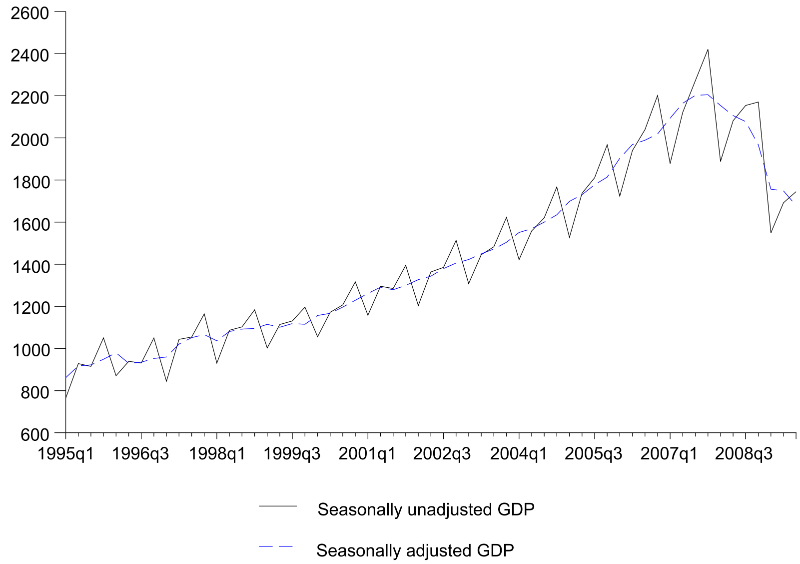

Figure 1: Latvia's quarterly GDP series. The first five observations get lost to make the seasonally unadjusted series stationary. If the rest part is divided in halves, the first half contains a smooth growth (a matter to calculate within-a-business-cycle-phase RMSFEs), whereas the second half contains a pronounced switch of business cycle phases from growth to a deep recession (a matter to calculate between-business-cycle-phases RMSFEs). Source: Central Statistical Bureau of Latvia.

Nº	Model	RMSFE	$\text{RMSFE}^{\text{within}}_{\text{phase}}$	$\text{RMSFE}^{\text{between}}_{\text{phases}}$
1	RW	0.0318026	0.0258327	0.0370907
2	AR(1)	0.0289930	0.0174793	0.0375119
3	AR(2)	0.0290639	0.0176315	0.0375493
4	VAR(GDP,cp)(2)	0.0228362	$\boxed{0.0142717}$	0.0292916
5	VAR(GDP,cp,nx)(2)	0.0220654	0.0167891	0.0265320
6	VAR(GDP,cp,m)(2)	0.0220319	0.0162761	0.0268117
7	VAR(GDP,cp,nx,m)(2)	0.0226704	0.0181780	0.0266128
8	FAVAR(GDP,fs1)(2)	0.0287139	0.0226375	0.0339835
9	FAVAR(GDP,fs1,fs2)(2)	$\boxed{0.0210557}$	0.0172919	$\boxed{0.0244165}$
10	FAVAR(GDP,fd11(0,1))(2)	0.0311457	0.0213921	0.0388925
11	FAVAR(GDP,fd11(0,2))(2)	0.0305525	0.0219591	0.0375667
12	FAVAR(GDP,fd11(1,0))(2)	0.0311457	0.0213921	0.0388925
13	FAVAR(GDP,fd11(1,1))(2)	0.0314799	0.0208982	0.0397221
14	FAVAR(GDP,fd11(1,2))(2)	0.0311515	0.0226767	0.0381240
15	FAVAR(GDP,fd11(2,0))(2)	0.0305525	0.0219591	0.0375667
16	FAVAR(GDP,fd11(2,1))(2)	0.0303605	0.0219320	0.0372617
17	FAVAR(GDP,fd11(2,2))(2)	0.0310249	0.0220388	0.0383071
18	FAVAR(GDP,fd12(0,1))(2)	0.0309646	0.0207075	0.0389871
19	FAVAR(GDP,fd12(0,2))(2)	0.0307738	0.0222302	0.0377692
20	FAVAR(GDP,fd12(1,0))(2)	0.0309646	0.0207075	0.0389871
21	FAVAR(GDP,fd12(1,1))(2)	0.0285258	0.0210894	0.0347042
22	FAVAR(GDP,fd12(1,2))(2)	0.0281124	0.0227255	0.0328676
23	FAVAR(GDP,fd12(2,0))(2)	0.0307738	0.0222302	0.0377692
24	FAVAR(GDP,fd12(2,1))(2)	0.0299854	0.0217410	0.0367513
25	FAVAR(GDP,fd12(2,2))(2)	0.0297038	0.0236371	0.0349993
26	FAVAR(GDP,fd12(3,2))(2)	0.0285759	0.0220408	0.0341588
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	0.0284383	0.0208394	0.0347163
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	0.0319796	0.0219138	0.0399636
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	0.0284383	0.0208394	0.0347163
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	0.0285031	0.0206047	0.0349731
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	0.0218924	0.0174116	0.0258022
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	0.0319796	0.0219138	0.0399636
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	0.0257208	0.0162391	0.0329062
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	0.0220505	0.0184446	0.0253147
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	0.0230179	0.0183390	0.0271056
36	FAVAR(GDP,fd12(0,1),fs2)(2)	0.0231555	0.0170880	0.0281907
37	FAVAR(GDP,fd12(0,2),fs2)(2)	0.0226396	0.0161733	0.0278978
38	FAVAR(GDP,fd12(1,0),fs2)(2)	0.0231555	0.0170880	0.0281907
39	FAVAR(GDP,fd12(1,1),fs2)(2)	0.0250382	0.0198881	0.0295278
40	FAVAR(GDP,fd12(1,2),fs2)(2)	0.0214880	0.0176637	0.0249052
41	FAVAR(GDP,fd12(2,0),fs2)(2)	0.0226396	0.0161733	0.0278978
42	FAVAR(GDP,fd12(2,1),fs2)(2)	0.0220661	0.0156102	0.0272847
43	FAVAR(GDP,fd12(2,2),fs2)(2)	0.0217977	0.0179440	0.0252448
44	FAVAR(GDP,fd12(3,2),fs2)(2)	0.0216962	0.0174938	0.0253990

Table 1: A comparison of pseudo real-time nowcasting performance from RW, AR, VAR, static, dynamic and mixed FAVAR models in terms of RMSFE for the full sample, first half of the sample ($\text{RMSFE}^{\text{within}}_{\text{phase}}$) and second half of the sample ($\text{RMSFE}^{\text{between}}_{\text{phases}}$). Factors are formed from cp, nx and m. The least RMSFE in each sample space is framed. Source: author's calculations.

Nº	Model	RMSFE	$\text{RMSFE}^{\text{within}}_{\text{phase}}$	$\text{RMSFE}^{\text{between}}_{\text{phases}}$
1	RW	0.0318026	0.0258327	0.0370907
2	AR(1)	0.0289930	0.0174793	0.0375119
3	AR(2)	0.0290639	0.0176315	0.0375493
4	VAR(GDP,cp)(2)	0.0228362	$\boxed{0.0142717}$	0.0292916
5	VAR(GDP,cp,imp)(2)	0.0215953	0.0167962	0.0257184
6	VAR(GDP,cp,m)(2)	0.0220319	0.0162761	0.0268117
7	VAR(GDP,cp,imp,m)(2)	0.0224097	0.0186059	0.0258339
8	FAVAR(GDP,fs1)(2)	0.0260125	0.0231283	0.0287528
9	FAVAR(GDP,fs1,fs2)(2)	0.0206503	0.0177169	0.0233581
10	FAVAR(GDP,fd11(0,1))(2)	0.0224924	0.0183811	0.0261502
11	FAVAR(GDP,fd11(0,2))(2)	0.0214698	0.0151657	0.0265611
12	FAVAR(GDP,fd11(1,0))(2)	0.0224924	0.0183811	0.0261502
13	FAVAR(GDP,fd11(1,1))(2)	0.0304735	0.0225634	0.0370518
14	FAVAR(GDP,fd11(1,2))(2)	0.0307515	0.0230551	0.0372039
15	FAVAR(GDP,fd11(2,0))(2)	0.0310795	0.0245940	0.0367185
16	FAVAR(GDP,fd11(2,1))(2)	0.0309126	0.0235684	0.0371382
17	FAVAR(GDP,fd11(2,2))(2)	0.0308145	0.0237475	0.0368485
18	FAVAR(GDP,fd12(0,1))(2)	0.0309637	0.0220093	0.0382229
19	FAVAR(GDP,fd12(0,2))(2)	0.0309430	0.0238684	0.0369872
20	FAVAR(GDP,fd12(1,0))(2)	0.0309637	0.0220093	0.0382229
21	FAVAR(GDP,fd12(1,1))(2)	0.0290716	0.0203661	0.0360673
22	FAVAR(GDP,fd12(1,2))(2)	0.0303737	0.0209814	0.0378587
23	FAVAR(GDP,fd12(2,0))(2)	0.0309430	0.0238684	0.0369872
24	FAVAR(GDP,fd12(2,1))(2)	0.0300290	0.0247287	0.0347714
25	FAVAR(GDP,fd12(2,2))(2)	0.0302149	0.0241580	0.0355197
26	FAVAR(GDP,fd12(3,2))(2)	0.0303710	0.0247376	0.0353711
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	0.0286298	0.0230006	0.0335768
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	0.0305384	0.0238844	0.0362770
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	0.0286298	0.0230006	0.0335768
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	0.0304164	0.0233809	0.0364130
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	0.0300896	0.0231319	0.0360204
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	0.0305384	0.0238844	0.0362770
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	$\boxed{0.0201239}$	0.0171694	$\boxed{0.0228393}$
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	0.0204244	0.0175510	0.0230802
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	0.0205891	0.0174345	0.0234715
36	FAVAR(GDP,fd12(0,1),fs2)(2)	0.0230062	0.0177711	0.0274830
37	FAVAR(GDP,fd12(0,2),fs2)(2)	0.0249251	0.0169611	0.0312164
38	FAVAR(GDP,fd12(1,0),fs2)(2)	0.0230062	0.0177711	0.0274830
39	FAVAR(GDP,fd12(1,1),fs2)(2)	0.0276600	0.0218205	0.0327263
40	FAVAR(GDP,fd12(1,2),fs2)(2)	0.0225046	0.0162396	0.0276310
41	FAVAR(GDP,fd12(2,0),fs2)(2)	0.0249251	0.0169611	0.0312164
42	FAVAR(GDP,fd12(2,1),fs2)(2)	0.0204239	0.0176408	0.0230065
43	FAVAR(GDP,fd12(2,2),fs2)(2)	0.0210700	0.0180169	0.0238809
44	FAVAR(GDP,fd12(3,2),fs2)(2)	0.0213406	0.0175809	0.0247054

Table 2: A comparison of pseudo real-time nowcasting performance from RW, AR, VAR, static, dynamic and mixed FAVAR models in terms of RMSFE for the full sample, first half of the sample ($\text{RMSFE}^{\text{within}}_{\text{phase}}$) and second half of the sample ($\text{RMSFE}^{\text{between}}_{\text{phases}}$). Factors are formed from *cp*, *imp* and *m*. The least RMSFE in each sample space is framed. Source: author's calculations.

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1	RW	0.0318026	0.0258327	0.0370907
2	AR(1)	0.0289930	0.0174793	0.0375119
3	AR(2)	0.0290639	0.0176315	0.0375493
4	VAR(GDP,cp)(2)	0.0228362	0.0142717	0.0292916
5	VAR(GDP,cp,exp)(2)	0.0246127	0.0156999	0.0314042
6	VAR(GDP,cp,m)(2)	0.0220319	0.0162761	0.0268117
7	VAR(GDP,cp,exp,m)(2)	0.0246114	0.0181739	0.0299559
8	FAVAR(GDP,fs1)(2)	$\boxed{0.0203668}$	0.0152080	0.0246805
9	FAVAR(GDP,fs1,fs2)(2)	0.0210957	0.0172162	$\boxed{0.0245439}$
10	FAVAR(GDP,fd11(0,1))(2)	0.0259890	0.0215006	0.0300187
11	FAVAR(GDP,fd11(0,2))(2)	0.0259896	0.0215011	0.0300193
12	FAVAR(GDP,fd11(1,0))(2)	0.0259890	0.0215006	0.0300187
13	FAVAR(GDP,fd11(1,1))(2)	0.0215494	0.0143788	0.0271507
14	FAVAR(GDP,fd11(1,2))(2)	0.0265101	0.0213003	0.0310889
15	FAVAR(GDP,fd11(2,0))(2)	0.0259896	0.0215011	0.0300193
16	FAVAR(GDP,fd11(2,1))(2)	0.0265314	0.0212507	0.0311622
17	FAVAR(GDP,fd11(2,2))(2)	0.0265228	0.0213221	0.0310954
18	FAVAR(GDP,fd12(0,1))(2)	0.0280333	0.0179168	0.0357500
19	FAVAR(GDP,fd12(0,2))(2)	0.0304157	0.0193830	0.0388182
20	FAVAR(GDP,fd12(1,0))(2)	0.0280332	0.0179168	0.0357500
21	FAVAR(GDP,fd12(1,1))(2)	0.0256516	0.0133507	0.0341466
22	FAVAR(GDP,fd12(1,2))(2)	0.0215638	0.0143646	0.0271822
23	FAVAR(GDP,fd12(2,0))(2)	0.0218458	0.0151925	0.0271691
24	FAVAR(GDP,fd12(2,1))(2)	0.0245792	0.0150116	0.0317050
25	FAVAR(GDP,fd12(2,2))(2)	0.0255007	$\boxed{0.0131364}$	0.0340016
26	FAVAR(GDP,fd12(3,2))(2)	0.0218912	0.0148546	0.0274409
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	0.0250081	0.0212546	0.0284477
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	0.0274378	0.0202447	0.0334064
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	0.0250081	0.0212546	0.0284476
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	0.0220628	0.0157017	0.0272236
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	0.0221738	0.0168278	0.0266917
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	0.0227554	0.0154786	0.0285025
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	0.0239331	0.0176469	0.0291470
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	0.0215297	0.0155495	0.0264256
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	0.0227821	0.0148757	0.0288839
36	FAVAR(GDP,fd12(0,1),fs2)(2)	0.0238716	0.0211854	0.0264198
37	FAVAR(GDP,fd12(0,2),fs2)(2)	0.0318656	0.0216314	0.0399390
38	FAVAR(GDP,fd12(1,0),fs2)(2)	0.0238716	0.0211854	0.0264198
39	FAVAR(GDP,fd12(1,1),fs2)(2)	0.0246262	0.0153620	0.0316022
40	FAVAR(GDP,fd12(1,2),fs2)(2)	0.0221364	0.0165884	0.0267862
41	FAVAR(GDP,fd12(2,0),fs2)(2)	0.0226920	0.0174114	0.0271875
42	FAVAR(GDP,fd12(2,1),fs2)(2)	0.0251418	0.0165523	0.0318011
43	FAVAR(GDP,fd12(2,2),fs2)(2)	0.0249269	0.0156704	0.0319256
44	FAVAR(GDP,fd12(3,2),fs2)(2)	0.0229169	0.0170985	0.0277796

Table 3: A comparison of pseudo real-time nowcasting performance from RW, AR, VAR, static, dynamic and mixed FAVAR models in terms of RMSFE for the full sample, first half of the sample ($\text{RMSFE}^{\text{within}}_{\text{phase}}$) and second half of the sample ($\text{RMSFE}^{\text{between}}_{\text{phases}}$). Factors are formed from *cp*, *exp* and *m*. The least RMSFE in each sample space is framed. Source: author's calculations.

Nº	Model	RMSFE	$\text{RMSFE}^{\text{within}}_{\text{phase}}$	$\text{RMSFE}^{\text{between}}_{\text{phases}}$
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4	VAR(GDP,cp)(2)	0.0228362	$\boxed{0.0142717}$	0.0292916
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6	VAR(GDP,cp,m)(2)	0.0220319	0.0162761	0.0268117
7	VAR(GDP,cp,imp,exp,m)(2)	0.0248828	0.0203759	0.0288985
8	FAVAR(GDP,fs1)(2)	0.0256165	0.0228124	0.0282842
9	FAVAR(GDP,fs1,fs2)(2)	0.0204351	0.0172098	0.0233700
10	FAVAR(GDP,fd11(0,1))(2)	0.0282710	0.0236975	0.0324177
11	FAVAR(GDP,fd11(0,2))(2)	0.0284761	0.0235986	0.0328607
12	FAVAR(GDP,fd11(1,0))(2)	0.0282710	0.0236975	0.0324177
13	FAVAR(GDP,fd11(1,1))(2)	0.0277797	0.0223808	0.0325339
14	FAVAR(GDP,fd11(1,2))(2)	0.0305259	0.0229294	0.0369025
15	FAVAR(GDP,fd11(2,0))(2)	0.0284761	0.0235986	0.0328607
16	FAVAR(GDP,fd11(2,1))(2)	0.0307390	0.0235240	0.0368704
17	FAVAR(GDP,fd11(2,2))(2)	0.0313731	0.0240910	0.0375756
18	FAVAR(GDP,fd12(0,1))(2)	0.0297968	0.0224068	0.0360045
19	FAVAR(GDP,fd12(0,2))(2)	0.0308035	0.0237780	0.0368086
20	FAVAR(GDP,fd12(1,0))(2)	0.0258522	0.0187909	0.0316563
21	FAVAR(GDP,fd12(1,1))(2)	0.0292438	0.0249366	0.0332008
22	FAVAR(GDP,fd12(1,2))(2)	0.0294269	0.0244588	0.0339027
23	FAVAR(GDP,fd12(2,0))(2)	0.0308035	0.0237780	0.0368086
24	FAVAR(GDP,fd12(2,1))(2)	0.0242365	0.0183938	0.0291743
25	FAVAR(GDP,fd12(2,2))(2)	0.0287405	0.0202267	0.0356011
26	FAVAR(GDP,fd12(3,2))(2)	0.0303592	0.0248137	0.0352937
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	0.0282704	0.0237917	0.0323435
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	0.0306262	0.0233457	0.0367971
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	0.0260043	0.0216621	0.0299229
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	0.0207281	0.0175698	0.0236162
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	0.0203595	0.0174192	0.0230678
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	0.0306262	0.0233457	0.0367971
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	0.0237122	0.0164012	0.0295430
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	0.0296081	0.0220533	0.0359151
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	0.0206198	0.0173209	0.0236158
36	FAVAR(GDP,fd12(0,1),fs2)(2)	0.0240083	0.0175455	0.0293386
37	FAVAR(GDP,fd12(0,2),fs2)(2)	0.0245587	0.0170764	0.0305448
38	FAVAR(GDP,fd12(1,0),fs2)(2)	0.0259484	0.0194808	0.0313755
39	FAVAR(GDP,fd12(1,1),fs2)(2)	0.0198448	0.0171102	0.0223790
40	FAVAR(GDP,fd12(1,2),fs2)(2)	$\boxed{0.0196263}$	0.0174304	$\boxed{0.0217107}$
41	FAVAR(GDP,fd12(2,0),fs2)(2)	0.0245587	0.0170764	0.0305448
42	FAVAR(GDP,fd12(2,1),fs2)(2)	0.0255631	0.0191685	0.0309247
43	FAVAR(GDP,fd12(2,2),fs2)(2)	0.0267351	0.0211375	0.0315991
44	FAVAR(GDP,fd12(3,2),fs2)(2)	0.0209596	0.0171758	0.0243328

Table 4: A comparison of pseudo real-time nowcasting performance from RW, AR, VAR, static, dynamic and mixed FAVAR models in terms of RMSFE for the full sample, first half of the sample ($\text{RMSFE}^{\text{within}}_{\text{phase}}$) and second half of the sample ($\text{RMSFE}^{\text{between}}_{\text{phases}}$). Factors are formed from *cp*, *imp*, *exp* and *m*. The least RMSFE in each sample space is framed. Source: author's calculations.

Nº	Model	RMSFE	$\text{RMSFE}^{\text{within}}_{\text{phase}}$	$\text{RMSFE}^{\text{between}}_{\text{phases}}$
1	RW	0.0318026	0.0258327	0.0370907
2	AR(1)	0.0289930	0.0174793	0.0375119
3	AR(2)	0.0290639	0.0176315	0.0375493
4	VAR(GDP,cp)(2)	0.0228362	$\boxed{0.0142717}$	0.0292916
5	VAR(GDP,cp,nx)(2)	0.0220654	0.0167891	0.0265320
6	VAR(GDP,cp,m)(2)	0.0220319	0.0162761	0.0268117
7	VAR(GDP,cp,imp,nx,m)(2)	0.0248828	0.0203759	0.0288985
8	FAVAR(GDP,fs1)(2)	0.0290343	0.0237453	0.0337427
9	FAVAR(GDP,fs1,fs2)(2)	$\boxed{0.0197060}$	0.0165628	$\boxed{0.0225618}$
10	FAVAR(GDP,fd11(0,1))(2)	0.0304416	0.0230029	0.0367102
11	FAVAR(GDP,fd11(0,2))(2)	0.0305231	0.0230925	0.0367898
12	FAVAR(GDP,fd11(1,0))(2)	0.0304416	0.0230029	0.0367102
13	FAVAR(GDP,fd11(1,1))(2)	0.0307994	0.0247906	0.0360872
14	FAVAR(GDP,fd11(1,2))(2)	0.0289453	0.0197760	0.0362057
15	FAVAR(GDP,fd11(2,0))(2)	0.0305231	0.0230925	0.0367898
16	FAVAR(GDP,fd11(2,1))(2)	0.0319682	0.0256426	0.0375209
17	FAVAR(GDP,fd11(2,2))(2)	0.0313462	0.0245974	0.0371799
18	FAVAR(GDP,fd12(0,1))(2)	0.0306933	0.0234999	0.0368082
19	FAVAR(GDP,fd12(0,2))(2)	0.0309543	0.0236157	0.0371779
20	FAVAR(GDP,fd12(1,0))(2)	0.0306933	0.0234999	0.0368082
21	FAVAR(GDP,fd12(1,1))(2)	0.0307451	0.0251624	0.0357175
22	FAVAR(GDP,fd12(1,2))(2)	0.0281373	0.0180688	0.0358371
23	FAVAR(GDP,fd12(2,0))(2)	0.0309543	0.0236157	0.0371779
24	FAVAR(GDP,fd12(2,1))(2)	0.0319632	0.0256678	0.0374939
25	FAVAR(GDP,fd12(2,2))(2)	0.0305662	0.0260846	0.0346860
26	FAVAR(GDP,fd12(3,2))(2)	0.0309303	0.0256625	0.0356699
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	0.0220867	0.0158666	0.0271622
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	0.0213687	0.0159650	0.0258888
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	0.0220867	0.0158666	0.0271622
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	0.0282545	0.0207398	0.0344696
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	0.0270338	0.0184717	0.0338138
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	0.0213687	0.0159650	0.0258888
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	0.0329777	0.0283760	0.0372353
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	0.0234946	0.0161173	0.0293499
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	0.0244488	0.0170426	0.0303828
36	FAVAR(GDP,fd12(0,1),fs2)(2)	0.0208817	0.0163307	0.0248064
37	FAVAR(GDP,fd12(0,2),fs2)(2)	0.0206215	0.0166317	0.0241375
38	FAVAR(GDP,fd12(1,0),fs2)(2)	0.0208817	0.0163307	0.0248064
39	FAVAR(GDP,fd12(1,1),fs2)(2)	0.0219988	0.0171137	0.0261965
40	FAVAR(GDP,fd12(1,2),fs2)(2)	0.0208572	0.0174249	0.0239614
41	FAVAR(GDP,fd12(2,0),fs2)(2)	0.0206215	0.0166317	0.0241375
42	FAVAR(GDP,fd12(2,1),fs2)(2)	0.0217766	0.0180553	0.0251231
43	FAVAR(GDP,fd12(2,2),fs2)(2)	0.0209726	0.0159909	0.0251956
44	FAVAR(GDP,fd12(3,2),fs2)(2)	0.0229908	0.0171765	0.0278543

Table 5: A comparison of pseudo real-time nowcasting performance from RW, AR, VAR, static, dynamic and mixed FAVAR models in terms of RMSFE for the full sample, first half of the sample ($\text{RMSFE}^{\text{within}}_{\text{phase}}$) and second half of the sample ($\text{RMSFE}^{\text{between}}_{\text{phases}}$). Factors are formed from *cp*, *imp*, *nx* and *m*. The least RMSFE in each sample space is framed. Source: author's calculations.

Nº	Model	Rank	$\text{Rank}^{\text{within}}_{\text{phase}}$	$\text{Rank}^{\text{between}}_{\text{phases}}$
1	RW	42	44	28
2	AR(1)	26	12	30
3	AR(2)	27	14	31
4	VAR(GDP,cp)(2)	13	$\boxed{1}$	31
5	VAR(GDP,cp,nx)(2)	8	7	7
6	VAR(GDP,cp,m)(2)	6	6	9
7	VAR(GDP,cp,nx,m)(2)	12	17	8
8	FAVAR(GDP,fs1)(2)	25	40	20
9	FAVAR(GDP,fs1,fs2)(2)	$\boxed{1}$	10	$\boxed{1}$
10	FAVAR(GDP,fd11(0,1))(2)	38	28	38
11	FAVAR(GDP,fd11(0,2))(2)	31	34	32
12	FAVAR(GDP,fd11(1,0))(2)	38	28	38
13	FAVAR(GDP,fd11(1,1))(2)	41	26	42
14	FAVAR(GDP,fd11(1,2))(2)	40	41	36
15	FAVAR(GDP,fd11(2,0))(2)	31	34	32
16	FAVAR(GDP,fd11(2,1))(2)	30	33	29
17	FAVAR(GDP,fd11(2,2))(2)	37	36	37
18	FAVAR(GDP,fd12(0,1))(2)	35	22	40
19	FAVAR(GDP,fd12(0,2))(2)	33	38	34
20	FAVAR(GDP,fd12(1,0))(2)	35	22	40
21	FAVAR(GDP,fd12(1,1))(2)	23	27	22
22	FAVAR(GDP,fd12(1,2))(2)	19	42	18
23	FAVAR(GDP,fd12(2,0))(2)	33	38	34
24	FAVAR(GDP,fd12(2,1))(2)	29	30	27
25	FAVAR(GDP,fd12(2,2))(2)	28	43	26
26	FAVAR(GDP,fd12(3,2))(2)	24	37	21
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	20	24	23
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	43	31	43
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	20	24	23
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	22	21	25
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	5	11	6
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	43	31	43
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	18	5	19
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	7	19	4
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	14	18	10
36	FAVAR(GDP,fd12(0,1),fs2)(2)	15	8	14
37	FAVAR(GDP,fd12(0,2),fs2)(2)	10	3	12
38	FAVAR(GDP,fd12(1,0),fs2)(2)	15	8	14
39	FAVAR(GDP,fd12(1,1),fs2)(2)	17	20	17
40	FAVAR(GDP,fd12(1,2),fs2)(2)	2	15	2
41	FAVAR(GDP,fd12(2,0),fs2)(2)	10	3	12
42	FAVAR(GDP,fd12(2,1),fs2)(2)	9	2	11
43	FAVAR(GDP,fd12(2,2),fs2)(2)	4	16	3
44	FAVAR(GDP,fd12(3,2),fs2)(2)	3	13	5

Table 6: Model ranking based on the RMSFEs reported in Table 1. The top rank in each sample space is framed.

Nº	Model	Rank	$\text{Rank}^{\text{within}}_{\text{phase}}$	$\text{Rank}^{\text{between}}_{\text{phases}}$
1	RW	44	44	37
2	AR(1)	24	10	40
3	AR(2)	25	13	41
4	VAR(GDP,cp)(2)	15	$\boxed{1}$	18
5	VAR(GDP,cp,imp)(2)	9	5	8
6	VAR(GDP,cp,m)(2)	10	4	13
7	VAR(GDP,cp,imp,m)(2)	11	21	9
8	FAVAR(GDP,fs1)(2)	20	31	17
9	FAVAR(GDP,fs1,fs2)(2)	5	15	4
10	FAVAR(GDP,fd11(0,1))(2)	12	19	10
11	FAVAR(GDP,fd11(0,2))(2)	8	2	12
12	FAVAR(GDP,fd11(1,0))(2)	12	19	10
13	FAVAR(GDP,fd11(1,1))(2)	33	27	36
14	FAVAR(GDP,fd11(1,2))(2)	36	30	39
15	FAVAR(GDP,fd11(2,0))(2)	43	41	32
16	FAVAR(GDP,fd11(2,1))(2)	38	34	38
17	FAVAR(GDP,fd11(2,2))(2)	37	35	33
18	FAVAR(GDP,fd12(0,1))(2)	41	25	43
19	FAVAR(GDP,fd12(0,2))(2)	39	36	34
20	FAVAR(GDP,fd12(1,0))(2)	41	25	43
21	FAVAR(GDP,fd12(1,1))(2)	26	22	28
22	FAVAR(GDP,fd12(1,2))(2)	31	23	42
23	FAVAR(GDP,fd12(2,0))(2)	39	36	34
24	FAVAR(GDP,fd12(2,1))(2)	27	42	24
25	FAVAR(GDP,fd12(2,2))(2)	29	40	26
26	FAVAR(GDP,fd12(3,2))(2)	30	43	25
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	22	28	22
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	34	38	29
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	22	28	22
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	32	33	31
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	28	32	27
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	34	38	29
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	$\boxed{1}$	8	$\boxed{1}$
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	3	11	3
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	4	9	5
36	FAVAR(GDP,fd12(0,1),fs2)(2)	16	16	14
37	FAVAR(GDP,fd12(0,2),fs2)(2)	18	6	19
38	FAVAR(GDP,fd12(1,0),fs2)(2)	16	16	14
39	FAVAR(GDP,fd12(1,1),fs2)(2)	21	24	21
40	FAVAR(GDP,fd12(1,2),fs2)(2)	14	3	16
41	FAVAR(GDP,fd12(2,0),fs2)(2)	18	6	19
42	FAVAR(GDP,fd12(2,1),fs2)(2)	2	14	2
43	FAVAR(GDP,fd12(2,2),fs2)(2)	6	18	6
44	FAVAR(GDP,fd12(3,2),fs2)(2)	7	12	7

Table 7: Model ranking based on the RMSFEs reported in Table 2. The top rank in each sample space is framed.

N^o	Model	Rank	$\text{Rank}_{\text{phase}}^{\text{within}}$	$\text{Rank}_{\text{phases}}^{\text{between}}$
1	RW	43	44	40
2	AR(1)	40	24	41
3	AR(2)	41	25	42
4	VAR(GDP,cp)(2)	15	3	21
5	VAR(GDP,cp,exp)(2)	22	15	30
6	VAR(GDP,cp,m)(2)	8	17	8
7	VAR(GDP,cp,exp,m)(2)	21	29	22
8	FAVAR(GDP,fs1)(2)	$\boxed{1}$	10	2
9	FAVAR(GDP,fs1,fs2)(2)	2	22	$\boxed{1}$
10	FAVAR(GDP,fd11(0,1))(2)	30	39	23
11	FAVAR(GDP,fd11(0,2))(2)	32	41	25
12	FAVAR(GDP,fd11(1,0))(2)	30	39	23
13	FAVAR(GDP,fd11(1,1))(2)	4	5	9
14	FAVAR(GDP,fd11(1,2))(2)	34	37	27
15	FAVAR(GDP,fd11(2,0))(2)	32	41	25
16	FAVAR(GDP,fd11(2,1))(2)	36	34	29
17	FAVAR(GDP,fd11(2,2))(2)	35	38	28
18	FAVAR(GDP,fd12(0,1))(2)	39	27	38
19	FAVAR(GDP,fd12(0,2))(2)	42	30	43
20	FAVAR(GDP,fd12(1,0))(2)	38	27	38
21	FAVAR(GDP,fd12(1,1))(2)	29	2	37
22	FAVAR(GDP,fd12(1,2))(2)	5	4	11
23	FAVAR(GDP,fd12(2,0))(2)	6	9	10
24	FAVAR(GDP,fd12(2,1))(2)	20	8	32
25	FAVAR(GDP,fd12(2,2))(2)	28	$\boxed{1}$	36
26	FAVAR(GDP,fd12(3,2))(2)	7	6	14
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	25	35	17
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	37	31	35
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	25	35	16
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	9	16	13
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	11	20	6
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	13	12	18
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	19	26	20
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	3	13	5
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	14	7	19
36	FAVAR(GDP,fd12(0,1),fs2)(2)	17	32	3
37	FAVAR(GDP,fd12(0,2),fs2)(2)	44	43	44
38	FAVAR(GDP,fd12(1,0),fs2)(2)	17	32	3
39	FAVAR(GDP,fd12(1,1),fs2)(2)	23	11	31
40	FAVAR(GDP,fd12(1,2),fs2)(2)	10	19	7
41	FAVAR(GDP,fd12(2,0),fs2)(2)	12	23	12
42	FAVAR(GDP,fd12(2,1),fs2)(2)	27	18	33
43	FAVAR(GDP,fd12(2,2),fs2)(2)	24	14	34
44	FAVAR(GDP,fd12(3,2),fs2)(2)	16	21	15

Table 8: Model ranking based on the RMSFEs reported in Table 3. The top rank in each sample space is framed.

Nº	Model	Rank	$\text{Rank}^{\text{within}}_{\text{phase}}$	$\text{Rank}^{\text{between}}_{\text{phases}}$
1	RW	44	44	41
2	AR(1)	30	13	42
3	AR(2)	31	16	43
4	VAR(GDP,cp)(2)	9	$\boxed{1}$	12
5	VAR(GDP,cp,exp)(2)	15	2	20
6	VAR(GDP,cp,m)(2)	8	3	8
7	VAR(GDP,cp,imp,exp,m)(2)	16	22	10
8	FAVAR(GDP,fs1)(2)	18	28	9
9	FAVAR(GDP,fs1,fs2)(2)	4	9	4
10	FAVAR(GDP,fd11(0,1))(2)	25	35	24
11	FAVAR(GDP,fd11(0,2))(2)	27	33	27
12	FAVAR(GDP,fd11(1,0))(2)	25	35	24
13	FAVAR(GDP,fd11(1,1))(2)	23	26	26
14	FAVAR(GDP,fd11(1,2))(2)	37	29	40
15	FAVAR(GDP,fd11(2,0))(2)	27	33	27
16	FAVAR(GDP,fd11(2,1))(2)	40	32	39
17	FAVAR(GDP,fd11(2,2))(2)	43	40	44
18	FAVAR(GDP,fd12(0,1))(2)	35	27	34
19	FAVAR(GDP,fd12(0,2))(2)	41	37	37
20	FAVAR(GDP,fd12(1,0))(2)	19	18	22
21	FAVAR(GDP,fd12(1,1))(2)	32	43	29
22	FAVAR(GDP,fd12(1,2))(2)	33	41	30
23	FAVAR(GDP,fd12(2,0))(2)	41	37	37
24	FAVAR(GDP,fd12(2,1))(2)	12	17	11
25	FAVAR(GDP,fd12(2,2))(2)	29	21	32
26	FAVAR(GDP,fd12(3,2))(2)	36	42	31
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	24	39	23
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	38	30	35
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	21	24	15
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	6	15	6
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	3	11	3
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	38	30	35
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	10	4	14
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	34	25	33
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	5	10	5
36	FAVAR(GDP,fd12(0,1),fs2)(2)	11	14	13
37	FAVAR(GDP,fd12(0,2),fs2)(2)	13	5	16
38	FAVAR(GDP,fd12(1,0),fs2)(2)	20	20	19
39	FAVAR(GDP,fd12(1,1),fs2)(2)	2	7	2
40	FAVAR(GDP,fd12(1,2),fs2)(2)	$\boxed{1}$	12	$\boxed{1}$
41	FAVAR(GDP,fd12(2,0),fs2)(2)	13	5	16
42	FAVAR(GDP,fd12(2,1),fs2)(2)	17	19	18
43	FAVAR(GDP,fd12(2,2),fs2)(2)	22	23	21
44	FAVAR(GDP,fd12(3,2),fs2)(2)	7	8	8

Table 9: Model ranking based on the RMSFEs reported in Table 4. The top rank in each sample space is framed.

Nº	Model	Rank	$\text{Rank}^{\text{within}}_{\text{phase}}$	$\text{Rank}^{\text{between}}_{\text{phases}}$
1	RW	41	42	36
2	AR(1)	25	19	42
3	AR(2)	27	20	44
4	VAR(GDP,cp)(2)	16	$\boxed{1}$	18
5	VAR(GDP,cp,nx)(2)	13	14	12
6	VAR(GDP,cp,m)(2)	12	8	13
7	VAR(GDP,cp,imp,nx,m)(2)	20	25	17
8	FAVAR(GDP,fs1)(2)	26	35	21
9	FAVAR(GDP,fs1,fs2)(2)	$\boxed{1}$	11	$\boxed{1}$
10	FAVAR(GDP,fd11(0,1))(2)	28	27	30
11	FAVAR(GDP,fd11(0,2))(2)	30	29	32
12	FAVAR(GDP,fd11(1,0))(2)	28	27	30
13	FAVAR(GDP,fd11(1,1))(2)	36	37	28
14	FAVAR(GDP,fd11(1,2))(2)	24	24	29
15	FAVAR(GDP,fd11(2,0))(2)	30	29	32
16	FAVAR(GDP,fd11(2,1))(2)	43	39	43
17	FAVAR(GDP,fd11(2,2))(2)	40	36	39
18	FAVAR(GDP,fd12(0,1))(2)	33	31	34
19	FAVAR(GDP,fd12(0,2))(2)	38	33	37
20	FAVAR(GDP,fd12(1,0))(2)	33	31	34
21	FAVAR(GDP,fd12(1,1))(2)	35	38	26
22	FAVAR(GDP,fd12(1,2))(2)	22	22	27
23	FAVAR(GDP,fd12(2,0))(2)	38	33	37
24	FAVAR(GDP,fd12(2,1))(2)	42	41	41
25	FAVAR(GDP,fd12(2,2))(2)	32	43	24
26	FAVAR(GDP,fd12(3,2))(2)	37	40	25
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	14	2	14
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	8	4	9
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	14	2	14
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	23	26	23
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	21	23	22
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	8	4	9
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	44	44	40
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	18	7	19
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	19	15	20
36	FAVAR(GDP,fd12(0,1),fs2)(2)	5	9	5
37	FAVAR(GDP,fd12(0,2),fs2)(2)	2	12	3
38	FAVAR(GDP,fd12(1,0),fs2)(2)	5	9	5
39	FAVAR(GDP,fd12(1,1),fs2)(2)	11	16	11
40	FAVAR(GDP,fd12(1,2),fs2)(2)	4	18	2
41	FAVAR(GDP,fd12(2,0),fs2)(2)	2	12	3
42	FAVAR(GDP,fd12(2,1),fs2)(2)	10	21	7
43	FAVAR(GDP,fd12(2,2),fs2)(2)	7	6	8
44	FAVAR(GDP,fd12(3,2),fs2)(2)	17	17	16

Table 10: Model ranking based on the RMSFEs reported in Table 5. The top rank in each sample space is framed.

Nº	Model	Rank	$\text{Rank}^{\text{within}}_{\text{phase}}$	$\text{Rank}^{\text{between}}_{\text{phases}}$
1	RW	44	44	40
2	AR(1)	31	13	43
3	AR(2)	34	18	44
4	VAR(GDP,cp)(2)	12	$\boxed{1}$	17
5	VAR(GDP,cp,...)(2)	11	3	15
6	VAR(GDP,cp,m)(2)	3	2	5
7	VAR(GDP,cp,m,...)(2)	16	22	11
8	FAVAR(GDP,fs1)(2)	18	33	12
9	FAVAR(GDP,fs1,fs2)(2)	$\boxed{1}$	6	$\boxed{1}$
10	FAVAR(GDP,fd11(0,1))(2)	26	34	24
11	FAVAR(GDP,fd11(0,2))(2)	24	32	26
12	FAVAR(GDP,fd11(1,0))(2)	26	34	24
13	FAVAR(GDP,fd11(1,1))(2)	30	24	30
14	FAVAR(GDP,fd11(1,2))(2)	39	38	36
15	FAVAR(GDP,fd11(2,0))(2)	37	42	33
16	FAVAR(GDP,fd11(2,1))(2)	41	40	38
17	FAVAR(GDP,fd11(2,2))(2)	42	43	39
18	FAVAR(GDP,fd12(0,1))(2)	40	27	42
19	FAVAR(GDP,fd12(0,2))(2)	43	41	41
20	FAVAR(GDP,fd12(1,0))(2)	38	25	37
21	FAVAR(GDP,fd12(1,1))(2)	31	27	31
22	FAVAR(GDP,fd12(1,2))(2)	23	27	26
23	FAVAR(GDP,fd12(2,0))(2)	35	37	35
24	FAVAR(GDP,fd12(2,1))(2)	25	31	29
25	FAVAR(GDP,fd12(2,2))(2)	33	34	32
26	FAVAR(GDP,fd12(3,2))(2)	28	39	23
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	22	26	22
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	36	30	34
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	21	21	18
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	19	20	21
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	12	19	9
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	29	23	28
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	19	17	19
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	9	11	9
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	6	5	7
36	FAVAR(GDP,fd12(0,1),fs2)(2)	8	15	3
37	FAVAR(GDP,fd12(0,2),fs2)(2)	17	8	19
38	FAVAR(GDP,fd12(1,0),fs2)(2)	14	16	6
39	FAVAR(GDP,fd12(1,1),fs2)(2)	15	13	16
40	FAVAR(GDP,fd12(1,2),fs2)(2)	2	6	2
41	FAVAR(GDP,fd12(2,0),fs2)(2)	5	4	8
42	FAVAR(GDP,fd12(2,1),fs2)(2)	9	10	13
43	FAVAR(GDP,fd12(2,2),fs2)(2)	7	12	14
44	FAVAR(GDP,fd12(3,2),fs2)(2)	4	9	4

Table 11: Model ranking based on the mean rank calculated from the rankings reported in Table 6 to Table 10. The top rank in each sample space is framed.

Nº	Model	Rank	$\text{Rank}^{\text{within}}_{\text{phase}}$	$\text{Rank}^{\text{between}}_{\text{phases}}$
1	RW	44	44	40
2	AR(1)	31	12	43
3	AR(2)	34	15	44
4	VAR(GDP,cp)(2)	8	$\boxed{1}$	12
5	VAR(GDP,cp,...)(2)	9	3	14
6	VAR(GDP,cp,m)(2)	3	2	3
7	VAR(GDP,cp,m,...)(2)	13	19	9
8	FAVAR(GDP,fs1)(2)	17	33	10
9	FAVAR(GDP,fs1,fs2)(2)	$\boxed{1}$	6	$\boxed{1}$
10	FAVAR(GDP,fd11(0,1))(2)	26	31	25
11	FAVAR(GDP,fd11(0,2))(2)	24	35	24
12	FAVAR(GDP,fd11(1,0))(2)	26	31	25
13	FAVAR(GDP,fd11(1,1))(2)	32	25	33
14	FAVAR(GDP,fd11(1,2))(2)	39	37	36
15	FAVAR(GDP,fd11(2,0))(2)	35	41	32
16	FAVAR(GDP,fd11(2,1))(2)	41	39	37
17	FAVAR(GDP,fd11(2,2))(2)	42	43	39
18	FAVAR(GDP,fd12(0,1))(2)	40	26	42
19	FAVAR(GDP,fd12(0,2))(2)	43	40	41
20	FAVAR(GDP,fd12(1,0))(2)	37	22	38
21	FAVAR(GDP,fd12(1,1))(2)	30	30	29
22	FAVAR(GDP,fd12(1,2))(2)	23	29	27
23	FAVAR(GDP,fd12(2,0))(2)	36	36	34
24	FAVAR(GDP,fd12(2,1))(2)	25	34	28
25	FAVAR(GDP,fd12(2,2))(2)	29	38	30
26	FAVAR(GDP,fd12(3,2))(2)	28	42	23
27	FAVAR(GDP,{fd12,fd22}(0,1))(2)	20	27	19
28	FAVAR(GDP,{fd12,fd22}(0,2))(2)	38	28	35
29	FAVAR(GDP,{fd12,fd22}(1,0))(2)	18	23	16
30	FAVAR(GDP,{fd12,fd22}(1,1))(2)	19	20	20
31	FAVAR(GDP,{fd12,fd22}(1,2))(2)	14	18	11
32	FAVAR(GDP,{fd12,fd22}(2,0))(2)	33	24	31
33	FAVAR(GDP,{fd12,fd22}(2,1))(2)	22	21	21
34	FAVAR(GDP,{fd12,fd22}(2,2))(2)	16	9	13
35	FAVAR(GDP,{fd12,fd22}(3,2))(2)	6	5	7
36	FAVAR(GDP,fd12(0,1),fs2)(2)	7	14	4
37	FAVAR(GDP,fd12(0,2),fs2)(2)	21	17	22
38	FAVAR(GDP,fd12(1,0),fs2)(2)	11	16	6
39	FAVAR(GDP,fd12(1,1),fs2)(2)	15	13	18
40	FAVAR(GDP,fd12(1,2),fs2)(2)	2	7	2
41	FAVAR(GDP,fd12(2,0),fs2)(2)	5	4	8
42	FAVAR(GDP,fd12(2,1),fs2)(2)	12	10	15
43	FAVAR(GDP,fd12(2,2),fs2)(2)	10	11	17
44	FAVAR(GDP,fd12(3,2),fs2)(2)	4	8	5

Table 12: Model ranking based on the root mean squared rank calculated from the rankings reported in Table 6 to Table 10. This ranking penalizes unstable model performance with respect to the choice of variables to a higher degree compared to the ranking reported in Table 11. The top rank in each sample space is framed.

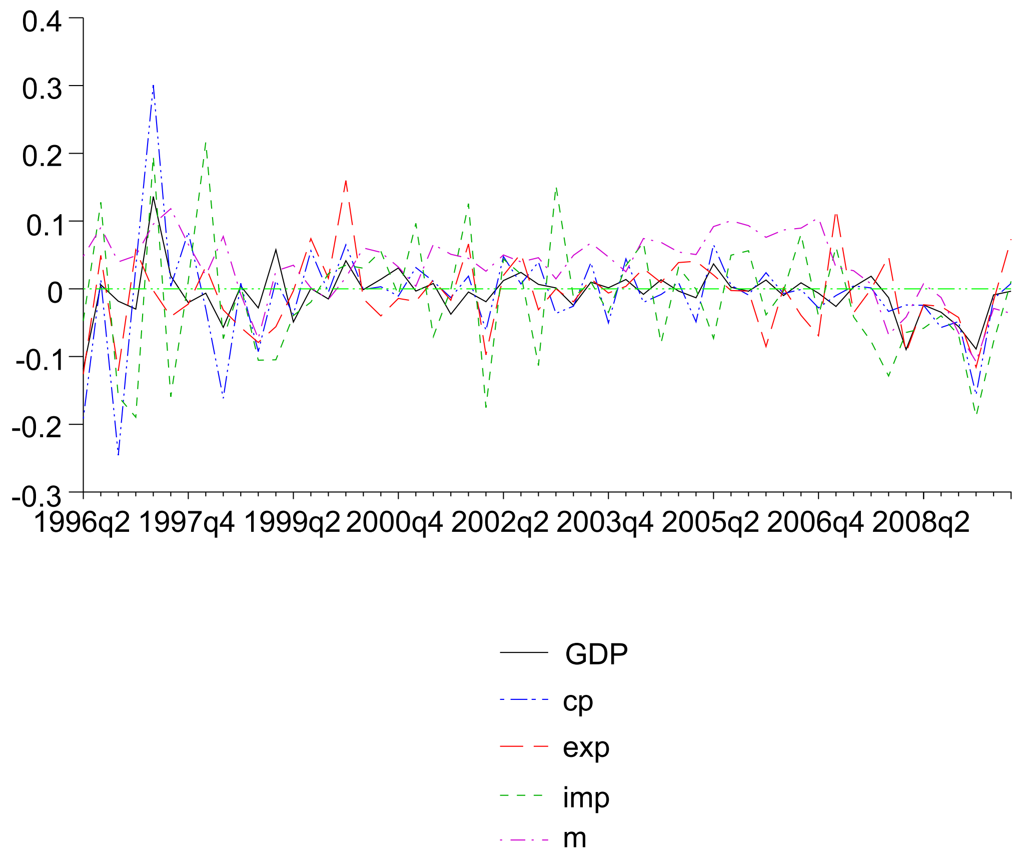

Figure 2: Stationary GDP and its explanatory variables, calculated from seasonally unadjusted data. Stationarity is achieved by taking logs, and applying one seasonal and one regular difference, except for series m, which is not seasonally differenced. Source: Central Statistical Bureau of Latvia and author's calculations.

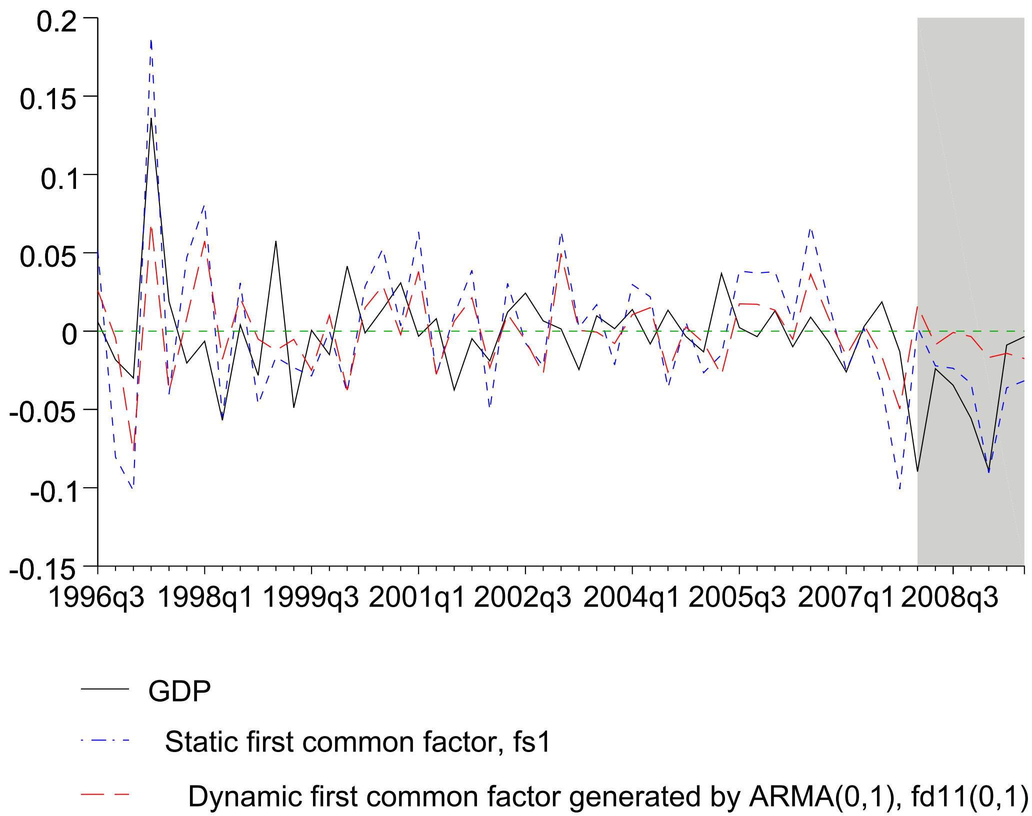

Figure 3: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(0,1) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor hardly detects the recession period and never its depth. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

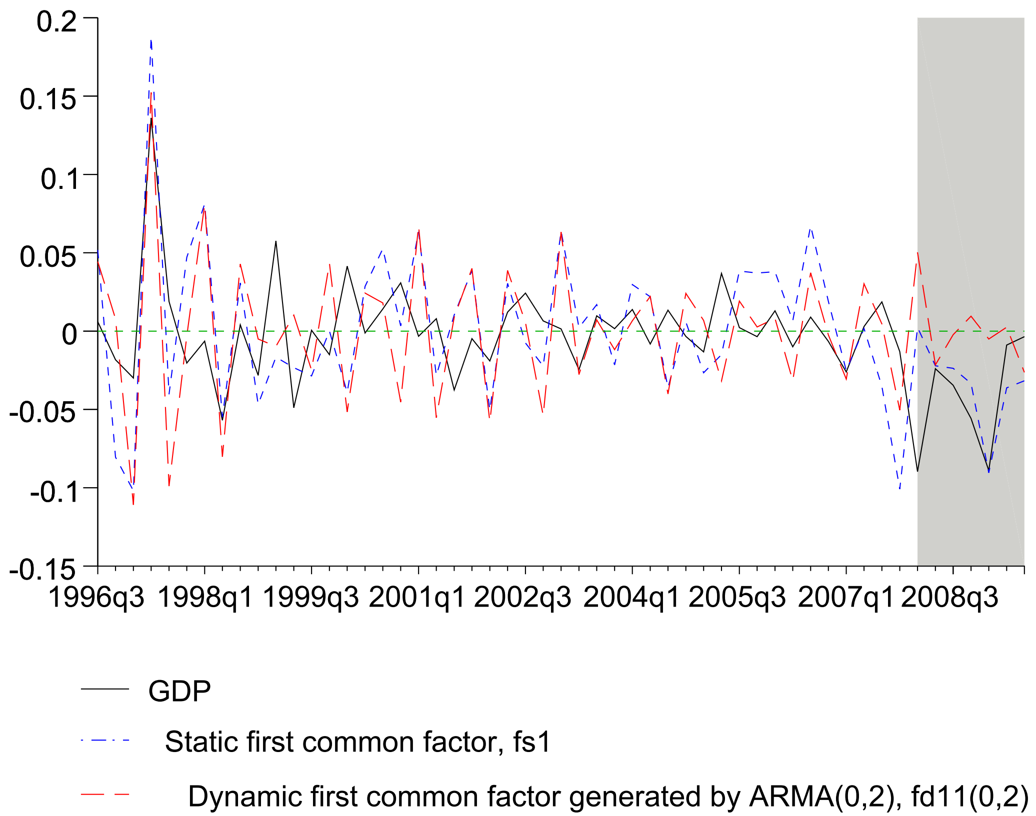

Figure 4: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(0,2) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor is unable to detect the recession period. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

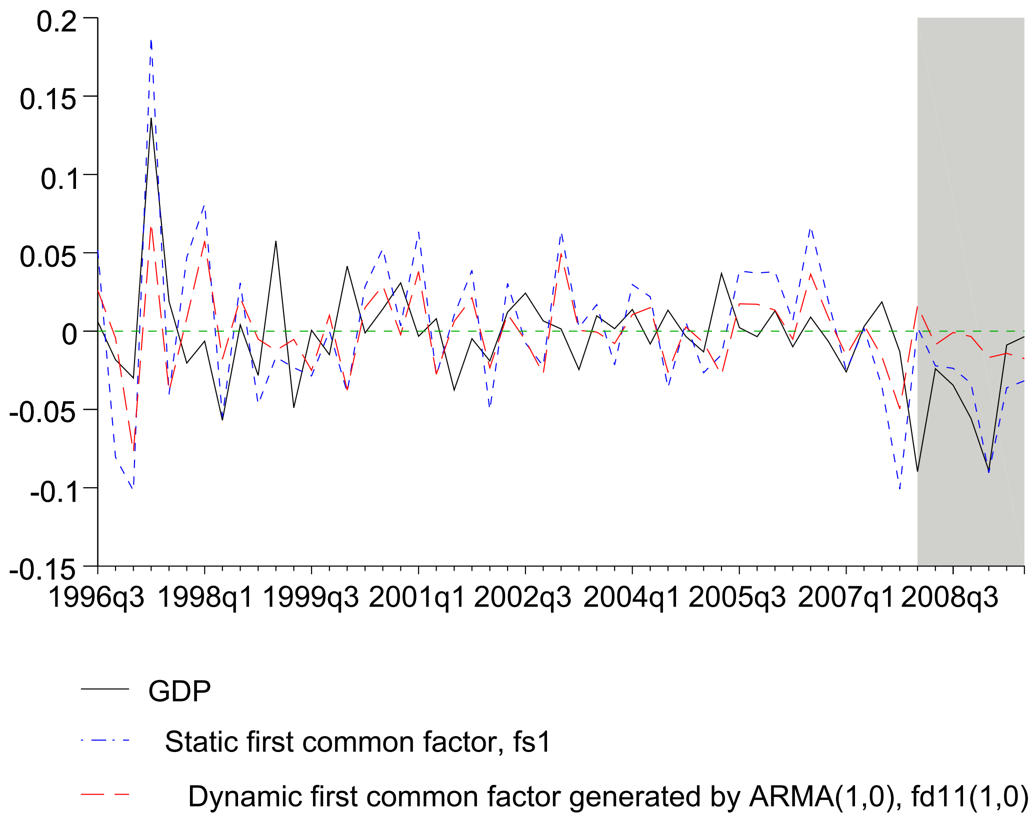

Figure 5: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(1,0) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor is unable to detect the recession period. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

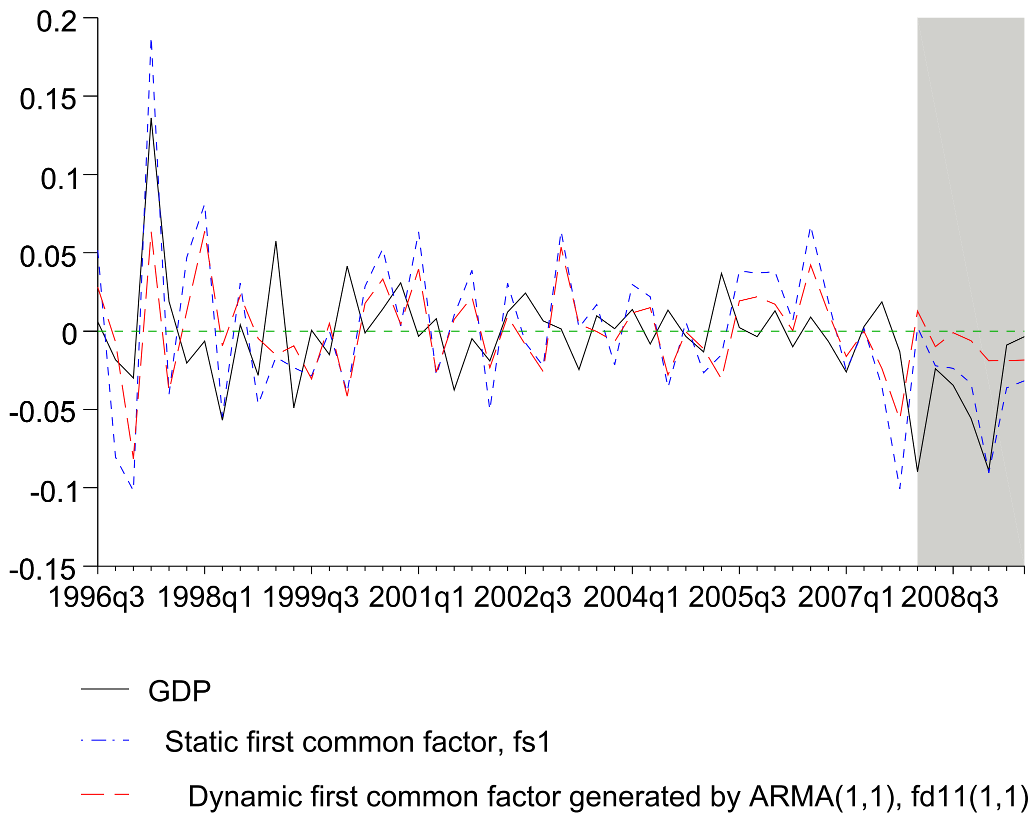

Figure 6: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(1,1) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor hardly detects the recession period and never its depth. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

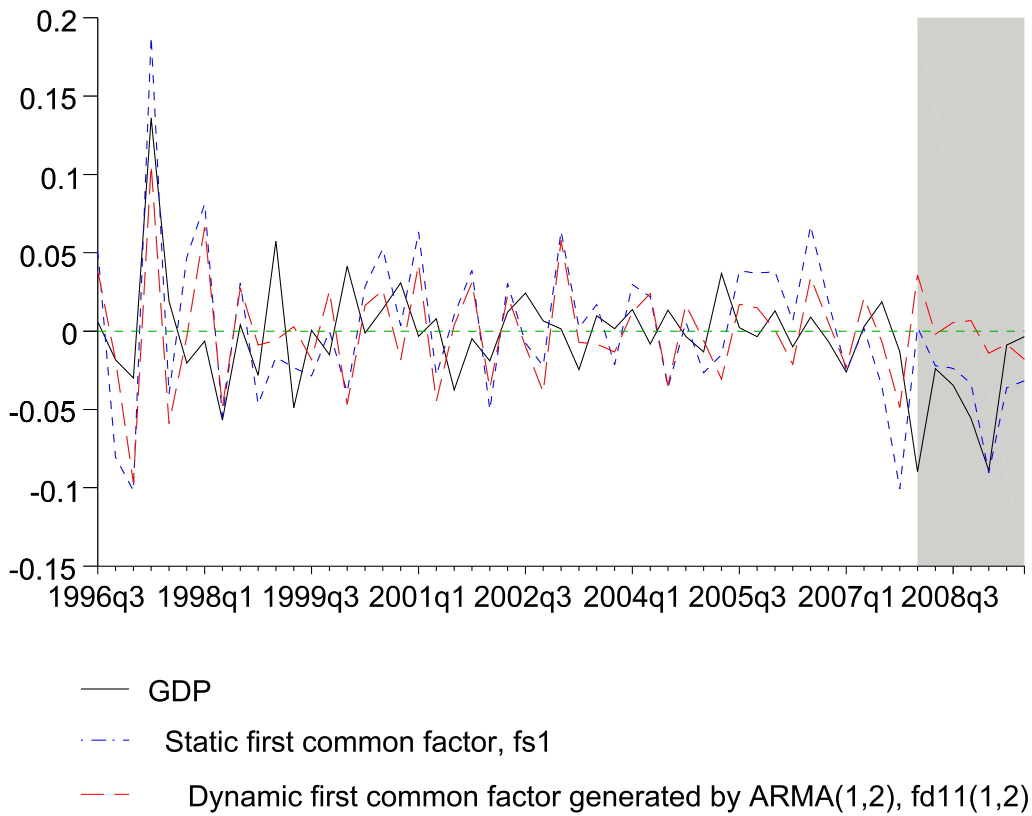

Figure 7: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(1,2) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor is unable to detect the recession period. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

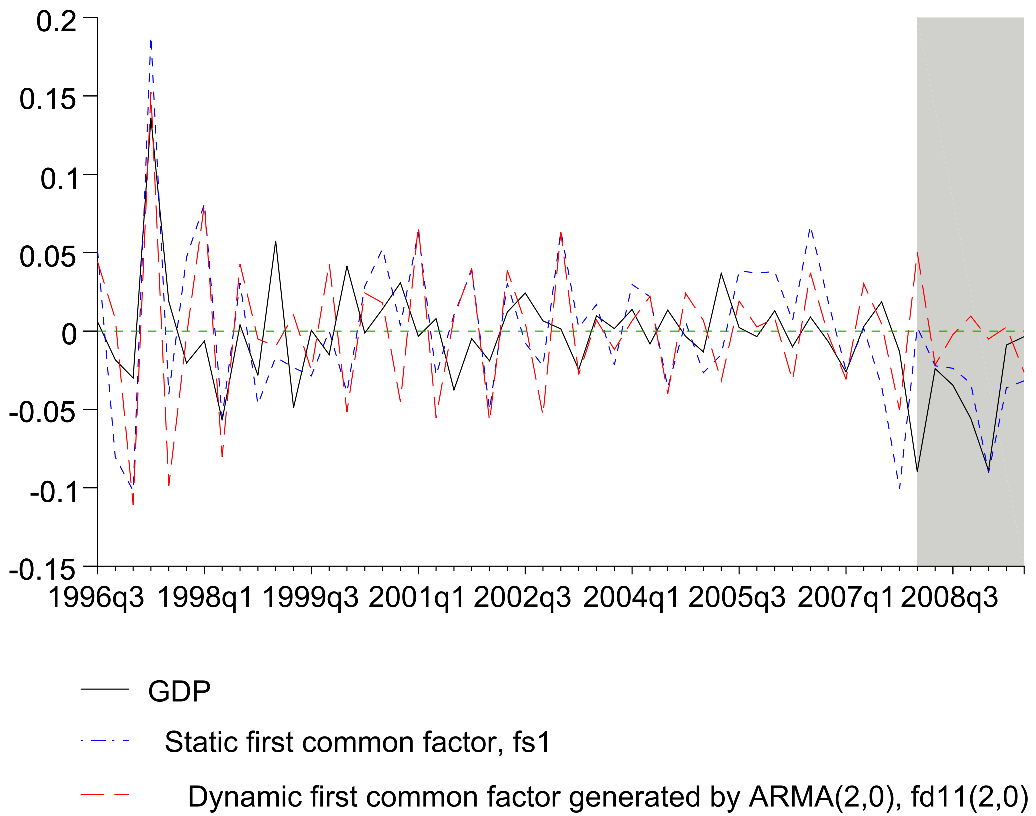

Figure 8: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(2,0) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor is unable to detect the recession period. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

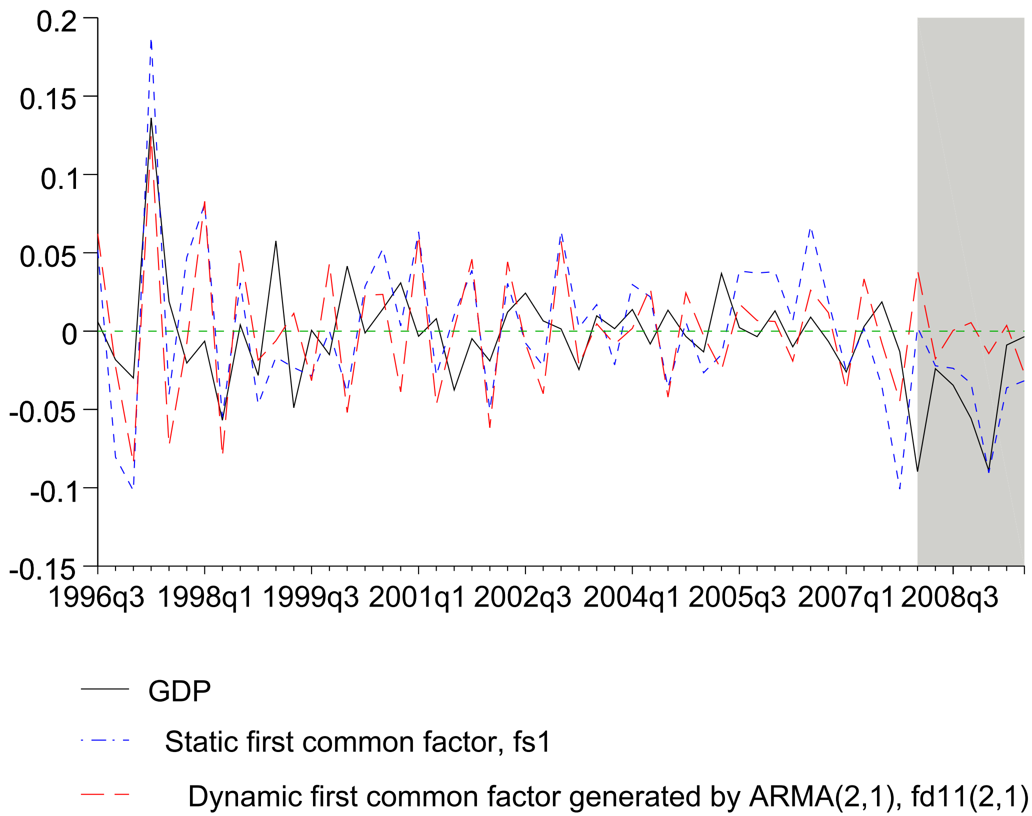

Figure 9: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and best-performing (in terms of RMSFE) dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables cp, nx and m with the factor subject to an ARMA(2,1) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that even the best-performing (in terms of RMSFE) dynamic common factor calculated from a single-factor model is unable to detect the recession period. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

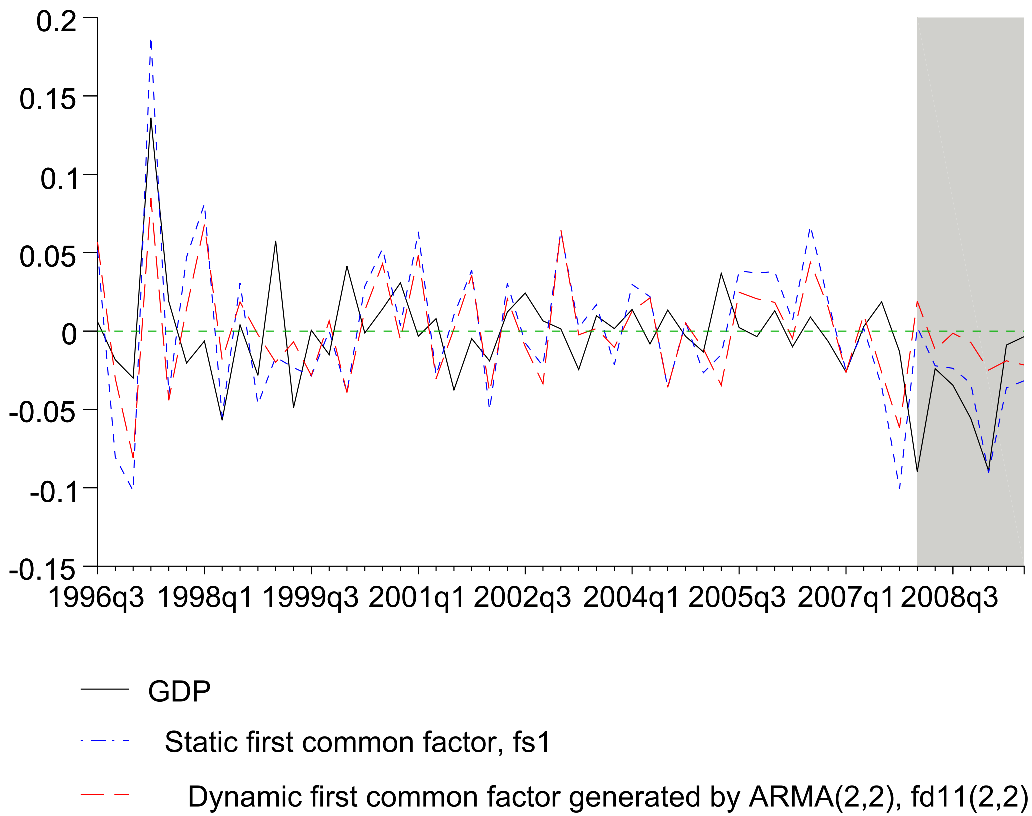

Figure 10: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and a dynamic first common factor (dashed line, long dashes) calculated from a single-factor model using variables *cp*, *nx* and *m* with the factor subject to an ARMA(2,2) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that the dynamic common factor hardly detects the recession period and never its depth. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

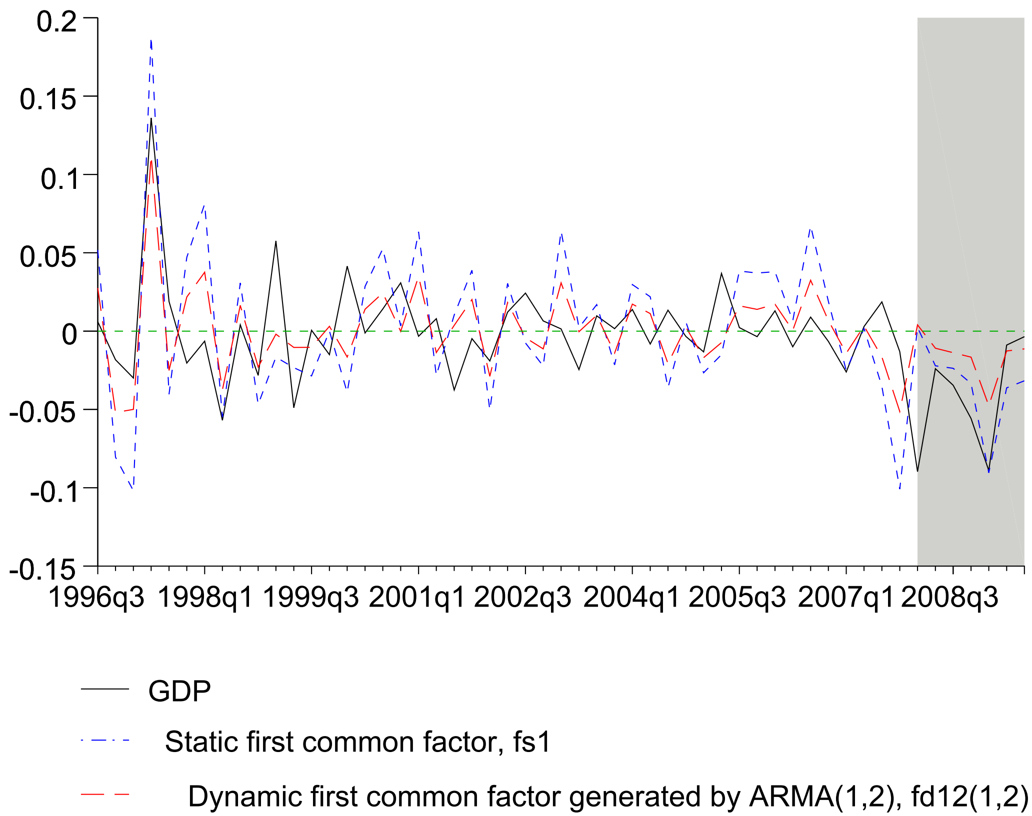

Figure 11: Once regularly and once seasonally differenced logged seasonally unadjusted GDP series (solid line), static first common factor (dashed line, short dashes) and the best-performing (in terms of RMSFE) dynamic first common factor (dashed line, long dashes) calculated from two-factors model using variables *cp*, *nx* and *m* with each factor subject to an ARMA(1,2) process. Shaded area marks the period of Latvia's latest recession, starting from 2008Q1 till the series ends at 2009Q3. It is shown that even the best-performing (in terms of RMSFE) dynamic common factor calculated from a two-factors model is performing slightly worse than its static counterpart in detecting the recession period and depth. Thus, the static factor is considered a better explanatory variable for now-/forecasting GDP during the switch of business cycle phases. Source: Central Statistical Bureau of Latvia and author's calculations.

The list of data used in the paper. All national accounts series are chain-priced as of 2000.

Series	Definition	Source
GDP	Gross domestic product	Central Statistical Bureau of Latvia
C	Output in mining and quarrying industry	Central Statistical Bureau of Latvia
D	Output in manufacturing industry	Central Statistical Bureau of Latvia
E	Output in electricity, gas and water supply industry	Central Statistical Bureau of Latvia
F	Output in construction industry	Central Statistical Bureau of Latvia
cp	Sum of C,D,E and F	Derived by the author
exp	Exports	Central Statistical Bureau of Latvia
imp	Imports	Central Statistical Bureau of Latvia
nx	Ratio of exports over imports, exp/imp	Derived by the author
m	Monetary aggregate M1, quarterly average	Bank of Latvia