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SUITE OF LATVIA'S GDP FORECASTING MODELS

CONTENTS

ABBREVIATIONS

AR – autoregression
BM – bridge model
BVAR – Bayesian vector autoregression
CSB – Central Statistical Bureau of Latvia
ECFIN – Directorate General for Economic and Financial Affairs
EM – expectation maximisation
ESI – Economic Sentiment Indicator
EURIBOR – Euro Interbank Offered Rate
Eurostat – Statistical Bureau of the European Union
FM – factor model
GDP – gross domestic product
HICP– Harmonised Index of Consumer Prices
MFI – monetary financial institution
MIG – main industrial groupings
MSE – mean squared error
MSFE – mean squared forecast error
NACE Rev. 1.1, NACE Rev. 2 – Statistical Classification of Economic Activities in the European Community
OECD – Organisation for Economic Co-operation and Development
PPI – Producer Price Index
RIGIBOR – Riga Interbank Offered Rate
RMSFE – root mean squared forecast error
RTD – real-time database
RW – random walk
SIC – Schwarz Information Criterion
UK – United Kingdom
US – United States
VAR – vector autoregression

ABSTRACT

We develop and assess a suite of statistical models for forecasting Latvia's GDP. Various univariate and multivariate econometric techniques are employed to obtain short-term GDP projections and to assess the performance of the models. We also compile information contained in the GDP components and obtain short-term GDP projections from a disaggregate perspective. We propose a novel approach assessing GDP from the production side in real time, which is subject to changes in NACE classification. Forecast accuracy of all individual statistical models is assessed recursively by out-of-sample forecasting procedure. We conclude that factor-based forecasts tend to dominate in the suite. Encouraging results are also obtained using disaggregate models of factor and bridge models, which could be considered as good alternatives to aggregate ones. Furthermore, combinations of the forecasts of the statistical models allow obtaining robust and accurate forecasts which lead to a reduction of forecast errors.

Keywords: out-of-sample forecasting, real-time estimation, forecast combination, disaggregate approach

JEL codes: C32, C51, C53

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NON-TECHNICAL SUMMARY

The GDP growth data are published with some delay in time. However, economic policy makers require timely information on the current state of the economy. Exploiting most recent monthly statistical information and employing various econometric techniques enable us to provide early estimates of GDP growth.

This paper performs an evaluation exercise of the GDP forecasting models one and two quarters ahead and compares model forecast accuracy. The analysis allows us to have a better understanding about which econometric model is the most accurate and could serve as a work-horse model in short-term forecasting. The paper considers a range of univariate and multivariate econometric models.

A feature of the analysis in this paper lies in real-time estimation of the GDP forecasts. It means that every single GDP forecast was made with a particular vintage of GDP time series, which was available for the analysis in the past. The GDP time series is subject to methodological changes, precisions and corrections. The profile of GDP growth rates has been changing over time. It implies that the forecaster could obtain two different GDP forecasts in specific point of time using different vintages of the GDP time series. To avoid it, we build up a real-time database of Latvia's GDP and its components. We proceed with out-of-sample estimation of forecasts, which means that we reserve roughly a half of the available full-sample data to make estimations and use the second half as a training sample to assess forecasting accuracy of econometric models. We assume that we are back in January 2004 and obtain a GDP forecast with data which were available solely until January 2004. Then every next month (adding more data) we make forecasts, store them and compare with the outturns. It enables us to calculate forecast errors and assess forecast accuracy of every individual model in the suite.

In addition, the paper expands its analysis by introducing disaggregate forecasts of several econometric models in the suite. The disaggregate forecast means that a forecast of the GDP growth is obtained indirectly, i.e. by forecasting GDP components and aggregating them thereafter. The approach of indirectly obtained forecasts might be superior over direct forecasts, because it contains more information about the structure of the economy and therefore could contribute towards a better performance. However, empirically it is not clear-cut which approach is superior only because estimation errors of one approach may be higher than those of another approach. One might find good fit of the model for aggregate time series, but fail to fit some of the GDP components, thus driving the estimation error higher. We examine two bottom-up approaches of aggregating GDP from its components, namely the expenditure side and the production side. We use standard GDP components published by the CSB. However, in the case of production side we merge few economic sections so as to reduce such estimation errors that stem from hardly predictable sections of the economy.

Having a pool of GDP forecasts available, we embark on the analysis of whether the situation is necessarily dubious, if one has two equally accurate forecasts, and which one of them to choose. As the analysis of the forecast accuracy of individual models suggests, econometric models may perform differently in distinct periods of time as well as depend on forecast horizon and the stance of current state of economy, meaning that none of the econometric models is perfect in all times. We show that usefulness of individual forecasts can be improved by combining the forecasts, and the improvement is rather robust across forecast horizons and forecast weighting schemes.

1. INTRODUCTION

Timely information on economic developments is highly important for economic policy analysis and decision making. It is essential for economic policy makers and business community to recognise the economic environment they operate in, to adequately assess the operative information and to make appropriate and effective policy decisions.

This paper develops and assesses a suite of statistical models, which nowcast and forecast Latvia's gross domestic product (GDP). Various econometric techniques are employed to process most recently published statistical information in a suitable manner to obtain short-term projections. The performance of individual statistical models is assessed by forecast evaluation exercise over an out-of-sample period and compared with a standard benchmark model. In addition, this paper also studies forecast performance of disaggregate models and combinations of individual forecasts from the suite of models.

This paper assesses GDP forecasts in real time. We compile a real-time database (RTD) of quarterly GDP, which contains monthly vintages of GDP and its components from the expenditure and production side that were initially released by the CSB. RTD is exploited in order to take into account GDP data revisions for forecasting purposes. A number of research papers have been published emphasising the importance of real-time data either for forecasting macroeconomic variables and analysing monetary policy effects. Among them are the papers by such authors as Diebold and Rudebusch (1991), Croushore and Stark (2001; 2002), Orphanides (2001), etc.

Many studies have been undertaken and methods developed to forecast GDP in the short-term period (Ingenito and Trehan (1996), Rünstler and Sédillot (2003), Stock and Watson (2002a), Forni et al. (2005), Boivin and Ng (2006), Bai and Ng (2008), Clements and Galvão (2009), Bańbura et al. (2010), Kuzin et al. (2011), Bańbura and Modugno (2014)). In this study, commencing with the simplest univariate models, we proceed to more advanced bridge and factor models. We also partly review previous studies by Beņkovskis (2008) and Ajevskis and Dāvidsons (2008) regarding evaluation of Latvia's GDP forecasts with more recent and up-to-date empirical work.

The analysis in this paper is expanded by modelling GDP from a disaggregate point of view. We develop sub-models in order to forecast individual components of GDP both from expenditure and production side and further aggregate them to obtain GDP forecasts indirectly. Empirical evidence suggests mixed results as to whether the disaggregate approach is superior over the aggregate one (Marcellino et al. (2003), Baffigi et al. (2004), Hubrich (2005), Hahn and Skudelny (2008), Bessonovs (2010), Hendry and Hubrich (2011)).

We conclude that factor-based forecasts, either aggregated or disaggregated from the expenditure and production side, tend to dominate over other models in the suite. Moreover, the study reveals that the disaggregate models could provide equally satisfactory forecast accuracy as the aggregate ones, although the results are not clear-cut. Furthermore, we conclude that a combination of forecasts consistently contributes to higher forecast accuracy in comparison with individual models and may be regarded as a robust method in the race of selecting a final forecast.

The paper is structured as follows. Section 2 discusses the dataset exploited in the paper. Section 3 reviews the statistical models and their specifications in the suite. Section 4 examines the disaggregate approach implemented in the paper, whereas Section 5 discusses an approach of combined forecasts. In Section 6, we report the results of the forecast evaluation exercise, and Section 7 concludes.

2. DATA

We compile a real-time database of Latvia's GDP. It allows taking into account GDP data revisions over time. Real-time data vintages for GDP are collected from March 2004 till May 2014. Thus we have 123 vintages of quarterly GDP available on a monthly basis. This allows us to evaluate out-of-sample GDP forecasts starting from the first quarter of 2004 till the fourth quarter of 2013 (40 quarters in total). In technical terms, this RTD means that each out-of-sample iteration step uses a respective GDP vintage, i.e. a GDP data release which was available at the respective month.

Similar to aggregate GDP, we also collect vintages of GDP components from expenditure and production sides in order to make projections from a disaggregate perspective. We exploit typical components of GDP published by the CSB. The expenditure side contains private consumption (C), government consumption (G), gross capital formation (I), exports (X) and imports (M). The production side components of GDP contain 17 economic sections of NACE Rev. 1.1 and 17 economic sections of NACE Rev. 2 classification (for detailed transcription, see Table A.2).

Our forecast exercise uses seasonally adjusted data. As regards GDP and its components, we exploit seasonally adjusted data released by the CSB. Unfortunately, no seasonally adjusted data are available for expenditure and production side components for vintages before 2008; hence early vintages are seasonally adjusted by X-12-ARIMA with default settings.

We consider a large dataset of monthly variables as predictors to forecast Latvia's GDP. Yet, compared to the RTD of GDP, a large monthly dataset of explanatory variables is compiled on a pseudo real-time basis. A pseudo real-time dataset means that we backcast past vintages using the final vintage of the dataset.

The factor model, which is one of the individual models in the suite, by definition requires numerous explanatory variables to obtain latent factors and to make forecasts thereafter. However, there are no certain criteria for selecting explanatory variables for this model. As the rule of thumb, data are collected on the main aspects of the economy (see Table 1), and the breakdown of categories is kept up to the 1st level of disaggregation. The database contains 187 monthly variables, which comprise statistics of business and consumer surveys, industrial production, retail sales, consumer price indices, producer price indices, foreign trade, labour market, monetary statistics, exchange rates and interest rates, balance of payments and fiscal statistics (for detailed description see Table A.1).

Table 1
Description of database of monthly variables

Category	Number of variables	Category	Number of variables
Surveys	48	Interest rates	4
Industry	22	Exchange rates	4
Retail trade	16	Monetary statistics	9
HICP	13	Fiscal statistics	9
PPI	11	Balance of payments	7
Foreign trade	40	Others	4
TOTAL			**187**

The time span of monthly variables is from January 1996 till January 2014. Most of the time series are seasonally adjusted by X-12-ARIMA method with specifications set by default, except interest rates and exchange rates, and those times series that already are published by statistical offices in seasonally adjusted form. The data are transformed to make them stationary, i.e. most data are log differenced, while data with negative values are first differenced. In addition, input data for the factor model are normalised before estimating factors in order to neutralise differences in the scale of variables.

3. METHODOLOGICAL ISSUES

3.1 Real-time forecast design

Numerous studies show that real-time data are relevant both in monetary policy analysis and in forecasting tasks. Diebold and Rudebusch (1991) provide an example, emphasising the importance of real-time data. They show that the index of leading indicators provides much worse accuracy for predicting future movements of industrial production in real time than it does after the data are revised. Croushore and Stark (2001) construct real-time dataset for the US and examine real output properties across vintages. They provide an example showing that data revisions may cause forecasts to be considerably different depending on whether they are made in real time or using the latest available data. Croushore and Stark (2002) develop a novel method showing how changes in the data, i.e. different vintages, affect forecasts. They show that the range of forecasts produced by different data vintages is remarkable and suggest that data revisions are a major source of uncertainty yet ignored in nearly all calculations of forecast uncertainty. Orphanides (2001) examines the informational content of data in terms of real time, implementing and interpreting simple monetary policy rules. He demonstrates that policy recommendations based on real-time data differ considerably from those obtained using revised data. Therefore, he indicates that policy reaction functions based on revised data could provide misleading description of historical policy and could confuse monetary policy decisions made in real time. Croushore (2011) shows that in most studies forecasting ability in real time is much worse than forecasting ability resulting from revised data. The most likely reason is that data revisions tend to be correlated over time.

Having GDP vintages available, we proceed with the out-of-sample forecasting as follows. We assume that GDP data are published in September 2013 and the last actual observation of GDP is for the second quarter of 2013 (see Table 2).

Table 2
Timeliness of forecasts

Current date: GDP data up to:	Sep. 2013 Q2 2013	Oct. 2013 Q2 2013	Nov. 2013 Q2 2013	Dec. 2013 Q3 2013	Jan. 2014 Q3 2013	Feb. 2014 Q3 2013
	1st month	2nd month	3rd month	1st month	2nd month	3rd month
1 quarter ahead:	Q3 2013	Q3 2013	Q3 2013	Q4 2013	Q4 2013	Q4 2013
2 quarters ahead:	Q4 2013	Q4 2013	Q4 2013	Q1 2014	Q1 2014	Q1 2014

In September 2013, we forecast out-of-sample one and two periods ahead, Q3 2013 and Q4 2013 respectively, and denote September as the 1st month when the forecast is made. Consequently, we may forecast Q3 2013 and Q4 2013 in October and November (2nd and 3rd month respectively) up to December 2013 when the next release of GDP is available. Rolling recursively backwards and estimating out-of-sample forecasts from Q1 2004 till Q4 2013, we evaluate one and two quarters ahead for three consecutive months. It should be noted that in every consecutive month there is more monthly information than before, which may potentially enhance the forecast accuracy.

Evidently, all monthly variables are released by statistical offices and respective officials with some delay or within an individual schedule of publication as the current month passes by. Therefore, inevitably at any moment of time, we observe unbalanced panel of data or ragged edge of data (see, e.g. Table 3).

Table 3
Timeliness of selected monthly indicators in dataset on 4 February 2014

Date / Variable	ESI	Industrial production	Retail sales	Nominal exports	HICP	Money supply M3
Nov. 2013	✓	✓	✓	✓	✓	✓
Dec. 2013	✓	✓	✓	na	✓	✓
Jan. 2014	✓	na	na	na	na	na
Feb. 2014	na	na	na	na	na	na

Notes. (✓) marks published observations. (na) means that observations on 4 February 2014 were not yet published.
Sources: CSB, Eurostat and Latvijas Banka.

Studies show that it is crucial to exploit the most recent statistical information to provide more accurate forecasts (see, e.g. Bańbura and Rünstler (2011), Bańbura and Modugno (2014)). Therefore, we employ an EM algorithm to fill out the missing observations in the database, obtain a balanced panel of data and take into account all the timely information. We follow suggestions of Stock and Watson (2002a), stacking a vector of time series X_t with its lags, in which case principal components of the stacked data are obtained (for details, see Table A1 in Appendix). The estimated static factors F_t can include dynamic factors f_t, therefore the data vector X_t can contain lags of the time series.

Running real-time experiments and evaluating forecasts out-of-sample, one has to keep in mind the amount of information published at every point of time in the past. Timeliness of monthly variables in Table 3 suggests the amount of information available on 4 February 2014. This information is employed to forecast GDP in February 2014. We observe that the earliest estimate at hand – the ESI index – is already available for January. The other variables lack 1–2 observations of previous months to shape a balanced panel. Knowing a systematic regularity of statistical information published by official institutions, one can assume that a similar pattern of ragged edge appears in any month earlier. For example, to construct a dataset for 4 January 2014, we preserve the same ragged edge of dataset as on 4 February 2014, only assuming one observation less for each variable. Rolling the dataset backwards, we simulate the patterns of data and obtain pseudo real-time monthly vintages of monthly variables. Thus it ensures that only timely available statistical information in the past is exploited in out-of-sample forecasting evaluation. Then every monthly vintage of the dataset is seasonally adjusted, transformed and estimated by EM algorithm to shape a balanced panel.

3.2 Aggregate vs. disaggregate approach

We expand our analysis by modelling GDP indirectly or from a disaggregate point of view. Disaggregate forecasts of GDP mean that individual components of GDP are forecast and aggregated to obtain GDP forecasts indirectly.

In theory, forecasting individual components and aggregating them is a more efficient approach than forecasting the sum directly. At least this is because a contemporaneously aggregate forecast (i.e. a combined forecast from disaggregates) uses more information than a direct forecast (Lütkepohl (2005)). Disaggregate variables can be predicted more accurately than aggregate ones using tailor-made explanatory variables, as specifications may vary across disaggregate variables. Another argument in favour of disaggregation is that forecast errors of disaggregate variables might partly cancel out, leading to more accurate predictions of the aggregate (Hubrich (2005)).

Nevertheless, empirical evidence suggests mixed results as to whether disaggregate approach is superior over aggregate one. Marcellino et al. (2003) study disaggregation across the euro area countries. They argue that the pooled forecasts of country-specific models outperform the forecasts of the euro area constructed using aggregate data. Baffigi et al. (2004) confirm that the aggregation of forecasts by country performs better in forecasting the euro area GDP. However, they find that disaggregation by components seems to be a less useful forecasting of area-wide GDP. Hahn and Skudelny (2008) develop bridge models for production side components of euro area GDP and run extensive numerical procedures to uncover best-performing equations. Their results show that the disaggregate models outperform the benchmark models. However, only univariate models, not equations with explanatory variables, are used as benchmarks, meaning that in such a way disaggregate models may be overvalued. Bessonovs (2010) shows the evidence in the case of Latvia that disaggregate forecasts of GDP (from either production or expenditure side) could perform equally as the forecasts modelled directly do. Espasa et al. (2002) analyse disaggregate forecasts of inflation both by countries and components. They find that disaggregate forecasts by components provide superior forecasts over the aggregate ones; however, disaggregate forecasts by countries are inferior. Papers by Hubrich (2005), Hendry and Hubrich (2006; 2011) suggest that disaggregation does not necessarily help to forecast euro area and US inflation. Their theoretical and empirical studies strongly imply that misspecification and estimation uncertainty play an important role in relative forecast accuracy across different approaches used to forecast an aggregate. Hendry and Hubrich (2011) argue that the aggregation of forecasts of components is at least as accurate as directly forecasting the aggregate if data generating process is known. By contrast, if data generating process is not known, the properties of the latter determine whether a combination of disaggregate forecasts improves the accuracy of aggregate forecasts. Therefore, it is purely an empirical question whether a disaggregate forecast outperforms an aggregate one.

To study whether the disaggregate approach improves the forecast accuracy in this paper we model GDP indirectly by using two approaches, i.e. from the expenditure side and the production side. The forecast of GDP from the expenditure side is obtained modelling directly all five components. It should be noted that gross capital formation is used without splitting it into sub-components of gross fixed capital formation and stock changes. One might argue that it is reasonable to model stock changes separately because of their highly volatile nature; however, it is difficult to find explanatory variables to track the development of stock changes. Moreover, Latvian stock changes reflect a higher proportion of GDP (in real terms), if, for instance, compared to the euro area. Historically, the contribution of stock changes to GDP in Latvia averages to 3.3%, compared with 0.4% in the euro area. Forecast errors of stock changes can erode the accuracy of total GDP and, thus, falsely signal disadvantages of the disaggregate method from expenditure side.

The forecast of GDP from production side is obtained by modelling seven combined economic sections of NACE Rev. 1.1 and NACE Rev. 2 classification. GDP data of both classifications are used due to a methodological structural break in September 2011 when a shift between classifications occurred. The structural break discontinues compatibility of data of economic sections between NACE Rev. 1.1 and NACE Rev. 2, thus precluding the estimation of forecasts in the chosen out-of-sample period. Nevertheless, we overcome the issue of incompatibility by modelling combined economic sections, which are very close to each other in both classifications (see Table 4).

Table 4

Combined economic sections within NACE Rev. 1.1 and NACE Rev. 2 classification (percentage share of respective economic section in GDP in 2010 given in parentheses)

Combined economic section	NACE Rev 1.1		NACE Rev. 2	
Primary sector	A + B	(3.9)	A	(3.9)
Industry	C + D + E	(14.9)	B + C + D + E	(16.3)
Construction	F	(4.6)	F	(6.0)
Wholesale and retail trade, hotels and restaurants, transportation, storage	G + H + I	(31.8)	G + H + I	(33.2)
Public services	L + M + N	(11.6)	O + P + Q	(10.6)
Commercial services	J + K + O	(25.6)	J+K+L+M+N+R+S+T+U	(22.7)
Net taxes	D21 – D31	(7.5)	D21 – D31	(7.4)

Notes. Letters denoting economic section description differ in NACE Rev. 1.1 and NACE Rev. 2. For more details see Eurostat (2008).

The combined economic sections are the following: a) agriculture, forestry, fishing (primary sector), b) mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply (industry), c) construction, d) wholesale and retail trade, transportation and storage, accommodation and food service activities, e) public administration and defence, compulsory social security, education, human health and social work activities (public services), f) information and communication, financial and insurance activities, professional, scientific and technical activities; administrative and support service activities; other service activities, arts, entertainment and recreation (commercial services), g) taxes on products minus subsidies on products (net taxes). Thereby we obtain seven disaggregate economic sections (components) of GDP. The combined economic sections in Table 4 reduce the number of sections for forecasting and enable us to forecast GDP from production side in real time continuously between both classifications NACE Rev. 1.1 and NACE Rev. 2.

4. THE SUITE OF MODELS

In this Section, we overview the econometric models used in the suite. The forecasts of Latvia's GDP are obtained exploiting the most common econometric techniques in short-term forecasting – autoregression, bridge, factor, vector autoregression and Bayesian vector autoregression models.

We expand the suite of models and develop disaggregate versions of autoregression, bridge and factor models. Disaggregate models are developed in order to forecast individual components of GDP both from expenditure side and production side. Using more statistical information, the purpose is to study whether disaggregate models are helpful in forecasting procedure in terms of forecast accuracy.

4.1 Univariate models

4.1.1 Random walk

The simplest model is the RW model. It assumes no change in the variable of interest. The model is given as follows:

$$y_t = y_{t-1} + \varepsilon_t \tag{1}$$

where y_t is annual growth rate of real GDP.

The h-step ahead forecast of the RW model is the following:

$$\hat{y}_{t+h|t} = y_t \tag{2}$$

where $\hat{y}_{t+h|t}$ is the h-step forecast of annual growth rate of real GDP with given information up to time t.

Typically, the RW model is referred to as a benchmark model in comparison with other econometric models in a way that it can bring the easiest and simplest guess that we are able to obtain without using too much information.

4.1.2 Autoregression models

AR models are the simplest univariate models. It is easy to construct and apply an AR model in economic forecasting. The main idea is to find the best and most appropriate time series model, where observations are modelled as a function of past observations. Its general form is the following:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{3}$$

where y_t is quarterly growth rate of real GDP, φ_i and c are coefficients to be estimated, and p is the order of AR terms, and $\varepsilon_t \sim i.i.d.N(0, \sigma^2)$.

We recursively iterate equation (3) forward and obtain the forecast as follows:

$$\hat{y}_{t+h|t} = \hat{c} + \sum_{i=1}^{p} \hat{\varphi}_i y_{t-i+h} \tag{4}$$

where $\hat{y}_{t+h|t}$ is the h-step forecast of quarterly growth rate of real GDP with given information up to time t.

Disaggregate versions of an AR model are obtained by running an AR model for every component individually and summing up forecasts to form a disaggregate GDP forecast. The lag structure of either the aggregate AR model or AR models for disaggregate components is selected automatically according to the Schwarz Information Criterion (SIC) for each out-of-sample period.

4.1.3 Bridge models

To assess the latest developments in economic activity, economic agents and forecasters focus on economic conjuncture indicators that are available much faster than the official GDP release and mostly at a monthly frequency. These indicators typically are: volume of industrial production, real retail trade turnover, business and consumer surveys, financial indicators, etc. Consequently, monthly figures can be used in the forecasting model by means of bridging them to quarterly GDP growth estimates.

Bridge models are successfully applied when forecasting the economic activity of developed countries (see, e.g. Ingenito and Trehan (1996), Rünstler and Sédillot (2003), Baffigi et al. (2004), and Diron (2008)). Beņkovskis (2008) uses bridge models to forecast the GDP growth in Latvia.

Rünstler and Sédillot (2003) conclude that bridge equations significantly improve the quality of forecasts in comparison with conventional ARIMA model forecasts. Baffigi et al. (2004) note that the results obtained by the bridge model are always better than those produced by univariate models, if at least some monthly indicators of the forecasting period are available. Diron (2008) uses bridge models and evaluates pseudo real-time information as opposed to real-time experiments; she also evaluates relative importance of the four possible measurement errors for the forecasting process (model specification, false extrapolation of monthly figures, monthly information revisions and GDP revisions).

The bridge model takes the following form:

$$y_t^Q = \mu + \sum_{i=1}^{p} \varphi_i y_{t-i}^Q + \sum_{j=1}^{k} \delta_j x_{j,t}^Q + \varepsilon_t \tag{5}$$

where y_t^Q is the quarterly growth rate of real GDP, p is the number of lags of GDP growth rate, $x_{j,t}^Q$ is quarterly growth rate of monthly indicators μ, φ_i, δ_j are coefficients, k is the number of monthly indicators, and $\varepsilon_t \sim i.i.d.N(0, \sigma^2)$.

The forecast is made, rolling forward equation (5) and using the available and timely information of monthly indicators as follows:

$$\hat{y}^{Q}_{t+h|t} = \mu + \sum_{i=1}^{p} \hat{\varphi}_i y^{Q}_{t-i+h} + \sum_{j=1}^{k} \hat{\delta}_j x^{Q}_{j,t+h} \qquad (6)$$

where $\hat{y}^{Q}_{t+h|t}$ is the h-step forecast of quarterly growth rate of real GDP with given information up to time t.

Missing observations over a relevant forecast horizon for each monthly variable $x_{j,t}$ are forecast using an AR model. AR model fits the number of lags according to SIC with no more than four lags:

$$x^{M}_{j,t} = \mu_j + \sum_{i=1}^{p} \alpha_i x^{M}_{j,t-1} + u_{j,t} \qquad (7)$$

where $x^{M}_{j,t}$ is monthly growth rates of variable j, but p is the number of lags.

Monthly growth rates of variables $x^{M}_{j,t}$ relate to quarterly growth rates, exploiting the transformation suggested by Mariano and Murasawa (2003) in the third month of each quarter as follows:

$$x^{Q}_{\tau} = \frac{1}{3}x^{M}_{t} + \frac{2}{3}x^{M}_{t-1} + x^{M}_{t-2} + \frac{2}{3}x^{M}_{t-3} + \frac{1}{3}x^{M}_{t-4} \qquad (8)$$

where x^{Q}_{t} is quarterly growth rate, x^{M}_{t} is monthly growth rate, $\tau = 1, \ldots, \frac{T}{3}$; $t = 1, \ldots, T$, τ and T denote the number of quarters and months respectively.

A feature of the bridge model precludes the use of many explanatory indicators. Relatively short time series and a loss of degrees of freedom typically confine the analysis to only few variables. Therefore, we are encouraged to use the most important information in order to effectively forecast with a bridge model. We select four indicators, which might describe the economic activity most and are timely available for the forecasting procedure. Then aggregate GDP is modelled as follows:

GDP aggregate

GDP = *f* (*IP*, *RS*, *M3*, *XG*)

where explanatory variables are real industrial production (*IP*), real retail sales (*RS*), money supply M3 (*M3*) and nominal exports of goods (*XG*).

To forecast each component of GDP, the bridge model requires explanatory variables to be at least of monthly frequency and timely available to obtain an early estimate. Additional explanatory variables are selected and employed in disaggregate models, which is reasonable, statistically significant and predicts a correct direction. In some cases, we use proxies which might be reasonable explanatory variables. Bridge models for GDP components are as follows:

GDP expenditure side

- Private consumption = *f* (*RS*, *MG*)
- Government consumption = *f* (*BEXP*)
- Gross capital formation = *f* (*ESI*)
- Exports = *f* (*XG*, *XS*)
- Imports = *f* (*MG*, *MS*)

GDP production side

- Primary sector = *f* (*CCI*)
- Industry = *f* (*IP*, *ICI*)

- Construction = *f* (*BCI*)
- Trade, transportation, accommodation = *f* (*RS*, *PT*, *MG*)
- Public services = *f* (*M3*)
- Commercial services = *f* (*M3*)
- Net taxes = *f* (*CCI*, *RTCI*)

where GDP and its components are the functions of real retail sales (*RS*), real industrial production (*IP*), nominal imports of goods (*MG*), nominal budget expenditures (*BEXP*), nominal exports of goods (*XG*), exports of services (*XS*), imports of services (*MS*), money supply M3 (*M3*), total economic sentiment indicator (*ESI*), industrial confidence indicator (*ICI*), consumer confidence indicator (*CCI*), construction confidence indicator (*BCI*), ports turnover (*PT*), retail trade confidence indicator (*RTCI*).

According to Beņkovskis (2008), broad money M3 variable was a good predictor for assessing GDP; hence M3 is exploited in this paper. However, it should be noted that after accessing the euro area, monetary aggregate M3 for Latvia is no longer compatible with the one published before. Therefore in the future, in order to forecast GDP for empirical reasons, a proxy of broad money M3, e.g. demand deposits and deposits with a maturity, could be used.

4.2 Multivariate models

4.2.1 Factor models

During the last two decades, factor models proved to be a very effective tool in short-term forecasting and economic analysis. Information technology, computing and machine learning have made a huge leap towards improvement in this time. Nowadays, advanced methods enable us to analyse a large number of variables.

Studies claim that a small number of factors could explain a large portion of variation among many macroeconomic variables. In this case, if forecasters can accurately assess unobserved factors, the prediction exercise becomes much easier, because instead of N variables we can use just few r factors ($r \ll N$).

The effectiveness of factor models varies across countries and methods but still most researchers emphasise their usefulness. Brisson et al. (2003) for Canada, Camacho and Sancho (2003) for Spain, den Reijer (2005) for the Netherlands, Schneider and Spitzer (2004) for Austria, Shintani (2005) for Japan, Siliverstovs and Kholodilin (2009) for Germany, Stock and Watson (2002a) for US all report significant improvements in the forecast accuracy using principal components. On the other hand, there are some studies that stress that factor models are less successful in forecasting (e.g. Schumacher and Dreger (2004) and Schumacher (2007) for Germany, and Artis et al. (2005) for the UK). Mixed results are reported in Ajevskis and Dāvidsons (2008) for Latvia.

In this study, we exploit an approximate dynamic factor model in the spirit of Stock and Watson's (2002a) diffusion indices. It is assumed that $F_t = (F_{1t}, F_{2t}, \dots, F_{rt})$ is a vector of unobservable static factors which have pervasive effect throughout the economy, and the dependent variable is explained as follows:

$$y_t = \alpha + \sum_{i=1}^{r} \beta_i F_{it} + \sum_{j=1}^{p} \gamma_j y_{t-j} + \varepsilon_t \quad (9)$$

where y_t is quarterly growth rate of real GDP, y_{t-j} is jth lagged variable, F_{it} is ith factor $i = 1, \dots, r$; α and β_i are estimated coefficients, p is an order of autoregression, $\varepsilon_t \sim i.i.d. N(0, \sigma^2)$. Then data X_t admit the following factor structure:

$$X_t = \Lambda F_t + u_t \tag{10}$$

where $X_t = (X_{1t}, \dots, X_{Nt})'$ is the vector of N variables at time $t = 1, \dots, T$, F_t is $r \times 1$ vector of factors, Λ is $N \times r$ vector of factor loadings, u_t is idiosyncratic error, which is allowed to be serially correlated and weakly cross-sectionally correlated. Equation (10) is estimated by principal components. Stock and Watson (2002b) derive the conditions, under which principal components consistently recover factor estimates.

We obtain forecasts h-step ahead using a direct multistep method:

$$\hat{y}_{t+h|t} = \hat{\alpha} + \sum_{i=1}^{r} \hat{\beta}_{ih} F_{it} + \sum_{j=1}^{p} \hat{\gamma}_j y_{t-j+h} \tag{11}$$

where $\hat{y}_{t+h|t}$ is the h-step forecast of quarterly growth of real GDP and F_{it} are estimated factors.

The forecasts of GDP components are estimated in the following way. We estimate common factors in equation (10) using the entire database, run regressions of GDP components on factor estimates in equation (9) and obtain forecasts in equation (11).

In our empirical application, we proceed with one lag of the dependent variable to keep up moderate dynamics. We run the formal Bai–Ng statistical test to identify the number of static factors (Bai and Ng (2002)). The number of factors is automatically estimated and chosen for each out-of-sample period.

4.2.2 Vector autoregression models

By virtue of Sims (1980; 1986) empirical contribution to economic analysis, the vector autoregression model (VAR) became very popular in the economic system analysis and forecasting. As argued by Sims (1980), VAR model provides a promise of a coherent and credible approach to data description, forecasting and policy analysis.

Small-scale VAR models are often used in macroeconomic forecasting. Marcellino et al. (2003) use a three variable VAR to construct euro area forecasts. Jacobson et al. (2001) use a VAR model with long-term restrictions in inflation forecasting. Favero and Marcellino (2005) exploit a VAR model in forecasting fiscal variables of largest euro area countries. Stock and Watson (2001) use a VAR model in its classical form by conducting the analysis of three variables, namely, inflation, unemployment and interest rate of the US economy. Kapetanios et al. (2008) develop GDP and inflation forecasts also by means of VAR models. Rünstler et al. (2009) carry out an intensive short-term forecasting task and evaluate various types of short-term forecasting models, including VAR models, for nine EU countries and the euro area.

We assume that y_t is $n \times 1$ vector of variables at time t. Then y_t dynamics can be described by the p-th order of the Gaussian autoregression model:

$$y_t = c + \Phi_1 \mathrm{y}_{\mathrm{t-1}} + \Phi_2 \mathrm{y}_{\mathrm{t-2}} + \cdots + \Phi_{\mathrm{p}} \mathrm{y}_{\mathrm{t-p}} + \varepsilon_{\mathrm{t}} \tag{12}$$

$$E(\varepsilon_t \varepsilon_s') = \Omega, \text{ if } t = s$$

$$E(\varepsilon_t \varepsilon_s') = 0, \text{ if } t \neq s$$

$$E(\varepsilon_t) = 0$$

where y_t is the vector of variables of interest, Φ_{i} are matrices of coefficients, $i = 1, \ldots, p$, $\varepsilon_t \sim N(0, \Omega)$. The VAR form easily allows us to obtain forecasts by iterating (12) h-steps ahead:

$$\hat{y}_{t+h|t} = \hat{c} + \widehat{\Phi}_1 \mathrm{y}_{\mathrm{t-1+h}} + \widehat{\Phi}_2 \mathrm{y}_{\mathrm{t-2+h}} + \cdots + \widehat{\Phi}_{\mathrm{p}} \mathrm{y}_{\mathrm{t-p+h}} \tag{13}$$

where $\hat{y}_{t+h|t}$ is h-step ahead forecast of the vector of variables.

The standard VAR model typically includes three variables, which measure such main economic developments as real economic activity, inflation and interest rates. VAR model herein contains four variables covering real GDP, headline HICP, 3-month EURIBOR and, taking into account the character of Latvias economy, VAR is also augmented with money supply (M3), thus forming the so called monetary VAR. The lag order of VAR p is selected by SIC. However, we restrict the lag order to $p_{max} = 4$.

4.2.3 Bayesian vector autoregression models

BVAR models are known as models that provide more accurate results than VAR models. The Bayesian estimator helps to avoid the overparametrisation problem and may allow researchers to exploit a greater number of variables in a model. It seems very attractive to apply the Bayesian techniques to VAR modelling in the case of Latvia due to relatively short time series of macroeconomic variables.

The works by Doan et al. (1984) and Litterman (1986) give great impetus to the BVAR model development and implementation in macroeconomic forecasting. Recent literature on BVAR models (see, e.g. Bańbura et al. (2010), Bloor and Matheson (2011), Koop (2013)) shows how Bayesian techniques allow us to exploit a large number of variables in VAR models.

We write a BVAR model as follows:

$$y_t = c + \mathrm{B}_1 \mathrm{y}_{\mathrm{t-1}} + \mathrm{B}_2 \mathrm{y}_{\mathrm{t-2}} + \cdots + \mathrm{B}_{\mathrm{p}} \mathrm{y}_{\mathrm{t-p}} + \upsilon_t \tag{14}$$

$$E(\upsilon_t \upsilon_s') = \Sigma, t = s$$

$$E(\upsilon_t \upsilon_s') = 0, t \neq s$$

$$E(\upsilon_t) = 0$$

where y_t is $n \times 1$ vector of variables at time $t = 1, \ldots, T$, $\{c, B_1, \ldots, B_p, \Sigma\}$ are parameters of the model. Let us put the model coefficients in one vector $\theta = \{c, B_1, \ldots, B_p\}'$; in such a case, the prior information is given by $p(\theta) \sim N(\theta_0, \Sigma_0)$ where θ_0 is a mean and Σ_0 is a diagonal variance matrix. Analogically, BVAR forecasts are obtained by iterating system (14) h-steps ahead:

$$\hat{y}_{t+h|t} = \hat{c} + \widehat{\mathrm{B}}_1 \mathrm{y}_{\mathrm{t-1+h}} + \widehat{\mathrm{B}}_2 \mathrm{y}_{\mathrm{t-2+h}} + \cdots + \widehat{\mathrm{B}}_{\mathrm{p}} \mathrm{y}_{\mathrm{t-p+h}} \tag{15}$$

where $\hat{y}_{t+h|t}$ is h-step ahead forecast of the vector of variables.

We exploit the same four variables as in VAR, and they are real GDP, headline HICP, 3-month EURIBOR and money supply M3. There are various schemes for prior identification in order to estimate the model (see Doan et al. (1984), Leeper et al. (1996), Sims and Zha (1998), Bańbura et al. (2010)). We employ the simplest Minnesota or Litterman prior (Litterman, (1986)), which incorporates the assumption that each element of y_t follows an AR(1) process but the prior variance is assumed to be diagonal and controlled by hyperparameters. The error covariance matrix Σ is assumed to be known; however, it can be replaced by an estimated error covariance matrix $\hat{\Sigma}$. Hyperparameters depend on three parameters: λ_1 controls the variance of the prior of the first lag, λ_2 controls the variance of the prior on lags of variables other than dependent, and λ_3 controls the relative tightness of the variance of lags other than the first one. To identify the BVAR model in our suite of models, we set four lags. We impose "industry standard" values on prior assumptions, namely, $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 1$ (see Canova (2007), Litterman (1986), Kapetanios et al. (2008)) to keep the model simple. Admittedly, the best priors might be chosen by grid searching over the space of parameters and evaluating forecasts respectively.

5. COMBINATION OF FORECASTS

In an early paper, Bates and Granger (1969) stress the importance of combining the forecasts. Two separate sets of forecasts (provided by different models) of the same variable could contain some independent information due to which a combination of forecasts can yield a lower mean squared error than either of the original forecasts. Forecast combination is viewed as and has proved to be a very effective way to robustify forecasting performance over the individual models. Since then, academics and practitioners have paid great attention to forecast combinations. Clemen (1989) has contributed an extensive overview of literature and annotated bibliography on the issue of forecast combinations.

Given that a forecast combination has frequently been found in empirical literature to produce, on average, better forecasts, it is important to understand the reasons for better performance. First, information sets used to produce forecasts may differ in underlying models. Clemen (1987) points out that the higher the degree of overlap of information sets among underlying models, the less useful a combination of forecasts is supposed to be. However, Stock and Watson (1999) draw forecasts from a large number of univariate models and empirically show that forecast combinations still perform better than individual forecasts do, either equally-weighted, MSE-based or median-weighted. This conclusion is surprising, since information sets used to combine are the same.

Second, Hendry and Clements (2004), Aiolfi and Timmermann (2006), and Aiolfi et al. (2011) stress that individual models are differently affected by structural breaks, thus forecast combinations may be justified. Hendry and Clements (2004) show, both analytically and by Monte Carlo simulations, that combined forecasts may overcome some deterministic shifts in data generating processes. Aiolfi et al. (2011) evaluate the performance of different forecast combination schemes in the presence of occasional shifts and conduct a Monte Carlo study in the context of a simple factor model. They study forecast combination in the presence of structural breaks and find that an improvement in forecast combination cannot be well explained by a stable factor structure. Conversely, allowing for structural breaks in factor loadings or breaks in factor dynamics improves the relative performance of forecast combinations in comparison to the single best model.

The third reason is that individual models could be subject to misspecification bias. Clemen (1989) argues that the idea of combining forecasts implicitly assumes that underlying processes cannot be identified. Therefore, it is possible to misspecify the underlying model, parameter estimates and generated forecasts. Stock and Watson (2004) study combination forecasts of output growth in seven OECD countries, obtaining 73 forecasts per country based on individual predictors. They argue that the performance of individual models is unstable due to current economic shocks or policy particulars; however, they find that simple combination forecasts are stable and reliably outperform univariate autoregressive benchmark forecasts.

There are a lot of papers that study the weighting schemes of forecasts. Bates and Granger (1969), Granger and Ramanathan (1984), Diebold and Pauly (1987; 1990), and Stock and Watson (1999; 2004) exploit linear and time-varying methods to estimate the forecast weights. As noted by Aiolfi et al. (2011) and other authors, the equal-weighted forecast is surprisingly difficult to beat. Stock and Watson (2004) point out that the combination methods with the lowest MSFEs are the simplest, either with equal weights or with weights that are very nearly equal and change little over time. Smith and Wallis (2009) clarify the reasons why a simple average combination works well in comparison with other weighting schemes and argue that if optimal combining weights are equal or close to equality, the simple average is more accurate, at least because there is no need to estimate the weights. Furthermore, they recommend ignoring the forecast error covariance when calculating the combining weights proposed by Bates and Granger (1969).

A standard approach of forecast combination techniques is the weighted average of individual forecasts. One can obtain a combined forecast by applying a particular weighting scheme where the standard form is the following:

$$y^c_{t+h|t} = \sum_{i=1}^{n} w_{i,t+h|t} y_{i,t+h|t} \tag{16}$$

where $y^c_{t+h|t}$ is a combined forecast, $y_{i,t+h|t}$ is an individual forecast made at time t for h period ahead, $w_{i,t+h|t}$ is the weight of model i at time t for h period ahead.

In this paper, we consider several forecast combination methods. Weights have the following general form:

$$w_{i,t+h|t} = m^{-1}_{i,t+h|t} / \sum_{j=1}^{n} m^{-1}_{j,t+h|t}; \tag{17}$$

where $m_{i,t+h|t}$ equals to

$$m_{i,t+h|t} = 1, \text{ for all } i = 1, \ldots, n; \quad \text{– equal weights} \tag{17a}$$

$$m_{i,t+h|t} = \sqrt{\frac{1}{T}\sum_{s=t+1}^{T}\left(y_s - y_{s|s-h}\right)^2} \quad \text{– full sample RMSFE weights} \tag{17b}$$

$m_{i,t+h|t} = \sqrt{\frac{1}{v}\sum_{s=t-v+1}^{t}\left(y_s - y_{s|s-h}\right)^2}$ – recursive RMSFE weights (17c)

$m_{i,t+h|t} = \frac{1}{T}\sum_{s=t+1}^{T}\left(y_s - y_{s|s-h}\right)^2$ – full sample MSFE weights (17d)

$m_{i,t+h|t} = \frac{1}{v}\sum_{s=t-v+1}^{t}\left(y_s - y_{s|s-h}\right)^2$ – recursive MSFE weights (17e)

$m_{i,t+h|t} = R_{i,T}$ – full sample rank weights (17f)

$m_{i,t+h|t} = R_{i,t,t-h}$ – recursive rank weights (17g)

where v is the expanding window of previous periods.

We use standard equal weights, RMSFE, MSFE and rank weights. The three latter weighting schemes are estimated over full out-of-sample period and recursively. MSFE puts more penalty on individual forecast errors compared to RMSFE due to its quadratic form. However, full out-of-sample weights are tested against recursive ones, where recursive weights depend on historical performance. Rank weights exploit h-period performance of ith model. The model with the lowest RMSFE performance gets rank 1, the second best gets rank 2, etc. Compared with the former weighting schemes, this combination is supposed to ignore the correlation across forecast errors.

6. EMPIRICAL RESULTS

6.1 Modelling issues

Typically, the forecast accuracy is measured by a loss function. There are several ways how forecast accuracy is reported (see, e.g. de Gooijer and Hyndman (2006)). It is common in the empirical literature to exploit the RMSFE loss function in order to examine the forecasting performance of econometric models.

$$RMSFE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i^f\right)^2} \quad (18)$$

where y_i is actual realisation, y_i^f is forecast value, N is the number of out-of-sample forecasts.

Intuition of RMSFE is straightforward. It measures the average deviation of forecasts from actual observations and is defined in the same units as the analysed variables. The concept of RMSFE is closely related to the notion of standard error and is therefore intuitively understandable.

We report forecast errors in terms of annual growth rates of quarterly GDP. However, it should be noted that statistical models provide quarter-on-quarter growth rates. Quarterly growth rates are converted into annual growth rates and compared with outturns. The reason for converting the growth rates is that quarterly growth rates of Latvia's GDP (seasonally adjusted data) are subject to large revisions from one release to another owing to seasonal adjustment estimation of the series. Therefore, the forecast accuracy measure would contain a large portion of data measurement error of actual data, but not a model error.

6.2 Evaluation of individual forecasts

We estimate statistical models out-of-sample recursively over the period from the first quarter of 2004 to the fourth quarter of 2013 (40 estimated quarters in total). Notably, the database contains GDP monthly vintages, meaning that forecasts can be estimated every month. The forecast accuracy results for numerous models are reported in Table 5. In total, 12 individual forecasts are assessed, including 6 forecasts of aggregate models and 6 forecasts of models from expenditure and production side. Forecasts are obtained for one and two quarters ahead in the 1st month since a new GDP data release has become available (see explanation in Table 2), and RMSFE is calculated with respect to the first release of GDP data. RMSFE then is compared to a RW model, i.e. the obtained relative RMSFE, thus the number larger (less) than 1 indicates that the particular model is less (more) accurate than RW. Therefore, the RMSFE of RW model in the first line in Table 5 is equal to 1. Relative RMSFE provides comparability of the forecast accuracy across individual models.

The quality of forecasts might be affected by business cycle swings, and the performance of the model may depend on the current state of the economy. In the environment of significant structural breaks, it might be misleading to rely only on full sample evidence; hence in our exercise we split the entire out-of-sample period in several parts. In addition, outliers were also excluded, for they significantly distort the comparison of forecast accuracy. In light of the recent financial crisis, the analysis herein distinguishes five time periods. The first sample estimates RMSFE over the full period from the first quarter of 2004 to the fourth quarter of 2013; the second is the full sample excluding the first quarter of 2010[1]; the full sample is split into the pre-crisis period (Q1 2004–Q4 2007), the crisis period (Q1 2008–Q4 2009), and the post-crisis period (Q2 2010–Q4 2013).

Relative RMSFEs in Table 5 show that over the full-time-sample period from the first quarter of 2004 throughout the fourth quarter of 2013, most models outperform a simple benchmark model (RW) at both forecast horizons, gaining forecast accuracy from about 2% (AR and BM_EXP) up to 24% (FM). However, if outliers are excluded (which significantly distorts RW model sample of errors), only few models can beat RW, and they are factor-based models, accounting for 5%–9%, and the bridge model, with 1%–6% of accuracy gain in both forecast periods.

[1] The first quarter of 2010 is excluded from the full sample due to a severe outlier produced by RW benchmark model. As the benchmark appears in all relative RMSFE, the outlier is seen to have a great impact and distorts the comparison of forecasts. The outlier stems mainly from base effects of GDP and does not correspond to the abrupt change of economic activity. The same effect has an impact on forecasts 2 quarters ahead. Therefore for these forecasts the first quarter and the second quarter of 2010 are excluded.

Table 5
Relative RMSFE results for the suite of statistical models

MODEL	1 quarter ahead					2 quarters ahead				
	Full sample Q1 2004– Q4 2013	Full sample[2] excl. Q1 2010	Pre-crisis Q1 2004– Q4 2007	Crisis Q1 2008– Q4 2009	Post-crisis Q2 2010– Q4 2013	Full sample Q1 2004– Q4 2013	Full sample[2] excl. Q1 2010, Q2 2010	Pre-crisis Q1 2004– Q4 2007	Crisis Q1 2008– Q4 2009	Post-crisis Q3 2010– Q4 2013
RW	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR	0.98	1.18	**0.90**	1.38	0.70	1.01	1.24	1.02	1.37	0.68
BM	0.78	0.94	0.91	1.03	0.67	0.81	0.99	0.99	1.06	0.92
FM	**0.76**	**0.91**	1.03	**0.95**	0.67	0.76	0.92	1.01	**0.95**	0.81
VAR	0.95	1.15	0.97	1.30	0.77	0.97	1.20	1.04	1.31	1.03
BVAR	0.94	1.13	0.99	1.29	0.69	0.99	1.20	1.04	1.33	0.82
AR_EXP	1.11	1.27	1.15	1.33	1.16	1.19	1.34	1.59	1.42	1.18
BM_EXP	0.98	1.19	1.14	1.30	0.85	0.96	1.18	**0.69**	1.30	1.12
FM_EXP	0.78	0.94	0.98	1.04	**0.55**	**0.75**	**0.91**	0.78	1.00	0.69
AR_OUT	1.31	1.59	1.08	1.91	0.69	1.26	1.55	1.44	1.72	**0.63**
BM_OUT	0.83	1.00	1.15	1.07	0.60	0.89	1.07	1.13	1.15	0.70
FM_OUT	0.79	0.95	0.95	1.04	0.65	0.82	1.01	1.23	1.04	0.90
Average	*0.93*	*1.10*	*1.02*	*1.22*	*0.75*	*0.95*	*1.14*	*1.08*	*1.22*	*0.87*

Notes. Model acronyms stand for random walk (RW), autoregression (AR), bridge (BM), factor (FM), vector autoregression (VAR), Bayesian vector autoregression (BVAR); EXP denotes disaggregate model from expenditure side, and OUT denotes the production side of the respective model. Relative RMSFEs in grey report numbers below 1, i.e. the forecast accuracy is larger than in RW; numbers in bold denote the largest accuracy gain in a given time period.

The results obtained for periods before, during and after the financial crisis are more mixed and uneven. First, in the pre-crisis period forecasting one period ahead, AR model and BM outperform the benchmark model by 9%–10% and provide the most accurate forecast in this time span, followed by factor models from the production and expenditure side (2%–5%) and VAR-based models (1%–3%). However, different results are obtained forecasting two quarters ahead in this period. The best forecast performance is displayed by the bridge model from expenditure side, with a 31% forecast accuracy gain over the benchmark, followed by the factor model from expenditure side, with a 22% gain in accuracy. In the period of financial turmoil which significantly affected economic activity, almost all statistical models failed to outperform the benchmark model. Underperformance of models in the crisis period is explained by the fact that all models in the suite are linear and assume reverting to the trend of the sample. Against the backdrop of unfolding financial crisis, statistically speaking – evolved nonlinearly, the forecasts of RW were optimal, at least because of being flat. FM, which outperforms the RW model by 5% in both forecast horizons, is an exception. Supposedly large statistical information which is captured by FM enables it to deliver a better forecast accuracy. FMs from expenditure and production side support this point of view by performing close to RW in terms of forecast accuracy, albeit not beating it.

[2] See footnote 1.

Unlike the pre-crisis and crisis periods, the post-crisis period, characterised by stable and sustainable economic environment, might be regarded in some sense as a period which "truly" reflects the performance of the models. Virtually, almost all models outperform significantly the benchmark model. The forecast accuracy gain ranges from 15% (BM from expenditure side) to 45% (FM from expenditure side) forecasting one quarter ahead, and from 17% (BM from production side) to 40% (FM from expenditure side) forecasting two quarters ahead.

The results of disaggregate models are not clear-cut. The performance of disaggregate models is heterogeneous, varying from totally weak, as in the case of AR model from expenditure side, to the best performing FM from expenditure side. Although BM and FM from expenditure and output side indicate decent accuracy gains over the benchmark model in full sample and both forecast horizons, the performance of these disaggregate models, however, significantly varies in distinct periods of time. FM from expenditure side beats the benchmark model virtually in all the observed periods of time, except the periods of financial crisis. FM from output side exhibits similar performance but falls short in the crisis and pre-crisis periods two quarters ahead. From expenditure side, investment is a typical component with the highest forecast error, as it lacks effective leading monthly indicators and is highly volatile by its nature. Among the components from production side, construction and net taxes reflect high forecast errors due to the same reasons. In fact, better calibration of these GDP components could potentially yield higher accuracy gains. It points to the fact that the selection of explanatory variables is an important task, which might significantly affect the outcome. As the results show, the performance of disaggregate models depends on the model and disaggregation type as well as the forecast horizon.

Usefulness of individual forecasts can be improved by combining the forecasts. We explore seven types of weights to combine individual forecasts: equal weights, weights based on RMSFE and MSFE performance of individual models, and weights based on the rank of an individual model within the set of models. Three latter weighting schemes are estimated using full out-of-sample (full sample) and recursive techniques (recursive), meaning that weights are based only on historical performance. The results of combined forecasts are summarised in Table 6. The numbers are given in relative terms against the RW model.

The results in Table 6 show that all forecast weighting schemes outperform the RW model on average by 20% one quarter ahead and by 18% two quarters ahead. Yet, the results indicate more parsimonious forecast accuracy gains, once outliers of benchmark are excluded. One quarter ahead, almost all combined forecasts outperform the benchmark averaging to 3%; however, two quarters ahead, only full sample rank scheme succeeds in beating the benchmark. As is seen from Table 6, such parsimonious performance owes to the fact that combined forecasts fail to deliver any forecast accuracy gains over the period of financial crisis. This failure is explained by constant overestimation of forecasts by individual models against the backdrop of unfolding financial crisis. A combination of forecasts with non-negative weights (summing up to one) is unable to approach actual realisation, which rarely fall within the range of individual forecasts. On the other hand, the results in pre- and post-crisis periods substantially improve upon the benchmark and show marked performance across all weighting schemes.

Table 6
Relative RMSFE results for combination of forecasts

Weighting scheme	1 quarter ahead					2 quarters ahead				
	Full sample Q1 2004–Q4 2013	Full sample[3] excl. Q1 2010	Pre-crisis Q1 2004–Q4 2007	Crisis Q1 2008–Q4 2009	Post-crisis Q2 2010–Q4 2013	Full sample Q1 2004–Q4 2013	Full sample[3] excl. Q1 2010, Q2 2010	Pre-crisis Q1 2004–Q4 2007	Crisis Q1 2008–Q4 2009	Post-crisis Q3 2010–Q4 2013
Equal	0.83	1.00	**0.90**	1.15	0.53	0.85	1.05	0.89	1.17	**0.59**
RMSFE (full sample)	0.81	0.98	0.91	1.12	0.52	0.83	1.03	0.89	1.14	0.59
RMSFE (recursive)	0.82	0.99	0.90	1.13	0.52	0.85	1.04	0.84	1.15	0.59
MSFE (full sample)	**0.79**	0.96	0.91	1.09	**0.51**	0.81	1.00	0.89	1.11	0.60
MSFE (recursive)	0.81	0.97	0.91	1.11	0.51	0.83	1.03	0.79	1.13	0.60
RANK (full sample)	0.77	**0.93**	0.94	**1.04**	0.52	**0.77**	**0.96**	0.84	**1.05**	0.63
RANK (recursive)	0.80	0.96	0.95	1.08	0.53	0.81	1.00	**0.74**	1.10	0.63
Average	*0.80*	*0.97*	*0.92*	*1.10*	*0.52*	*0.82*	*1.02*	*0.84*	*1.12*	*0.61*

Note. Relative RMSFEs in grey report numbers below 1, i.e. the forecast accuracy is larger than RW; numbers in bold denote the largest accuracy gain in a given time period.

Across weighing schemes, discrimination by neither higher punishment of errors (MSFE compared to RMSFE) nor recursive over full sample schemes indicates any tangible improvement of forecast accuracy gains in favour of any respective method. Surprisingly, a moderate performance is attributed to equal weights amid the set of weighting schemes. Nonetheless, this strategy of combining forecasts leads to satisfactory results and ranks the top among individual forecasts regardless of its straightforward implementation. The performance of weights based on the rank of the model does not reveal substantial gains compared with the other combination schemes but emphasises the importance of the magnitude of errors affecting the outcome of combined forecast. Overall, the results show that a combination of forecasts consistently contributes to higher forecast accuracy compared with any individual models and points towards the optimal strategy which may be employed by forecasters. Combined forecasts supposedly immunise to individual models' parameter instability and misspecification, thus leading to a better forecast performance.

[3] See footnote 1.

7. CONCLUSIONS

The paper conducts a forecast evaluation exercise in order to assess the performance of individual statistical models over out-of-sample period and to compare them against a standard benchmark model.

Overall, the obtained results are diverse. However, they lead to the following conclusions. First, factor-based forecasts, either aggregated or disaggregated from expenditure and production side, tend to dominate over other models in the suite.

Second, mixed results of disaggregate approach do not uncover clear-cut properties. The performance of disaggregate models depends on the model and disaggregation type as well as the forecast horizon. Yet, specified models from disaggregate approaches deliver marked forecast accuracy gains. Better calibration of GDP components can potentially yield higher accuracy gains and stresses the importance of selective procedures of explanatory variables. Notwithstanding this, modelling GDP from disaggregate perspective is a good alternative to aggregate models and can be employed in forecasting procedures.

Third, findings indicate that by combining and weighting individual forecasts one can persistently improve the forecast accuracy vis-à-vis the benchmark. A combination of forecasts consistently contributes to higher forecast accuracy compared with individual models and may be regarded as a robust method in the race of selecting a final forecast.

The analysis conducted herein could virtually be extended by augmenting more statistical models, e.g. dynamic factor models, models with time-varying parameters and such non linear models as Markov–Switching or threshold models. Taking into account the evolution and magnitude of recent financial crisis which affected Latvias economy, the forecast performance of non-linear models is intriguing. The paper would benefit from making cross country comparisons of model performances in other Baltic States (Lithuania and Estonia), as to our best knowledge, there is no such study conducted as yet.

APPENDIX

Table A.1
Dataset of macroeconomic variables

No	Variable	Form	Source	Transfor-mation
	Business and consumer surveys			
1	Total Sentiment Indicator	SA	ECFIN	Δlog
	Industry survey			
2	Confidence Indicator	SA	ECFIN	Δ
3	Production trend observed in recent months	SA	ECFIN	Δ
4	Assessment of order-book levels	SA	ECFIN	Δ
5	Assessment of export order-book levels	SA	ECFIN	Δ
6	Assessment of stocks of finished products	SA	ECFIN	Δ
7	Production expectations for the months ahead	SA	ECFIN	Δ
8	Selling price expectations for the months ahead	SA	ECFIN	Δ
9	Employment expectations for the months ahead	SA	ECFIN	Δ
	Services survey			
10	Confidence Indicator	SA	ECFIN	Δ
11	Business situation development over past 3 months	SA	ECFIN	Δ
12	Evolution of the demand over past 3 months	SA	ECFIN	Δ
13	Expectations of the demand over next 3 months	SA	ECFIN	Δ
14	Evolution of employment over past 3 months	SA	ECFIN	Δ
15	Expectations of employment over next 3 months	SA	ECFIN	Δ
16	Expectations of prices over next 3 months	SA	ECFIN	Δ
	Consumers survey			
17	Confidence Indicator	SA	ECFIN	Δ
18	Financial situation over last 12 months	SA	ECFIN	Δ
19	Financial situation over next 12 months	SA	ECFIN	Δ
20	General economic situation over last 12 months	SA	ECFIN	Δ
21	General economic situation over next 12 months	SA	ECFIN	Δ
22	Price trends over last 12 months	SA	ECFIN	Δ
23	Price trends over next 12 months	SA	ECFIN	Δ
24	Unemployment expectations over next 12 months	SA	ECFIN	Δ
25	Major purchases at present	SA	ECFIN	Δ
26	Major purchases over next 12 months	SA	ECFIN	Δ
27	Savings at present	SA	ECFIN	Δ
28	Savings over next 12 months	SA	ECFIN	Δ
29	Statement on financial situation of household	SA	ECFIN	Δ
	Retail survey			
30	Confidence Indicator	SA	ECFIN	Δ
31	Business activity (sales) development over past 3 months	SA	ECFIN	Δ
32	Volume of stock currently hold	SA	ECFIN	Δ
33	Orders expectations over next 3 months	SA	ECFIN	Δ
34	Business activity expectations over next 3 months	SA	ECFIN	Δ
35	Employment expectations over next 3 months	SA	ECFIN	Δ
36	Price expectations over next 3 months	SA	ECFIN	Δ

No	Variable	Form	Source	Transfor-mation
	Building survey			
37	Confidence Indicator	SA	ECFIN	Δ
38	Building activity development over past 3 months	SA	ECFIN	Δ
	Main factors currently limiting building activity:			
39	*None (%)*	SA	ECFIN	Δ
40	*Insufficient demand (%)*	SA	ECFIN	Δ
41	*Weather conditions (%)*	SA	ECFIN	Δ
42	*Shortage of labour force (%)*	SA	ECFIN	Δ
43	*Shortage of material and/or equipment (%)*	SA	ECFIN	Δ
44	*Other factors (%)*	SA	ECFIN	Δ
45	*Financial constraints (%)*	SA	ECFIN	Δ
46	*Evolution of current overall order books*	SA	ECFIN	Δ
47	*Employment expectations over next 3 months*	SA	ECFIN	Δ
48	*Prices expectations over next 3 months*	SA	ECFIN	Δ
	Industry (index: 2010 = 100)			
49	Mining and quarrying	WDA	Eurostat	Δlog
50	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply	WDA	Eurostat	Δlog
51	Manufacturing	WDA	Eurostat	Δlog
52	Manufacture of food products	WDA	Eurostat	Δlog
53	Manufacture of beverages	WDA	Eurostat	Δlog
54	Manufacture of textiles	WDA	Eurostat	Δlog
55	Manufacture of wearing apparel	WDA	Eurostat	Δlog
56	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	WDA	Eurostat	Δlog
57	Manufacture of paper and paper products	WDA	Eurostat	Δlog
58	Printing and reproduction of recorded media	WDA	Eurostat	Δlog
59	Manufacture of chemicals and chemical products	WDA	Eurostat	Δlog
60	Manufacture of rubber and plastic products	WDA	Eurostat	Δlog
61	Manufacture of other non-metallic mineral products	WDA	Eurostat	Δlog
62	Manufacture of basic metals	WDA	Eurostat	Δlog
63	Manufacture of fabricated metal products, except machinery and equipment	WDA	Eurostat	Δlog
64	Manufacture of electrical equipment	WDA	Eurostat	Δlog
65	Manufacture of machinery and equipment n.e.c.	WDA	Eurostat	Δlog
66	Manufacture of motor vehicles, trailers and semi-trailers	WDA	Eurostat	Δlog
67	Manufacture of other transport equipment	WDA	Eurostat	Δlog
68	Manufacture of furniture	WDA	Eurostat	Δlog
69	Other manufacturing	WDA	Eurostat	Δlog
70	Electricity, gas, steam and air conditioning supply	WDA	Eurostat	Δlog
	Turnover and volume of sales in wholesale and retail trade (index: 2010 = 100)			
71	Retail trade, except of motor vehicles and motorcycles	SA	Eurostat	Δlog
72	Retail sale of food, beverages and tobacco	SA	Eurostat	Δlog
73	Retail sale of non-food products (including fuel)	SA	Eurostat	Δlog
74	Retail sale of non-food products (except fuel)	SA	Eurostat	Δlog
75	Retail sale of textiles, clothing, footwear and leather goods in specialised stores	SA	Eurostat	Δlog

No	Variable	Form	Source	Transfor-mation
76	Dispensing chemist; retail sale of medical and orthopaedic goods, cosmetic and toilet articles in specialised stores	SA	Eurostat	Δlog
77	Retail sale of information and communication equipment; other household equipment (except textiles); cultural and recreation goods, etc. in specialised stores	SA	Eurostat	Δlog
78	Retail sale of computers, peripheral units and software; telecommunications equipment, etc. in specialised stores	SA	Eurostat	Δlog
79	Retail sale of audio and video equipment; hardware, paints and glass; electrical household appliances, etc. in specialised stores	SA	Eurostat	Δlog
80	Retail trade, except of motor vehicles, motorcycles and fuel	SA	Eurostat	Δlog
81	Retail sale in non-specialised stores	SA	Eurostat	Δlog
82	Retail sale in non-specialised stores with food, beverages or tobacco predominating	SA	Eurostat	Δlog
83	Other retail sale in non-specialised stores	SA	Eurostat	Δlog
84	Retail sale of food, beverages and tobacco in specialised stores	SA	Eurostat	Δlog
85	Retail sale of automotive fuel in specialised stores	SA	Eurostat	Δlog
86	Retail sale via mail order houses or via Internet	SA	Eurostat	Δlog
	HICP (index: 2005 = 100)			
87	All-items HICP	NSA	Eurostat	Δlog
88	Food and non-alcoholic beverages	NSA	Eurostat	Δlog
89	Alcoholic beverages, tobacco and narcotics	NSA	Eurostat	Δlog
90	Clothing and footwear	NSA	Eurostat	Δlog
91	Housing, water, electricity, gas and other fuels	NSA	Eurostat	Δlog
92	Furnishings, household equipment and routine maintenance of the house	NSA	Eurostat	Δlog
93	Health	NSA	Eurostat	Δlog
94	Transport	NSA	Eurostat	Δlog
95	Communications	NSA	Eurostat	Δlog
96	Recreation and culture	NSA	Eurostat	Δlog
97	Education	NSA	Eurostat	Δlog
98	Restaurants and hotels	NSA	Eurostat	Δlog
99	Miscellaneous goods and services	NSA	Eurostat	Δlog
	Producer prices in industry (index: 2010 = 100)			
100	Mining and quarrying	NSA	Eurostat	Δlog
101	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply	NSA	Eurostat	Δlog
102	Manufacturing	NSA	Eurostat	Δlog
103	Electricity, gas, steam and air conditioning supply	NSA	Eurostat	Δlog
104	Water collection, treatment and supply	NSA	Eurostat	Δlog
105	MIG – Capital goods	NSA	Eurostat	Δlog
106	MIG – Consumer goods	NSA	Eurostat	Δlog
107	MIG – Durable consumer goods	NSA	Eurostat	Δlog
108	MIG – Intermediate goods	NSA	Eurostat	Δlog
109	MIG – Non-durable consumer goods	NSA	Eurostat	Δlog
110	MIG – Energy	NSA	Eurostat	Δlog
	Foreign trade (thousands of lats)			
111	Exports, total	NSA	CSB	Δlog
112	Live animals and animal products	NSA	CSB	Δlog
113	Vegetable products	NSA	CSB	Δlog

No	Variable	Form	Source	Transfor-mation
114	Fats and oils	NSA	CSB	Δlog
115	Prepared foodstuffs, including alcoholic and non-alcoholic beverages and tobacco products	NSA	CSB	Δlog
116	Mineral products	NSA	CSB	Δlog
117	Products of the chemical and allied industries	NSA	CSB	Δlog
118	Plastics and articles thereof; rubber and articles thereof	NSA	CSB	Δlog
119	Raw hides, leather, fur skins and articles thereof	NSA	CSB	Δlog
120	Wood and articles of wood	NSA	CSB	Δlog
121	Pulp of wood; paper and paperboard	NSA	CSB	Δlog
122	Textiles and textile articles	NSA	CSB	Δlog
123	Footwear, headgear, umbrellas and other articles	NSA	CSB	Δlog
124	Articles of stone, plaster, cement, glassware and ceramic products	NSA	CSB	Δlog
125	Precious, semiprecious stone, precious metals, metals clad with precious metal	NSA	CSB	Δlog
126	Base metals and articles of base metals	NSA	CSB	Δlog
127	Machinery and mechanical appliances; electrical equipment	NSA	CSB	Δlog
128	Transport vehicles	NSA	CSB	Δlog
129	Optical instruments and apparatus inc. medical; clocks and watches; musical instruments	NSA	CSB	Δlog
130	Miscellaneous manufactured articles	NSA	CSB	Δlog
131	Imports, total	NSA	CSB	Δlog
132	Live animals and animal products	NSA	CSB	Δlog
133	Vegetable products	NSA	CSB	Δlog
134	Fats and oils	NSA	CSB	Δlog
135	Prepared foodstuffs including alcoholic and non-alcoholic beverages and tobacco products	NSA	CSB	Δlog
136	Mineral products	NSA	CSB	Δlog
137	Products of the chemical and allied industries	NSA	CSB	Δlog
138	Plastics and articles thereof; rubber and articles thereof	NSA	CSB	Δlog
139	Raw hides, leather, fur skins and articles thereof	NSA	CSB	Δlog
140	Wood and articles of wood	NSA	CSB	Δlog
141	Pulp of wood; paper and paperboard	NSA	CSB	Δlog
142	Textiles and textile articles	NSA	CSB	Δlog
143	Footwear, headgear, umbrellas and other articles	NSA	CSB	Δlog
144	Articles of stone, plaster, cement, glassware and ceramic products	NSA	CSB	Δlog
145	Precious, semiprecious stone, precious metals, metals clad with precious metal	NSA	CSB	Δlog
146	Base metals and articles of base metals	NSA	CSB	Δlog
147	Machinery and mechanical appliances; electrical equipment	NSA	CSB	Δlog
148	Transport vehicles	NSA	CSB	Δlog
149	Optical instruments and apparatus inc. medical; clocks and watches; musical instruments	NSA	CSB	Δlog
150	Miscellaneous manufactured articles	NSA	CSB	Δlog
	Interest rates			
151	EURIBOR 3m (%)	NSA	ECB	Δ
152	EURIBOR 6m (%)	NSA	ECB	Δ
153	RIGIBOR 3m (%)	NSA	Latvijas Banka	Δ

No	Variable	Form	Source	Transfor-mation
154	RIGIBOR 6m (%)	NSA	Latvijas Banka	Δ
	Exchange rates			
155	NEER13 (1996m01 = 100)	NSA	Eurostat	Δlog
156	REERCPI13 (1996m01 = 100)	NSA	Eurostat	Δlog
157	REERPPI13 (1996m01 = 100)	NSA	Eurostat	Δlog
158	EUR/USD	NSA	Eurostat	Δlog
	Monetary statistics (millions of lats)			
159	Money Stock M1	SA	Latvijas Banka	Δlog
160	Money Stock M2	SA	Latvijas Banka	Δlog
161	Money Stock M3	SA	Latvijas Banka	Δlog
162	Total deposits of residents held at monetary financial institutions (consolidated)	NSA	Latvijas Banka	Δlog
163	Central government deposits held at monetary financial institutions	NSA	Latvijas Banka	Δlog
164	Deposits of other residents held at monetary financial institutions	NSA	Latvijas Banka	Δlog
165	Loans to total residents granted by monetary financial institutions (consolidated)	NSA	Latvijas Banka	Δlog
166	Loans to general government granted by monetary financial institutions	NSA	Latvijas Banka	Δlog
167	Loans to other residents granted by monetary financial institutions	NSA	Latvijas Banka	Δlog
	Fiscal sector (thousands of lats)			
168	General government tax revenues	NSA	Treasury	Δlog
169	Personal income tax	NSA	Treasury	Δlog
170	Enterprise income tax	NSA	Treasury	Δlog
171	Social contributions	NSA	Treasury	Δlog
172	Real estate tax	NSA	Treasury	Δlog
173	Value added tax	NSA	Treasury	Δlog
174	Excise tax	NSA	Treasury	Δlog
175	General government expenditure	NSA	Treasury	Δlog
176	General government budget balance	NSA	Treasury	Δ
	Balance of payments (thousands of lats)			
177	Services exports	NSA	Latvijas Banka	Δlog
178	Services imports	NSA	Latvijas Banka	Δlog
179	Net income	NSA	Latvijas Banka	Δ
180	Net transfers		Latvijas Banka	Δ
181	Net direct investment	NSA	Latvijas Banka	Δ
182	Net portfolio investment	NSA	Latvijas Banka	Δ
183	Net other investment	NSA	Latvijas Banka	Δ
	Other data			
184	Unemployment rate (percent)	NSA	SEA	Δ
185	Job vacancies (thousands)	NSA	SEA	Δlog
186	Port turnover (thousands, tons)	NSA	CSB	Δlog
187	Brent oil price (lats)	NSA	Reuters	Δlog

Note. SA – seasonally adjusted data; WDA – working day adjusted data; NSA – not seasonally adjusted data; n.e.c. – not elsewhere classified; Treasury – Treasury of the Republic of Latvia; SEA – State Employment Agency of Latvia.

Table A.2
NACE Rev. 1.1 and NACE Rev. 2 classifications published by CSB

NACE Rev. 1.1 classification		NACE Rev. 2 classification	
Section	Description	Section	Description
A	Agriculture, hunting and forestry	A	Agriculture, forestry and fishing
B	Fishing	BDE	Mining and quarrying; electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities
C	Mining and quarrying	C	Manufacturing
D	Manufacturing	F	Construction
E	Electricity, gas, and water supply	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
F	Construction	H	Transportation and storage
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	I	Accommodation and food service activities
H	Hotels and restaurants	J	Information and communication
I	Transport, storage and communications	K	Financial and insurance activities
J	Financial intermediation	L	Real estate activities
K	Real estate, renting and business activities	MNS	Professional, scientific and technical activities; administrative and support service activities; other service activities
L	Public administration and defence; compulsory social security	O	Public administration and defence; compulsory social security
M	Education	P	Education
N	Health and social work	Q	Human health and social work activities
O	Other community, social and personal services activities	R	Arts, entertainment and recreation
D21	Taxes on products	D21	Taxes on products
D31	Subsidies on products	D31	Subsidies on products

Notes. This is not a complete list of NACE sections but only the one published by the CSB. For complete list see Eurostat (2008).

A.1 Expectation maximisation algorithm with stacked time series suggested by Stock and Watson (2002a)

Stack X_t with its own two lags;

Obtain $\hat{X}_t$ dataset comprising original observations if elements are not missing, $\hat{X}_t = X_t$, and equal to zero if missing, $\hat{X}_t = 0$;

Estimate factors F_t^0 as the first r principal components of dataset $\hat{X}_t$;

Recover $\hat{X}_t$ with non-missing elements, $\hat{X}_t = X_t$, and missing elements set to $\hat{X}_t = \hat{\Lambda}^{f_0} \hat{F}_t^0$;

Estimate F_t^1 as the first r principal components of $\hat{X}_t$;

Back to step 4 using F_t^1 instead of F_t^0.

We exploit two factors ($r = 2$) in EM algorithm and stacked X_t. By iterating steps in the algorithm shown above, we obtain stable estimates of the missing values. It should be noted that the iteration mechanism does not affect non-missing values. They remain unchanged throughout iterations. For more information on general EM algorithm solutions see Dempster et al. (1977).

Table A3.1
RMSFE results of AR models

	1 quarter ahead			2 quarters ahead		
	1st	2nd	3rd	1st	2nd	3rd
AR						
p = 1	2.92	2.89	2.88	5.22	5.49	5.50
p = 2	2.98	2.94	2.93	5.35	5.60	5.60
p = 3	3.00	2.95	2.94	5.48	5.72	5.72
p = 4	3.10	3.04	3.03	5.74	5.84	5.84
AR_EXP						
p = 1	2.73	2.63	2.60	5.07	5.16	5.15
p = 2	2.69	2.67	2.65	4.97	4.96	4.94
p = 3	2.93	2.95	2.94	5.33	5.38	5.36
p = 4	3.12	3.14	3.12	5.68	5.75	5.72
AR_OUT						
p = 1	3.42	3.35	3.34	5.89	6.08	6.08
p = 2	3.80	3.73	3.72	6.33	6.53	6.53
p = 3	3.77	3.71	3.69	6.20	6.39	6.39
p = 4	4.04	3.97	3.95	6.91	7.10	7.09

Notes. 1st, 2nd and 3rd denote consecutive months since the publication of GDP. Model acronyms denote aggregate AR, AR model from expenditure side (AR_EXP) and AR model from production side (AR_OUT), and p is the number of lags of dependent variable.

Table A3.2
RMSFE results of BMs

	1 quarter ahead			2 quarters ahead		
	1st	2nd	3rd	1st	2nd	3rd
BM						
p = 1	2.34	2.24	2.24	4.25	4.25	4.31
p = 2	2.32	2.26	2.28	4.27	4.31	4.43
p = 3	2.36	2.33	2.35	4.48	4.48	4.61
p = 4	2.40	2.38	2.41	4.59	4.66	4.84
BM_EXP						
p = 1	2.94	2.88	2.86	5.01	4.29	4.75
p = 2	3.20	3.02	3.05	5.21	4.51	4.94
p = 3	3.42	3.34	3.34	5.19	4.58	4.99
p = 4	3.41	3.16	3.24	5.06	4.44	4.86
BM_OUT						
p = 1	2.50	2.45	2.32	4.66	4.50	4.32
p = 2	2.79	2.70	2.57	5.48	5.19	5.03
p = 3	2.77	2.68	2.56	5.44	5.19	5.05
p = 4	2.89	2.82	2.69	6.00	5.77	5.59

Notes. 1st, 2nd and 3rd denote consecutive months since the publication of GDP. Model acronyms denote aggregate BM, BM from expenditure side (BM_EXP) and BM from production side (BM_OUT), and p is the number of lags of dependent variable. In the case of disaggregated models, the number of lags is applied to each component of respective disaggregate approach.

Table A3.3
RMSFE results of FMs

	1 quarter ahead			2 quarters ahead		
	1st	2nd	3rd	1st	2nd	3rd
FM, p = 1						
m = 0, r = 1	2.21	2.20	2.09	3.79	3.88	3.76
m = 0, r = 2	2.26	2.15	2.14	3.97	3.97	3.95
m = 0, r = 3	2.29	1.97	2.10	3.97	3.98	4.02
m = 0, r = 4	2.04	2.00	2.03	3.78	3.73	3.73
m = 1, r = 1	2.21	2.21	2.12	3.84	3.97	3.92
m = 1, r = 2	2.25	2.12	2.10	4.10	4.13	4.13
m = 1, r = 3	2.28	1.81	2.02	4.25	4.02	4.26
m = 1, r = 4	1.91	1.93	1.78	3.76	3.47	3.52
FM_EXP, p = 1						
m = 0, r = 1	2.29	2.26	2.19	3.92	3.87	3.70
m = 0, r = 2	2.35	2.24	2.24	3.95	3.77	3.70
m = 0, r = 3	2.38	2.16	2.34	3.96	4.20	3.79
m = 0, r = 4	2.13	2.08	2.05	4.01	4.06	3.77
m = 1, r = 1	2.24	2.12	2.13	3.96	3.91	3.77
m = 1, r = 2	2.42	2.15	2.25	4.01	3.74	3.52
m = 1, r = 3	2.40	2.14	2.26	4.18	4.27	3.97
m = 1, r = 4	2.30	2.52	2.20	3.91	3.86	3.58
FM_OUT, p = 1						
m = 0, r = 1	2.35	2.37	2.25	4.20	4.34	4.13
m = 0, r = 2	2.36	2.29	2.26	4.31	4.31	4.27
m = 0, r = 3	2.31	2.42	2.17	4.04	4.59	4.15
m = 0, r = 4	2.44	2.94	2.81	3.90	4.35	4.20
m = 1, r = 1	2.13	2.17	2.17	4.00	4.29	4.17
m = 1, r = 2	2.21	2.10	2.14	4.28	4.28	4.20
m = 1, r = 3	2.15	2.12	1.91	4.16	4.30	4.19
m = 1, r = 4	2.36	3.08	2.45	3.79	3.80	3.66

Notes. 1st, 2nd and 3rd denote consecutive months since the publication of GDP. Model acronyms denote aggregate FM, FM from expenditure side (FM_EXP) and FM from production side (FM_OUT). In the case of disaggregate models, the number of lags is applied to each component of respective disaggregate approach. r is the number of factors, m is the number of factor lags, and p is the number of lags of dependent variable.

Table A3.4
RMSFE results of VAR models

	1 quarter ahead			2 quarters ahead		
VAR	1st	2nd	3rd	1st	2nd	3rd
p = 1	2.86	2.78	2.77	5.07	5.20	5.20
p = 2	2.95	2.84	2.86	5.28	5.33	5.35
p = 3	3.13	3.05	3.05	5.43	5.62	5.65
p = 4	3.50	3.46	3.45	5.62	5.45	5.46

Note. 1st, 2nd and 3rd denote consecutive months since the publication of GDP and p is the number of lags.

Table A3.5
RMSFE results of BVAR models

	1 quarter ahead			2 quarters ahead		
BVAR	1st	2nd	3rd	1st	2nd	3rd
p = 1	2.84	2.81	2.79	5.09	5.36	5.36
p = 2	2.86	2.81	2.80	5.19	5.40	5.40
p = 3	2.85	2.81	2.80	5.18	5.41	5.41
p = 4	2.86	2.81	2.80	5.20	5.42	5.42

Note. 1st, 2nd and 3rd denote consecutive months since the publication of GDP and p is the number of lags.

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