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KONSTANTĪNS BEŅKOVSKIS

SHORT-TERM FORECASTS OF LATVIA'S REAL GROSS DOMESTIC PRODUCT GROWTH USING MONTHLY INDICATORS

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WORKING PAPER

CONTENTS

ABBREVIATIONS

ARIMA – autoregressive integrated moving average
CIF – cost, insurance and freight at the importer's border
CPI – consumer price index
CSB – Central Statistical Bureau of Latvia
DM test – Diebold-Mariano test
EC – European Commission
ESI – economic sentiment indicator
FOB – free on board at the exporter's border
GDP – gross domestic product
LM – Lagrange multiplier
M3 – broad money aggregate
MFI – monetary financial institution
NEER – nominal effective exchange rate
PPI – producer price index
RMSE – root mean square error
SIC – Schwartz information criterion
VAR – vector autoregression

ABSTRACT

The conjunctural information from monthly indicators, e.g. industrial production, retail trade turnover, M3, confidence indicators, etc. could partly replace GDP data before the first official release is published. It is possible to incorporate monthly indicators into short-term forecasting models of GDP using quarterly bridge equations or state space models. In many cases monthly indicators are released with a lag, and GDP forecasts based on actual figures are available only shortly before the official release. To eliminate this drawback, missing observations of monthly indicators could be forecasted using simple univariate time-series models.

To perform real-time analysis of the forecasting performance of bridge equations and state space models, a real-time database containing real GDP series with 28 vintages of quarterly real GDP was created.

According to calculations, only bridge equations and state space models containing M3 monthly data perform better than the benchmark ARIMA model. Both model types using M3 provide valuable information forecast for the first and final releases of GDP. This does not mean, however, that other conjunctural indicators should not be used in forecasting, as the analysis does not take into account possible future changes in links between monthly indicators and quarterly GDP growth.

JEL classification: C22, C53, E37

Key words: bridge equations, state space model, out-of-sample forecasting, real-time database, interpolation.

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INTRODUCTION

Timely information about processes occurring in the economy is crucial for the analysis and decision making for economic policy purposes. Quarterly information on GDP is of great relevance to policy makers as it is a broad indicator of domestic activity covering all sectors of the economy. However, this information on domestic activity comes with a significant delay: the first official release is available only in 70 days after the end of the quarter and this information lag creates a significant problem for analysing, forecasting and decision making.

Fortunately, GDP is not the only source of information on economic activity. Statistical offices and other organisations provide data on industrial production, retail sales, international trade in goods, business confidence, M3, etc. Although these indicators capture only partial information on domestic activity, they have a significant advantage over GDP statistics in terms of availability. These data are released much faster than GDP figures; moreover, they are available at a monthly frequency, providing some guideline on economic processes even before the end of the quarter.

Obviously, the conjunctural information from monthly indicators could partly replace GDP data before the first official release is published. Usually, this information is used in a qualitative manner. The goal of this paper is to investigate the benefits of incorporating conjunctural indicators into short-term forecasting models of Latvia's GDP. In other words, we are going to check whether information from monthly indicators could improve our forecasts of GDP in the recent quarter.

Two methodologies of including such information in short-term forecasts are used in the paper. First, we study univariate forecasting equations, called also bridge equations. This methodology allows us to predict the quarterly real GDP growth using data on monthly indicators, aggregated to a quarterly frequency. The second method is unobserved component model, which allows for the estimation of GDP figure at a monthly frequency, providing interpolation based on information from monthly indicators. The forecasting ability of the two methodologies with various monthly indicators is checked by out-of-sample forecasting exercises and compared with a benchmark naïve autoregressive model. To increase reliability of the tests, we created a real-time database for Latvia's GDP.

The structure of the paper is as follows. Section 1 describes the real-time database of real GDP and provides information on monthly indicators used in the paper as well as presents the time table of statistical data releases in Latvia. Section 2 deals with the idea behind bridge equations and checks the forecasting performance of quarterly bridge equations when missing observations of monthly indicators are forecasted by ARIMA models. Unobserved component models for Latvia's GDP as well as their forecasting performance are discussed in Section 3. The last Section concludes.

1. DESCRIPTION OF THE DATA SET

1.1 Real-Time GDP Data

Some studies have already assessed the performance of various models in forecasting Latvia's real GDP using the so-called pseudo real-time analysis (see (14) for forecasting performance of business and consumer survey data, and (1) for forecasting performance of dynamic factor models). While these exercises partly mimic the real-time situation, they ignore the possibility of data revisions in the GDP and other series. However, policy makers and business society use predictions that are made before data revisions become known; therefore, the evaluation of the impact of data revisions is vitally necessary to assess the reliability of short-term forecasts.

Quarterly data on Latvia's real GDP are published on the 70th day after the end of the reference period or in other words, GDP figures are available with more than a 2-month lag. Moreover, GDP data are subject to revisions after the annual balancing of the System of National Accounts. As of 2007, the CSB also publishes flash estimates of real GDP annual growth based on available statistical data and econometric models. These estimates are published on the 40th day after the end of the reference period and are available one month earlier than the first release. However, the history of flash estimates is too short to make any systematic analysis, and preliminary estimations of real GDP are ignored in this paper.

To perform the real-time analysis of forecasting performance, we created a real-time database, which contains real GDP series with different vintages. In other words, we do not use just one latest GDP data row but create a set of GDP time series – one for each quarter. Using such database, one can discover historical GDP figures available for analysis at any particular period of time. In addition, the real-time database allows us to find out what and when GDP data revisions were made.

The database was prepared using CSB quarterly publications of *Macroeconomic Indicators of Latvia* and contains 28 vintages of quarterly real GDP, both seasonally adjusted and unadjusted, starting with the data available at the beginning of June 2001 (1995 Q1–2001 Q1) and finishing with the data available at the beginning of March 2008 (1995 Q1–2007 Q4).

Appendix 1 shows the revisions made between the first release (published on the 70th day after the end of the reference quarter) and final release (data available at the beginning of December 2007). According to Chart A1, the revisions in seasonally unadjusted real GDP annual growth were 0.25 percentage point between 2001 and 2007 on average and did not exceed 1.0 percentage point. These revisions are small in comparison with the annual GDP growth in Latvia (9% on average during the observed period). The largest revisions were made in 2001 and 2002 data, while there are no revisions in 2007 data, as no annual balancing has been done as yet.

Although annual growth of seasonally unadjusted real GDP is usually in the focus of attention for policy makers and society, modellers prefer to use the quarterly growth of seasonally adjusted GDP. Chart A2 shows that the revisions in seasonally adjusted real quarterly GDP growth are bigger, 0.4 percentage point on average, and are relatively large in comparison with the quarterly GDP growth (2.2% on average during the observed period). Higher revisions come from the fact that now changes in data are driven not only by the changes in seasonally unadjusted GDP, but also by the changes in seasonal factors when more data become available. The disregard of such revisions can lead to incorrect evaluation of forecasting performance of the model.

1.2 Monthly Indicators

The next step is to choose monthly indicators that could be useful in explaining the dynamics of Latvia's real GDP. The selection of explanatory monthly variables was based on the following criteria. First, the selected monthly indicator should be available as quickly as possible after the end of the quarter, and, definitely, it should be available before the first GDP release. Second, there should be an economic reason for this variable to be a good indicator for real GDP. Third, data on the monthly indicator should be available at least from the beginning of 1996. The following monthly indicators fulfil the abovementioned criteria and their predicting ability is checked further in the paper.

- The volume index of industrial production (seasonally unadjusted data), capturing changes in the volume of industrial output. Industry includes mining and quarrying (C), manufacturing (D), and electricity, gas and water supply (E). This index is calculated on the basis of industrial activity surveys and published on the 38th day after the end of the reference period.
- Exports (in current FOB values) and imports (in current CIF values) of goods, calculated using INTRASTAT monthly surveys of enterprises engaged in trade with the EU Member States and customs declarations on trade with third countries. Monthly data are published on the 40th working day after the end of the reference period.
- The retail trade turnover index at constant prices, including enterprises selling motor vehicles and retailing automotive fuel. This index is calculated on the basis of monthly turnover surveys and published on the 30th day after the end of the reference period.
- M3, comprising currency in circulation, overnight deposits in all currencies held with MFIs, deposits redeemable at a period of notice of up to and including 3 months in all currencies, and deposits with an agreed maturity of up to and including 2 years in all currencies held with MFIs, repurchase agreements, debt securities with a maturity of up to and including 2 years issued by MFIs, and money market fund shares and units. Data on M3 are published on the 17th working day after the end of the reference month. Data on M3 are available only from 1998, therefore data for 1996–1997 were estimated using the growth rate of money aggregate M2X.
- CPI, reflecting changes in the prices of consumer goods and services. CPI is calculated using sample survey of consumer prices and released on the 6th working day after the end of the reference month.
- PPI, describing changes in producer prices in industry. The index is calculated using sample surveys of producer prices and published on the 15th working day after the end of the reference month.

– Interest rate on short-term loans in lats, i.e. average interest rates of commercial banks on credits in lats (with adjustable interest rate and initial adjustment period of up to 1 year) to non-financial corporations and households. Data are based on information of the Bank of Latvia and published on the 20th day following the end of the reference month.

– Expenditure of the general government consolidated budget. Monthly data on budget execution are reported in the aggregated report of the Treasury *General Government Consolidated Budget Execution* published on the 16th day of the next month (the 20th day in January).

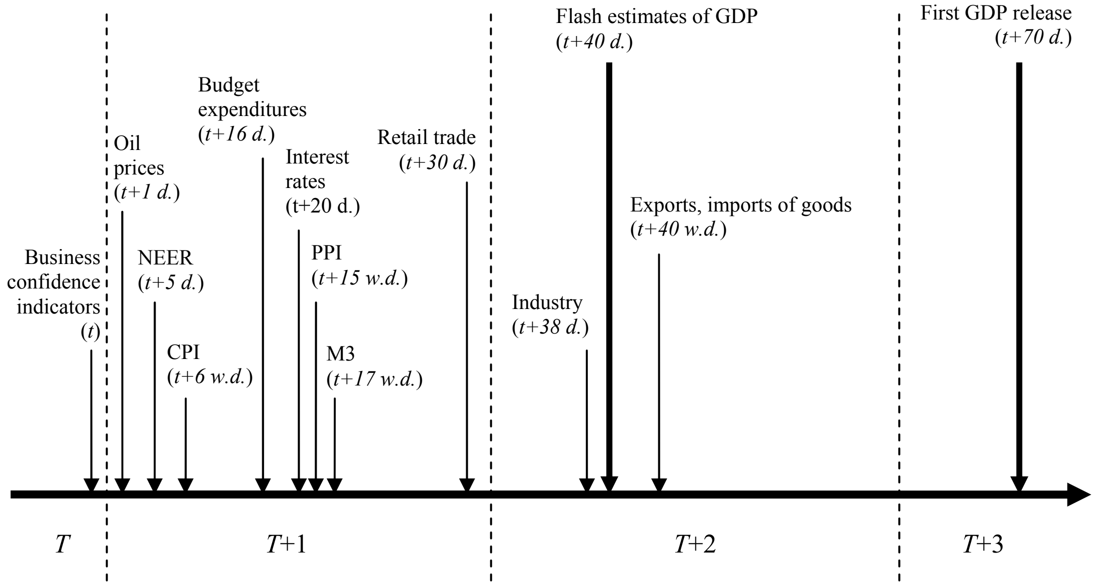
– Brent crude oil prices (in USD), with data available in real time.

– The nominal effective exchange rate (NEER) of the lats, i.e. average weighted rates of the lats against the currencies of Latvia's 13 major trade partners (Denmark, Estonia, Finland, France, Germany, Italy, Lithuania, the Netherlands, Poland, Russia, Sweden, the United Kingdom and the United States). An increase in NEER index points to the appreciation of the lats against major trade partners' currencies. The index is published on the 5th day after the end of the reference month.

– Business confidence indicators, i.e. indicators based on qualitative economic surveys intended for short-term economic analysis. We use seasonally adjusted industrial, construction and retail trade confidence indicators as well as the overall ESI for Latvia (consumer and service indicators were not used because of short series). Confidence indicators are released before the end of the current month.

Chart 1
Timing of GDP and monthly indicator releases

(*T* – last month of the reference quarter, *t* – last day of the reference quarter, *d.* – day, *w.*d. – working day)



Sources: CSB, EC, Treasury and Bank of Latvia.

Unlike for real GDP, we were not able to create a real-time database for monthly indicators due to information limitations. However, this should not significantly distort the results of real-time analysis, as many monthly indicators are not subject to data revisions (CPI, M3, interest rates, oil prices, NEER and business confidence indicators). We use data on seasonally adjusted indicators when possible (business confidence indicators). In other cases when data have seasonal pattern, monthly indicators are seasonally adjusted by X12-ARIMA using the real-time approach.

2. QUARTERLY BRIDGE EQUATIONS

2.1 Description of Bridge Equations

One way to use information from indicators that are released more promptly than the GDP figures and are available at a monthly frequency is to employ such information in a univariate forecasting equation, called also bridge equation, in which the quarterly real GDP growth is estimated from monthly indicators, aggregated to a quarterly frequency:

$$\rho(L)\Delta y_t = \sum_{j=1}^{k} \delta_j(L)\Delta x_{j,t} + \varepsilon_t \qquad [1]$$

where y_t denotes the log of real GDP at a quarterly frequency, $x_{j,t}$ denotes monthly indicators aggregated to a quarterly frequency, $\rho(L)$ and $\delta_j(L)$ denote lag polynomials and *k* is the number of monthly indicators in the bridge equation.

Such methodology has been successfully used for data of various developed countries for the last 20 years at the least. The works of R. Ingenito and B. Trehan (13) for the United States data, G. Rünstler and F. Sédillot (16), A. Baffigi, R. Golinelli and G. Parigi (2), and M. Diron (6) for the euro area are only a short extraction from the list of papers exploiting bridge equations.

Since the data on monthly indicators $x_{j,t}$ are available in advance of the first GDP release, equation [1] can be used to obtain predictions of GDP for the same quarter. However, bridge equations do not provide particularly timely forecasts of GDP, as this method requires indicators to be known for the entire quarter. In some cases (for example, when exports or imports of goods are used in equation [1], see Chart 1), GDP forecasts from a bridge equation are available after flash estimates and only two weeks before the official release of GDP, thus adding little information to policy analysis.

To avoid this drawback, several authors (13, 16) proposed to produce an auxiliary model that generates forecasts of monthly indicators themselves. In this case, predictions of GDP can be obtained even if monthly indicators are only partially available within the quarter. Then GDP predictions explicitly depend also on the properties of forecasts of monthly indicators. The list of proposed models for forecasting monthly indicators consists of univariate autoregressive models, vector autoregression (VAR) models, Bayesian VAR and state space models. In this paper, we restrict the analysis to a univariate ARIMA model for simplicity reasons.

Further analysis of bridge equations for Latvia's real GDP will proceed in three steps. First, assuming that monthly indicators are available for the entire quarter, we will choose monthly indicators for various versions of bridge equation [1] and study their forecasting ability. Second, we will derive time series models to forecast monthly indicators. Finally, we will check the out-of-sample forecasting properties of bridge equations derived in step 1, combined with time series models derived in step 2.

2.2 Choice of Monthly Indicators for Bridge Equations

In this section, we choose monthly indicators and derive various versions of bridge equation [1] to forecast Latvia's real GDP, assuming that monthly indicators are available for the entire quarter. We start with forming four sets of monthly indicators on the basis of simple economic logic.

- Indicators describing GDP from the production side: the volume index of industrial production, retail trade, construction confidence indicator.
- Indicators describing GDP from the expenditure side: the retail turnover index at constant prices (approximation for private consumption), expenditure of the general government consolidated budget (approximation for government consumption), exports of goods and imports of goods.
- Financial and price indicators: M3, interest rate on short-term loans in lats, NEER of lats, CPI and PPI.
- Business confidence indicators: industrial, construction and retail trade confidence indicators as well as the overall ESI.

Our first goal is to check whether monthly indicators from a particular set are able to provide valuable information for GDP forecasts. Therefore, four bridge equations ([2]–[5]) were created using indicators of production and expenditure sides, financial and price indicators, and also confidence indicators accordingly. The list of monthly indicators and their lags included in each bridge equation was selected on the basis of SIC requiring the correct sign of coefficients before indicators (positive for industrial production, exports, retail trade, M3, government expenditure and confidence indicators, ambiguous for other indicators). The lagged real GDP was included according to SIC.

Our second goal is to find a quarterly bridge equation with the best out-of-sample forecasting performance using all available monthly indicators. To do it, the specific-to-general approach was employed. First, we chose an equation with one monthly indicator, which showed the best out-of-sample performance (based on the lowest RMSE for the final release of GDP when information on monthly indicators is available for the entire quarter). Then we added another monthly indicator, which, compared with other indicators, ensured the biggest improvement in the out-of-sample performance of equation. The process of adding monthly indicators was repeated as long as the out-of-sample RMSE of bridge equation decreased. As before, monthly indicators were included in equation [6] only in the case of coefficients having the right sign.

The structure of Latvia's economy experienced significant changes during the observed period. That is why it is possible that the link between some monthly indicators and quarterly GDP has likewise changed; this could create a problem if we use only logs of monthly indicators in equation [1]. To overcome this problem, we propose to modify monthly indicators using $\left(\frac{x_{t-1}}{y_{t-1}}\right)\Delta\ln x_t$ instead of $\Delta\ln x_t$ [1].

This modification allows us to account for structural changes in the economy, e.g. the decreasing share of industry in GDP, increasing share of trade in GDP, increasing M3 ratio to GDP, etc. Modified monthly indicators will be used when they improve SIC or RMSE statistics of the bridge equation.

We got the following bridge equations for Latvia's real GDP (estimation was made on a quarterly basis for a sample period from the second quarter of 1996 to the fourth quarter of 2007, *t*-statistics in parenthesis). Residuals of all bridge equations are normally distributed with no signs of autocorrelation and heteroskedasticity (except for equation [5], for which we can reject the hypothesis of no heteroskedasticity). Autocorrelation was detected by the Breusch-Godfrey serial correlation LM test, heteroskedasticity by the White test, and normality by the Jarque-Bera statistics.[2] The recursive coefficients of equations are reported in Appendix 2.

Production side indicators

$$\Delta\ln y_t = \underset{(12.019)}{0.017} + \underset{(4.634)}{0.202}\cdot\Delta\ln ip_t$$

$$R^2 = 0.323 \qquad [2]$$

$$SIC = -6.343$$

where y_t is real GDP, and ip_t is the volume index of industrial production. The elasticity of real GDP in real industry is close to the share of industry in total GDP at the end of the sample period.

Expenditure side indicators

$$\Delta\ln y_t = \underset{(4.773)}{0.011} + \underset{(3.990)}{0.140}\cdot\Delta\ln xg_t + \underset{(2.360)}{0.282}\cdot ratio\_trade\_gdp_{t-1}\cdot\Delta\ln trade_t$$

$$R^2 = 0.337 \qquad [3]$$

$$SIC = -6.282$$

where xg_t denotes merchandise exports, $trade_t$ is the retail trade turnover index at constant prices, and $ratio\_trade\_gdp_t$ is the share of trade's nominal value added in nominal GDP[3]. It turned out that the modified monthly indicator of retail trade (multiplied by ratio to GDP) outperformed the traditional indicator in equation [3] capturing the importance of changes in the GDP structure. The coefficient before

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[1] Note that from $\Delta\ln y_t = \beta\cdot\left(\frac{x_{t-1}}{y_{t-1}}\right)\Delta\ln x_t$ and $\Delta\ln y_t \approx \left(\frac{y_t}{y_{t-1}}-1\right)$ it follows that $\Delta y_t \approx \beta\cdot\Delta x_t$; therefore, if industrial production or retail trade turnover is used as a monthly indicator, this form ensures insensitivity to structural changes, as both parts are denoted in lats (at constant prices).

[2] Results are available by request.

[3] Nominal ratios were used, as they are independent of the choice of base year. Moreover, some monthly indicators, e.g. M3 or budget expenditure, are nominal as well.

goods exports is relatively low and does not coincide with the share of exports in total GDP.

Financial and price indicators

$$\Delta \ln y_t = \underset{(3.264)}{0.008} + \underset{(4.916)}{0.162} \cdot ratio\_m3\_gdp_{t-1} \cdot \Delta \ln m3_t$$

$$R^2 = 0.349 \qquad [4]$$

$$SIC = -6.382$$

where $m3_t$ is M3 and $ratio\_m3\_gdp_t$ is the ratio of M3 to nominal GDP. There is some inconsistency in equation [4], since we have a real variable on the left-hand side and a nominal one on the right-hand side. However, using real money (M3 deflated by CPI or PPI) significantly worsens SIC, as does also the inclusion of CPI or PPI in the right-hand side of equation. The in-sample explanation power of equation [4] is better when we use money aggregate M3 multiplied by ratio of M3 to nominal GDP, thus taking into account the growing ratio of money to GDP in Latvia.

Confidence indicators

$$\Delta \ln y_t = \underset{(4.652)}{0.014} + \underset{(1.760)}{0.244} \cdot \Delta \ln y_{t-2} + \underset{(0.733)}{0.00008} \cdot \Delta ind\_bc_t$$

$$R^2 = 0.074 \qquad [5]$$

$$SIC = -5.950$$

where ind_bc_t denotes the industrial confidence indicator. The inclusion of business confidence indicators gives the worst results in terms of in-sample fit. Moreover, only the industrial confidence indicator and overall ESI enter the bridge equation with a positive (albeit statistically insignificant) sign.

Best forecasting performance

Finally, we derived one more bridge equation, choosing monthly indicators to maximise out-of-sample performance (RMSE) preserving the right signs of coefficients before monthly indicators.

$$\Delta \ln y_t = \underset{(3.518)}{0.008} + \underset{(3.693)}{0.124} \cdot ratio\_m3\_gdp_{t-1} \cdot \Delta \ln m3_t + \underset{(3.144)}{0.137} \cdot \Delta \ln ip_t +$$

$$+ \underset{(2.045)}{0.071} \cdot \Delta \ln xg_t - \underset{(-0.781)}{0.027} \cdot \Delta \ln mg_t \qquad [6].$$

$$R^2 = 0.560$$

$$SIC = -6.528$$

In addition to the best out-of-sample forecasting performance, equation [6] has also a better in-sample fit in comparison with equations [2]–[5]. Bridge equation [6] includes four monthly indicators: M3 (multiplied by ratio of M3 to nominal GDP), volume index of industrial production, exports of goods and imports of goods.

Table 1
Out-of-sample forecasting performance of bridge equation models
(Latvia's real GDP forecasts in the previous quarter)

Model	Indicator	First release	Final release
Production side: industrial production (equation [2])	RMSE Relative RMSE*	0.961 1.24	0.890 1.25
Expenditure side: retail trade and exports of goods (equation [3])	RMSE Relative RMSE*	0.913 1.18	0.731 1.03
Financial side: M3 (equation [4])	RMSE Relative RMSE*	**0.536** **0.69**	**0.532** **0.75**
Confidence indicators: industrial confidence indicator (equation [5])	RMSE Relative RMSE*	0.769 0.99	0.710 1.00
Best forecasting performance: M3, industrial production, exports and imports of goods (equation [6])	RMSE Relative RMSE*	**0.427** **0.55**	**0.381** **0.54**

Source: author's calculations.
* The ratio of bridge equation's RMSE to benchmark model's RMSE.

The forecasting performance of bridge equations [2]–[6], assuming that monthly indicators are available for the entire quarter, is analysed in Table 1. Similar to G. Rünstler and F. Sédillot (16), we follow the rule of thumb in using one third of available sample for conducting the out-of-sample forecasts, which leaves an out-of-sample period starting from 2004 Q1. Table 1 reports RMSE of Latvia's quarterly growth (both the first and final releases) and compares it with RMSE of benchmark model[4].

Out-of sample forecasting results indicate that only these bridge equations that contain the M3 monthly indicator (equations [4] and [6]) perform better than the benchmark ARIMA model; however, the forecasting power of money could be improved using data on industrial production and foreign trade (equation [6]). Moreover, we found that the usage of modified monthly indicators in equations [4] and [6] significantly improved the out-of-sample forecasting performance of bridge equations.

2.3 Forecasting Monthly Indicators

To investigate the forecasting performance of bridge equations in the event that monthly indicators are only partially available within the quarter, we need to develop monthly time series models to forecast the missing observations of monthly indicators. For simplicity reasons, we use only univariate time series, i.e. ARIMA, models. The lag length selection was based on the lowest RMSE for 1-month ahead out-of-sample forecasts (see Table 2).[5]

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[4] We choose ARIMA (2, 1, 0) model as a benchmark model both because of the lowest out-of-sample RMSE and lowest SIC.

[5] Some authors select lag length based on SIC, see, for example, (16). However, application of this criterion did not significantly change the out-of-sample forecasting performance of bridge equations and state space models.

Table 2
Out-of-sample 1-month ahead forecasting performance of ARIMA models

Indicator	ARIMA(p, i, q) with lowest RMSE (p – AR lag, i – integration order, q – MA lag)
Industrial production	ARIMA(2, 1, 0)
Exports of goods	ARIMA(1, 1, 2)
Imports of goods	ARIMA(1, 1, 0)
Retail trade	ARIMA(5, 1, 3)
Money aggregate M3	ARIMA(7, 1, 3)
Interest rate	ARIMA(6, 1, 3)
NEER of lats	ARIMA(1, 1, 0)
PPI	ARIMA(4, 1, 1)
CPI	ARIMA(4, 1, 0)
Budget expenditure	ARIMA(3, 1, 0)

Source: author's calculations.

Forecasting models have been produced only for those monthly indicators that are available with a time lag, therefore we do not need a forecasting model for business confidence indicators (data available before the end of current month) and oil prices (data available in real time).

2.4 Forecasting Performance of Bridge Equations

Now we can examine the forecasting performance of bridge equations [2]–[6] when the missing observations of monthly indicators are forecasted by ARIMA models. The out-of-sample forecasting performance for the period between the first quarter of 2004 and fourth quarter of 2007 is calculated for three different moments of forecasting: the beginning of the 1st, 2nd and 3rd month after the end of the reference quarter.

In addition to simple comparison between the RMSE of bridge equation and benchmark ARIMA model, we use some formal tests to define the best model of the two. First, it was done using the traditional Diebold-Mariano (DM) test (5), which checks the null hypothesis of pairwise equal forecast accuracy of two models. If the bridge model has lower RMSE and it is possible to reject the null hypothesis of equal forecast accuracy, we can conclude that the bridge equation has a better forecasting performance. Second, we used the forecast encompassing test (12), which defines whether one model's forecast encompasses the other model's forecast. If the forecast encompassing test rejects the hypothesis of the benchmark model encompassing the bridge equation, we can conclude that the bridge equation contains additional information for the ARIMA model. On the other hand, in case the test cannot reject the hypothesis that the bridge equation encompasses the benchmark model, the ARIMA model has no additional content for the bridge equation model. As the out-of-sample experiment period is short, we use a small sample correction for both tests proposed by D. Harvey, S. Leybourne and P. Newbold (11).

The results of the out-of-sample forecasting exercise are presented in Table 3. Bridge equations [2] and [3] using monthly indicators from production and expenditure side perform worse compared with the benchmark model. This is especially pronounced for forecasts made right after the end of the reference quarter when data on monthly indicators are not available for the entire quarter (see DM and forecast encompassing test results). Therefore, industrial production, retail trade and exports data do not add any valuable information to the benchmark ARIMA model.

Table 3

Out-of-sample forecasting performance of bridge equation models combined with ARIMA models for monthly indicators

(Latvia's real GDP forecasts in the previous quarter, *p*-values of DM and forecast encompassing tests in parenthesis)

		First release			Final release		
Months after end of reference quarter		1	2	3	1	2	3
Model	Indicator						
Equation [2]	RMSE	1.114	1.021	0.961	1.036	0.978	0.890
	Relative RMSE*	1.44	1.32	1.24	1.46	1.38	1.25
	DM test**	(0.003)	(0.009)	(0.032)	(0.004)	(0.021)	(0.091)
	Encompassing test***	(0.801)	(0.532)	(0.355)	(0.722)	(0.547)	(0.299)
	Encompassing test****	(0.001)	(0.002)	(0.003)	(0.001)	(0.005)	(0.013)
Equation [3]	RMSE	1.021	0.956	0.913	0.859	0.785	0.731
	Relative RMSE*	1.32	1.24	1.18	1.21	1.10	1.03
	DM test**	(0.018)	(0.086)	(0.095)	(0.045)	(0.311)	(0.497)
	Encompassing test***	(0.801)	(0.534)	(0.335)	(0.394)	(0.175)	(0.088)
	Encompassing test****	(0.008)	(0.032)	(0.027)	(0.015)	(0.088)	(0.106)
Equation [4]	RMSE	**0.544**	**0.536**	**0.536**	**0.520**	**0.532**	**0.532**
	Relative RMSE*	**0.70**	**0..69**	**0.69**	**0.73**	**0.75**	**0.75**
	DM test**	**(0.262)**	**(0.317)**	**(0.323)**	**(0.302)**	**(0.487)**	**(0.494)**
	Encompassing test***	**(0.020)**	**(0.019)**	**(0.018)**	**(0.019)**	**(0.017)**	**(0.016)**
	Encompassing test****	**(0.130)**	**(0.060)**	**(0.063)**	**(0.048)**	**(0.032)**	**(0.033)**
Equation [5]	RMSE	0.769	0.769	0.769	0.710	0.710	0.710
	Relative RMSE*	0.99	0.99	0.99	1.00	1.00	1.00
	DM test**	(0.596)	(0.596)	(0.596)	(0.295)	(0.295)	(0.295)
	Encompassing test***	(0.289)	(0.289)	(0.289)	(0.369)	(0.369)	(0.369)
	Encompassing test****	(0.546)	(0.546)	(0.546)	(0.448)	(0.448)	(0.448)
Equation [6]	RMSE	**0.561**	**0.430**	**0.427**	**0.452**	**0.399**	**0.381**
	Relative RMSE*	**0.73**	**0.56**	**0.55**	**0.64**	**0.56**	**0.54**
	DM test**	**(0.352)**	**(0.091)**	**(0.092)**	**(0.238)**	**(0.165)**	**(0.137)**
	Encompassing test***	**(0.027)**	**(0.018)**	**(0.015)**	**(0.023)**	**(0.024)**	**(0.017)**
	Encompassing test****	**(0.424)**	**(0.774)**	**(0.696)**	**(0.444)**	**(0.608)**	**(0.544)**

Source: author's calculations.

* The ratio of bridge equation's RMSE to benchmark model's RMSE.

** The null hypothesis: pairwise equal forecast accuracy of the bridge equation and benchmark model.

*** The null hypothesis: the benchmark model encompasses the bridge equation.

**** The null hypothesis: the bridge equation encompasses the benchmark model.

The forecasting performance of bridge equation with a confidence indicator is almost equal to that of benchmark model, which is not surprising as equation [5] contains two lags of GDP growth (similar to the benchmark model), while the coefficient before the confidence indicator is not significant. According to the test, confidence indicators do not provide any additional information to improve the accuracy of GDP forecasts. This conclusion is in line with inferences made by A. Meļihovs and S. Rusakova (14) who state that information from Latvia's business surveys does not provide opportunities for short term forecasting of real GDP and real value added. According to their calculations, the application of only some industrial survey indicators to econometric modelling allows for forecasting real value added of the industrial and goods sectors with a higher precision than do the benchmark models.

Only bridge equations containing M3 monthly indicators (equations [4] and [6]) perform better than the benchmark ARIMA model. The DM test rejects the hypothesis of equal accuracy only for bridge equation [6] where the first GDP release is forecasted in the 2nd month after the end of the reference quarter. However, the forecast encompassing test rejects the encompassment of benchmark model for equations [4] and [6] when both the first and final releases are projected. Quarterly bridge equations containing M3 have some additional information for the benchmark ARIMA model, especially while forecasting the first release of GDP.

Another interesting fact is that bridge equations [4] and [6] outperform the benchmark model even at the time when monetary statistics are not available for the entire quarter. Therefore, even incomplete data on M3 add valuable new information to improve the accuracy of the first release forecast. Afterwards, as more monetary statistics on the reference quarter become available, the dominance of bridge equation forecasts is increasing further.

3. UNOBSERVED COMPONENTS MODELS

3.1 Interpolation and Forecasting of GDP Using State Space Models

Another method to incorporate information from various monthly indicators is to use models with unobserved components or state space models. Although this methodology is more complicated, it has one clear advantage over bridge equations. The aggregation of monthly to quarterly data used in bridge equations is associated with a considerable loss of information as the dynamics within a quarter are no longer explicit. Models with unobserved components, however, allow for the estimation of GDP figures at a monthly frequency, providing interpolation based on information from monthly indicators. The combination of monthly and quarterly data series is possible in a state space framework; on the basis of the Kalman filter technique one can estimate a monthly GDP series as an unobserved component using monthly indicators, as was proposed by A. Harvey and R. Pierse (10). In this paper we mostly follow the approach used by G. Fenz and M. Spitzer (8). Other examples of state space representations can be found in N. Cuche and M. Hess (4), M. Evans (7) and J. Mitchell et al. (15).

The basic idea is that observable quarterly time series (y_t^Q, quarterly GDP) can be explained by a vector of unobserved monthly components (y_t^m, monthly GDP). A state space model consists of a measurement equation and a transition equation. The unobserved components are linked to observed monthly variables in the transition equation. At the same time, unobserved monthly components are also constrained by observable quarterly GDP via the measurement equation.

Transition equation [7] describes the path of unobserved monthly components (monthly growth rates of GDP) over time. The unobserved monthly component is linked to an autoregressive part (lagged growth of monthly GDP) and such exogenous monthly indicators as confidence indicators, industrial production, retail trade turnover, etc.

$$\Delta \ln y_t^m = \zeta \cdot \Delta \ln y_{t-1}^m + \beta_1 \cdot \Delta \ln x_{1,\,t}^m + ... + \beta_N \cdot \Delta \ln x_{N,\,t}^m + e_t \qquad [7]$$

where y_t^m denotes the unobserved monthly GDP, $x_{n,t}^m$ is the explanatory monthly indicator with $n = 1, ..., N$, e_t is an error term and t is the index of months. An important advantage of this transition equation is that variables and parameters have a straightforward economic interpretation, as the effect of each single explanatory variable can be stated explicitly.

A special feature of the model is the application of a weighted aggregation scheme to derive the quarterly GDP growth rate from monthly GDP growth rates. This ensures that quarterly growth rates are dependent on monthly growth rates. Following G. Rünstler and F. Sédillot (16), measurement equation [8] which approximately equals the actual and the estimated quarterly GDP growth rates is the following:

$$\Delta \ln y_\tau^Q = \frac{1}{3}\Delta \ln y_t^m + \frac{2}{3}\Delta \ln y_{t-1}^m + \Delta \ln y_{t-2}^m + \frac{2}{3}\Delta \ln y_{t-3}^m + \frac{1}{3}\Delta \ln y_{t-4}^m + \xi_\tau \qquad [8]$$

$$\tau = 1, 2, 3, ..., T/3; \quad t = 1, 2, 3, ..., T;$$

where y_τ^Q denotes quarterly GDP growth rates, ξ_τ is an error term (it is included because of approximation, although in practice its variation is minor) and τ is the index of quarters. The quarterly growth rate of GDP is a weighted sum of the present and past four monthly growth rates of GDP.

The state space model will take the following form:

$$\begin{pmatrix} \Delta\ln y_{t+1}^m \\ \Delta\ln y_t^m \\ \Delta\ln y_{t-1}^m \\ \Delta\ln y_{t-2}^m \\ \Delta\ln y_{t-3}^m \\ e_{t+1} \end{pmatrix} = \begin{pmatrix} \zeta & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \Delta\ln y_t^m \\ \Delta\ln y_{t-1}^m \\ \Delta\ln y_{t-2}^m \\ \Delta\ln y_{t-3}^m \\ \Delta\ln y_{t-4}^m \\ e_t \end{pmatrix} + \begin{pmatrix} \beta_1 & \cdots & \beta_N \\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} \Delta\ln x_{1,t}^m \\ \vdots \\ \Delta\ln x_{N,t}^m \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \sigma^2 \end{pmatrix} u_{t+1} \qquad [9]$$

$$\Delta\ln y_\tau^Q = \frac{1}{3}\Delta\ln y_t^m + \frac{2}{3}\Delta\ln y_{t-1}^m + \Delta\ln y_{t-2}^m + \frac{2}{3}\Delta\ln y_{t-3}^m + \frac{1}{3}\Delta\ln y_{t-4}^m + \xi_\tau$$

where u_t is innovation assumed to be normally distributed with mean zero and variance one.

To summarise, state space model [9] allows for the estimation of an unobserved series of monthly GDP growth rates using monthly indicators and ensures that these estimates are in line with actual quarterly GDP growth rates. A new time series, that of monthly GDP, is calculated; it gives an opportunity to describe and analyse the situation at a higher frequency. On the other hand, the model is able to forecast monthly GDP as far as information on monthly indicators is available.

3.2 Choice of Monthly Indicators for State Space Models

The choice of monthly indicators for the transition equation of model [9] was made similarly to the choice of monthly indicators for bridge equations (see Section 2.2). Four sets of monthly indicators were formed using economic logic: indicators describing GDP from the production side, indicators of expenditure side, financial and price indicators as well as business confidence indicators. In contrast to bridge equations, the use of modified monthly indicators in state space models was not confirmed by SIC or RMSE statistics.

The list of monthly indicators within a set was based on the Schwartz information criterion requiring the correct sign of coefficient before the indicator (the sample period for estimation of state space models was from 1996 Q2 to 2007 Q4, *z*-statistics is reported in parenthesis).

Production side indicators

$$\Delta\ln y_t^m = \underset{(9.450)}{0.0025} + \underset{(12.017)}{0.535} \cdot \Delta\ln y_{t-1}^m + \underset{(11.362)}{0.138} \cdot \Delta\ln ip_t$$

$$\sigma^2 = 7.70 \cdot 10^{-6} \qquad [10].$$

$$SIC = -15.882$$

As in equation [2], the model with industrial production index has the best SIC of all other models in this set. Elasticity of real GDP in industry is positive and statistically significant, although in equation [10] elasticity in industrial production is lower than in the quarterly bridge equation.

Expenditure side indicators

$$\Delta \ln y_t^m = \underset{(4.377)}{0.0014} + \underset{(12.746)}{0.539} \cdot \Delta \ln y_{t-1}^m + \underset{(11.347)}{0.115} \cdot \Delta \ln xg_t$$
$$\sigma^2 = 7.57 \cdot 10^{-6} \qquad [11].$$
$$SIC = -15.896$$

According to SIC, exports of goods are the best monthly indicator from the expenditure side (however, the inclusion of retail trade worsened the in-sample performance only marginally). The coefficient before exports is relatively low and does not coincide with the export share in GDP, which partly could be explained by a high coefficient before the lagged monthly GDP growth.

Financial and price indicators

$$\Delta \ln y_t^m = \underset{(1.335)}{0.0005} + \underset{(9.202)}{0.535} \cdot \Delta \ln y_{t-1}^m + \underset{(6.785)}{0.134} \cdot \Delta \ln m3_t$$
$$\sigma^2 = 8.42 \cdot 10^{-6} \qquad [12].$$
$$SIC = -15.794$$

Equation [12] is close to bridge equation [4], although M3 monthly indicator multiplied by the ratio of M3 to GDP performs slightly worse than the traditional indicator in a state space model.

Confidence indicators

$$\Delta \ln y_t^m = \underset{(6.672)}{0.0023} + \underset{(10.127)}{0.612} \cdot \Delta \ln y_{t-1}^m + \underset{(2.068)}{0.00033} \cdot \Delta total\_esi_t$$
$$\sigma^2 = 9.63 \cdot 10^{-6} \qquad [13]$$
$$SIC = -15.609$$

where $total\_esi_t$ is the overall economic sentiment indicator (ESI) for Latvia. In contrast to quarterly bridge equation [5], the best in-sample fit among confidence indicators is ensured by ESI, although SIC shows that the in-sample explanatory power of this equation is worse than for other state space models.

Best forecasting performance

We also derived one more transition equation which has the best out-of-sample performance according to RMSE criterion. As in the previous section, we followed the specific-to-general approach, adding monthly indicators while RMSE was decreasing and coefficients had the correct sign. Again, it appears that this equation has likewise the best in-sample fit according to SIC.

$$\Delta \ln y_t^m = \underset{(1.986)}{0.0009} + \underset{(7.475)}{0.461} \cdot \Delta \ln y_{t-1}^m + \underset{(4.582)}{0.086} \cdot \Delta \ln m3_t + \underset{(7.350)}{0.094} \cdot \Delta \ln ip_t +$$
$$+ \underset{(7.982)}{0.080} \cdot \Delta \ln xg_t - \underset{(-3.554)}{0.023} \cdot \Delta \ln mg_t \qquad [14].$$
$$\sigma^2 = 6.37 \cdot 10^{-6}$$
$$SIC = -16.013$$

The best combination of monthly indicators for state space models is the same as in quarterly bridge equations: M3, industrial production index, as well as exports and imports of goods.

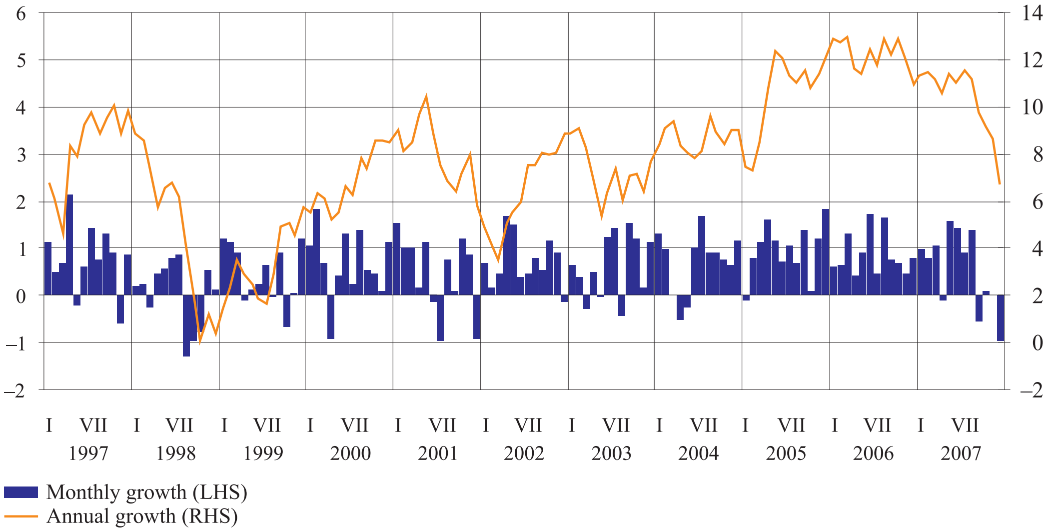
3.3 Forecasting Performance and Interpolation

An important advantage of state space models is the possibility to obtain monthly GDP figures that give additional information on the economic performance at a higher frequency. Chart 2 shows monthly and yearly growth of the monthly GDP estimated by state space model [14].

Chart 2

Estimated annual and monthly real GDP growth in Latvia

(based on final release data, monthly frequency, seasonally adjusted, January 1997–December 2007, %)



Finally, we can examine the forecasting performance of state space models with transition equations [10]–[14] when missing observations of monthly indicators are forecasted by ARIMA models. As previously, the out-of-sample forecasting period starts from the first quarter of 2004, and the forecasting performance is calculated for three moments of forecast: the beginning of the 1st, 2nd and 3rd month after the end of the reference quarter.

The out-of-sample forecasting exercise for equations [10], [11] and [13] once again indicates that the performance of state space models using only monthly indicators from production and expenditure sides as well as confidence indicators is worse or similar to the benchmark ARIMA model (see Table 4). As before, this is especially pronounced when little information is available on monthly indicators, and the forecaster should rely on ARIMA models described in Section 2.3. Later, when hard data on industrial production, trade and exports become available, the forecasting performance of state space models [10] and [11] improves, although, according to the DM test, it is just similar to the forecasting performance of the benchmark ARIMA model and, according to the encompassing test, only model [11] contains useful information for the forecast of final release. In other words, data on abovementioned monthly indicators do not add a lot of new information to improve the accuracy of Latvia's real GDP forecasts.

Table 4

Out-of-sample forecasting performance of state space models combined with ARIMA models for monthly indicators

(Latvia's real GDP forecasts in the previous quarter, *p*-values of DM and forecast encompassing tests in parenthesis)

		First release			Final release		
Months after end of reference quarter		1	2	3	1	2	3
Model	Indicator						
Equation [10]	RMSE	0.806	**0.732**	**0.697**	**0.694**	**0.648**	**0.590**
	Relative RMSE*	1.04	**0.95**	**0.90**	**0.98**	**0.91**	**0.83**
	DM test**	(0.358)	**(0.937)**	**(0.809)**	**(0.764)**	**(0.920)**	**(0.603)**
	Encompassing test***	(0.284)	**(0.121)**	**(0.094)**	**(0.177)**	**(0.121)**	**(0.085)**
	Encompassing test****	(0.098)	**(0.308)**	**(0.424)**	**(0.217)**	**(0.377)**	**(0.564)**
Equation [11]	RMSE	0.789	0.782	0.782	**0.656**	**0.660**	**0.659**
	Relative RMSE*	1.02	1.01	1.01	**0.92**	**0.93**	**0.93**
	DM test**	(0.484)	(0.709)	(0.636)	**(0.588)**	**(0.648)**	**(0.692)**
	Encompassing test***	(0.204)	(0.117)	(0.048)	**(0.052)**	**(0.058)**	**(0.036)**
	Encompassing test****	(0.094)	(0.080)	(0.088)	**(0.412)**	**(0.271)**	**(0.179)**
Equation [12]	RMSE	**0.657**	**0.642**	**0.639**	**0.552**	**0.538**	**0.537**
	Relative RMSE*	**0.85**	**0.83**	**0.83**	**0.78**	**0.76**	**0.76**
	DM test**	**(0.612)**	**(0.555)**	**(0.525)**	**(0.210)**	**(0.255)**	**(0.237)**
	Encompassing test***	**(0.054)**	**(0.046)**	**(0.044)**	**(0.033)**	**(0.028)**	**(0.026)**
	Encompassing test****	**(0.231)**	**(0.252)**	**(0.300)**	**(0.261)**	**(0.286)**	**(0.346)**
Equation [13]	RMSE	0.812	0.812	0.812	0.714	0.714	0.714
	Relative RMSE*	1.05	1.05	1.05	1.00	1.00	1.00
	DM test**	(0.572)	(0.572)	(0.572)	(0.996)	(0.996)	(0.996)
	Encompassing test***	(0.248)	(0.248)	(0.248)	(0.126)	(0.126)	(0.126)
	Encompassing test****	(0.071)	(0.071)	(0.071)	(0.072)	(0.072)	(0.072)
Equation [14]	RMSE	**0.675**	**0.616**	**0.595**	**0.492**	**0.472**	**0.442**
	Relative RMSE*	**0.87**	**0.80**	**0.77**	**0.69**	**0.66**	**0.62**
	DM test**	**(0.774)**	**(0.370)**	**(0.267)**	**(0.245)**	**(0.205)**	**(0.131)**
	Encompassing test***	**(0.057)**	**(0.035)**	**(0.026)**	**(0.027)**	**(0.029)**	**(0.020)**
	Encompassing test****	**(0.297)**	**(0.497)**	**(0.528)**	**(0.583)**	**(0.689)**	**(0.714)**

Source: author's calculations.

* The ratio of state space model's RMSE to benchmark model's RMSE.

** The null hypothesis: pairwise equal forecast accuracy of state space model and benchmark model.

*** The null hypothesis: the benchmark model encompasses the state space model.

**** The null hypothesis: the state space model encompasses the benchmark model.

Similar to bridge equations, the employment of the M3 indicator significantly improves the forecasting performance of state space models: models [12] and [14] have lower RMSE in comparison with the benchmark model. Moreover, the forecast encompassing test shows that models [12] and [14] have additional information for the benchmark ARIMA, which is pronounced for forecasts made in all three time periods. However, in contrast to bridge equations, the DM test cannot reject the equal forecasting performance for both models.

CONCLUSIONS

The conjunctural information from monthly indicators, e.g. industrial production, retail trade turnover, M3, confidence indicators, etc could partly replace GDP data before the first official data release is known. Usually, this information is used in a qualitative manner. However, it is possible to incorporate monthly indicators into short-term forecasting models of GDP. There are two widespread methodologies of including information from monthly indicators in short-term forecasting models. The first methodology is a univariate forecasting equation, called also bridge equation. This methodology allows predicting quarterly real GDP growth using data on monthly indicators, aggregated to a quarterly frequency. The second method is an unobserved components or state space model, which allows for the estimation of GDP figure at a monthly frequency, providing also interpolation based on information from monthly indicators.

The choice of monthly indicators for bridge equations and state space models is based on simple economic logic. We formed four sets of potential conjunctural indicators: 1) describing GDP from the production side (industrial production, retail trade, construction confidence indicator), 2) describing GDP from expenditure side (retail trade turnover, budget expenditure, exports and imports of goods), 3) financial and price indicators, and 4) business confidence indicators. The decision on the usage of monthly indicators was based on SIC requiring the correct sign of the coefficient. Moreover, one more bridge equation and a state space model with the best out-of-sample forecasting performance were derived.

Monthly indicators are often released with a lag, and GDP forecasts based on actual figures are available only shortly before the official release. To cope with this drawback, missing observations of monthly indicators were forecasted using a simple univariate ARIMA model.

To perform the real-time analysis of forecasting performance of bridge equations and state space models, we created a real-time database, which contains real GDP series with 28 vintages of quarterly real GDP, starting with data available at the beginning of June 2001. The out-of-sample forecasting performance of Latvia's GDP was based on the RMSE criterion and comparison with RMSE of the benchmark ARIMA model. In addition, we used the standard DM and forecast encompassing tests to define the best performance via comparing the models with conjunctural indicators with the benchmark model.

The results of out-of-sample forecasting exercise are rather similar for both types of models. According to our calculations, models based solely on indicators from the production and expenditure sides (industrial production, retail trade turnover, exports) perform worse or produce results similar to the benchmark model. Consequently, data on the abovementioned monthly indicators do not add a lot of new information to improve the accuracy of Latvia's real GDP forecasts. The same conclusion could be drawn for models with confidence indicators.

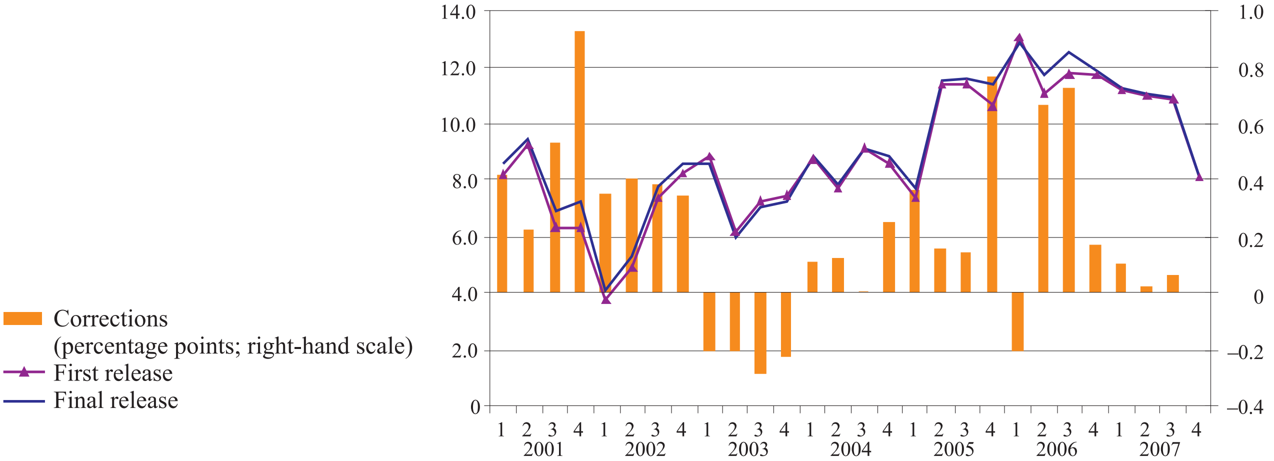
Only bridge equations and state space models containing monthly data on M3 perform better than the benchmark ARIMA model. Even partial information on M3 in the reference quarter improves the accuracy of GDP forecasting, which is especially pronounced for bridge equations. Afterwards, as more monetary statistics on the reference quarter become available, the dominance of bridge equation forecasts is increasing further. Both quarterly bridge equations and state space models using M3 provide valuable information while forecasting the first and final releases of GDP.

The abovementioned conclusions do not mean, however, that indicators from production and expenditure sides as well as business confidence indicators should not be used and the focus should solely be on M3 indicators. The analysis of this paper shows the absence of statistical evidence in the past. It does not take into account possible future changes in the relationship between monthly indicators and quarterly GDP growth likely to be experienced when the business cycle enters an economic downturn. Hence to capture possible changes, the estimation of forecasting performance should be redone on a regular basis.

APPENDICES

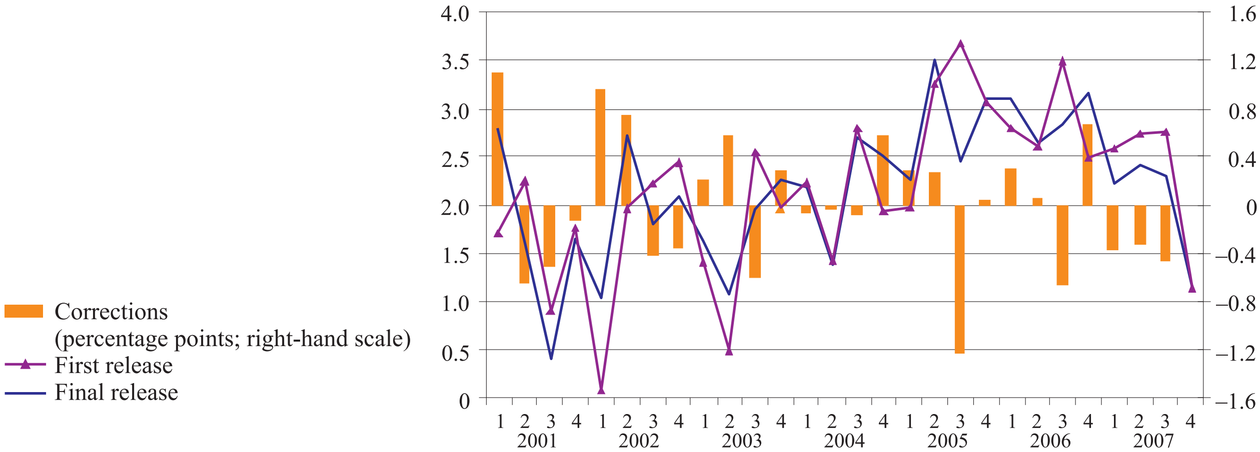
Appendix 1
First and final releases of Latvia's real GDP growth

Chart A1
First and final real GDP annual growth releases
(seasonally unadjusted; 2001 Q1–2007 Q4; in % and percentage points)



Sources: CSB and author's calculations.

Chart A2
First and final real GDP quarterly growth releases
(seasonally adjusted; 2001 Q1–2007 Q4; in % and percentage points)



Sources: CSB and author's calculations.

Appendix 2
Recursive coefficients of quarterly bridge equations

Chart A3
Recursive coefficients of quarterly bridge equation [2]
(2004 Q1–2007 Q4)

$$\Delta \ln y_t = C(1) + C(2) \cdot \Delta \ln ip_t$$

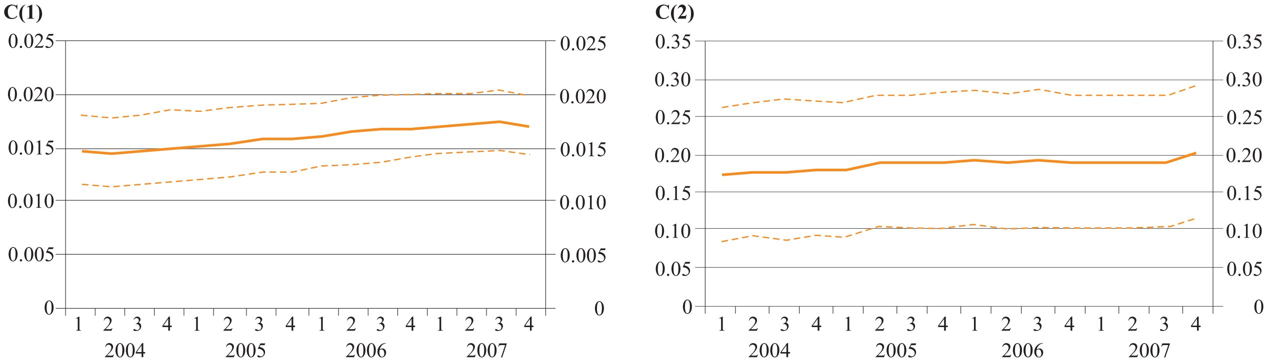


Chart A4
Recursive coefficients of quarterly bridge equation [3]
(2004 Q1–2007 Q4)

$$\Delta \ln y_t = C(1) + C(2) \cdot \Delta \ln xg_t + C(3) \cdot ratio\_trade\_gdp_{t-1} \cdot \Delta \ln trade_t$$

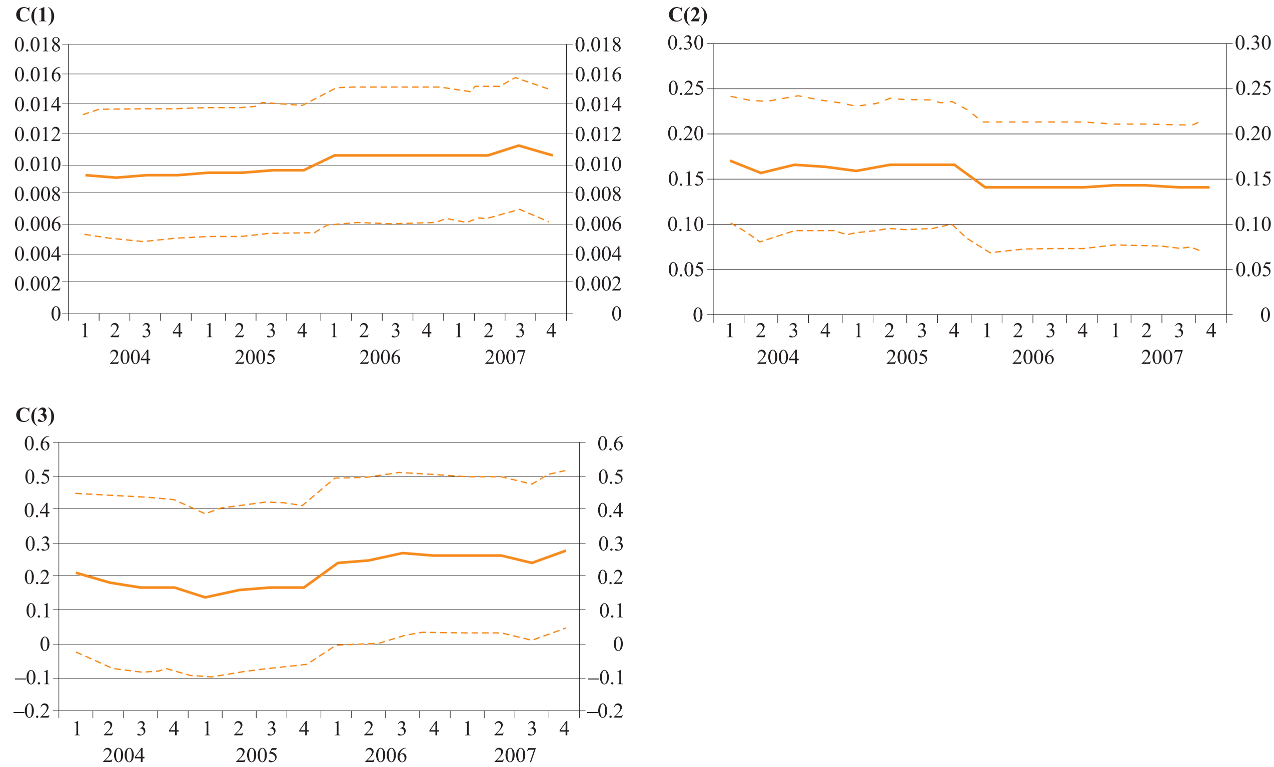


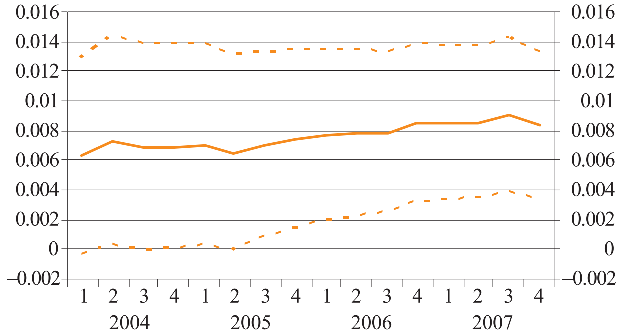
Chart A5

Recursive coefficients of quarterly bridge equation [4]

(2004 Q1–2007 Q4)

$$\Delta \ln y_t = C(1) + C(2) \cdot ratio\_m3\_gdp_{t-1} \cdot \Delta \ln m3_t$$

C(1)



C(2)

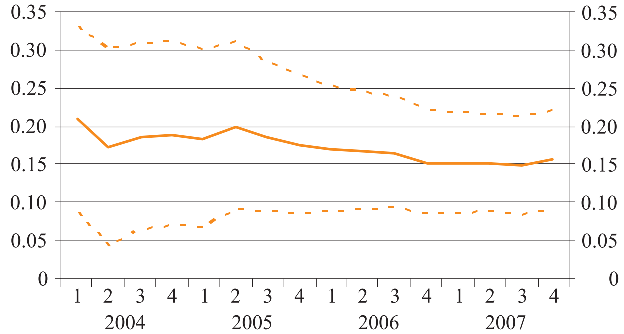


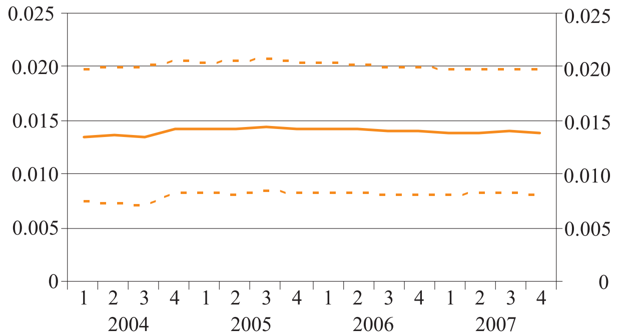
Chart A6

Recursive coefficients of quarterly bridge equation [5]

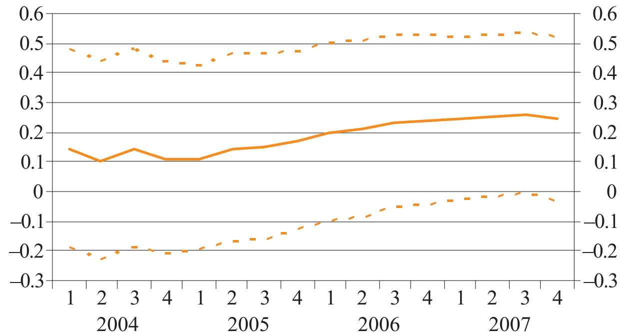
(2004 Q1–2007 Q4)

$$\Delta \ln y_t = C(1) + C(2) \cdot \Delta \ln y_{t-2} + C(3) \cdot \Delta ind\_bc_t$$

C(1)



C(2)



C(3)

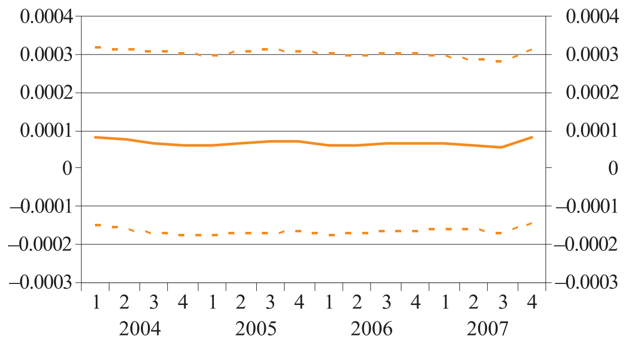
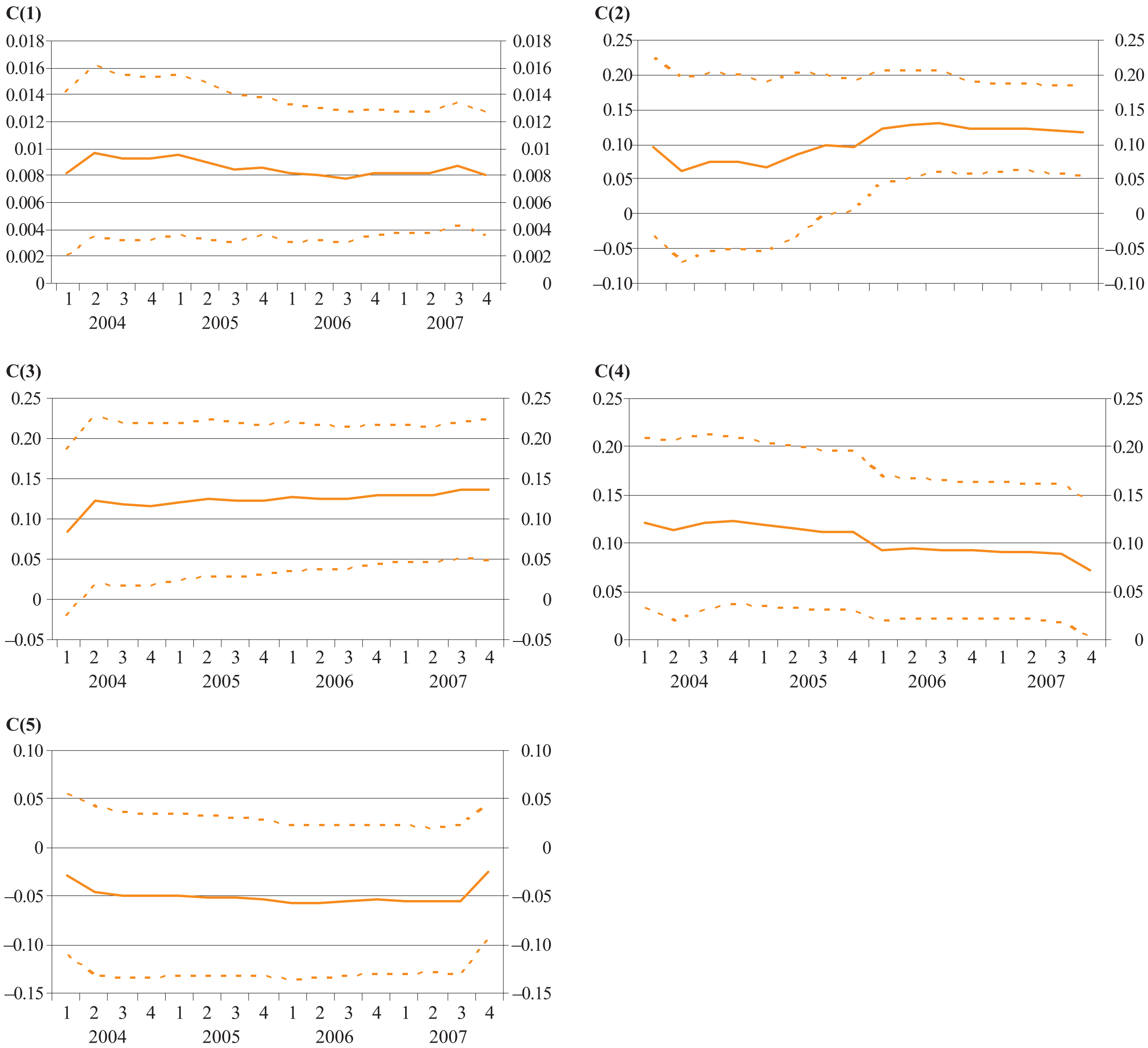


Chart A7

Recursive coefficients of quarterly bridge equation [6]

(2004 Q1–2007 Q4)

$$\Delta \ln y_t = C(1) + C(2) \cdot ratio\_m3\_gdp_{t-1} \cdot \Delta \ln m3_t + C(3) \cdot \Delta \ln ip_t +$$
$$+ C(4) \cdot \Delta \ln xg_t + C(5) \cdot \Delta \ln mg_t$$



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