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**LATCOIN: DETERMINING MEDIUM TO LONG-RUN
TENDENCIES OF ECONOMIC GROWTH IN LATVIA IN
REAL TIME**

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CONTENTS

Abstract	2
Introduction	3
1. Medium to Long-Run Growth of Latvia's GDP: Band-Pass Filter Approach	5
2. Improving Estimates of Medium to Long-Run Growth Using Macroeconomic Indicators	8
2.1 Generalised Dynamic Factor Analysis	8
2.2 Constructing Regressors Using Large Sample of Latvia's Macroeconomic Indicators	10
3. Estimating LATCOIN	13
4. Use of LATCOIN in Real Time	15
4.1 Real-Time Performance	15
4.2 Behaviour around Turning Points	16
Conclusions	18
Appendices	19
Bibliography	24

ABBREVIATIONS

CSB – Central Statistical Bureau of Latvia
EC – European Commission
EU – European Union
EUROCOIN – Euro Area Business Cycle Coincidence Indicator
GDP – gross domestic product
LATCOIN – Latvia's Business Cycle Coincidence Indicator
MLGR – medium to long-run growth
NACE – Nomenclature of Economic Activities in the European Communities

ABSTRACT

This paper presents a method of estimating the current state of Latvia's economy. The evaluation object is medium to long-run growth of real GDP, but not actual GDP itself, which helps to filter out various one-off effects and focus on medium and long-run tendencies. Our indicator, called LATCOIN (Latvia's Business Cycle Coincidence Indicator), could be viewed as a simple adaptation of EUROCOIN for Latvia with some changes in methodology. LATCOIN is a monthly estimate of the medium to long-run growth of Latvia's real GDP, which is produced on the 9th working day of the next month. Using a large panel of macroeconomic variables, few smooth unobservable factors describing the economy are constructed. Further, these factors are used for the estimation of LATCOIN.

Keywords: Latvia's real GDP, band-pass filter, coincidence indicator, generalised principal components, real-time performance, turning points

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INTRODUCTION

The most complete and popular indicator of economic activity is real GDP growth. However, there are two main drawbacks usually associated with this variable. First, information on domestic activity comes only on a quarterly basis and with a significant delay. The second drawback is related to short-run fluctuations of real GDP, which creates a significant problem for analysing, forecasting, and decision making in real time. Monetary policy makers usually are not interested in such fluctuations and are more concerned about medium-term and fundamental tendencies in the economy.

The first problem has already been addressed for the case of Latvia in several researches, which analysed short-term forecasting possibilities of Latvia's real GDP. A. Meļihovs and S. Rusakova (9) checked the forecasting ability of business and consumer survey data, V. Ajevskis and G. Dāvidsons (1) showed that dynamic factor models provide good forecasting performance in the short run, and K. Beņkovskis (5) used bridge equations with various conjunctural indicators to forecast real GDP. All these papers, however, do not address the second problem of short-term fluctuations in real GDP.

This paper presents an alternative method of estimating the current state of Latvia's economy. The main difference vis-à-vis previous research papers is that the evaluation object is medium to long-run growth of real GDP, but not actual GDP itself. This helps to filter out various one-off effects and focus on medium and long-run tendencies.

In creating such a method, the author closely follows the EUROCOIN (Euro Area Business Cycle Coincidence Indicator), which was developed by F. Altissimo et al. (2) and is actively used by *Banca d'Italia*.¹ Our indicator called LATCOIN (Latvia's Business Cycle Coincidence Indicator), could be viewed as a simple adaptation of EUROCOIN for Latvia with some changes in methodology. Our main contribution to literature is the application of estimation methodology to country that has recently undergone transformation and has a relatively short data history. LATCOIN is a monthly estimate of the medium to long-run growth of Latvia's real GDP produced on the 9th working day of the next month.

In the theoretical case of infinite data series, the evaluation of medium to long-run component could be easily done by applying the band-pass filter approach. In reality, however, band-pass filtering provides a good approximation in the middle of the sample, while approximations at its ends are very poor. Therefore, band-pass filtering is not an appropriate method for real-time analysis. The idea of the current approach is based on an assumption that various macroeconomic variables capture some information about the future GDP dynamics. Using a large panel of macroeconomic variables, a few smooth unobservable factors describing the economy are constructed. Further, these factors, called regressors, are used for the estimation of LATCOIN.

¹ An example of EUROCOIN use in *Banca d'Italia* can be found in <http://eurocoin.bancaditalia.it/>.

The paper is structured in the following way. Section 1 gives the definition of the medium to long-run growth of Latvia's real GDP. Section 2 describes the construction of regressors from a large panel of macroeconomic variables using the generalised dynamic factor analysis. The calculations of LATCOIN are given in Section 3, while Section 4 shows the real-time performance of LATCOIN. The final section concludes.

1. MEDIUM TO LONG-RUN GROWTH OF LATVIA'S GDP: BAND-PASS FILTER APPROACH

The most complete and popular indicator of economic activity is real GDP growth. However, there are two main drawbacks usually associated with this variable. First, information on domestic activity comes only on a quarterly basis and with a significant delay: in Latvia the flash estimates of real GDP are published in 40 days after the end of the quarter, while the first official release is available only in 70 days after the end of the quarter. The second drawback is related to short-run fluctuations of real GDP, which create a significant problem for analysing, forecasting, and decision making in real time. These short-run fluctuations are usually associated with different one-off events (especially pronounced for a small economy like Latvia) and seasonality. Monetary policy makers usually are not interested in such factors and are more concerned about medium-term and fundamental tendencies in the economy.

Therefore, we would be interested in an indicator of the economic activity which inherits the good features of real GDP (comprehensiveness, inclusion of all sectors of the economy, etc) and at the same time describes only the medium and long-run tendencies; moreover, it should be available shortly after the end of the reference period on a monthly basis. The paper will first focus on the medium and long-run tendencies of the economy.

Following F. Altissimo *et al.* (2), the medium to long-run growth (hereinafter, denoted by MLRG) of economic activity is obtained by removing from the quarterly growth of real GDP the fluctuations of a period shorter than or equal to one year. In other words, MLRG is a "smoothed" version of GDP growth. The choice of the one-year threshold is natural, since we are not interested in seasonality and shorter fluctuations.

MLRG is defined considering the spectral decomposition of y_t , quarterly growth of real GDP in Latvia.² Assuming stationarity, y_t can be represented as a sum of sine and cosine waves with different weights. Our goal is to exclude short waves with a frequency equal or higher than $\pi/6$ (corresponding to the period of one year), as a result MLRG or c_t is obtained.

Using the band-pass filter (see M. Baxter and R. King (4), and L. Christiano and T. Fitzgerald (6)), medium to long-run component c_t is the following infinite, symmetric, two-sided linear combination of the GDP growth series:

² $y_t = \ln(Y_t) - \ln(Y_{t-1})$, where Y_t is the seasonally adjusted real GDP for the period from the first quarter of 1996 to the third quarter of 2009. The data is provided by the CSB. Of course, it is possible to use non-adjusted GDP data and filter out seasonality using the band-pass filter approach. However, the choice between adjusted and non-adjusted data does not affect final results significantly.

$$c_t = \beta(L)y_t = \sum_{k=-\infty}^{\infty} \beta_k y_{t-k}, \quad \beta_k = \begin{cases} \frac{\sin(k\pi/6)}{k\pi} & \text{for } k \neq 0 \\ 1/6 & \text{for } k = 0 \end{cases} \quad [1].$$

Filter $\beta(L)$ is a low-pass filter which excludes waves of frequency equal or higher than $\pi/6$. Since $\beta(1) = 1$, the mean of y_t (denoted by μ), is retained in c_t while the mean of the excluded part of GDP growth is equal to zero.

Equation [1] cannot be applied in practice as the data on GDP are finite. So, within a finite sample it is possible to get only the approximations of c_t . According to F. Altissimo *et al.* (2), this is done by augmenting y_t with its sample mean $\hat{\mu}$ in both infinite directions:

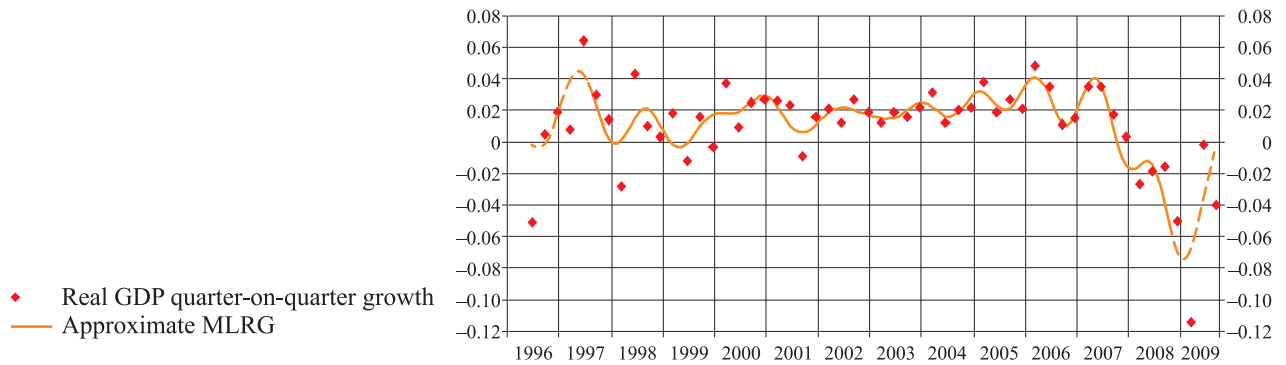
$$c_t^* = \beta(L)y_t^*, \quad \text{where } y_t^* = \begin{cases} y_t & \text{if } 1 \leq t \leq T \\ \hat{\mu} & \text{if } t < 1 \text{ or } t > T \end{cases} \quad [2].$$

This means a t -dependent asymmetric truncation of $\beta(L)$ applied to $y_t - \hat{\mu}$, and due to this asymmetry the approximation provided by c_t^* is very poor at the beginning and end of the sample.

Another problem arises due to the fact that y_t is observed only quarterly, while we are interested in a more frequent indicator of economic activity, therefore, interpolation is needed. Several interpolation options are possible. However, as argued by F. Altissimo *et al.* (2), "... we should keep in mind that the variable we are interested in is c_t but not y_t . It turns out that for this purpose the particular interpolation of the missing values in y_t makes no significant difference. .. Sensible interpolations of the two data points that are missing for each quarter only have effects on the short-run behaviour of the series. Since the short waves are filtered out by $\beta(L)$, the interpolation technique chosen has a negligible effect". Taking this into account we use the simplest possible interpolation technique, assuming that y_t is not changing within a quarter.

Chart 1

Approximate MLRG and quarterly (logarithmic) growth of seasonally adjusted real GDP in Latvia (June 1996–September 2009)



Sources: CSB and author's calculations.

Chart 1 shows approximate MLRG, calculated using equation [2] and the quarterly growth of real GDP in Latvia. MLRG is smoother and captures only medium and long-run tendencies in real GDP. As mentioned before, this is only an approximation of MLRG, which performs badly at the beginning and end of the sample while being reasonable in the middle of the sample. Of course, there is no clear threshold where a poor approximation changes into a good one; nevertheless, the first and the last 12 months are marked by a dashed line on the chart, indicating problems with these estimations.

Approximate MLRG fulfils the criteria about the focus on medium and long-run tendencies of the economic activity. However, it does not fulfil the timing criterion. Estimations of approximate MLRG are available only together with the data on actual real GDP (at least with a 40-day delay) moreover, the approximation of the last data point is very poor and will improve only gradually as more and more data on next quarters appear. We need another indicator by which to determine MLRG not only for the past but also in real time.

2. IMPROVING ESTIMATES OF MEDIUM TO LONG-RUN GROWTH USING MACROECONOMIC INDICATORS

Real GDP is not the only source of information on the economic activity. Statistical offices and other organisations provide data on industrial production, retail sales, international trade in goods, business and consumer confidence, money aggregates, 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. A large dataset of macroeconomic indicators could contain variables leading to current real GDP. F. Altissimo *et al.* (2) argue that "... the information contained in the future GDP can be partially recovered by projecting approximate MLRG onto a suitable set of linear combinations of current values of these variables".

One possibility is to choose several macroeconomic variables which would hopefully capture some information about the future GDP dynamics. Although this approach is simpler, it omits large amounts of information, as hundreds of different macroeconomic indicators are available for use. The dynamic factor analysis could be another option. The idea underpinning it is based on an assumption that the dynamics of macroeconomic variables is determined by a few unobservable factors that can be estimated using broad panel data. These unobservable factors could then be used as regressors for the MLRG variable.

2.1 Generalised Dynamic Factor Analysis

Each series in the dataset of macroeconomic indicators (x_{it}) is assumed to be a sum of two stationary, mutually orthogonal at all leads and lags, unobservable components – the common component (χ_{it}) and the idiosyncratic component (ξ_{it}):

$$x_{it} = \chi_{it} + \xi_{it} \quad [3].$$

The common component is driven by a small number (q) of common shocks u_{ht} , $h = 1, \dots, q$:

$$\chi_{it} = b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + \dots + b_{iq}(L)u_{qt} \quad [4].$$

For simplicity, the model is restricted by assuming that different idiosyncratic components are mutually orthogonal at all leads and lags.

Models [3] and [4] may be further specified by assuming that the common component can be described in terms of still small number of static factors F_{kt} , $k = 1, \dots, r$, by using static representation:

$$\chi_{it} = c_{i1}F_{1t} + c_{i2}F_{2t} + \dots + c_{ir}F_{rt} \quad [5].$$

The static factors can be found by the approach of J. Stock and M. Watson (10) using the first r principal components of variables x_{it} . The drawback of this

approach consists in the fact that the estimated static factors contain both medium to long-run and short-run components. As a result, MLRG (containing just medium and long-run waves) will be projected on variables which contain short-run fluctuations.

The innovation of the approach by F. Altissimo *et al.* (2) is that they remove both idiosyncratic and short-run components, so that the resulting factors are both common and smooth. Following M. Forni *et al.* (7), they use a two-step method, producing an estimate of the spectral density matrix of unobserved components and then use this estimate to obtain the factors by means of generalised principal components.

According to equation [3], the spectral density matrix of x_{it} ($S_x(\theta)$) can be decomposed into the common and idiosyncratic component:

$$S_x(\theta) = S_\chi(\theta) + S_\xi(\theta) \quad [6].$$

Moreover, as we are not interested in the short-term part of the common component, matrix $S_\chi(\theta)$ can be further decomposed into the medium to long-run and short-run component:

$$S_\chi(\theta) = S_\phi(\theta) + S_\psi(\theta) \quad [7]$$

where

$$S_\phi(\theta) = \begin{cases} S_\chi(\theta) & \text{for } |\theta| < \pi/6 \\ 0 & \text{for } |\theta| \geq \pi/6 \end{cases}$$

$$S_\psi(\theta) = S_\chi(\theta) - S_\phi(\theta)$$

The choice of q (the number of common shocks) is made using the criterion proposed by M. Hallin and R. Liška (8), and technical details about the estimation of $\hat{S}_\chi(\theta)$, $\hat{S}_\phi(\theta)$, $\hat{S}_\psi(\theta)$, and $\hat{S}_\xi(\theta)$ can be found in Appendix 1.

Integrating equations [6] and [7] over interval $[-\pi, \pi]$, the following decompositions of variance-covariance matrix of x_{it} (Σ_x) can be obtained:

$$\Sigma_x = \Sigma_\chi + \Sigma_\xi = \Sigma_\phi + \Sigma_\psi + \Sigma_\xi \quad [8].$$

The number of static factors r is determined by the criterion of J. Bai and S. Ng (3). Then, using the estimates of variance-covariance matrices $\hat{\Sigma}_\psi$, $\hat{\Sigma}_\phi$, and $\hat{\Sigma}_\xi$, we can construct r smooth regressors by solving the generalised eigenvalue problem (see Appendix 1 for technical details).

As a result, we will obtain smooth regressors (denoted as w_{kt}^m , $k = 1, \dots, r$, with the superscript m indicating that regressors are expressed as month-on-month changes)

extracted from large panel of macroeconomic variables x_{it} . It is assumed that these regressors contain information about future GDP.

2.2 Constructing Regressors Using Large Sample of Latvia's Macroeconomic Indicators

We use a dataset consisting of 153 monthly macroeconomic variables during the period between January 1996 and December 2009. Most of the variables describe Latvia's economic activity, while we also take into account the importance of international environment and include some indicators of the Estonian, Lithuanian, and euro area economy. The choice of the variables was based on two criteria: theoretical relevance for the economic activity in Latvia and time of release.

The main blocks of macroeconomic indicators are as follows:

- Business and consumer confidence indicators (63 variables) – the largest block containing variables on Latvia, with the remaining variables on Estonia, Lithuania, and the euro area.
- Industrial production indices (32 variables). Detailed 2 digit NACE categories for Latvia and broad categories for Estonia, Lithuania, and the euro area.
- Retail trade turnover at constant prices in Latvia for different categories of goods (30 variables).
- Variables describing external transactions: exports and imports of goods, services, balance of payments monthly data on the financial account (12 variables).
- Financial data: monetary variables, interest rates, effective exchange rates (12 variables).
- Other variables containing budget indicators, registered unemployment and turnover at ports.

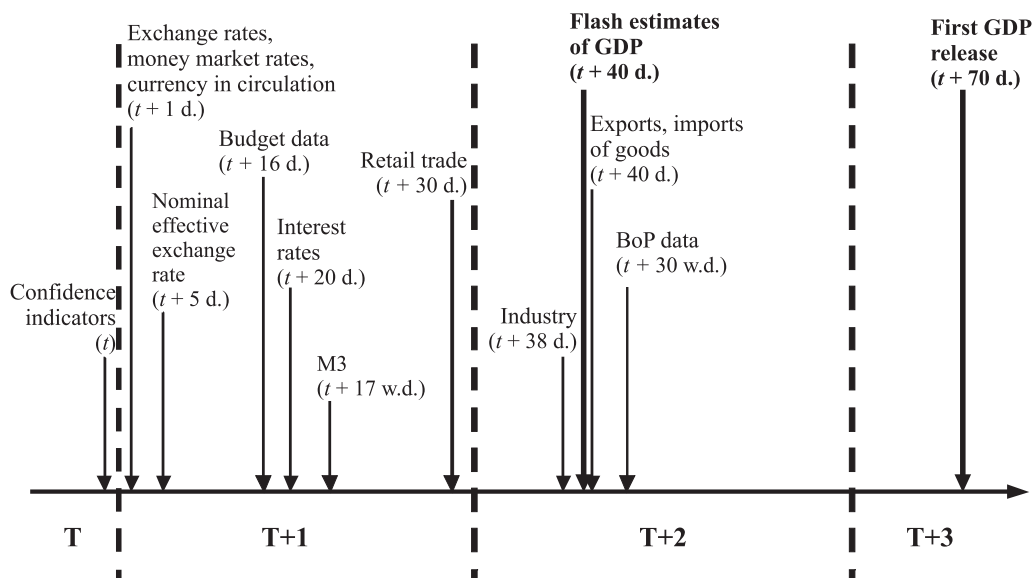
Chart 2 shows the time of data release for the main groups of indicators. It can be noted that the bulk of data are released during the first month after the end of the reference period (except for industry and external transaction statistics).

All 153 series were transformed to remove seasonal factors and non-stationarity. Seasonal adjustment was conducted by regressing variables on a set of seasonal dummies, while non-stationarity was removed by first differencing or first log-differencing. Finally, the series were normalised.

Panel data x_{it} are far from being balanced: some indicators are missing data at the end of the sample (e.g. exports and imports of goods), many variables are starting later than 1996, while other variables are missing observations in the middle (e.g. consumer surveys). F. Altissimo *et al.* (2) solve the problem of end-of-sample unbalance by shifting the time series with missing observations forward. This approach does not work for Latvia, however, as many variables are subject of the beginning-of-sample problem.

Chart 2

Timing of macroeconomic indicator release



Sources: CSB, EC, Treasury, and *Latvijas Banka*.

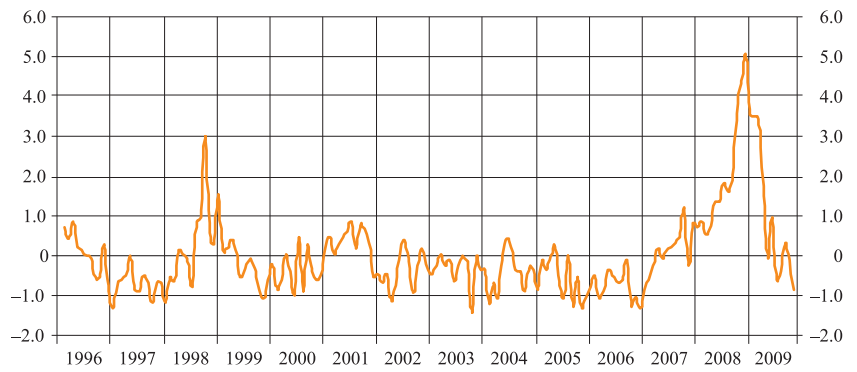
To solve the problem of unbalanced panel, expectations-maximisation (EM) iterative algorithm introduced by J. Stock and M. Watson (10) is used. As the first step, the missing values are simply set equal to the unconditional mean of the series, and the initial estimation of factors and loadings is made by principal components. At the j th step, this reduces to the usual principal component eigenvalue calculation where the missing data are replaced by their expectation conditional on the observed data and the loadings from the previous iteration are used. The process is terminated when the changes in missing observations become negligible.

As has already been stated, the choice of q and r was made according to M. Hallin and R. Liška (8), and J. Bai and S. Ng (3) respectively. The results of information criteria for different q and r are reported in Appendix 2. According to author's calculations, the proper choice is $q=1$ and $r=1$, suggesting that a set of macroeconomic variables should be described by one stochastic shock and one static factor. Such a result when information criteria indicate the smallest possible number of lags or factors is very typical for Latvia and could be explained by the short length of time series.³ The same value of r was also used in the EM algorithm.

³ The increase of the number of factors did not improve the final results. On the contrary, a higher number of factors led to poor performance of the indicator in real time as high historical revisions were observed at the end of the sample.

Chart 3

Common factor calculated by generalised dynamic factor analysis (February 1996–December 2009)



Source: author's calculations.

Chart 3 reports the result of the generalised dynamic factor analysis of the panel consisting of 153 macroeconomic variables. This factor describes monthly changes in the medium to long-run component of Latvia's economic activity (with a negative sign). The factor clearly indicates the periods of two crises: the Russian financial crisis in 1998 and the financial crisis in 2008–2009.

3. ESTIMATING LATCOIN

When a small number of smooth regressors are constructed, they can be used to estimate MLRG or c_t . Before doing it, the last transformation of regressors is needed, as w_{kt}^m is expressed as month-on-month changes, while c_t is expressed as quarter-on-quarter changes (changes over a three-month-ago period). To transform the regressors into quarter-on-quarter change, the following transformation is used:

$$w_{kt} = (1 + L + L^2)^2 w_{kt}^m \quad [9]$$

where w_{kt} is a regressor expressed as quarter-on-quarter change and L is lag operator.

LATCOIN is obtained by projecting c_t on regressors $w_t = (w_{1t}, \dots, w_{rt})'$ and the constant:

$$\hat{c}_t = \hat{\mu} + \hat{\Sigma}_{cw} \hat{\Sigma}_w^{-1} w_t \quad [10]$$

where $\hat{\Sigma}_{cw}$ is the estimated row vector of covariance between c_t and w_t , and $\hat{\Sigma}_w$ is the estimated covariance matrix of w_t . While the estimation of $\hat{\Sigma}_w$ is a standard one, the estimation of $\hat{\Sigma}_{cw}$ is not so straightforward. One possibility is to calculate covariance between c_t^* (approximate MLRG) and w_t . As c_t^* is not an accurate approximation of c_t at the beginning and end of the sample, the end-of sample and beginning-of-sample data should be left aside. As already stated above, there is no clear threshold to classify an approximation as good or poor, therefore the question of how many observations should be excluded is open.

F. Altissimo *et al.* (2) propose another approach to estimate $\hat{\Sigma}_{cw}$ directly from cross-covariance between y_t and w_t using cross-spectrum $\hat{S}_{yw}(\theta)$ and integrating it over the interval $[-\pi/6, \pi/6]$ (see Appendix 3 for technical details). Although the results obtained by these two methods are similar, the second approach does not require making subjective decisions about data exclusion and therefore is preferable.

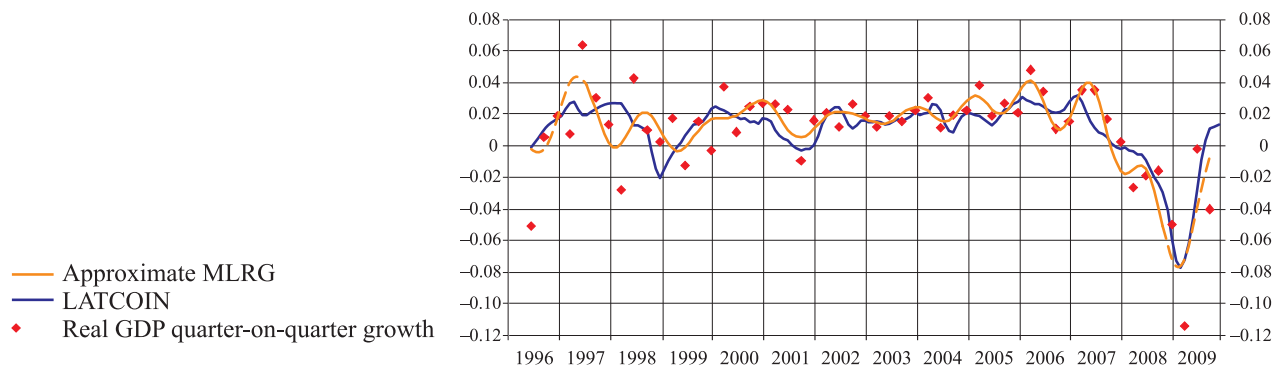
Using smooth common factor obtained in the previous part and equations [9] and [10], it is now possible to estimate LATCOIN – the indicator of medium to long-run growth of real GDP in Latvia. LATCOIN (based on information available in January 2010) is reported in Chart 4. An advantage of LATCOIN over approximate MLRG obtained by band-pass filtering is clearly obvious. Unlike approximate MLRG, the estimates of LATCOIN are available until December 2009. Therefore, LATCOIN is able to give information about MLRG of real GDP almost in real time, i.e. just a few days after the end of the reference month.

LATCOIN is quite smooth (it refers to the medium and long-run component of GDP growth) and is very similar to the approximation of MLRG in the middle of the

sample (2001–2004). The smoothness and fit could be described also formally, using the number of turning points in LATCOIN and R^2 of regression of c_t^* over the period $[13, T-12]$ (without the first and the last 12 months of approximate MLRG). The number of turning points of LATCOIN in the sample period is 34, i.e. significantly higher than the number of turning points in approximate MLRG (21). However, a large part of these turning points refer to a relatively short period (2002–2004). The determination coefficient is 0.439 or at a rather low level (especially compared with one in the research by F. Altissimo *et al.* (2)), which can be explained by the lack of pronounced cycles in Latvia's economy during the sample period.

Chart 4

LATCOIN, approximate MLRG and quarterly (logarithmic) growth of seasonally adjusted real GDP in Latvia (June 1996–December 2009)



Sources: CSB and author's calculations.

LATCOIN clearly indicates two periods when MLRG of Latvia's real GDP was negative: the first one at the end of 1998 and beginning of 1999 associated with the Russian financial crisis, and the second, more pronounced and prolonged from mid-2008 to end-2009. LATCOIN also captures the period of boom in Latvia's economy (2002–2007) when the average quarterly growth of medium to long-run component of real GDP was close to 2% (8% in annual terms).

4. USE OF LATCOIN IN REAL TIME

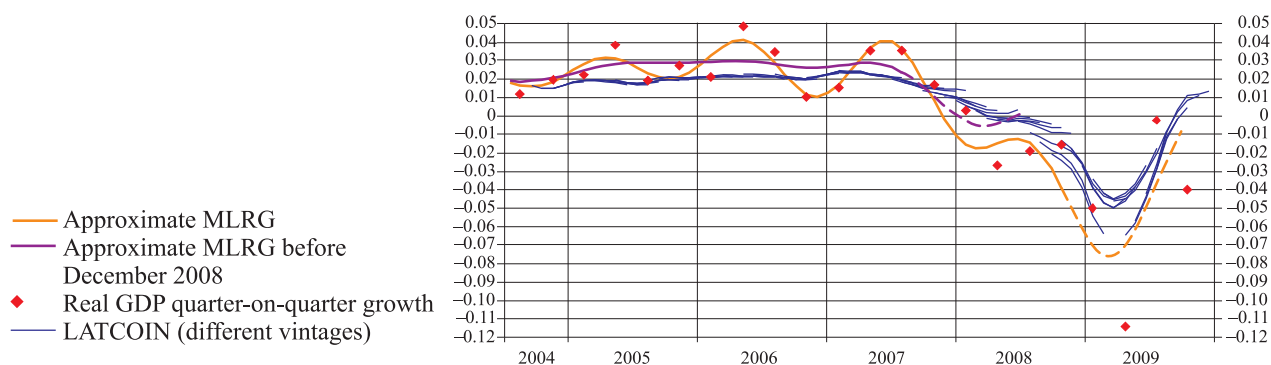
4.1 Real-Time Performance

To analyse the real-time performance of LATCOIN, a real-time database containing GDP series with different vintages was created. Using this database, one can discover historical GDP figures available for analysis at any particular period of time. In addition, the real-time database allows finding out what and when GDP data revisions were made. Regrettably, due to the lack of information it was not possible to create a real-time database for macroeconomic indicators.

The real-time database contains 61 vintages of quarterly seasonally adjusted real GDP, starting with the data available in January 2005 (1996 Q1–2004 Q3) and finishing with the data available in January 2010 (1996 Q1–2009 Q3). Appendix 4 compares some vintages of real GDP: the first available in the database (January 2005), the last available (January 2010), and one in the middle (July 2007). It can be noted that in several quarters the revisions are quite remarkable. These changes come from two sources: revisions in non-adjusted real GDP numbers, and changes due to the seasonal adjustment procedure. The GDP figures available in 2009 display the most significant differences due to the fact that starting from December 2008 the CSB switched to chain-linked real GDP estimation.

Chart 5

**Real time performance of LATCOIN from January 2005 until January 2010
(June 2004–December 2009)**



Sources: CSB and author's calculations.

Chart 5 reports a pseudo real time evaluation of LATCOIN ("pseudo" refers to the absence of real-time data on macroeconomic indicators). The exercise imitates the estimates of LATCOIN on a monthly basis starting from January 2005 until January 2010. The estimations are made on the 9th working day of the next month, and LATCOIN values for 6 previous months are reported.

The exercise shows that historical revisions of LATCOIN are small, with a single exception of the end of 2008 and the beginning of 2009. However, even these revisions could be regarded as small compared with the magnitude of contraction in the activity during the period. Therefore, it can be concluded that LATCOIN provides a stable evaluation of MLRG in real time.

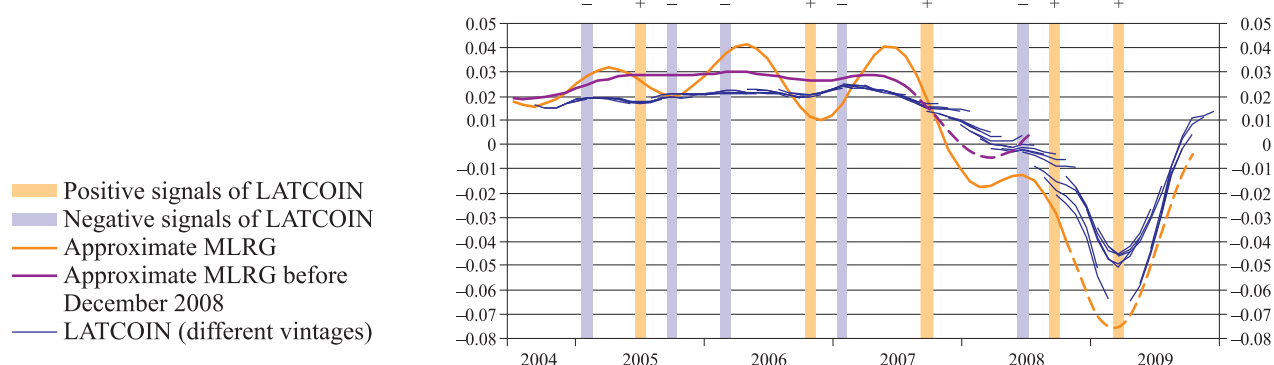
4.2 Behaviour around Turning Points

Another important characteristic of LATCOIN is the ability to give a correct signal of MLRG turning points in real time. Let $\hat{c}_t(\tau)$ be the LATCOIN value at time t , estimated at time point τ (it should be noted that the latest available value of the indicator at time t is always $\hat{c}_{t-1}(t)$). Following the approach of F. Altissimo *et al.* (2), LATCOIN is considered to signal the slope sign change of MLRG in the previous month if:

- there is a sign change between $\Delta\hat{c}_{t-1}(t)$ and $\Delta\hat{c}_{t-2}(t)$. Obviously, if the sign changes from negative to positive, the signal is positive;
- the signs of $\Delta\hat{c}_{t-2}(t)$ and $\Delta\hat{c}_{t-2}(t-1)$ coincide indicating that the signal is consistent;
- the signs of $\Delta\hat{c}_{t-3}(t-1)$ and $\Delta\hat{c}_{t-2}(t-1)$ coincide ruling out two consecutive opposite signals.

Chart 6

Signals of MLRG turning points from LATCOIN (May 2004–December 2009)



Sources: CSB and author's calculations.

The short period of the real-time exercise does not allow us to conduct a formal test on the performance of LATCOIN around the turning points of MLRG. Moreover, the evaluation of LATCOIN turning point signals (see Chart 6) is made even more difficult by changes in the methodology by the CSB. As mentioned in the previous subsection, starting from December 2008 the CSB switched to the chain-linked real GDP estimation. Unlike many other data revisions without any significant effect on approximate MLRG, the switch to chain-linked data had a major impact on approximate MLRG and consequently on LATCOIN calculations.

The next factor, last but not least, that makes the formal evaluation of LATCOIN performance more complicated is the absence of pronounced business cycles in Latvian data until recent times. A real-time exercise shows that LATCOIN gave several turning point signals in 2005–2006, yet MLRG had only minor fluctuations around the average level (with reference to approximate MLRG calculated before December 2008).

The first pronounced change in the medium to long-run tendency occurred in May–June of 2007 while LATCOIN gave a negative signal as early as December 2006 (the negative slope of LATCOIN in early 2007 is clearly seen also in Chart 5). It is difficult to judge whether this signal of LATCOIN should be treated as right or wrong, yet it is more likely that the macroeconomic variables were in advance pointing to a medium to long-run slowdown in Latvia's economy. Also, the positive signal in August 2007 came prior to a short-lived increase in approximate MLRG. The next signal came in May 2008 giving a very timely indication of a pending negative turning point. It is too early to evaluate the preciseness of the next two signals, although the information available so far shows that the first signal was wrong (or probably indicated a future turning point in advance), while the second was almost in time.

CONCLUSIONS

This paper presents the method of estimating the current state of Latvia's economy. The evaluation object is medium to long-run growth of real GDP, but not actual GDP itself. This helps to filter out various one-off effects and focus on medium and long-run tendencies. Our indicator, LATCOIN, could be viewed as a simple adaptation of EUROCOIN for Latvia with some changes in methodology. Our main contribution to literature is the implementation of methodology to a country which has recently undergone the process of transformation and has a relatively short data history. LATCOIN is a monthly estimate of the medium to long-run growth of Latvia's real GDP produced on the 9th working day of the next month.

Our target, MLRG, has been defined as a quarterly GDP growth filtered out from all fluctuations of the period which is shorter than one year. To avoid a potentially large end-of-sample bias, the target was projected on smooth regressors describing the main medium to long-run tendencies of the economy. The regressors, in turn, were obtained using a large panel of macroeconomic variables.

LATCOIN can give information about MLRG of Latvia's real GDP almost in real time, i.e. a few days after the end of the reference period. The indicator is smooth and is very similar to the approximation of MLRG in the middle of the sample. Although the determination coefficient is low, this could be explained by the lack of pronounced cycles in Latvia's economy during the sample period. Also, the performance of LATCOIN as a real time estimator has been analysed. The reliability of the signal is reinforced by the fact that revisions of indicator are small. As to the behaviour around turning points, the evidence is mixed. Some signals were right, although came almost half a year in advance. However, LATCOIN was precisely signalling the last negative turning point in May 2008. It could be concluded, that LATCOIN has a good potential and could be used for estimating the current state of Latvia's economy, although some additional formal test should be conducted when more information becomes available.

APPENDICES

Appendix 1

GENERALISED DYNAMIC FACTOR ANALYSIS

First, covariance matrices of x_t at lags $k = -M, \dots, M$ are estimated:

$$\hat{\Sigma}_x(k) = \frac{1}{(T-k)} \sum_t x_t x_{t-k}' \quad [\text{A1.1}]$$

where t varies from $\max[1, 1+k]$ to $\min[T, T+k]$. The spectrum of x_t at $2J+1$ equally spaced points θ_j is estimated using the Bartlett lag-window estimator:

$$\hat{S}_x(\theta_j) = \frac{1}{2\pi} \sum_{k=-M}^M W_k \hat{\Sigma}_x(k) e^{-i\theta_j k} \quad [\text{A1.2}]$$

where

$$W_k = 1 - \frac{|k|}{M+1}$$

$$\theta_j = \frac{2\pi j}{2J+1}, \quad j = -J, \dots, J.$$

Following F. Altissimo *et al.* (2), $J = 60$ and $M = 24$.

Second, the eigenvalues and eigenvectors of $\hat{S}_x(\theta)$ at each frequency are computed. Let $\Lambda(\theta)$ be the $q \times q$ diagonal matrix having on the diagonal the first q eigenvalues in descending order, and $U(\theta)$ be the matrix having on the columns the first q eigenvectors. The estimate of S_χ for every θ_j is

$$\hat{S}_\chi(\theta) = U(\theta)\Lambda(\theta)U'(\theta) \quad [\text{A1.3}].$$

Third, $\hat{S}_\chi(\theta)$ is integrated over all points θ_j to get the estimate of Σ_χ , and $\hat{S}_\chi(\theta)$ is integrated over frequency interval $[-\pi/6, \pi/6]$ to get the estimate of Σ_ϕ :

$$\hat{\Sigma}_\chi = \frac{2\pi}{2J+1} \sum_{j=-J}^J \hat{S}_\chi(\theta_j) \quad [\text{A1.4}].$$

$$\hat{\Sigma}_\phi = \frac{2\pi}{2J+1} \sum_{j=-10}^{10} \hat{S}_\chi(\theta_j) \quad [\text{A1.5}].$$

The estimate of idiosyncratic variance-covariance matrix Σ_ξ is obtained as

$$\hat{\Sigma}_\xi = \text{diag}(\hat{\Sigma}_x - \hat{\Sigma}_\chi) \quad [\text{A1.6}]$$

where all off-diagonal elements of $\hat{\Sigma}_\xi$ are set to zero. This is consistent with the assumption of mutual orthogonality of idiosyncratic components.

Finally, after matrices $\hat{\Sigma}_\chi$, $\hat{\Sigma}_\phi$, and $\hat{\Sigma}_\xi$ are estimated, we determine the linear combination of variables in the panel that maximises variance of the common component in the low-frequency band. Then we determine another linear combination with the same property under the constraint of orthogonality to the first, and so on.

According to F. Altissimo *et al.* (2), we look for vectors v_k , $k = 1, \dots, n$, and the corresponding linear combinations $w_{kt}^m = v_k' x_t$, solving the sequence of maximisation problems:

$$\max_{v \in R^n} v' \hat{\Sigma}_\phi v, \text{ s.t. } v' (\hat{\Sigma}_\chi + \hat{\Sigma}_\xi) v = 1, v' (\hat{\Sigma}_\chi + \hat{\Sigma}_\xi) v_h = 0, \text{ for } h < k, \text{ where } v_0 = 0, \text{ and } v_h \text{ solves problem } h.$$

The solution of this sequence of problems is given by generalised eigenvectors v_1, \dots, v_n associated with generalised eigenvalues $\lambda_1, \dots, \lambda_n$, ordered from biggest to smallest, of the pair of matrices $(\hat{\Sigma}_\phi, \hat{\Sigma}_\chi + \hat{\Sigma}_\xi)$, i.e. the vectors satisfying:

$$\hat{\Sigma}_\phi v_k = \lambda_k (\hat{\Sigma}_\chi + \hat{\Sigma}_\xi) v_k \quad [\text{A1.7}]$$

with the normalisation constraints $v_k' (\hat{\Sigma}_\chi + \hat{\Sigma}_\xi) v_k = 1$ and $v_k' (\hat{\Sigma}_\chi + \hat{\Sigma}_\xi) v_h = 0$ for $k \neq h$.

*Appendix 2***DETERMINATION OF q AND r** *Table A2***Information Criteria for Different q and r**

q	M. Hallin and R. Liška (8) information criteria	r	J. Bai and S. Ng (3) information criteria ($q = 1$)
1	0.1704	1	-0.0427
2	0.1990	2	-0.0093
3	0.2334	3	0.0419
4	0.2725	4	0.0937
5	0.3149	5	0.1507

Source: author's calculations.

Appendix 3

ESTIMATION OF CROSS-COVARIANCE BETWEEN c_t^* AND w_t

First, the covariance between y_t and w_t is estimated at lags $k = -M, \dots, M$:

$$\hat{\Sigma}_{yw}(k) = \frac{1}{\lfloor (T-k)/3 \rfloor - 1} \sum_l y_{3l-1} w'_{3l-1-k} \quad [\text{A3.1}]$$

where l varies from $\max[1, 1 + \lfloor (k+1)/3 \rfloor]$ to $\min[\lfloor T/3 \rfloor, \lfloor (T+k)/3 \rfloor]$.

Second, cross-spectrum S_{yw} at $2J+1$ equally spaced points θ_j is estimated using the Bartlett lag-window estimator:

$$\hat{S}_{yw}(\theta_j) = \frac{1}{2\pi} \sum_{k=-M}^M W_k \hat{\Sigma}_{yw}(k) e^{-i\theta_j k} \quad [\text{A3.2}]$$

where

$$W_k = 1 - \frac{|k|}{M+1}$$

$$\theta_j = \frac{2\pi j}{2J+1}, \quad j = -J, \dots, J.$$

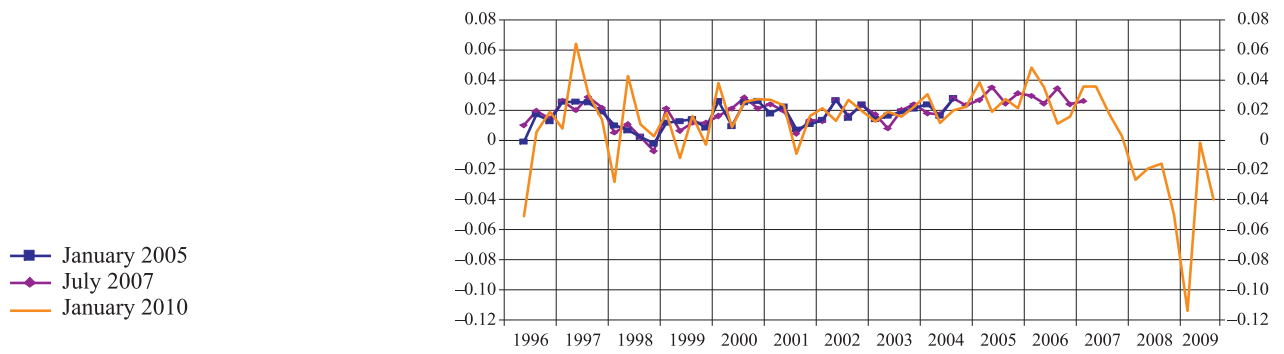
As in Appendix 2, $J = 60$ and $M = 24$.

Finally, $\hat{\Sigma}_{cw}$ is calculated by integrating the cross-spectrum over the relevant frequency interval $[-\pi/6, \pi/6]$:

$$\hat{\Sigma}_{cw} = \frac{2\pi}{2J+1} \sum_{j=-10}^{10} \hat{S}_{yw}(\theta_j) \quad [\text{A3.3}].$$

Appendix 4
REAL GDP DATA REVISIONS

Chart A4
Different vintages of quarterly growth of Latvia's seasonally adjusted real GDP (1996 Q2–2009 Q3)



Sources: CSB and author's calculations.

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