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Forecasting Economic Activity for Estonia: The Application of Dynamic Principal Components Analysis

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Working Paper Series
2/2008

The Working Paper is available on the Eesti Pank web site at:
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ISBN 978-9949-404-68-1
ISSN 1406-7161

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Abstract

In this paper, the dynamic common factors method of Forni et al. (2000) is applied to a large panel of economic time series on the Estonian economy. In order to improve forecasting of economic activity in Estonia, we derive a leading indicator composed of the common components of twelve series, which were identified as leading. The resulting indicator performs better than two other indicators, which are based on a small-scale state-space model used by Stock and Watson (1991) and a large-scale static principal components model used by Stock and Watson (2002), respectively. It also clearly outperforms the naïve benchmark in both in-sample and out-of-sample forecast comparisons.

JEL Code: C32, C33, C53, E37

Keywords: Estonia, forecasting, turning points, dynamic factor models, dynamic principal components, forecast performance

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The views expressed are those of the author and do not necessarily represent the official views of Eesti Pank.

Non-technical summary

The Estonian economy, like most economies of the Central and Eastern European Countries (CEEC) is growing at a very fast pace. However, many observers are worried about the strong foreign currency inflows and high current account deficits, particularly in Estonia (IMF World..., 2007:89–92). As the strong economic growth and the business opportunities associated with this are reasons for these inflows, particularly foreign direct investment, considerable attention is being directed at good short-term forecasts of economic activity in Estonia. National institutions (central bank, ministries), international institutions (e. g. EU, IMF) and the local and international financial communities rely on continuously improving forecasting methods.

In this paper, we apply a method developed by Forni, Hallin, Lippi and Reichlin (FHLR, 2000), to derive a short-term leading indicator for economic activity in Estonia. The advantages of this method include:

- The method allows the efficient use of large panels of economic time series: there are many economic time series available for Estonia; however, compared to the data available for most Western countries, the length of the time series is rather short. The use of large panels therefore increases the total information available.
- The method allows the derivation of one or few common factors which can be used for forecasting: the information contained in the large panel of data is condensed into only one leading indicator based on the "common" components of the time series, i. e. cleaned of their ididosyncratic components.
- The method allows the discrimation between series as leading or lagging with respect to economic activity at relevant frequencies: dynamic principal components methodology allows us to look at measures of coherence at relevant cycle lengths. Other methodologies like static principal components are prone to the overemphasis on very short-term correlations.

We find that indeed, the derived leading indicator, which is a combination of the common components of twelve leading time series, outperforms alternative forecasting models. Both in-sample testing according to Diebold and Mariano (1995) and pseudo out-of-sample testing according to Clark and McCracken (2001) indicate clear improvements over models based on small-scale state-space models (Stock and Watson, 1991) and large scale static principal components based models (Stock and Watson, 2002).

In this paper, we pay additional attention to a correct specification of growth cycles in Estonia. We find that a particularly good way to do this is the use of a three-state Markov switching model, similar to the one used by Hamilton (1989). Estonia has been in a true recession (by Western standards) only once in the aftermath of the Russian crisis in the late 1990s. Before and after, however, growth has been shifting between periods of sustainable growth (particularly for the five years following the Russian crisis) and periods of booming and probably unsustainable growth just before the Russian crisis and since 2005. This endogenous cycle dating method seems to yield better results than the popular Bry and Boschan (1971) cycle dating method used by the American National Bureau of Economic Research (NBER).

Contents

1. Introduction

The Baltic countries have been enjoying an economic boom for many years now and are rapidly catching up with Western European countries on a number of important indices of economic development; for instance, output per capita. According to Walter et al. (2006), Estonia will have overtaken Portugal in terms of GDP per capita in purchasing-power parity equivalents by 2020, while Lithuania will not be far behind. However, there have repeatedly been concerns and warnings that at least the pace of this catch-up process is not sustainable at its current levels. For example, Fitch, the rating agency, warned Latvia in March 2007 of the downgrading of its debt if it does not get its rampant current-account deficit of about 20% under control.[1] It is often said that the mix of rapidly rising property prices and the inflexible currency board exchange rate regimes fuels the presumably unsustainable booms in these countries.[2] On the other hand, some studies take a more positive stance on this topic, as particularly in Estonia, much of the current account deficit is financed by foreign direct investment.[3] In any case, because of the relatively high inflation rates, the adoption of the single currency will not occur in the short-term, so the countries' central banks will have to remain vigilant with regard to output and price developments. In this paper, we will take a look at the data from Estonia and try to figure out which elements really drive Estonian economic activity. The aim is to develop reliable short-term leading indicators for economic activity in order to improve the tools available for macroeconomic analysis.

When we forecast economic activity, large panels of macroeconomic data are usually available. Intuitively, it is attractive to use the information revealed in as much of this data as possible in order to perform forecasts. This is especially true when trying to forecast activity in Eastern European countries, where the length of the available data series is short and the frequency often low, so that the number of observations is small. There are several techniques that allow us to combine information from large panels of data, mainly with the aim of reducing the dimensionality of the data set to a small number of unobservable series which contain a very large proportion of the information. Two competing approaches in the current literature are static principal components, which were used by Stock and Watson (2002), and many others; and

[1]The Economist, March 10th 2007:54.

[2]All three Baltic countries operate currency-board-type exchange rate regimes with exchange rates fixed to the Euro, thereby effectively abandoning independent monetary policies. Estonia introduced a peg to the Deutsche Mark in 1992, Lithuania to the Euro in 2002 and Latvia to the Euro in 2005. Latvia had pegged its currency to the SDR-basket, which is dominated by the US Dollar.

[3]See Walter et al. (2006).

dynamic principal components, used by Forni et al. (2000). Having applied static principal components to an Estonian data set with mixed results, our aim in this paper is to add to the existing forecasting literature by applying dynamic principal components analysis.[4] We will start by briefly outlining the model used, estimate the common components and use this step to investigate relationships between the variables and the reference series, which will be real economic growth, specifically with respect to their leading characteristics. We will then proceed to combine the common components identified via dynamic principal components methodology in the frequency domain, and apply the resulting composite leading index to a forecasting model. Before concluding, we will compare the results to different alternative indicators and forecast specifications.[5] We use in-sample and out-of-sample testing procedures to conduct these tests.

2. Literature review

The application of dynamic principal components to the estimation of common factors and macroeconomic analysis was principally developed by Forni et al. (2000) and applied in numerous papers, first by the same authors in Forni et al. (2001) to a Euro zone data set. Many papers deal with economic forecasting, mainly for economic growth and inflation in countries or groups of countries. Forni et al. (2001) apply this methodology to the construction of coincident and leading indicators for the Euro Area, for instance, while Artis et al. (2001) do so for the United Kingdom. It is this methodology that we will be using in this paper. Static principal components were introduced to economic forecasting by Stock and Watson (2002), who apply their method to US data.

Several papers compare the results of the two methodologies; for instance D'Agostino and Giannone (2006), who compare dynamic and static principal component forecasts for the US economy and conclude that neither method outperforms the other. Similar results are achieved by Boivin and Ng (2005), and Schumacher (2005). Forni et al. (2003b) compare dynamic principal components to structural VARs, finding that although the forecasting applications of dynamic principal components have been successful, identification and, particularly, economic interpretation are difficult. They go on to attempt to overcome this.

Forni et al. (2003a) note that the original dynamic principal components methodology may not be suitable for forecasts as it is based on a two-sided

[4] See Schulz (2007).
[5] See Schulz (2007).

filter and is therefore weak at the two ends of the sample. Consequently, they enhance the method to a two-step procedure, which makes it a one-sided estimation and forecast. They find that the resulting forecasts outperform Stock and Watson's (2002) static principal components-based forecasts for the same US data set. Kapetanios and Marcellino (2006) add impulse-response functions as a tool for analysing structural models based on dynamic principal components analysis.[6]

There is another branch of the literature based on dynamic principal components which does not deal with economic forecasting. Much of it is based on the fact that the frequency domain can also be used for measures of cohesion; that is, synchronisation, as proposed by Croux et al. (2001), where a measure of cohesion is used to analyse business cycle synchronisation. Eickmeier and Breitung (2005) use dynamic principal components to analyse the level of synchronisation between EMU countries and EU accession countries, and within these respective groups of countries. Forni et al. (2007) use dynamic principal components to identify and estimate structural shocks to an economy, where they show that their model is superior to VAR models when very large cross-sections of data are being used.

Besides these papers, which deal with the estimation of common factors by principal components-type models, there are some papers that develop additional techniques, such as the optimal choice of the number of factors to be included in the forecasting model (Bai and Ng, 2002). Another field is the development of in-sample and out-of-sample forecast performance testing methods; for example, in Diebold and Mariano (1995) or Clark and McCracken (2001). An additional tool occasionally referred to in this literature is the use of business cycle dating methods like the one developed by Bry and Boschan (1971), which is an essential foundation for the frequency domain literature, where standard definitions of typical business cycle lengths are relevant to the estimation techniques. We will make use of some of these techniques, particularly in testing, where suitable.

In addition to the principal-components-related literature, there is also a section of literature on small-scale state-space-type common factor models, building on work by Stock and Watson (1991). More recently, this branch of the literature has focused on state-dependent analysis, particularly Markov switching as introduced by Hamilton (1989). These models using a single factor have been applied to the US by Kim and Nelson (1999) and Chauvet (1998), and to Germany by Bandholz and Funke (2003); or the use of two factors for Europe by Kholodolin and Yao (2005). These techniques will not be explicitly referred to in this paper.

[6] Kapetanios and Marcellino (2006) use the Stock and Watson (2002a) data set for the US.

3. Empirical framework

In this paper, we will apply dynamic principal components analysis, an approach developed by Forni, Hallin, Lippi and Reichlin (2000). We start by decomposing a data set $\mathbf{x}_t$ into two unobservable components:[7]

$$\mathbf{x}_t = \gamma_t^q + \xi_t^q \tag{1}$$

The data set is assumed to be stationary and zero-mean; that is, the data set has to be pre-transformed accordingly. The residual vector ξ_t^q represents the idiosyncratic components of the data set after the common component has been subtracted. The term $\gamma_t^q = (\gamma_{1t}^q ... \gamma_{nt}^q)$ contains the common part of the series and reflects the linear projection of $\mathbf{x}_t$ on the space generated by unobservable q common factors $\mathbf{z}_t$.

$$z_{ht} = \mathbf{p}_h\left(L\right)\mathbf{x}_t, h = 1, ..., q \tag{2}$$

These common factors are a linear combination of the leads and lags of $\mathbf{x}_t$, so L is the lag operator and $\mathbf{p}_h(L)$ is a $(1 \times n)$ row vector of two-sided linear filters. Any two common factors are mutually orthogonal and the filters are normalised so that $\mathbf{p}_h(L)\mathbf{p}_k(L-1)' = 0$ when $h \neq k$ and 1 otherwise. We can therefore expand (1) as follows:

$$\mathbf{x}_t = \gamma_t^q + \xi_t^q = C^q(L)\mathbf{z}_t^q + \xi_t^q = K^q(L)\mathbf{x}_t + \xi_t^q \tag{3}$$

If the filters $\mathbf{p}_h(L)$ and the common component processes $\mathbf{z}_t$ maximise the explained variance $\sum_{j=1}^{n} var(\gamma_{jt}^q)$, then they can be called the "dynamic principal components" of $\mathbf{x}_t$. They are very similar to the static principal components used for instance in Stock and Watson (2002) in the sense that they are related to the eigenvalues and eigenvectors of a matrix. However, instead of the variance-covariance matrix, the spectral density matrix of $\mathbf{x}_t$, $\sum(\omega)$ is used here where $-\pi < \omega < \pi$ is the frequency at which the spectral density matrix is evaluated. The filter vector $\mathbf{p}_h(e^{-i\omega})$ is the eigenvector associated with the h-th eigenvalue of the spectral density matrix, after sorting these eigenvalues in descending order.

As with the static case, the filters $C^q(L)$ and $K^q(L)$ can be expressed explicitly as follows:

[7] More details on the methodology can be found in Forni at al. (2000). The software we implemented was the BUSY software (http://eemc.jrc.ec.europa.eu/softwareBUSY.htm) developed by Fiorentini and Planas (2003). Following the notation in Forni et al. (2000), vectors and matrices are printed in bold letters, with scalar variables in italics.

$$C^q(L) = \left(\mathbf{p}_1(L^{-1})' \ldots \mathbf{p}_q(L^{-1})'\right) \quad (4)$$

$$\mathbf{K}^q(L) = C^q(L)\mathbf{C}^q(L^{-1})' = \mathbf{p}_1(L^{-1})'\mathbf{p}_1(L) + \ldots + \mathbf{p}_q(L^{-1})'\mathbf{p}_q(L) \quad (5)$$

$K^q(L)$ is first estimated in the frequency domain as

$$\mathbf{K}^q(\omega) = \mathbf{p}_1(\omega)'\mathbf{p}_1(\omega) + \ldots + \mathbf{p}_q(\omega)'\mathbf{p}_q(\omega) \quad (6)$$

This matrix must be evaluated over a finite number of frequencies, a procedure described in Forni et al. (2000) by first estimating the spectral density matrix $\sum(\omega)$ at each frequency and then using the eigenvalues and eigenvectors of each spectral density matrix to compute $\mathbf{K}^q(e^{-i\theta})$. $\mathbf{K}^q(L)$ is then estimated using the inverse Fourier transform of $\mathbf{K}^q(e^{-i\theta})$.[8] $\mathbf{K}^q(L)$ can now be used as the filter to derive the common components:

$$\gamma_t^q = \mathbf{K}^q(L)\mathbf{x}_t \quad (7)$$

Therefore, we can decompose each series into a common part and an idiosyncratic part:

$$\mathbf{x}_t = \gamma_t^q + \xi_t^* \quad (8)$$

In the following sections, we will make use of these common parts for two purposes. First, they may be used to classify the series as leading or lagging with respect to a reference series. Secondly, they can be used in forecasting.

4. The Estonian Data Set

The data set for Estonia includes 76 economic time series.[9] All the series are of quarterly frequency and are available from the first quarter of 1994 until

[8] For a thorough treatment of frequency domain time series analysis, in particular dynamic principal components, spectral density matrices, fourier transforms and power spectra, consult Brillinger (1981).

[9] This number is in line with other studies that use similar data panels and estimation techniques for business cycle analysis or forecasting exercises; e. g., Eickmeier and Breitung (2005) use 235 series (but only a maximum of 41 different ones for each country), Kapetanios and Marcellino (2006) use 148 series for the US, and Forni et al. (2007) use 89 series, again for the US. A Study on Eastern Europe by Banerjee et al. uses between 40 and 60 quarterly series for each country from 1994:1 until 2002:4 (2006). These authors are not using the same methodology in their papers, however.

the fourth quarter of 2006. Like other authors (Banerjee et al., 2006), we find that monthly series are not always available for the whole time period in Central and Eastern Europe. The data set includes (see Appendix 1):

- Financial data: monetary aggregates, loan aggregates, price indices, interest rates, and monetary reserves. In addition, stock market indices for the Tallinn stock exchange, as well as an American (S&P 500), a Euro zone (EuroStoxx 50) and an Emerging Markets (BRIC) stock exchange index are included;

- Survey-type data: European Commission surveys of industry, consumers, construction, service and retail on various aspects such as order books, economic expectations, and perceptions of the current economic situation and the recent past;

- Trade-related data: data on principal trading partners (Euro zone, Finland, Russia), as well as Estonian imports and exports;

- Sectoral data: data on the various sectors of the Estonian economy in value-added terms.

All series have been converted to year-on-year growth rates. This avoids more complicated techniques for de-seasonalisation and achieves stationarity in all the series. Several other techniques for de-seasonalisation and stationarity are available, among them in particular Baxter-King-type band-pass filters and the Hodrick-Prescott filter. While these techniques are interesting for business cycle analysis, their results are more difficult to interpret for forecasting exercises.[10]

If we want to predict the economic situation in Estonia, we first have to look at its growth pattern over a period we can consider (see Figure 1). To avoid the early transition pains encountered by Estonia as it struggled to shake off Soviet influence, we start in the first quarter of 1995. Another reason for beginning at this point is that the data before is only partially available and of sometimes questionable quality. At this time, we use the GDP time series as they were published before 2006. In 2006, major changes were made in the collection and calculation methodologies as part of the harmonisation process with EU standards. This update changed GDP levels by up to 6.0%, according to the 2006 Annual Report by Statistics Estonia, and growth figures, which are more relevant to this paper, changed somewhat as well. Unfortunately, only

[10]Another implication for forecasting is that because of the rather short time series available, only short-term forecasts of one quarter ahead should be performed (Banerjee et al., 2006).

data from 2000 onwards is currently available under the new methodology. This time span is too short for the methodologies we employ later on. Therefore, until the longer time series under the new methodology are ready and published by the Statistics Office of Estonia later this year, we must link the old data with the new.

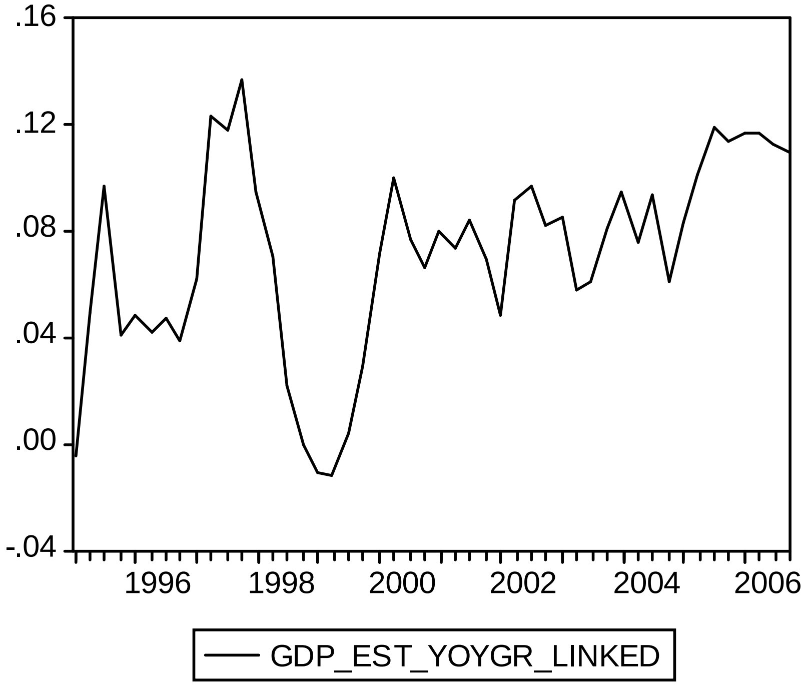

Figure 1: Real GDP Growth in Estonia (% yoy, constant 2000 prices)

Year-on-year-growth (from –4% up to +16%) is presented on the y-axis, and it can be seen that since 2000, growth has fluctuated, but has been positive throughout. Before, there was a brief phase of strong growth running up until 1998, followed by a sharp decline in growth and even a brief period of negative growth. It can also be seen that growth has significantly exceeded the corridor between 5% and 9% since 2005.

We employ two techniques in order to obtain a feeling for the cyclicality of economic growth in Estonia. Firstly, we use the Markov switching method as a descriptive statistic of phases, similarly to Hamilton (1989); and secondly, the NBER dating algorithm, further on below. Markov switching allows us to model the time series of growth rates, where the average growth rate depends upon the state the economy is in; for example, "expansion" or "recession", which are treated as "probabilistic objects".[11] Certain parameters (only the mean growth rate in our case) are assumed to follow a state-dependent data

[11]Diebold and Rudebusch (1996).

generation process.[12] In other words, the state is assumed to be endogenous rather than pre-determined, and there is a probability p_s at each point t for the economy being in state s_t. Therefore, we start by fitting the following AR(2) switching model to the series of seasonally adjusted[13] quarterly growth rates:

$$gdp_t^q - \mu_s = \phi_1(gdp_{t-1}^q - \mu_{s_{t-1}}) + \phi_2(gdp_{t-2}^q - \mu_{s_{t-2}}) \tag{9}$$

The state-variable s_t takes on the values 1, 2 and 3 and is assumed to follow a first-order latent three-state Markov chain process with transition probability matrix **M**, where $p_{12} = prob(s_t = 2 \,|s_{t-1} = 1)$ etc. The rows of **M** add up to 1.

$$\mathbf{M} = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{12} & p_{22} & p_{23} \\ p_{13} & p_{23} & p_{33} \end{pmatrix} \tag{10}$$

We deviate from Hamilton (1989), who only used two states, because a brief glance at the Estonian data shows that, except for the recession phase in the late nineties, growth is almost always high. Yet there might be differences in this high-growth pattern which could not be detected if only two states are allowed for.[14] The resulting conditional probabilities for being in the respective states are depicted in the Figure 2.[15] We display both filtered and smoothed probabilities. The former probabilities take into account information available up to the point of estimation, while the latter use information from the whole sample for smoothing.[16]

[12]Other authors allow more parameters that depend on states, such as the variance-covariance matrix (Lahiri and Wang, 1994).

[13]Seasonal adjustment is performed using the Census X12 method. We will continue to use the four-quarter growth rates later on, but in this analysis it makes more sense to use quarter-on-quarter growth rates to avoid persistence and derive clear cycle-lengths.

[14]Business cycles as defined classically in Burns and Mitchell (1946) are not identifiable in Estonia; "growth cycles" would be a more correct characterisation. This implies the two states of "expansion" and "contraction" mentioned before and applied in most of the relevant literature for mature economies (see Diebold and Rudebusch (1996) or Lahiri and Wang (1994)). There are papers that introduce more than two states as well (Emery and Koenig, 1992).

[15]We use the Ox-MSVAR-package.

[16]The filtered probabilities are $P(s_t = i\,|x_t)$ and the smoothed probabilities are $P(s_t = i\,|x_T)$, where x_t is the series of quarterly real GDP growth.

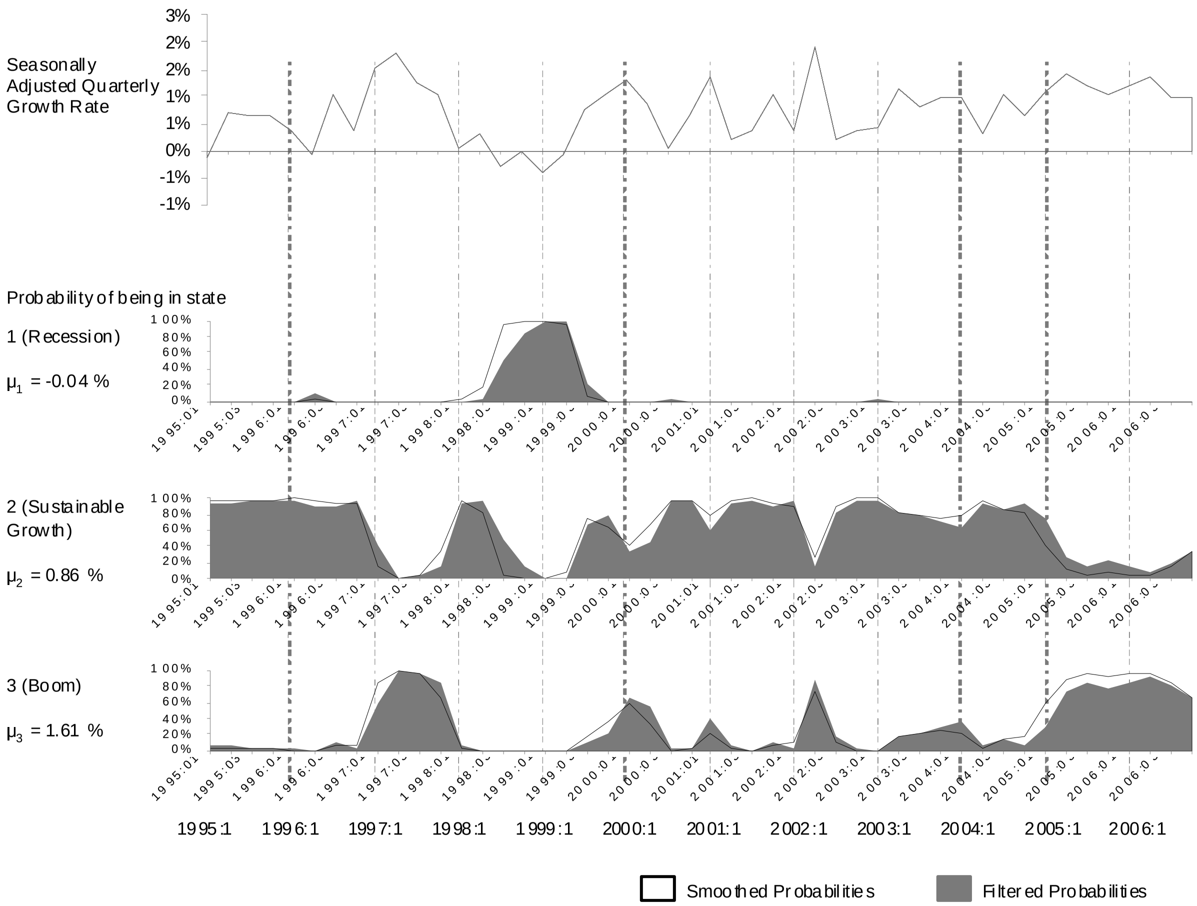

Figure 2: Markov-Switching State Probabilities for seasonally adjusted quarter-on-quarter growth rates

The first state indicates a recession and can only be found in the late nineties – during the Russian crisis. State 3, which had an average annualised growth rate of 6.6%, occurs significantly twice, once just before the Russian crisis and again towards the end of the sample.[17] As the transition probability p_{33} – that a boom quarter is followed by another boom quarter – is 0.67, the average duration of a boom is $1/(1-p_{33}) \approx 3$ quarters, so this latest boom should end very soon if the pattern is to repeat itself. The average annualised growth rate in state 2, dubbed "Sustainable Growth", is 3.5% and its average duration is 5 to 6 quarters. Notice that states 2 and 3 are not necessarily business cycles in the classical sense, but rather "growth cycles", the use of which for further analysis seems more practical given the pattern of continually high growth in Estonia. We will go on and compare the results to the NBER analysis.

To obtain another formalised view of potential business cycle turning points, a method developed by Bry and Boschan (1971) for dating business cycles is often used and referred to as the American National Bureau of Economic Research (NBER) method. Here, we adapt it to the identification of growth-cycles; that is, cycles in the quarterly year-on-year growth rates of GDP. The Figure 3 displays the results.

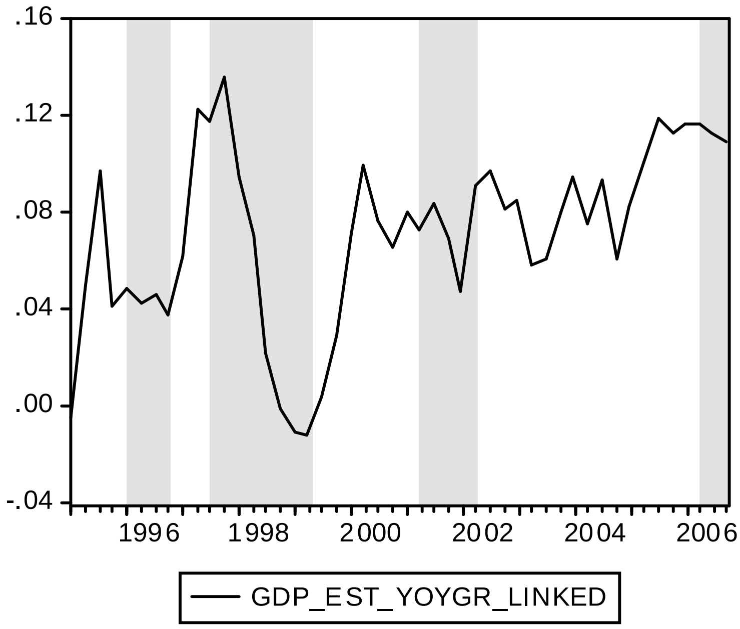

Figure 3: Growth Cycles of the Estonian Economy

[17]We attribute significance here when the conditional probability of one state exceeds 0.9, according to Neftci (1984). Alternatively, some papers suggest 0.5 as the critical value (Bandholz and Funke, 2003).

There are four growth-cycle recessions that can be identified using Bry and Boschan's method: 1996:1–1996:4, 1997:2–1999:2, 2001:2–2002:2, and 2006:1–. The last downturn in particular seems to contradict the results of the Markov switching analysis. However, upon close visual inspection, one might observe that the probability of being in state 3 – a "boom" – peaks at 2006:1 and then drops. This hints at a turning point to a less buoyant economic phase.

Next we analyse the measures of the co-movement of the data in the data set with respect to the reference series, which is real GDP growth in Estonia. This can be performed both in the time domain using cross-correlations at different leads and lags and in the frequency domain using measures of coherence, such as the one proposed by Croux et al. (2001). The cross-correlation of the reference series x_{rgdp} with series i at lead/lag k is defined as:

$$\rho_{rgdp,i}(k) = \frac{Cov(x_{rgdp,t}, x_{i,t-k})}{\sqrt{Var(x_{rgdp,t})Var(x_{i,t})}}, for\, i = 1, \ldots, N \tag{11}$$

(Squared) coherence of the reference series x_{rgdp} with series j at frequency ω is defined as the squared modulus of the cross-spectra divided by the product of the spectra of the reference series and of the j-th series:

$$Coh(\omega)^2 = \frac{|f_{rgdp,j}(\omega)|^2}{f_{rgdp,rgdp(\omega)f_{jj}(\omega)}}, for\, j = 1, \ldots, N \tag{12}$$

In other words, it is a continuum across the frequency band $[-\pi, \pi]$ and not one number, as with the cross-correlation. In this definition, f are the spectra and cross-spectra of the series in the data set, given by

$$f_{rgdp,j}(\omega) = \frac{1}{s\pi} \sum_{k=-\infty}^{\infty} \rho_{rgdp,j}(k) e^{-i\omega k} \tag{13}$$

We use the Bartlett spectral window instead of all the cross-covariances $\rho_{rgdp,j}$.[18] The results for both cross-correlation and coherence analysis are displayed in the following table. We use averages over the periodicities of 1–2 years and 2–8 years for coherence in order to avoid lengthy displays of coherence graphs. In addition to the descriptive statistics explained above, we show the transformations performed (none) and the frequency of the data input (all quarterly), as well as another descriptive statistic, the mean delay, which measures the lag in the movements of the series with respect to the reference series (see Table 1; the full names and sources of the series can be found in Appendix 1).[19]

[18] See Fuller (1996) for reference.

[19] The cross-spectrum between the reference series and another series j, which is generally complex, can be written in polar coordinates as $f_{rgdp,j}(\omega) = |f_{rgdp,j}(\omega)|\, w^{-iPh(\omega)}$. Then

Table 1: Behaviour of the Data Set with Respect to the Reference Series

SERIES	CHARACTERISTICS		COHERENCE		MEAN DELAY		CROSS-CORRELATION		
	Transf.	Freq.	2 Y-8 Y	1 Y-2 Y	2 Y-8 Y	1 Y-2 Y	r_0	r_{max}	t_{max} (1)
BRIC_yoygr	X	4	0,03	0,07	1,23	0,90	0,12	0,49	2
CA_SHARE	X	4	0,26	0,15	7,31	2,64	-0,32	-0,62	-2
CA_yoygr	X	4	0,08	0,06	0,32	0,41	0,17	0,31	1
CPI_yoygr	X	4	0,06	0,06	-7,30	-2,65	-0,25	-0,31	3
CREDIT_COM_RYOYGR	X	4	0,30	0,27	-0,02	-0,03	0,50	0,50	0
CREDIT_IND_RYOYGR	X	4	0,31	0,30	0,17	0,17	0,51	0,59	1
cs_confidence	X	4	0,40	0,34	0,04	0,05	0,54	0,55	1
cs_economy_com12m	X	4	0,20	0,15	0,13	0,15	0,34	0,43	1
cs_economy_past12m	X	4	0,35	0,31	0,11	0,11	0,51	0,55	1
cs_hh_fin_com12m	X	4	0,15	0,10	-0,06	-0,05	0,28	0,38	-2
cs_hh_fin_past12m	X	4	0,12	0,09	-0,01	0,02	0,26	0,41	-3
cs_purc_com12m	X	4	0,23	0,15	-0,03	-0,01	0,32	0,38	1
cs_unemployment	X	4	0,51	0,45	-7,43	-2,77	-0,63	-0,63	0
ct_activity_past3m	X	4	0,12	0,12	0,45	0,43	0,26	0,42	1
ct_confidence	X	4	0,25	0,21	-0,01	-0,02	0,42	0,44	-1
ct_employment_com3m	X	4	0,18	0,15	0,12	0,12	0,35	-0,44	-4
ct_lf_demand	X	4	0,25	0,17	-7,43	1,29	-0,37	-0,46	2
ct_lf_weather	X	4	0,01	0,02	-3,60	-1,29	0,04	0,32	-2
ct_orderbooks	X	4	0,26	0,21	-0,06	-0,08	0,41	0,47	-1
ct_prices_com3m	X	4	0,33	0,31	0,06	0,06	0,52	0,52	0
econ_sentiment_yoygr	X	4	0,52	0,44	-0,04	-0,05	0,60	0,62	-1
est_intrsprd_yoygr	X	4	0,11	0,09	0,08	0,06	0,27	0,39	4
eustoxx_yoygr	X	4	0,00	0,01	0,21	0,15	0,08	-0,29	-4
Exch_periodave_yoygr	X	4	0,38	0,38	-7,34	-2,69	-0,59	-0,59	0
exports_fin_yoygr	X	4	0,02	0,01	-0,10	-0,07	0,11	-0,21	4
exports_yoygr	X	4	0,17	0,15	-0,07	-0,08	0,36	0,37	-1
FDI_share	X	4	0,00	0,00	7,17	2,57	-0,05	0,23	-3
FDI_yoygr	X	4	0,02	0,01	0,07	0,07	0,11	0,26	-4
Fin_assets_yoygr	X	4	0,01	0,00	-7,17	-2,51	-0,05	-0,13	4
fin_cbass_yoygr	X	4	0,03	0,01	-0,07	-0,09	0,07	0,30	-2
fin_cblia_yoygr	X	4	0,01	0,01	0,30	0,37	0,07	-0,20	4
Fin_liab_yoygr	X	4	0,09	0,11	-0,30	-0,28	0,30	-0,40	4
forexreserve_yoygr	X	4	0,09	0,08	-0,16	-0,14	0,26	0,35	-4
gold_yoygr	X	4	0,19	0,17	0,05	0,06	0,39	0,40	1
imports_fin_yoygr	X	4	0,03	0,02	0,01	0,02	0,15	0,28	-3
Imports_yoygr	X	4	0,16	0,14	-0,05	-0,04	0,36	0,36	0
ind_prod_yoygr	X	4	0,64	0,63	0,06	0,05	0,77	0,77	0
intreserves_yoygr	X	4	0,09	0,08	-0,16	-0,14	0,27	0,35	-4
Intr_depo_yoygr	X	4	0,23	0,26	-0,49	-0,46	0,42	0,73	-2
Intr_lend_yoygr	X	4	0,03	0,08	-1,67	-1,05	0,10	0,71	-3
in_confidence	X	4	0,34	0,32	0,26	0,25	0,51	0,59	1
in_orderbooks	X	4	0,30	0,32	0,35	0,32	0,50	0,61	1
in_orderbooks_exp	X	4	0,27	0,30	0,30	0,27	0,50	-0,60	-4
in_price_com3m	X	4	0,11	0,11	0,31	0,31	0,28	0,38	3
in_production_com3m	X	4	0,08	0,06	0,17	0,21	0,19	0,28	1
in_prod_past3m	X	4	0,10	0,14	0,74	0,61	0,26	-0,51	-4
in_stock	X	4	0,34	0,28	-7,28	-2,62	-0,49	-0,50	1
M1REAL_YOYGR	X	4	0,46	0,45	0,25	0,25	0,62	0,74	1
M2real_yoygr	X	4	0,52	0,50	0,14	0,14	0,67	0,69	1
price_cons_yoygr	X	4	0,05	0,05	-7,36	-2,70	-0,24	-0,26	3
re_confidence	X	4	0,24	0,22	0,28	0,27	0,39	0,49	1

the mean delay is defined as the phase at frequency ω divided by that frequency or $Ph(\omega)/\omega$. For further reference, see Harvey (1990).

SERIES	CHARACTERISTICS		COHERENCE		MEAN DELAY		CROSS-CORRELATION		
	Transf.	Freq.	2 Y-8 Y	1 Y-2 Y	2 Y-8 Y	1 Y-2 Y	r_0	r_{max}	t_{max} (1)
re_emplo_com3m	X	4	0,45	0,36	-0,01	-0,02	0,54	0,54	0
re_order_supply_com3m	X	4	0,35	0,27	0,02	0,00	0,45	0,45	0
re_stocks	X	4	0,08	0,05	-7,26	-2,59	-0,15	-0,29	4
rgdp_euro_yoygr	X	4	0,00	0,00	7,38	2,73	-0,04	-0,45	4
rgdp_fin_yoygr	X	4	0,03	0,03	-0,24	-0,26	0,14	-0,39	4
rgdp_rus_yoygr	X	4	0,12	0,12	0,13	0,12	0,34	0,41	3
taxes_yoygr	X	4	0,75	0,70	0,02	0,01	0,80	0,80	0
Trade_bal_yoygr	X	4	0,03	0,03	0,03	0,07	0,17	0,17	0
us_snp500_yoygr	X	4	0,02	0,02	7,40	2,73	-0,12	-0,30	4
Va_agri_yoygr	X	4	0,12	0,10	-0,19	-0,17	0,29	0,29	0
va_bank_yoygr	X	4	0,37	0,31	0,27	0,27	0,46	0,55	1
va_cons_yoygr	X	4	0,42	0,40	-0,20	-0,20	0,58	0,63	-1
va_educ_yoygr	X	4	0,02	0,01	7,36	2,54	-0,08	-0,34	4
va_elec_yoygr	X	4	0,20	0,17	-0,14	-0,15	0,39	0,39	0
va_fish_yoygr	X	4	0,15	0,15	-0,07	-0,06	0,38	0,38	0
va_heal_yoygr	X	4	0,07	0,05	-7,35	-2,69	-0,18	-0,21	1
va_hosp_yoygr	X	4	0,14	0,15	-0,16	-0,16	0,38	0,38	0
va_manu_yoygr	X	4	0,71	0,69	0,05	0,05	0,80	0,80	0
va_mini_yoygr	X	4	0,45	0,42	0,09	0,09	0,62	0,62	0
va_publ_yoygr	X	4	0,08	0,06	7,33	2,62	-0,22	-0,39	4
va_real_yoygr	X	4	0,41	0,38	0,10	0,11	0,59	0,59	0
va_reta_yoygr	X	4	0,17	0,11	-0,17	-0,24	0,26	0,40	-1
va_soci_yoygr	X	4	0,26	0,24	0,12	0,12	0,47	0,47	0
va_tran_yoygr	X	4	0,20	0,19	-0,11	-0,10	0,40	0,40	0

Note: The +/(–) sign refers to a lead(lag) with respect to the reference series; Transformation X signals no further transformation

Given that we are looking for short-term leading indicators from a rather small sample, we shall consider only series with high cross-correlations at small lags (1 or 2) when we look at time domain cross-correlations. As in our previous paper, we find that financial data such as monetary aggregates or credit growth show particularly promising features. In addition, some survey-type series are leading, as well as the financial services series from the sectoral data. Trade-related data seems less promising.

Moving on to the frequency domain, we have to consider both coherence and the mean delay to identify the possibility of a useful leading series.[20] The estimation parameters were set as follows: as a smoothing type, we have used the Bartlett window as mentioned above. Another often discussed parameter is the number of dynamic common factors to be estimated. Here we include as many factors as we need to explain at least 50% of the variance in the data sample, a threshold used by other authors such as Eickmeier and Breitung

[20] Altissimo et al. (1999) propose considering cross-coherences of 0.4 or higher and consider mean delays of more than one period (>1.0) as useful leading series.

(2005), and Forni et al. (2003a).[21] In the estimation of the spectra, we include three cross-correlations for each series. We discuss the results of this specified estimation in the following section.

The classification of the series' leading or lagging behaviour with respect to the reference series can be performed using their common components' spectral density matrix $\sum_{\gamma}^{q^*}(\omega)$, or more specifically, the mean delay (see above) in its first row. This yields the results described in Table 2.

Table 2: Classification Results for the Time Series in the Data Set

PHASE OPPOSITION	LEADING SERIES	COINCIDENT SERIES		LAGGING SERIES
CA_SHARE	BRIC_yoygr	CA_yoygr	in_orderbooks	CA_SHARE
CPI_yoygr	CPI_yoygr	CREDIT_COM_RYOYGR	in_orderbooks_exp	ct_lf_demand
cs_unemployment	cs_unemployment	CREDIT_IND_RYOYGR	in_price_com3m	FDI_share
ct_lf_demand	ct_lf_weather	cs_confidence	in_production_com3m	FDI_yoygr
ct_lf_weather	Exch_periodave_yoygr	cs_economy_com12m	M1REAL_YOYGR	fin_cbass_yoygr
Exch_periodave_yoygr	Fin_assets_yoygr	cs_economy_past12m	M2real_yoygr	Fin_liab_yoygr
Fin_assets_yoygr	in_prod_past3m	cs_hh_fin_com12m	re_confidence	Intr_depo_yoygr
in_stock	in_stock	cs_hh_fin_past12m	re_emplo_com3m	Intr_lend_yoygr
price_cons_yoygr	price_cons_yoygr	cs_purc_com12m	re_order_supply_com3m	Us_snp500_yoygr
re_stocks	re_stocks	ct_activity_past3m	rgdp_euro_yoygr	va_heal_yoygr
rgdp_euro_yoygr	va_educ_yoygr	ct_confidence	rgdp_fin_yoygr	
va_educ_yoygr	va_publ_yoygr	ct_employment_com3m	rgdp_rus_yoygr	
va_heal_yoygr		ct_orderbooks	taxes_yoygr	
va_publ_yoygr		ct_prices_com3m	Trade_bal_yoygr	
		econ_sentiment_yoygr	Va_agri_yoygr	
		est_intrsprd_yoygr	va_bank_yoygr	
		Eustoxx_yoygr	va_cons_yoygr	
		exports_fin_yoygr	va_elec_yoygr	
		exports_yoygr	va_fish_yoygr	
		fin_cblia_yoygr	va_hosp_yoygr	
		forexreserve_yoygr	va_manu_yoygr	
		gold_yoygr	va_mini_yoygr	
		imports_fin_yoygr	va_real_yoygr	
		Imports_yoygr	va_reta_yoygr	
		ind_prod_yoygr	va_soci_yoygr	
		intreserves_yoygr	va_tran_yoygr	
		in_confidence		

The results differ dramatically from those before. Besides the methodological difference, this also has to do with the strict application of the criterion that the mean delay has to be larger than 1 period/quarter to make a series a leading one.[22] Interestingly, surveys like the assessment of stocks

[21] Other papers either use informal criteria to choose the number of factors (Stock and Watson, 2002a) or a formal criterion (Bai and Ng, 2002), where the results lead to a similar amount of explained variance.

[22] Accordingly, series where the mean delay is between 1 and –1 are considered as contemporaneous and series with a mean delay smaller than –1 are considered as lagging.

by retail businesses and industrial firms, which are both in phase opposition to the reference series, are among the leading series. The consumer price index is also on the list, as well as the effective exchange rate. In fact, all series, except for the BRIC stock index, are in phase opposition to the reference series.[23] A comparison with the classification in other studies (for example, Forni et al. (2001)), yields some resemblances. For instance, interest rates ($intr\_depo\_yoygr$ and $intr\_lend\_yoygr$) can be found among the lagging variables. By contrast, we do not find industrial order book variables ($in\_orderbooks$ and $in\_orderbooks\_exp$) among the leading variables. However, Forni et al. (2001) define variables as already leading when they have a mean delay of 0.33 quarters – one month – where we define a lead of more than one quarter as the threshold.

5. Forecasting Economic Growth for Estonia

There are obviously many ways to make use of the information contained in the estimated common components. Forni et al. (2001) suggest simply taking a weighted average of the series classified as leading according to the mean delays of their common components. In the following, we suggest using the common components directly. This is implicitly done by most papers that use static principal components, such as Stock and Watson (2002) or Banerjee et al. (2006), who use one or more static principal components of their respective entire data sets for forecasting, or this author, who uses only series previously identified as leading and combines them by applying static principal components. Our leading indicator will be defined as follows:

$$\Lambda^q = \frac{1}{m}\sum_{j=1}^{m}\frac{\gamma_j^q - \bar{\gamma}_j^q}{\sigma_{\gamma_j^q}}, for\, j = 1, \ldots, N \tag{14}$$

This is the equally weighted aggregate of the standardised common components of the m leading series. Series which were in phase opposition are multiplied by –1. It is important to notice that the estimate of the common components is poor at the ends of the sample as the filter $\mathbf{K}_q(L)$ is a two-sided filter with the length $2M + 1$, where M = 3 in our specification — for the last four and the first four periods there are no direct estimates of the common components. However, we replace these missing values using the linear projections of each common component on the present (forecasting) and past

[23] In the Appendix 1, we supply the time domain analysis of the common components. The short-term cross-correlations of the common components with respect to the reference series are displayed.

(backcasting) of the average of all the coincident variables and on the average of the leading variables.[24] The Figure 4 depicts the resulting leading indicator and the reference series, real GDP growth in Estonia.

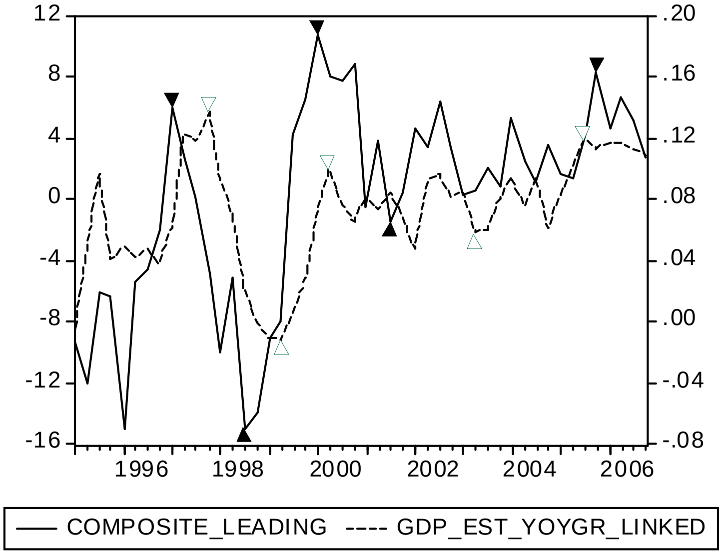

Figure 4: Reference Series and Indicator – Comparison and Turning Points

Note: Triangles denote turning points identified using the NBER dating method.

It can be seen that the leading indicator is in phase with the reference series — a rise indicates increasing growth in economic activity and a fall indicates decreasing growth in economic activity. As a crude measure of performance, we analysed the turning points in the original reference series and in the indicator series applying the NBER dating method, which is based on the method developed by Bry and Boschan (1971), adjusted for quarterly series.[25] It can be seen that the turning points in the first half of the sample are reliably predicted within a few quarters. Later, the trough in the reference series in 2003:1 is predicted 7 quarters ahead of its occurrence, which is too long a delay to be considered valuable information. The last peak in the reference series is missed by one quarter. However, the indicator series is much clearer than the

[24]Alternatively, we could have followed the much more complicated use of one-sided filtered covariance matrices of the common and idiosyncratic components of the variables proposed by Forni et al. (2003a).

[25]Some authors argue that the prediction of turning points is more important than number forecasts, at least in some circumstances, and particularly with policy makers (Chin et al., 2000).

reference series, which declines slightly and slowly after this peak. The indicator series shows that Estonia is clearly in a phase of declining economic growth after 2005.

As a plausibility check, we also construct the composite coincident and lagging indicators. To this end we combine the common components of the series in the data set, which were identified as coincident and lagging, respectively, according to formula (14).[26] The resulting cross-correlations profile of the three indicators with respect to the reference series (real GDP growth) is depicted in the Figure 5.

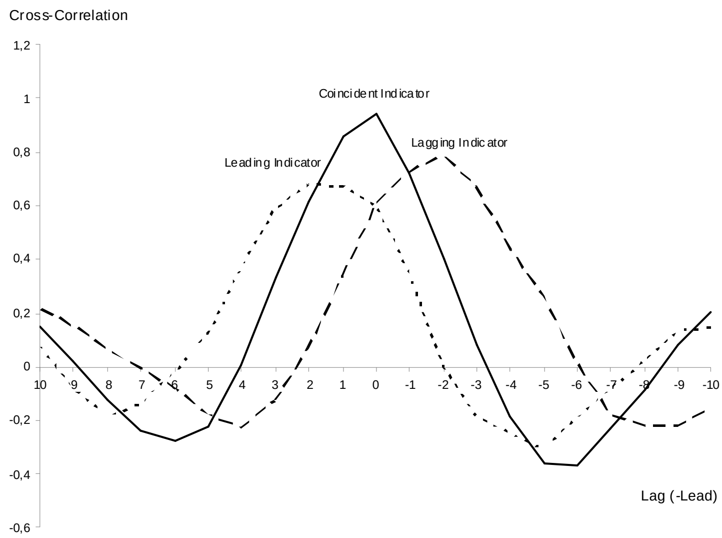

Figure 5: Phase-shifts between leading, coincident and lagging indicators

It can be seen that the dynamic principal components methodology has separated the series very well. The combined common components of the coincident series, for instance, achieve a coincident (lead/lag 0) cross-correlation of more than 0.9. The lagging indicator's cross-correlation profile peaks at lead 2 and the leading indicators at lag 2.

Following most of the literature on dynamic principal components, we compare the performance in number forecasting in comparison with alternative indicators and forecasting models. Here, we compare our new composite indicator with indicators we developed in our previous paper.[27] This paper suggested the following four indicators:

[26] See Table 2.

[27] Schulz (2007).

1. A state-space model using the industrial orderbooks assessment, monetary aggregate M1 and commercial loans based on methods used in Stock and Watson (1991) (i_{Ind3S}).

2. Another state-space model using the industrial orderbooks assessment, monetary aggregate M1 and the Tallinn Stock exchange based on the same method $(i_{io\_m1\_tsi})$.

3. A static principal components model based on 31 time series identified as leading by cross-correlation analysis based on the methods used in Stock and Watson (2002a) ("contemporaneous data set")(PC_{Cont}).

4. A static principal components model based on the 31 time series identified as leading and their respective first lags based on the same method ("stacked data set")(PC_{Stack}).

First, we will use the same in-sample testing routine developed by Diebold and Mariano (1995) to compare the indicators. The procedure regresses the difference between the absolute forecast errors of two series on a constant, using robust standard errors and checks the t-value of the constant.[28]

Overall, we compare six specifications, of which the naïve AR(1) model of real GDP growth (15) will serve as the benchmark model. Note that we use static fitted forecasts. This means that each quarter, the actual value of GDP growth is multiplied by the fitted regression coefficients rather than using a fitted value of GDP growth. This is done for all specifications pair-wise with the benchmark model, which is defined as follows:

$$gdp_t = c_{naive} + b_{1,naive} \cdot gdp_{t-1} + e_{naive} \tag{15}$$

The forecasting model for our composite dynamic principal components leading indicator is defined as follows:

$$gdp_t = c_{dyn} + b_{1,dyn} \cdot gdp_{t-1} + b_{2,dyn} \cdot \Lambda^q_{t-1} + e_{dyn} \tag{16}$$

The state-space models are very similar, only the composite leading indicator is replaced by the respective leading indicators derived by state-space modelling.

[28]Much of the dynamic principal components literature only uses the root-mean-squared forecasting error in order to compare different forecasts (D'Agostino and Giannone, 2006), which reveals whether differences between forecasts are significant. Other papers (Curran and Funke, 2006) use more sophisticated techniques; for instance, the procedures developed by Clark and McCracken (2001).

$$gdp_t = c_{ind3S} + b_{1,ind3S} \cdot gdp_{t-1} + b_{2,ind3S} \cdot i_{ind3S,t-1} + e_{ind3S} \tag{17}$$

$$\begin{aligned} gdp_t &= c_{io\_m1\_tsi} + b_{1,io\_m1\_tsi} \cdot gdp_{t-1} \\ &+ b_{2,io\_m1\_tsi} \cdot i_{io\_m1\_tsi,t-1} + e_{io\_m1\_tsi} \end{aligned} \tag{18}$$

Notice that we are dealing with a nested testing procedure, where only the first lag of the composite is added to the model in the first three models. For the two static principal components-based models, we use the first three components so the forecasting specifications appear as follows:

$$\begin{aligned} gdp_t &= c_{PC,Cont} + b_{1,PC1,Cont} \cdot gdp_{t-1} + b_{2,PC1,Cont} \cdot PC_{1,Cont,t-1} \\ &+ b_{3,PC2,Cont} \cdot PC_{2,Cont,t-1} + b_{4,PC3,Cont} \cdot PC_{3,Cont,t-1} + e_{PC,Cont} \end{aligned} \tag{19}$$

$$\begin{aligned} gdp_t &= c_{PC,Stack} + b_{1,PC1,Stack} \cdot gdp_{t-1} + b_{2,PC1,Stack} \cdot PC_{1,Stack,t-1} \\ &+ b_{3,PC2,Stack} \cdot PC_{2,Stack,t-1} + b_{4,PC3,Stack} \cdot PC_{3,Stack,t-1} + e_{PC,Stack} \end{aligned} \tag{20}$$

We calculate the p-values for the t-test on the constant; that is, a small p-value indicates that the alternative performs better than the benchmark. The Table 3 reports the p-values for different specifications and periods.

The results look very promising: as the only constructed indicator, our new composite leading indicator outperforms the benchmark model in every evaluation period, in many cases significantly so. Particularly important is the impressive performance in 2006, where all the other indicators performed badly. In many other periods, for instance 1999 or 2002, it is not far from the best forecasting model. We conclude that our new indicator presents a significant improvement over the other models.

Second, we use out-of-sample testing because many papers, including Curran and Funke (2006), D'Agostino and Giannone (2006), and Artis et al. (2001) suggest out-of-sample performance testing as a better tool for evaluation (see Table 4).[29] In out-of-sample testing, the forecasting model is estimated for a sub-sample of the entire available sample and then forecasts

[29] However, this is not done in all papers. Many only use in-sample testing; for instance, Bandholz and Funke (2003).

Table 3: Forecasting Performance of Alternative Models and Model Specifications

Period	State Space Specification 1	State Space Specification 2	Principal Components Contemporaneous Data Set	Principal Components Stacked Data Set	Dynamic Principal Components Data Set
1996Q1 – 1996Q4	x	x	0.75	0.54	**0.01*** **
1997Q1 – 1997Q4	x	x	0.10*	**0.09***	0.28
1998Q1 – 1998Q4	**0.00*** **	**0.00*** **	0.03**	0.25	**0.00*** **
1999Q1 – 1999Q4	0.20	0.11	0.11	0.06*	0.16
2000Q1 – 2000Q4	**0.08**	0.11	0.27	0.27	0.36
2001Q1 – 2001Q4	0.32	0.19	**0.00*** **	0.22	**0.00*** **
2002Q1 – 2002Q4	0.46	0.37	**0.09**	0.11	0.25
2003Q1 – 2003Q4	0.34	0.23	**0.01*** **	0.06	0.06*
2004Q1 – 2004Q4	0.31	**0.25**	0.46	0.27	0.49
2005Q1 – 2005Q4	0.19	**0.08***	0.34	0.29	0.30
2006Q1 – 2006Q4	0.98	0.46	0.61	0.90	**0.02*** *
1996Q1 – 2006Q4	x	x	**0.01*** **	0.02**	**0.01*** **
1998Q1 – 2006Q4	0.01***	**0.00*** **	0.02**	0.04**	0.01***
2004Q1 – 2006Q4	0.34	**0.11**	0.38	0.23	0.18
2005Q1 – 2006Q4	0.51	0.11	0.36	0.32	**0.10***
RMSFE	0.02	0.02	0.02	0.02	0.02

Note: The lowest/best p-value for each evaluation period is printed in bold letters.

Table 4: Clark and McCracken Test results (one-sided critical values)

Indicator	Sample	MSE-f	MSE-t	ENC-f	ENC-T
(16) State Space Specification 1	2004:1 – 2006:4	1.27*	0.47	3.30***	2.20***
	2005:1 – 2006:4	0.975*	0.33	3.76***	2.35***
	2006:1 – 2006:4	-3.35	3.37	2.01***	1.662***
(17) State Space Specification 2	2004:1 – 2006:4	0.64	0.21	3.61***	2.23***
	2005:1 – 2006:4	-0.01	-0.04	3.72***	2.25***
	2006:1 – 2006:4	-3.54	-3.017	1.588***	1.71**
(18) Principal Comp. Contemporaneous Data Set	2004:1 – 2006:4	-1.577	-0.317	2.433**	0.963
	2005:1 – 2006:4	3.33**	1.212**	2.64***	1.79**
	2006:1 – 2006:4	4.75***	0.57	6.85***	1.02
(19) Principal Components Stacked Data Set	2004:1 – 2006:4	-6.04	-1.12	0.78	0.36
	2005:1 – 2006:4	0.56	0.24	0.96	0.77
	2006:1 – 2006:4	-2.11	-0.73	0.73*	0.49
(20) Dynamic Principal Components	2004:1 – 2006:4	3.68***	2.32***	2.63***	3.11***
	2005:1 – 2006:4	2.87***	2.36***	1.90***	2.85***
	2006:1 – 2006:4	2.18***	1.98***	1.58***	2.70***

*Note: * indicates significance levels: * = 10%-level, ** = 5%-level, *** = 1%-level.*

for the remaining sample are evaluated with respect to the actual values. We perform the test procedures used by Clark and McCracken (2001) using the same nested forecasting model specifications as in (15) through (20), with (15) again serving as the benchmark model. Four different statistics are suggested by Clark and McCracken: the two MSE (mean squared error) statistics test for equal forecasting accuracy. The MSE-t test was proposed by Granger and Newbold (1977), while critical values for the MSE-f test were provided by McCracken (1999). The ENC (encompassing) statistics test for the benchmark model encompasses the alternative. The ENC-T test is described in Clark and McCracken (2001) and draws from Diebold and Mariano (1995), and Harvey et al. (1998). The ENC-f test was developed by Clark and McCracken (2001) and uses variance weighting to improve the small-sample performance of the encompassing test.

The results clearly show that the composite leading indicator based on dynamic principal components performs better in out-of-sample forecasting than the competing forecasting models. All tests for all selected periods show significance, indicating that the model outperforms the benchmark naïve model. The results are very encouraging as both in-sample and out-of-sample show a significant improvement in forecasting performance over all the competing models.

6. Conclusions

Economic forecasting for Eastern European economies is a challenging task as the available indicators have a short history and have been influenced by possibly singular events like the breakdown of the Soviet-dominated trading block and the emerging markets' crisis in the late 90s. As the length of the available time series is short, the present paper uses larger cross-sections of data to accumulate extra information. This idea has been partly exploited by other papers on Eastern European states, particularly by Banerjee et al. (2006). To our knowledge, this is the first study to undertake this task using dynamic principal components for Estonia.

We have successfully employed the dynamic principal components methodology to develop a short-term leading indicator for the Estonian economy. We used the common components of the data set identified using dynamic principal components analysis in the frequency domain to classify a sub-set of series as leading and using the common components of these series to construct a composite leading indicator. The results of the classification are quite different from the results in our earlier paper in the time domain, with variables from a variety of backgrounds (surveys, price indices, sectoral data) forming the group of leading variables.[30] However, the resulting indicator, which we constructed by simple aggregation, does seem to perform better than indicators developed using different methods, according to in-sample and out-of-sample testing. These other methods include state-space modelling as in Stock and Watson (1991) as well as static principal components as in Stock and Watson (2002a). It performs particularly well in 2006, the end of the estimation sample, where other indicators were shown to be rather deficient compared to simple autoregressive forecasts. We believe that this methodology should be used in regular forecasting exercises as it reveals a lot of extra information about the behaviour of the many series with respect to the reference series. The methodology also presents a more sophisticated way of performing the classification of series in leading, contemporaneous and lagging series with respect to the reference series than the classic cross-correlation analysis.[31]

[30] Schulz (2007).

[31] Using cross-correlations to analyse the leading and lagging characteristics of variables with respect to each other is standard in the empirical literature – for instance, see Bandholz and Funke (2003), and Forni et al. (2001). Gerlach and Yiu (2005) use contemporaneous correlations and principal components to pre-identify variables useful for the construction of a common factor of economic activity in Hong Kong.

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Appendix 1. Data Set and Sources and Cross-correlation with Respect to the Reference Series

Data Set and Sources

Short name	NAME	TYPE	SOURCE	DEFINITION
BRIC_yoygr	Emerging Markets Stock Index (Brazil, Russia, India, China)	Finance	IFC, Monthly Review of Emerging Stock Markets; Quarterly Review of Emerging Stock Markets	Composite stock market index (29/12/1983=100) in local currency; year-on-year-change as unweighted average of four stock exchanges
CA_SHARE	Current Account share of GDP seasonally adjusted	Trade	Eesti Pank	SA X12 census
CA_yoygr	Current-account balance	Trade	IMF, International Financial Statistics	Trade balance, plus net services, plus net income, plus net current transfers. Line 78ald in the IFS.
CPI_yoygr	Consumer price Index end of period	Finance	Statistical Office of Estonia, Eesti Pank	CPI 2000 = 100)
CREDIT_COM_RYOYGR	Loan Stock granted to commercial undertakings	Finance	Eesti Pank	Real year-on-year growth rate
CREDIT_IND_RYOYGR	Loan Stock granted to individuals	Finance	Eesti Pank	Real year-on-year growth rate
cs_confidence	Consumer confidence Indicator	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
cs_economy_com12m	Consumer perception of general economic situation over next 12 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
cs_economy_past12m	Consumer perception of general economic situation over past 12 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
cs_hh_fin_com12m	Consumer financial situation of household over next 12 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
cs_hh_fin_past12m	Consumer financial situation of household over past 12 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
cs_purc_com12m	Consumer major purchases over next 12 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
cs_unemployment	Consumer perception of change in unemployment	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ct_activity_past3m	Construction building activity over the past 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ct_confidence	Construction confidence indicator	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ct_employment_com3m	Construction employment over the next 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ct_lf_demand	Construction factors limiting building activity ** insufficient demand	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change

ct_lf_weather	Construction factors limiting building activity ** weather conditions	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ct_orderbooks	Construction order books	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ct_prices_com3m	Construction prices over the next 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
econ_sentiment_yoygr	Economic sentiment indicator	Survey	EU Economic and Financial Affairs	eop, seasonally adjusted data, weighted average of the other indices
est_intrsprd_yoygr	Estonian interest rate spread	Finance	Eesti Pank	weighted long term kroon interest rate (> 1 yr) minus weighted short term interest rates
Eustoxx_yoygr	Euro area (changing composition) - Equity/index - Dow Jones Euro STOXX 50 - Price index	Finance	European Central Bank	Historical close, average of observations through period - Euro
Exch_periodave_yoygr	Real effective exchange rate of the kroon	Finance	Eesti Pank	Quarterly average change year on year
exports_fin_yoygr	Finnish exports	Trade	IMF, International Financial Statistics	Total exports of goods on a free-on-board (fob) basis.
exports_yoygr	Total exports fob Change yoy	Trade	Based on Statistical Office of Estonia	Percentage change over previous year.
FDI_share	FDI as share of GDP	Finance	Eesti Pank	In constant 2000 prices (real FDI and real GDP)
FDI_yoygr	Foreign direct investment Change yoy	Finance	Based on Statistical Office of Estonia	Percentage change over previous year.
Fin_assets_yoygr	Assets with BIS-reporting banks	Finance	BIS, International Banking and Financial Market Developments	Debt owed by BIS-reporting banks vis-à-vis all sectors at end-period.
fin_cbass_yoygr	Commercial banks' foreign assets	Finance	IMF, International Financial Statistics	Foreign assets held by domestic commercial banks at end-period. Line 7a.d in the IFS.
fin_cblia_yoygr	Commercial banks' foreign liabilities	Finance	IMF, International Financial Statistics	Foreign liabilities of domestic commercial banks at end-period. Line 7b.d in the IFS.
Fin_liab_yoygr	Liabilities with BIS-reporting banks	Finance	BIS, International Banking and Financial Market Developments	Debt owed to BIS-reporting banks vis-à-vis all sectors at end-period.
forexreserve_yoygr	Foreign-exchange reserves	Finance	IMF, International Financial Statistics	Total reserves (excluding gold), including foreign exchange, reserve position with the IMF and SDRs at end-period. Line 1l.d in the IFS.
gdp_est_yoygr_linked	GDP Real change yoy (EIU)	Reference	Statistical Office of Estonia; EIU	Percentage change in real GDP, over previous year.
gold_yoygr	Gold, national valuation	Finance	IMF, International Financial Statistics	Level of gold reserves (national valuation) at end-period. Line 1and in the IFS.
imports_fin_yoygr	Finnish imports	Trade	IMF, International Financial Statistics	Total imports of goods on a cost, insurance and freight (cif) basis.
Imports_yoygr	Total imports cif Change yoy	Trade	Based on Statistical Office of Estonia	Percentage change over previous year.

in_confidence	Industrial confidence indicator	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
in_orderbooks	Industrial current overall order books	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
in_orderbooks_exp	Industrial current export order books	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
in_price_com3m	Industrial selling prices will over the next 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
in_prod_past3m	Industrial production over the past 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
in_production_com3m	Industrial production will over the next 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
in_stock	Industrial current stock of finished products	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
ind_prod_yoygr	Industrial production index	Sector	EIU	The industrial production index rebased to 1996=100 by the EIU
Intr_depo_yoygr	Deposit interest rate (%)	Finance	IMF, International Financial Statistics	Weighted average rate offered by commercial banks on local currency time and savings deposits of all maturities. Line 60l in IFS.
Intr_lend_yoygr	Lending interest rate (%)	Finance	IMF, International Financial Statistics	Weighted average rate offered by commercial banks on short-term local currency loans. Line 60p in IFS.
Intr_MM_yoygr	Money market interest rate (%)	Finance	IMF, International Financial Statistics	Weighted average rate on overnight money market financing rate. Line 60b in IFS.
intreserves_yoygr	International reserves	Finance	Derived from IMF, International Financial Statistics	Stock of foreign reserves plus gold (national valuation), end-period. Derived from lines 1l.d and 1and in the IFS.
M1REAL_YOYGR	Stock of money M1	Finance	Eesti Pank	Real year-on-year growth rate
M2real_yoygr	Stock of money M2	Finance	Eesti Pank	Real year-on-year growth rate
NEW_CAR_SALES_EST_YOYGR	New Car Registrations	Sector	Estonian Motor Vehicle Registration Centre	First registrations of Passenger Cars, year-on-year growth rate
price_cons_yoygr	Consumer price index (av)	Finance	Statistical Office of Estonia	Consumer price index (1997=100) in local currency, period average.
re_confidence	Retail Confidence indicator	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
re_emplo_com3m	Retail Employment over the next 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
re_order_supply_com3m	Retail Orders placed with suppliers during the next 3 months	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change
re_stocks	Retail Stocks	Survey	Estonian Economic Institute	Survey responses netted, 100 added to avoid negative values, year-on-year change

rgdp_euro_yoygr	Eurozone real GDP	Trade	European Central Bank	year-on-year growth rate, adjusted Eurozone-12 countries
rgdp_fin_yoygr	Finnish Real GDP	Trade	CSO Finland	Gross domestic product (GDP) at chained 2000 market prices.
rgdp_rus_yoygr	Russian real GDP	Trade	RosStat (EIU)	Constant 2003 prices
TALLINN_SI_LINKED_YOYGR	Tallinn Stock Market Index	Finance	OMX Tallinn	Linked Tallinn Stock exchange Index and Riga SE Index for years before
taxes_yoygr	Net taxes on products	Sector	Statistical Office of Estonia	Constant 2000 prices
Trade_bal_yoygr	Trade balance (fob-cif basis)	Trade	Derived from IMF, International Financial Statistics	Total exports of goods (fob) less total imports of goods (cif). Derived from lines 70 and 71 in the IFS and end-period exchange rate.
Us_snp500_yoygr	United States - Equity/index - S&P 500 COMPOSITE - PRICE INDEX	Finance	European Central Bank	Historical close, average of observations through period - US dollar
Va_agri_yoygr	Value Added in agriculture, Hunting	Sector	Statistical Office of Estonia	Constant 2000 prices
va_bank_yoygr	Value Added in Financial Intermediation	Sector	Statistical Office of Estonia	Constant 2000 prices
va_cons_yoygr	Value Added in Construction	Sector	Statistical Office of Estonia	Constant 2000 prices
va_educ_yoygr	Value Added in Education	Sector	Statistical Office of Estonia	Constant 2000 prices
va_elec_yoygr	Value Added in Electricity, Gas and Water Supply	Sector	Statistical Office of Estonia	Constant 2000 prices
va_fish_yoygr	Value Added in Fishing	Sector	Statistical Office of Estonia	Constant 2000 prices
va_heal_yoygr	Value Added in Health and Social Work	Sector	Statistical Office of Estonia	Constant 2000 prices
va_hosp_yoygr	Value Added in Hotels, Restaurants	Sector	Statistical Office of Estonia	Constant 2000 prices
va_manu_yoygr	Value Added in Manufacturing	Sector	Statistical Office of Estonia	Constant 2000 prices
va_mini_yoygr	Value Added in Mining, Quarrying	Sector	Statistical Office of Estonia	Constant 2000 prices
va_publ_yoygr	Value added in Public administration and defence; compulsory social security	Sector	Statistical Office of Estonia	Constant 2000 prices
va_real_yoygr	Value Added in Real Estate, Renting and Business Activities	Sector	Statistical Office of Estonia	Constant 2000 prices
va_reta_yoygr	Value Added in Wholesale and Retail Trade	Sector	Statistical Office of Estonia	Constant 2000 prices
va_soci_yoygr	Value Added in Other community, social and personal service activities	Sector	Statistical Office of Estonia	Constant 2000 prices
va_tran_yoygr	Value Added in Transport, Storage, Communication	Sector	Statistical Office of Estonia	Constant 2000 prices

Cross-correlations with Respect to the Reference Series

SERIES NAME	**(*)LAGS**						
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**
gdp_est_yoygr_linked	**0,127**	**0,287**	**0,642**	**1,000**	**0,642**	**0,287**	**0,127**
BRIC_yoygr	-0,192	-0,320	-0,133	0,266	0,445	0,398	0,148
CA_SHARE	-0,177	-0,474	-0,520	-0,501	-0,452	-0,251	-0,071
CA_yoygr	0,151	0,226	0,079	0,261	0,392	0,091	0,078
CPI_yoygr	-0,025	-0,063	-0,131	-0,286	-0,196	-0,143	-0,125
CREDIT_COM_RYOYGR	0,189	0,361	0,567	0,719	0,543	0,339	0,214
CREDIT_IND_RYOYGR	0,084	0,183	0,393	0,634	0,564	0,348	0,155
cs_confidence	0,126	0,273	0,452	0,695	0,570	0,327	0,130
cs_economy_com12m	0,054	0,180	0,310	0,538	0,532	0,319	0,093
cs_economy_past12m	-0,033	0,110	0,368	0,681	0,560	0,264	0,024
cs_hh_fin_com12m	0,223	0,362	0,375	0,402	0,347	0,217	0,073
cs_hh_fin_past12m	0,209	0,310	0,281	0,324	0,327	0,115	0,034
cs_purc_com12m	0,151	0,294	0,395	0,396	0,434	0,196	0,054
cs_unemployment	-0,114	-0,239	-0,503	-0,763	-0,590	-0,312	-0,079
ct_activity_past3m	-0,119	-0,111	0,220	0,546	0,444	0,285	0,001
ct_confidence	-0,044	0,158	0,502	0,724	0,446	0,213	-0,003
ct_employment_com3m	-0,087	0,066	0,320	0,681	0,462	0,202	-0,004
ct_lf_demand	-0,136	-0,284	-0,508	-0,612	-0,439	-0,307	-0,107
ct_lf_weather	0,054	0,239	0,092	0,003	-0,189	-0,200	-0,081
ct_orderbooks	-0,030	0,174	0,542	0,669	0,393	0,198	-0,001
ct_prices_com3m	-0,043	0,116	0,458	0,748	0,543	0,280	0,069
econ_sentiment_yoygr	0,072	0,324	0,684	0,853	0,519	0,217	0,006
est_intrsprd_yoygr	0,032	0,091	0,315	0,438	0,256	0,197	0,151
eustoxx_yoygr	-0,127	-0,066	0,067	0,152	0,049	-0,050	-0,063
Exch_periodave_yoygr	0,059	-0,050	-0,348	-0,689	-0,468	-0,250	-0,116
exports_fin_yoygr	0,033	0,088	0,138	0,165	0,184	0,019	-0,075
exports_yoygr	0,066	0,231	0,508	0,550	0,330	0,104	-0,087
FDI_share	0,233	0,284	0,118	-0,065	-0,107	-0,014	-0,038
FDI_yoygr	0,195	0,269	0,282	0,223	0,041	-0,016	-0,021
Fin_assets_yoygr	0,026	0,071	-0,104	-0,141	-0,139	-0,058	-0,106
fin_cbass_yoygr	0,191	0,264	0,190	0,103	0,208	0,155	-0,006
fin_cblia_yoygr	0,039	0,074	0,071	0,059	0,121	0,038	-0,050
Fin_liab_yoygr	0,127	0,255	0,309	0,275	0,108	-0,019	-0,035
forexreserve_yoygr	0,112	0,269	0,326	0,382	0,273	0,047	-0,016
gold_yoygr	0,093	0,187	0,334	0,488	0,447	0,317	0,165
imports_fin_yoygr	0,110	0,166	0,187	0,229	0,242	0,122	-0,015
Imports_yoygr	0,035	0,160	0,364	0,445	0,315	0,093	-0,058
ind_prod_yoygr	-0,011	0,123	0,538	0,938	0,625	0,285	0,059
intreserves_yoygr	0,112	0,270	0,328	0,385	0,275	0,048	-0,015
Intr_depo_yoygr	0,245	0,562	0,692	0,577	0,170	-0,109	-0,147
Intr_lend_yoygr	0,305	0,483	0,395	0,088	-0,187	-0,263	-0,107
in_confidence	-0,094	-0,019	0,252	0,655	0,555	0,297	0,080
in_orderbooks	-0,109	-0,089	0,203	0,643	0,542	0,298	0,080
in_orderbooks_exp	-0,152	-0,092	0,221	0,644	0,512	0,276	0,046
in_price_com3m	-0,144	-0,059	0,191	0,572	0,523	0,263	0,129
in_production_com3m	-0,115	0,061	0,236	0,378	0,372	0,158	-0,010
in_prod_past3m	-0,142	-0,214	-0,009	0,447	0,464	0,311	0,093
in_stock	0,007	-0,074	-0,287	-0,716	-0,601	-0,332	-0,151
M1REAL_YOYGR	0,003	0,025	0,289	0,765	0,709	0,495	0,243
M2real_yoygr	0,068	0,160	0,443	0,836	0,663	0,414	0,198

price_cons_yoygr	-0,029	-0,074	-0,143	-0,281	-0,177	-0,118	-0,112
re_confidence	-0,180	-0,084	0,146	0,568	0,498	0,275	0,098
re_emplo_com3m	-0,025	0,130	0,369	0,693	0,480	0,230	0,107
re_order_supply_com3m	-0,128	0,011	0,369	0,624	0,445	0,252	0,057
re_stocks	0,131	0,012	-0,116	-0,264	-0,276	-0,241	-0,128
rgdp_euro_yoygr	-0,145	-0,179	-0,055	-0,012	-0,031	-0,089	-0,186
rgdp_fin_yoygr	-0,020	0,089	0,272	0,213	0,079	-0,016	-0,120
rgdp_rus_yoygr	-0,032	0,034	0,192	0,429	0,330	0,239	0,128
taxes_yoygr	0,099	0,240	0,598	0,956	0,672	0,339	0,107
Trade_bal_yoygr	0,005	0,030	0,081	0,182	0,181	0,021	-0,031
us_snp500_yoygr	-0,109	-0,134	-0,144	-0,152	-0,131	-0,142	-0,076
Va_agri_yoygr	0,151	0,218	0,404	0,494	0,126	-0,027	0,005
va_bank_yoygr	-0,093	0,007	0,154	0,520	0,535	0,235	0,131
va_cons_yoygr	0,090	0,303	0,685	0,783	0,369	0,064	-0,039
va_educ_yoygr	-0,022	-0,051	-0,098	-0,115	-0,044	-0,172	-0,157
va_elec_yoygr	0,021	0,147	0,361	0,429	0,247	0,195	0,061
va_fish_yoygr	0,031	0,123	0,246	0,417	0,277	0,055	-0,025
va_heal_yoygr	-0,032	-0,103	-0,142	-0,249	-0,161	-0,018	-0,079
va_hosp_yoygr	-0,021	0,012	0,267	0,509	0,177	0,106	0,066
va_manu_yoygr	0,042	0,144	0,523	0,897	0,599	0,253	0,031
va_mini_yoygr	-0,022	0,080	0,403	0,855	0,630	0,319	0,122
va_publ_yoygr	0,006	-0,122	-0,316	-0,389	-0,257	-0,219	-0,075
va_real_yoygr	0,192	0,348	0,533	0,784	0,540	0,239	0,168
va_reta_yoygr	0,123	0,133	0,341	0,323	0,239	0,267	0,038
va_soci_yoygr	0,100	0,177	0,344	0,618	0,455	0,234	0,144
va_tran_yoygr	0,038	0,216	0,323	0,458	0,215	-0,003	0,057

(*): High cross-correlations at positive lags indicate a leading behaviour of the variable with respect to the reference series.