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Forecasting Economic Growth for Estonia: Application of Common Factor Methodologies

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Abstract

In this paper, the application of two different unobserved factor models to a data set from Estonia is presented. The small-scale state-space model used by Stock and Watson (1991) and the large-scale static principal components model used by Stock and Watson (2002) are employed to derive common factors. Subsequently, using these common factors, forecasts of real economic growth for Estonia are performed and evaluated against benchmark models for different estimation and forecasting periods. Results show that both methods show improvements over the benchmark model, but not for the all the forecasting periods.

JEL Code: C53, C22, C32, F43

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Non-technical summary

The forecasting of economic growth draws a lot of attention in all countries and new methods are constantly being developed to improve the performance of forecasting models. While all of these methods are universally applicable in principle, their appropriateness for particular settings has to be examined. As more and more macroeconomic time series data becomes easily available, there has been a shift in the development of these methods towards the inclusion of more time series into the forecasting models. One promising field is the study of unobservable common factors in large data sets, where the assumption is made that a small number of factors drive the whole data set and that the use of these factors can improve forecasts.

In this paper we apply two different methods to extract common factors from an Estonian data set of quarterly macroeconomic time series from 1994 to 2006. One is a small-scale state-space model which has been used by Stock and Watson (1991) for economic forecasting. This model is estimated using maximum likelihood and a Kalman filter procedure. As the number of time series variables, which can be included in this model, is small, it requires careful pre-selection. We use different specifications of the model, each based on three time series. To represent specificities of the Estonian economy, we include survey type data such as industrial order books as well as financial data such as monetary supply and stock exchange data. The latter two reflect the fact that our analysis suggests that financial data are more relevant for forecasts of the Estonian economy than other authors have found for many mature economies.

The second methodology we apply draws on the principal components literature. Following Stock and Watson (2002), we use a static principal components model based on a large data set of 34 time series, which represent a large part of the total available data set. This method is computationally rather simple and is computed for a contemporaneous data set and a "stacked" data set. The latter includes the first lags of the 34 time series to allow for the existence of phase shifts. This analysis yields several factors which can be interpreted with respect to the influence individual time series have upon them.

We follow a large part of the literature on forecasting in concluding with the evaluation of our resulting forecasting models compared to a benchmark naïve model. In-sample comparisons and out-of sample comparisons are presented. The latter uses a sub-sample of the whole data set to estimate the forecasting equation and then uses the remainder of the sample to evaluate and compare the performance.

The in-sample forecast evaluation according to Diebold and Mariano (1995) shows that our models outperform the naïve forecast for most of the evalua-

tion periods, particularly for the period of the Russian crisis in the late 1990s. However, this outperformance is not always significant and particularly for the end of the sample most models are actually worse than the naïve forecast. The out-of sample tests according to Clark and McCracken (2001) show that the additional information included in our models is not statistically irrelevant, however. The naïve model does not encompass our forecasting models.

Overall, common factor models do improve forecasts and reveal a lot of information about the underlying data set, particularly for the principal components approach.

Contents

1. Introduction

The Estonian economy has been growing quickly since the country regained its independence in the early nineties and this growth has recently increased to double digits, vastly exceeding the potential of 5–7% defined by the Bank of Estonia. Being able to make accurate predictions about such high growth rates is extremely relevant for policy makers and is pursued by several institutions both in Estonia and internationally. This paper extends the methodology currently used by the Bank of Estonia for short-term forecasting to include the use of common factor methodologies; namely, state-space dynamic common factor models and principal components analysis. We focus research on the prediction of economic growth, but similar models can also be used to forecast inflation or other macroeconomic variables.

State-space modelling was introduced to economic forecasting by Stock and Watson (1991). The idea is that from a small set of potentially leading variables a common dynamic trend is extracted, which excludes much of the idiosyncratic movements of the individual series. State-space modelling is used to describe the dynamic framework, the coefficients of which are subsequently estimated using Kalman filtering techniques. The result is a single leading indicator that can then be tested for its predictive capacity. Principal components analysis comes in two different forms — static and dynamic. Static principal components are widely used and have, for instance, been used by Stock and Watson (2002) for economic forecasting. It is an efficient method for deriving common factors from a large set of data. The idea is to derive components that explain the largest part of the cross-sectional variance. Therefore, static principal components are based on the variance-covariance matrix of a data set and can easily be computed using any standard econometric software package. Dynamic principal component methodology for economic forecasting was developed by Forni et al. (2000). It is based on the spectral density matrix of a data set and requires more specific software. We leave this application to future research. Obviously, evaluating the performance of the derived leading indicators requires some attention as well. We will use in-sample and out-of-sample tests to evaluate the performance of these indicators.

The remainder of this paper is laid out as follows. Section 2 takes a closer look at some of the specific features of the Estonian economy which need to be taken into account when constructing forecasts. In Section 3, we take a look at the data set and preliminarily analyse its predictive powers. In Section 4, we use dynamic common factor analysis following Stock and Watson (1991) to construct a leading indicator and evaluate its performance. In Section 5, the static principal components model is presented and a leading indicator is derived. This is then evaluated and compared to other forecasting models. Our conclusion is presented in Section 6.

2. Specific features of the Estonian economy

In this section we will focus on two aspects of the Estonian economy that may be important when trying to forecast future economic growth. One aspect is the existence of cycles, specifically growth cycles that may help when making forecasts. The other aspect is how the Estonian economy differs from other economies.

If we want to predict the economic situation in Estonia, we first have to look at its growth pattern over the period we can consider. 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 there is that the data before this period 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 Annual Report 2006 of Statistics Estonia, and growth figures, which are more relevant to this paper, changed somewhat as well. Unfortunately, only 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, we must link the old and new data before the longer time series under the new methodology is set and published by the Statistics Office of Estonia later this year.

In the Figure 1 year-on-year-growth (from –4% up to +16%) is presented on the y-axis. 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 long-term corridor between 5% and 9% since 2005.

In addition to economic growth as such, the reliable signalling of economic phases or business cycles is often required from forecasts and specifically from leading indicators. In business cycle analysis, the output gap is commonly used to identify the current position in the cycle. It represents the current usage of the production capacity of an economy. Under-usage of capacity indicates a recession; over-usage indicates a boom, with up- and downswings in between. The Ifo Institute for Economic Research has found an intuitive graphic

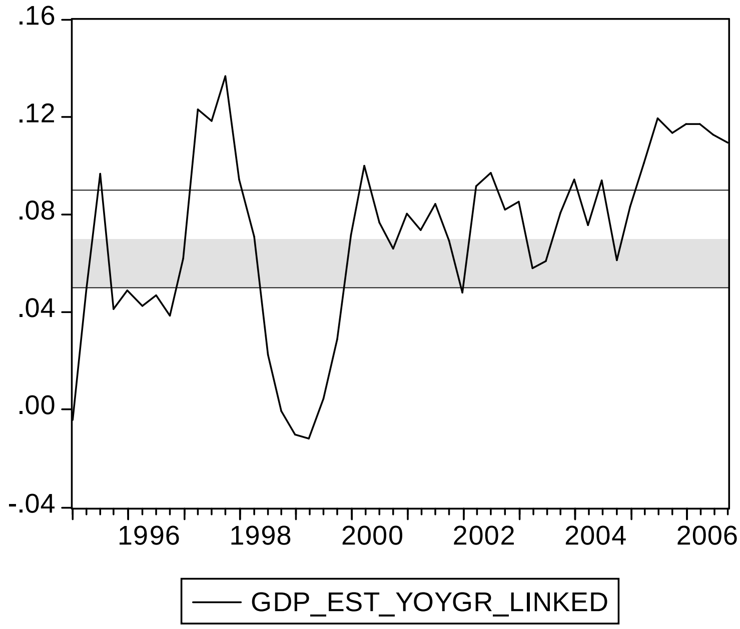


Figure 1: Real GDP Growth in Estonia (% yoy, constant 2000 prices)

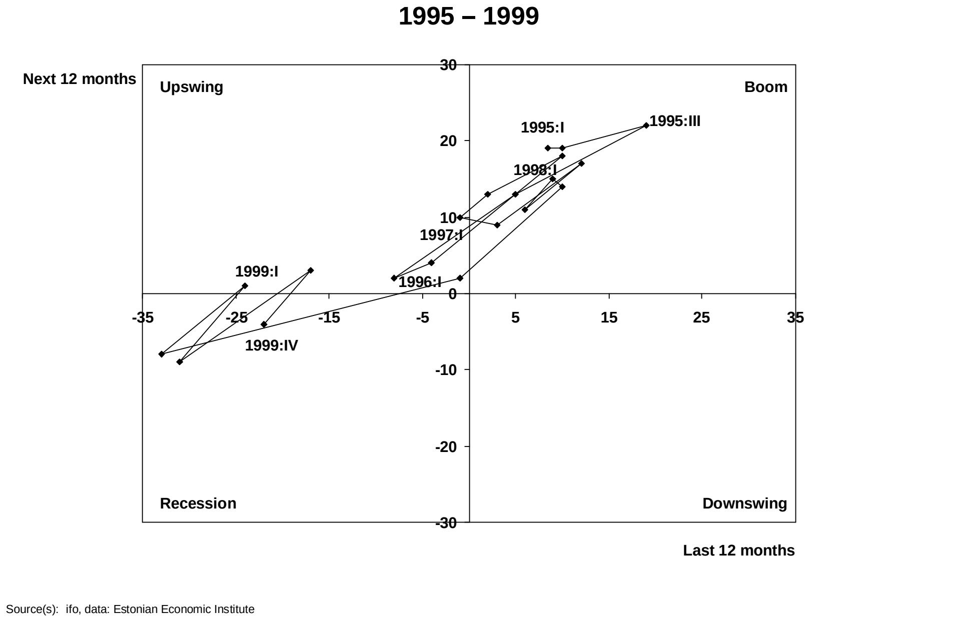
way of illustrating the current position of an economy (CESIfo, 2007)[1]. The "economic climate clock" plots an indicator of the perception of the current (or very recent) climate of the economy versus expectations. We do this for Estonia using the consumer climate indices published by the Estonian Economic Institute for the past twelve months (recent climate) and the coming twelve months (expectations). As the Russian crisis of 1998 clearly marks a break, we display two different graphs below: one for the period 1995–1999, the other for 2000–2006 (see Figure 2).

The four quadrants of the "economic clock" have different interpretations according to the relationship between the expectations and interpretations of the current situation or recent past. Table 1 represents interpretations for the different quadrants.

Neither of the two periods exhibits the typical smooth development from one economic phase to another[2]. Instead, there seems to be a lot more variation than we would find in more mature economies. From 1997 to 1998, the Russian crisis seemed to have taken the Estonian consumers by surprise, which is why the clock turned from boom to bust within a period of only two quarters. The second quadrant "downturn" was skipped; the economy dropped

[1] For further details on the economic clock and examples for Germany, see Nerb (2007).

[2] For examples of mature economies, see Nerb (2007).



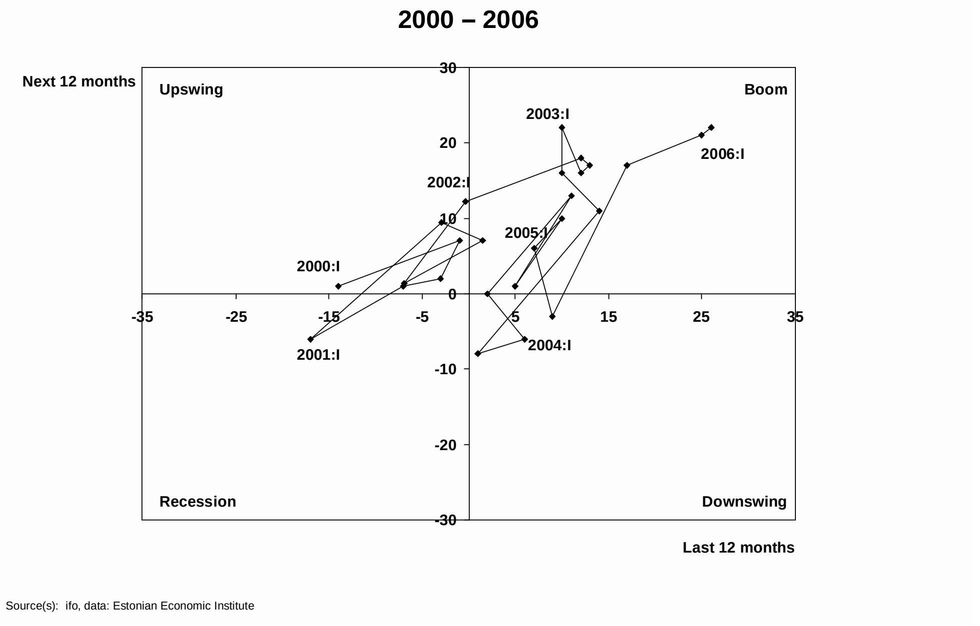


Figure 2: Economic clock — consumer perception of the general economic situation

Table 1: Interpretation of the economic clock figures

Quadrant	Perception of past 12 months	Expectations of future 12 mths.	Interpretation
I	Positive	Positive	Boom in the economy
IV	Positive	Negative	Downswing in the economy
III	Negative	Negative	Recession in the economy
II	Negative	Positive	Upswing in the economy

sharply into recession. At the beginning of the second half of the sample, the years 2000 and 2001 were still marked by a negative perception of the current state of the economy, but with improving expectations. The clock moved to the fourth quadrant "upswing" before entering the "boom" quadrant in 2002. In 2003, the clock signalled a downswing, which fortunately for Estonia, did not continue on to become a recession, but rather turned back to a boom in 2005 with the most recent values at record levels. This movement has been due to the fact that the current state of the economy is persistently seen as positive and only the expectations shift. However, the negative expectations did not seem to materialise, which is why the economy reverted to a boom. This discussion shows that traditional business cycle analysis is unlikely to lead to the same stable results as in mature economies when applied to an economy that is still emerging, such as Estonia. It also shows that there have only been three major cycles: strong and volatile growth until the Russian crisis, a sharp downturn during the Russian crisis, and strong, rather stable and accelerating economic growth ever since.

To obtain some sort of formalized view of the existence of cycles, we use the method developed by Bry and Boschan (1971) for dating business cycles, but we adapt it to the identification of growth-cycles; that is, cycles in the 4^{th} differences of GDP. The Figure 3 displays the results.

There are four growth-cycle recessions which can be identified using Bry and Boschan's method: 1996:1–1996:4, 1997:2–1999:2, 2001:2–2002:2 and 2006:1-.

In the search for leading indicators for Estonia, attention has to be paid to the economic specificities of its economy. There are three characteristics that we will take a closer look at:

- the Estonian economy's openness to trade,
- important sectors of the economy,
- the importance of foreign direct investment and the role of money supply.

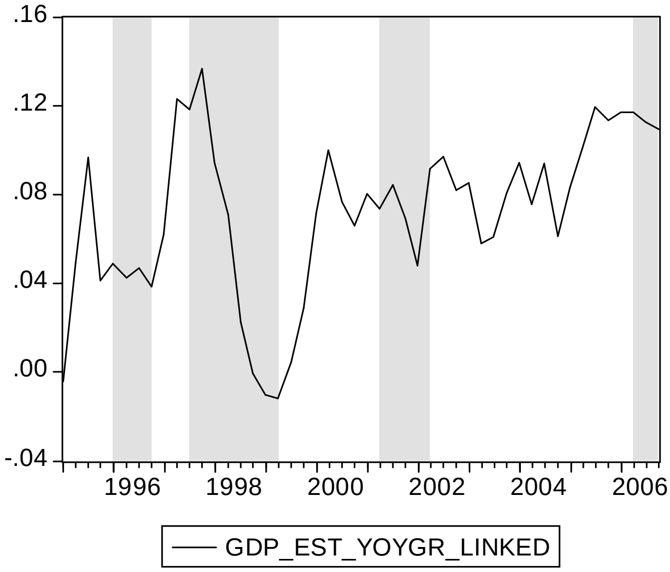


Figure 3: Growth cycle recessions in Estonia

Estonia is one of the world's most open economies, with trade (the sum of imports and exports of goods and services) amounting to almost 160% of the gross domestic product (see Figure 4). Therefore, when predicting macroeconomic variables for Estonia, special consideration might be taken of variables that represent the influence of trade on the Estonian economy. It should be noted, however, that openness seems to be a function of the size of an economy. This is shown in the following figure, which demonstrates that there is a negative linear relationship between the size of a country, represented by its population in Log-terms, and its openness.

Estonia is a very open economy, but it is not an outlier given the relationship above. This is reflected in the fact that we find Estonia above the estimated OLS-regression line, but not dramatically so[3]. Nonetheless, because of the importance of trade, we include macroeconomic variables from Estonia's important trade partners in the data set. We selected variables from Finland, the Euro zone and Russia, as these countries and areas comprise Estonia's most important trade partners, as can be seen in the Figure 5.

[3]The negative-sloping regression line shows that generally, in smaller countries, trade plays a bigger role than in larger ones.

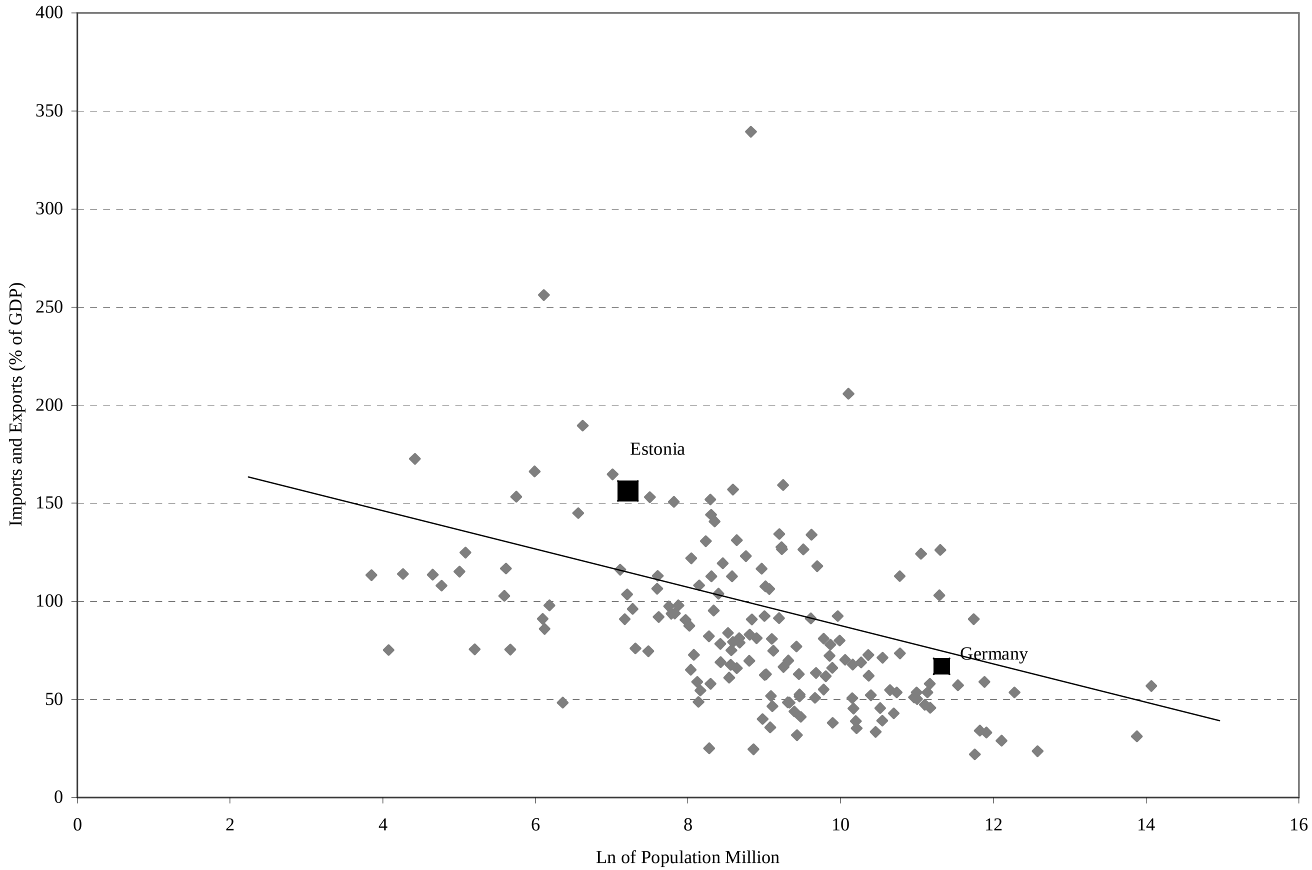


Figure 4: Openness versus Population

Source: Economist Intelligence Unit (EIU).

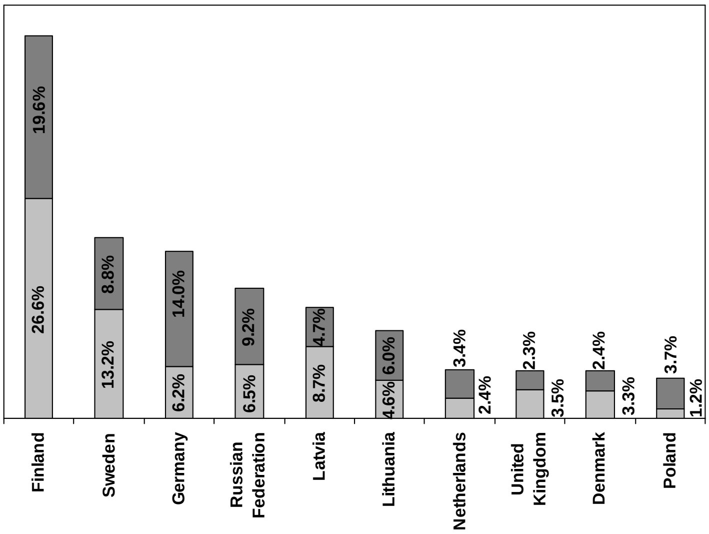


Figure 5: Trade partners of Estonia

Source: Statistical Office of Estonia.

The decomposition of GDP by sector yields the Figure 6, which shows both value added in different sectors and the respective compound annual growth rates for 1995–2005. All data is in constant year 2000 prices.

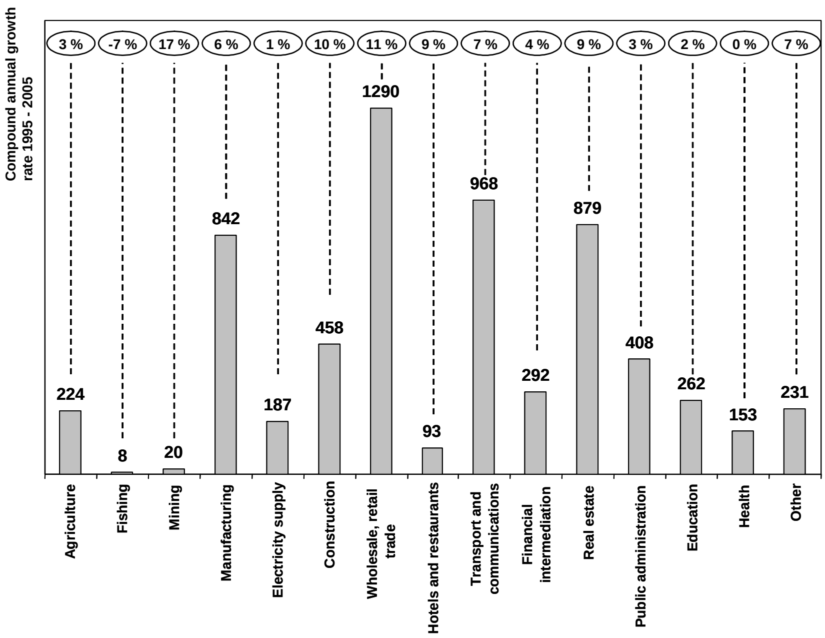


Figure 6: Estonian GDP by sectors

Source: Statistical Office of Estonia.

The largest sectors are trade (retail and wholesale), transport, real estate and manufacturing. Growth is spread rather evenly across sectors, with the secondary sector somewhat underperforming the tertiary sector. These results do not reveal ex-ante suppositions about possible leading indicators; however, the eventual choice of variables should be checked against this composition to avoid the use of economically insignificant variables. This would be the case for instance, if fishing turned out to be a good leading indicator statistically (which indeed it does).

Foreign direct investment is important to the Estonian economy for two reasons. First, it can be seen as a proxy for overall investment. Second, it is, as Zanghieri (2006) points out, the "only non-debt-creating foreign source of capital" to finance Estonia's persistent current account deficit (Zanghieri, 2006:257). There is a considerable amount of literature on the qualities of financial variables as leading indicators for economic cycles; for instance, Estrella and Mishkin (1998) and Fritsche and Stephan (2000). In general, their findings state that there are only very limited and unstable empirical relationships in developed countries. Yet for Estonia, the particularities of its economy will lead to different results, as this paper will suggest. This may be due to Estonia's monetary regime, the currency board linked with the Deutschmark (since 1999 with all European currencies and subsequently, the euro).

3. Identification of leading time series

There is a table in the appendix containing all the time series available in sufficient length and frequency as well as their respective cross-correlation characteristics with respect to real GDP growth as a reference series[4]. The table indicates the transformations made to achieve stationarity, their respective unit-root-test results (augmented Dickey-Fuller test) and maximum cross-correlations, and the lag (positive number) or lead (negative number) at which this maximum cross-correlation is recorded.

In the following section, we will explore the leading or lagging characteristics of the different types of variables with respect to real GDP growth in Estonia. The data was categorised into four groups: (1) financial variables, (2) trade variables, (3) GDP-sector variables and (4) survey-type variables.

The financial variables included in the data set exhibit very different char-

[4]Using cross-correlations to analyse the lagging and leading 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.

acteristics (see Figure 7). As a matter of illustration, they are spread over four quadrants here with the upper two quadrants indicating significant maximum correlation coefficients ($> \frac{2}{\sqrt{T}}$, equals 0.33 for T=44) and the lower two quadrants insignificant correlations. The right-hand side indicates a leading characteristic of the variable with respect to real GDP growth in Estonia, and the left-hand side indicates a lagging relationship; that is, the graph illustrates at which lag (or lead) of the explanatory variable the maximum cross-correlation is achieved.

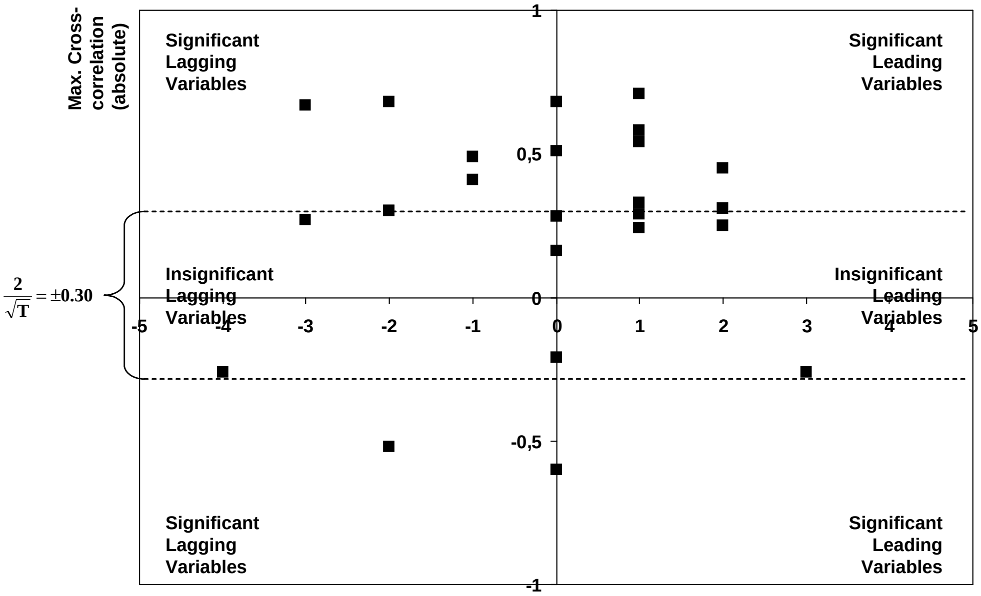


Figure 7: Cross-correlation characteristics of Financial Variables 1995–2006

Source: Statistical Office of Estonia; The Economist Intelligence Unit, European Central Bank; OECD.

For example, monetary supply ($M1$ and $M2$) exhibits a rather strong short-term leading characteristic, while interest rates seem to be lagging with high coefficients. The stock exchange indices for emerging markets that we have included display rather high correlations, yet at very different lags and leads. We have also included Estonian gold reserves (in national valuation) in the financial data set, even though they seem to correlate rather weakly with GDP growth.

Trade variables in the data set exhibit comparatively low maximum cross-correlations, yet they seem to have leading characteristics in general (see Figure 8). Finnish and Euro zone variables seem to have the strongest coefficients, with Finnish exports, Finnish GDP and euro zone GDP “scoring” the

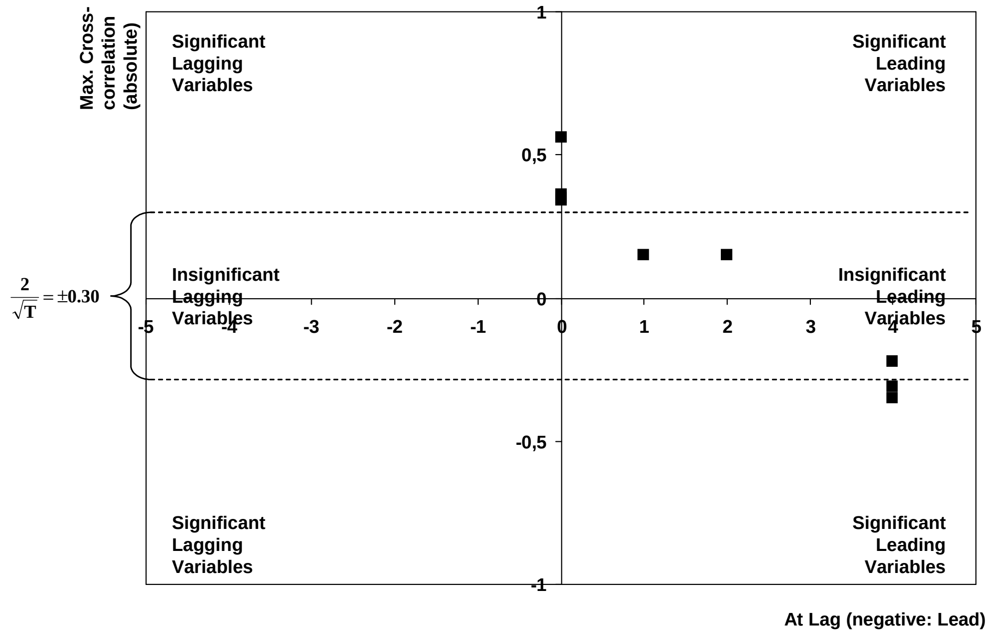


Figure 8: Cross-correlation characteristics of Trade Variables 1995–2006

Source: Statistical Office of Estonia; The Economist Intelligence Unit, European Central Bank; OECD.

highest. Russian variables, represented here by Russian GDP, exhibit weaker relationships. It seems that the Estonian economy is more strongly influenced by its new Western and Northern European partners than by its older Russian liaisons.

Most of the economic sectors in Estonia seem to have rather coincidental characteristics in terms of temporality with respect to Estonian GDP (see Figure 9). In particular, manufacturing displays a very high coincident cross-correlation. The only strongly short-term leading sectoral variable seems to be value added in the financial intermediation (banking) sector. Transportation and retail trade have a more long-term relationship, yet it is less pronounced. The health sector seems to be lagging, but here the strength of this relationship is rather low.

The different surveys again exhibit very different patterns (see Figure 10). Many of them have quite strong relationships with real GDP growth in Estonia. Among the leading variables, we find industrial order books surveys, industrial confidence, and retail trade confidence. Among the strongly lagging relationships we find construction order books and construction confidence.

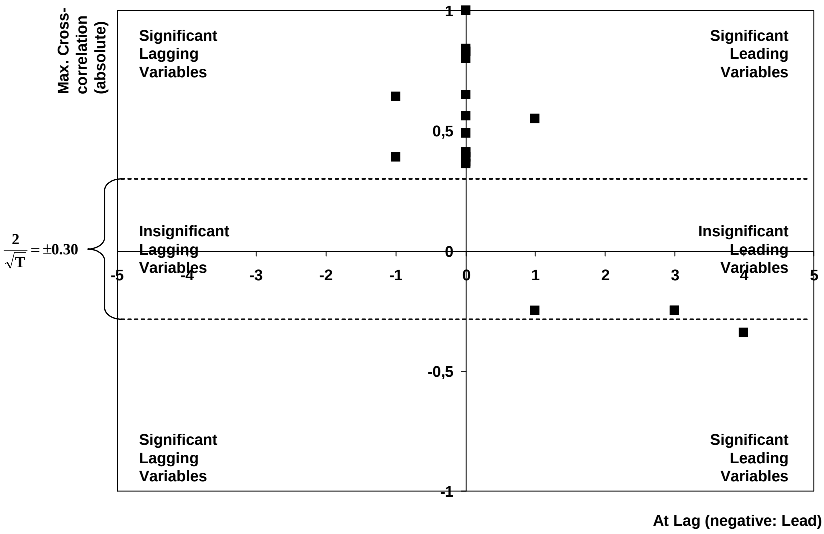


Figure 9: Cross-correlation characteristics of sectoral variables 1995–2006

Source: Statistical Office of Estonia; The Economist Intelligence Unit, European Central Bank; OECD.

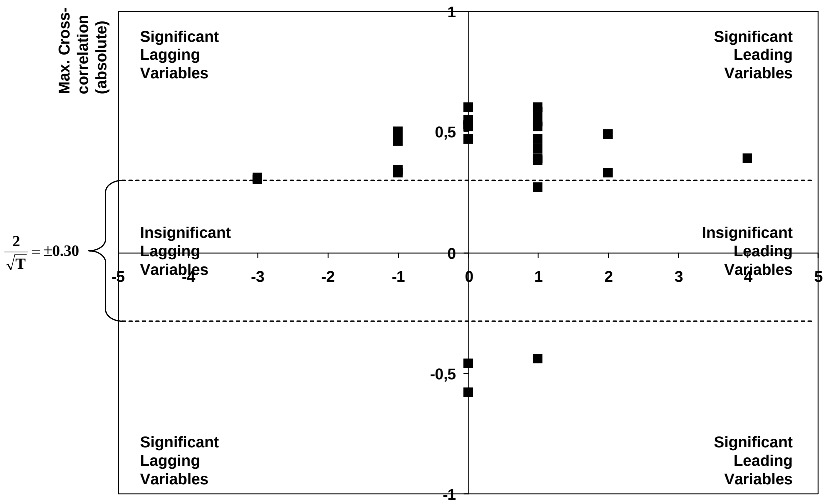


Figure 10: Cross-correlation characteristics of Survey-Type Variables 1995–2006

Source: Statistical Office of Estonia; The Economist Intelligence Unit, European Central Bank; OECD.

4. Common factor methodologies

4.1. The state-space model

In this section, we will employ methods originally developed by Kalman (1960) and Kalman (1963) to estimate a dynamic common factor model and to construct a leading indicator for the Estonian economy. This approach was initially also favoured by Stock and Watson (1991). The same methodology has been used successfully by other authors, for instance, Bandholz and Funke (2003) for Germany, Gerlach and Yiu (2005) for Hong Kong, and Curran and Funke (2006) for China.

The dynamic factor model's main identifying assumption is that the co-movements of the indicator series (observed variables) arise from one single unobserved common factor. This factor is expected to provide better forecasts of the reference series than the individual indicator series. The factor is constructed only from the observed series; that is, the reference series — in our case real GDP growth — is not used in the process. Constructing the common factor involves (1) formulating the model, (2) converting the model to state-space representation and (3) estimating the parameters using maximum likelihood (MLE) methodology, for which the Kalman filter is employed. The Kalman filter is composed of two recursive stages: (1) filtering and (2) smoothing. Filtering involves estimating the common factor for period t on the basis of information available at period $t-1$. The forecast error is minimised using MLE. The second stage, smoothing, then takes account of the information available over the entire sample period. The algorithm is computationally rather expensive; that is, achieving the convergence of the different coefficients and parameters is time-consuming[5]. Because of this technical restriction, only a few variables can be included in the model. This requires a careful selection of the input variables, for which there are numerous criteria. These are well summarised by Bandholz (2004). Among the formal criteria we find the following:

- A significant relationship between the lagged leading variable and the reference series in terms of general fit.
- The stability of this relationship.
- Improved out-of-sample forecasting.
- Timely identification of all turning points to avoid incorrect signals.

[5]The software we employed was kindly made available by Chang-Jin Kim and is described in Kim (1999).

Moreover, there are a number of informal criteria which should be looked at:

- Timely publication.
- High publication frequency
- Not subject to major ex-post revisions.
- Existence of theoretical background for leading relationship.

First, we would like to focus on the discussion of which system of leading variables might well represent the Estonian economy. For the German economy, industrial indicators such as order books are used as manufacturing plays a significant role there (Bandholz and Funke, 2003). For China, indicators representing the stock market, the real estate market and the exports industry are used as it is believed that these sectors play significant roles (Curran and Funke, 2006). Gerlach and Yiu (2005) use four different series for Hong Kong: namely, a stock market index, a residential property index, retail sales and total exports.

The mechanical choice of those variables that show their most significant cross-correlation with the reference series at lag 1 might be the obvious way forward, but we deviate here. Value added in financial services could be the third variable, but it would be rather problematic. There is no obvious economic reason why the banking and insurance sectors should lead economic growth. In fact, a lagging characteristic would be expected. Therefore, in order to avoid correlation by plain statistical coincidence, we will abstain from using this variable. We use real growth in $M1$ to represent monetary conditions and industrial order books to reflect business conditions. As a third variable, real growth in loans to individuals might be used to reflect the importance of private consumption, though a criticism can be levelled that $M1$ and loans to individuals might be correlated not just statistically (which they are), but also theoretically, as M1 drives credit growth via minimum reserve requirements. Therefore, we use a stock exchange index to reflect asset markets as an alternative. However, this comes at the cost of reducing the sample size, as stock market data is only available from 1996 onwards; that is, year-on-year growth rates are only available from 1997 onwards[6]. Therefore, we will display the results for both estimations and vary the variable $Y3$ according to the two alternatives in the following. Table 2 displays the criteria by which the variables were chosen.

In the following, we derive the state-space model following the notation by Kim (1999). Let Y_t be the vector of the time series from which the common

[6]In fact, stock indices for Tallinn are available on the website www.ee.omxgroup.com only from 2000 onwards. We have prolonged the series using old Riga stock exchange data.

Table 2: List of leading indicators

Selected Variables	Formal Criteria	Informal Criteria
Industrial Orderbooks (Survey)	**Max. Cross-correlation 0.61** **At lag 1**	**Good indicator for important industrial sector**
Real Money Supply M1 (year-on-year growth rate)	**Max. Cross-correlation 0.74** **At lag 1**	**Currency Board ER system means direct influence from payments balance**
Real Loans to Individuals (year-on-year growth rate)	**Max. Cross-correlation 0.59** **At lag 1**	**Drives Consumption**
Tallinn Stock Exchange Index (year-on-year growth rates from 1997 onwards)	**Max. Cross-correlation 0.54** **At lag 1**	**Incorporates Expectations**

factor will be derived. Its four elements are fourth differences in quarterly overall industrial order books (Y_{1t}), the year-on-year real growth of monetary supply $M1$ (Y_{2t}) and year-on-year real growth in loans to individuals or the Tallinn Stock Exchange Index, respectively (Y_{3t}). The unobserved common component is denoted by I_t.

$$Y_{1t} = D_1 + \gamma_{10} I_t + e_{1t} \tag{1}$$

$$Y_{2t} = D_2 + \gamma_{20} I_t + e_{2t} \tag{2}$$

$$Y_{3t} = D_3 + \gamma_{30} I_t + e_{3t} \tag{3}$$

$$(I_t - \delta) = \phi(I_{t-1} - \delta) + \omega_t, \quad \varpi \sim iid\, N\,(0,1) \tag{4}$$

$$e_{it} = \Psi_{i,1} e_{i,t-1} + \epsilon_{it}, \quad \epsilon_{it} \sim iid\, N\left(0, \sigma_i^2\right)\ and\ \ i = 1,2,3 \tag{5}$$

As constants D_i and δ cannot be separately identified, we write the model in terms of deviations from means. This concentrated form of the model is represented as follows:

$$y_{1t} = \gamma_{10} i_t + e_{1t} \tag{6}$$

$$y_{2t} = \gamma_{20} i_t + e_{2t} \tag{7}$$

$$y_{3t} = \gamma_{30} i_t + e_{3t} \tag{8}$$

$$i_t = \phi i_{t-1} + \omega_t, \quad \varpi \sim iid\, N\,(0,1) \tag{9}$$

$$e_{it} = \Psi_{i,1} e_{i,t-1} + \epsilon_{it}, \quad \epsilon_{it} \sim iid\, N\left(0, \sigma_i^2\right)\ and\ \ i = 1,2,3 \tag{10}$$

However, in order to estimate the Kalman filter the model has to be represented in state-space form. State-space representation is made up of two parts: the measurement equation and the transition equation. While the former represents the relationship between observable variables and the unobserved component, the latter represents the dynamics of the unobserved component between periods.

Measurement equation

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \gamma_{10} & 0 & 1 & 0 & 0 \\ \gamma_{20} & 0 & 0 & 1 & 0 \\ \gamma_{30} & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{11}$$

Transition equation

$$\begin{pmatrix} i_t \\ i_{t-1} \\ e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix} = \begin{pmatrix} \phi & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_{11} & 0 & 0 \\ 0 & 0 & 0 & \psi_{21} & 0 \\ 0 & 0 & 0 & 0 & \psi_{31} \end{pmatrix} \begin{pmatrix} i_{t-1} \\ i_{t-2} \\ e_{1,t-1} \\ e_{2,t-1} \\ e_{3,t-1} \end{pmatrix} + \begin{pmatrix} \varpi_t \\ 0 \\ \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{pmatrix} \tag{12}$$

Tables 3 and 4 display the results and diagnostics of the estimation. Following Gerlach and Yiu (2005), we test for autocorrelation in the error terms using the Ljung-Box Q-Test on the fourth lag and for normality using the Jarque-Bera test.

In both cases, all coefficients are significant at common significance levels, except for the error term's variance in (7); that is, in the equation using year-on-year real growth in monetary aggregate $M1$. The tests for the model's specification show mixed results, especially regarding autocorrelation, except for the test on the error terms in equation (7), which includes the stock exchange index. This hints at a missing variable problem; that is, the dependent variable is not strongly correlated with the indicator, or the need to include lagged error terms in the model. The latter has been attempted, but it seems to be impossible to achieve convergence in the ML-estimator. With similar diagnostics, Gerlach and Yiu (2005) conclude that their model fits the data reasonably well, so we will do the same here.

In addition to a discussion of the estimation results, a visual impression of the resulting leading indicators is given in Figure 11. It can be seen that both indicators seem to be leading the reference series, particularly in the times of

Table 3: Estimation results (three-series indicator including loans to individuals)

Coefficient	Estimates	Standard error	t-Values
γ_{10}	0.35	0.09	3.71***
γ_{20}	0.51	0.10	5.23***
γ_{30}	0.24	0.06	3.85***
φ	0.85	0.09	10.12***
ψ_{11}	0.60	0.13	3.50***
ψ_{21}	0.75	0.25	1.92**
ψ_{31}	0.91	0.05	18.70***
σ_1	0.47	0.11	4.33***
σ_2	0.07	0.12	0.85
σ_3	0.09	0.03	3.56 ***
Diagnostics	**Test statistic**	**Probability-values**	
LB(ε_1)	15.64***	0.00	
LB(ε_2)	23.38***	0.00	
LB(ε_3)	112.74***	0.00	
JB(ε_1)	2.05	0.36	
JB(ε_2)	12.88***	0.00	
JB(ε_3)	11.50***	0.00	
Log-likelihood	27.44		

Note I: LB(ϵ_i): Ljung-Box Q-test measuring AR(4) residual autocorrelation.
Note II: JB(ϵ_i): Jarque-Bera test for residual normality.
*Note III: * indicate significance levels: * = 10%-level, ** = 5%-level, *** = 1%-level.*

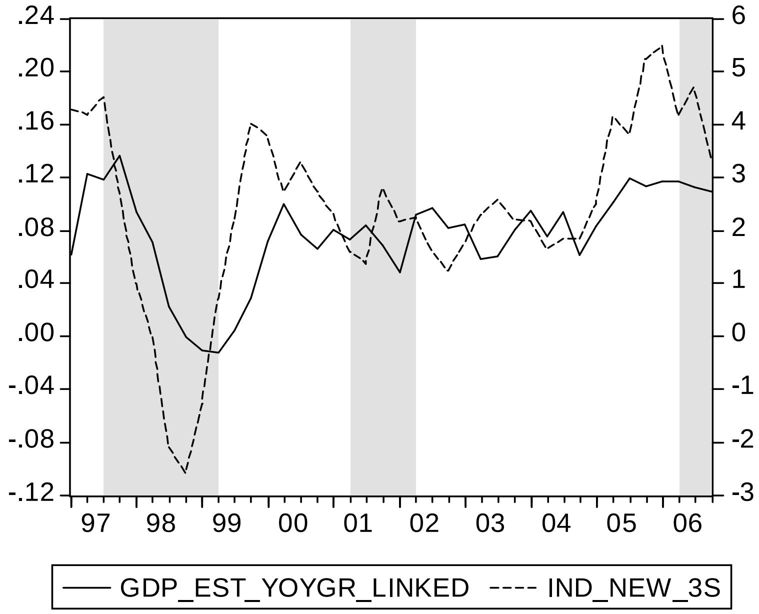
the Russian crisis and its aftermath. The decline of growth predicted in 2006 is mainly due to a slow-down in the growth of real money supply (but also nominal money supply). The stock market's performance decelerated as well. It can be seen very clearly that the jump in growth to double-digit levels was clearly predicted by both indicators.

The state space model includes only a very small number of variables and it might be questioned if the true power of the common factor idea comes to fruition in such a small-scale model. Unfortunately, as Kapetanios and Marcellino (2006:1) observe, "maximum likelihood estimation of a state space model is not practical when the dimension of the model becomes too large due to computational costs". This is why computationally more efficient methods like principal components analysis are being used, to which we will turn in the following section.

Table 4: Estimation results (three-series indicator including Tallinn Stock Index)

Coefficient	Estimates	Standard error	t-Values
γ_{10}	0.34	0.17	2.02**
γ_{20}	0.41	0.20	2.09**
γ_{30}	0.17	0.13	1.25
φ	0.83	0.10	8.28***
ψ_{11}	0.61	0.16	3.74***
ψ_{21}	0.72	0.18	3.92***
ψ_{31}	0.97	0.04	24.11***
σ_1	0.35	0.13	2.73**
σ_2	0.16	0.16	1.02
σ_3	0.30	0.08	4.03***
Diagnostics	**Test statistic**	**Probability-values**	
LB(ε_1)	11.79***	0.02	
LB(ε_2)	0.58	0.97	
LB(ε_3)	13.71***	0.01	
JB(ε_1)	15.7***	0.00	
JB(ε_2)	457.7***	0.00	
JB(ε_3)	617.7***	0.00	
Log-likelihood	0.46		

Note I: LB(ϵ_i): Ljung-Box Q-test measuring AR(4) residual autocorrelation.
Note II: JB(ϵ_i): Jarque-Bera test for residual normality.
*Note III: * indicate significance levels: * = 10%-level, ** = 5%-level, *** = 1%-level.*



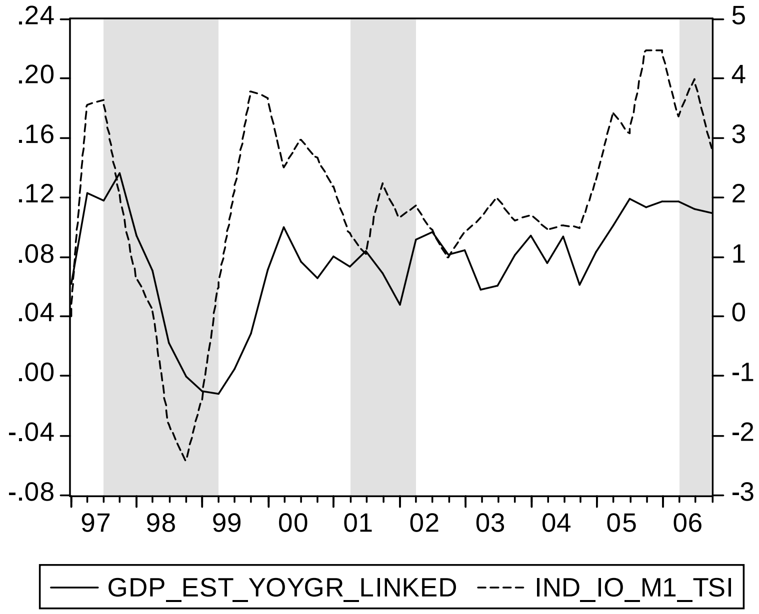


Figure 11: Resulting leading indicators from state-space-modelling

Note: in figure above Y3 means loans to individuals, in figure below Y3 means Tallinn Stock Exchange Index

4.2. Static principal components

The Stock and Watson (1991) approach using state-space-modelling is one way of combining information contained in several series in a new indicator which hopefully improves forecasting performance. However, there are other methods based on principal component analysis. Two competing methods often employed are static principal components analysis (Jolliffe, 2002), used for economic forecasting by Stock and Watson (2002), and dynamic principal component analysis or dynamic factor models (Forni et al., 2000), which has been used particularly successfully by the European Central Bank[7]. Static principal components have been used to construct the Chicago Fed National Activity Index (CFNAI) for the US, by Artis et al (2001) for the United Kingdom and by the German Council of Economic Experts (2005) for Germany. The different principal-components-based approaches have been compared to each other by a number of authors, with inconclusive results (e.g., D'Agostino and Giannone, 2006). Their simulation results indicate no systematic predictive improvement when the dynamic model is used. As the additional value of the dynamic principal components model is not certain and as it is computationally more complicated, we will use static principal components here to construct other indicators and then compare these to the result from the Stock and Watson (1991) approach.

The static factor model on which we will base the principal components analysis can be written as follows[8]:

$$X_t = \Lambda F_t + u_t, t = 1, ..., T \tag{13}$$

In this expression, $X_t = (X_{1t}, ..., X_{Nt})'$ is the N-dimensional column vector of observed variables. Λ is the matrix of factor loadings $\lambda_{ijk}, i = 1, ...N; j = 1, ..., q; k = 0, ..., p$ and is of order $N \times r$, where $r = q(p+1)$. So j indicates the factor and k the lag of the factor. As we will be dealing with a static model, we will not include lags of the factor, so $k = 0$ and Λ has the order $N \times j$. F_t is the r-dimensional column vector of factors and u_t is the N-dimensional column vector of idiosyncratic shocks. As we assume no contemporaneous or serial correlation between the factors and the idiosyncratic shocks u_t, the variance-covariance matrix of X_t, $\sum_X$, can be written as follows:

[7] Employing dynamic principal components is not straight-forward. This extension was made by Forni et al. (2003).

[8] The transformation from a dynamic factor model to a static model is left out here. The essential assumption of finite lag polynomials and the required transformations can be seen in Dreger and Schumacher (2004).

$$\sum_{X} = \Lambda \sum_{F} \Lambda' + \sum_{u} \tag{14}$$

$\sum_F$ and $\sum_u$ are the variance-covariance matrices of the factor vector and the idiosyncratic shocks vector, respectively.

The basic idea of principal components analysis is now to explain the variance reflected in the variance-covariance matrix by as few factors as possible; that is, to minimise the variance proportion due to the idiosyncratic shocks u_t. This minimisation problem is solved as follows: The factors can be represented as a linear combination of the observed variables:

$$F_t = BX_t \tag{15}$$

Now $B = (\beta_1, ..., \beta_N)'$ is a $(r \times N)$-dimensional matrix of parameters, the other two matrices being the same as above. The minimisation problem comes down to maximising the variance of the factor estimators $\hat{f}_{jt} = \hat{\beta}_j' X_t$. The estimator for the variance-covariance matrix of the observed variables is:

$$Var(X_t) = \frac{1}{T} \sum_{1=1}^{T} X_t X_t' = \hat{\Omega} \tag{16}$$

Therefore, the variance of $\hat{f}_{jt}$ is:

$$Var(\hat{f}_{jt}) = Var(\hat{\beta}_j' X_t) = \hat{\beta}_j' \hat{\Omega} \hat{\beta}_j \tag{17}$$

For standardisation, $\beta_j \beta_j' = 1$. The maximisation of this variance leads to a Lagrange function and the following Eigen value problem (Jolliffe, 2002):

$$\hat{\beta}_j' \hat{\Omega} = \hat{\mu}_j \hat{\beta}_j' \quad or \quad (\hat{\Omega} - \hat{\mu}_j I_N) \hat{\beta}_j = 0. \tag{18}$$

I_N is the $(N \times N)$ identity matrix. That is, the estimators for the j-th β are the eigenvectors associated with the j-th Eigen value. Additionally, it can be shown that the factors can be ordered with respect to their contribution to total variance by ordering them according to the magnitude of the respective Eigen value associated with them. Therefore, the factor associated with the highest Eigen value is the first principal component. Principal component analysis is readily available in most commonly used statistics software packages, such as Eviews or RATS.

In most applications of this methodology to forecasting, the principal components are derived from a very large data set without any ex-ante exclusion of data series; that is, including time series we know to be lagging GDP growth[9]. The idea is to identify the common factors that drive all the data and can be thought of as representing a business cycle. However, in the sections above we have come to the conclusion that a classic business cycle may be hard to identify in Estonia. Therefore, we see principal components analysis rather as another way of producing a dynamically weighted averaging of time series and we include time series which we already know have some sort of leading relationship with the reference series together with some other variables to make the sample more representative for the whole data set. A list of these 34 variables can be found in the appendix. All series were made stationary and de-seasonalised (by taking fourth differences) when necessary. Finally, we standardised all series to mean zero and standard deviation unity. We estimate two different models:

- Specification 1: Including only contemporaneous values of the 31 time series.
- Specification 2: Including the first lag of all the time series included. Stock and Watson (2002) refer to this as a "stacked" data set; therefore, 62 time series are included.

The first three principal components' characteristics of each specification are reported in Table 5:

Table 5: Principal components analysis: Eigenvalues and variance proportions

Contemporaneous only	**1st principal component**	**2nd principal component**	**3rd principal component**
Eigen value	9.50	4.46	3.40
Variance Proportion	0.31	0.14	0.11
Cumulative Proportion	0.31	0.45	0.56

Stacked Data set	**1st principal component**	**2nd principal component**	**3rd principal component**
Eigen value	16.28	7.74	6.00
Variance Proportion	0.28	0.13	0.10
Cumulative Proportion	0.28	0.41	0.51

In each case, the first three principal components represent approximately half of the total variation, which is large given the size of the data set. In

[9] For instance, see Stock and Watson (2002).

most applications of static principal components, a similar share of variance is accounted for by the derived principal components; for example, Eickmeier and Breitung (2005), Marcellino, Stock and Watson (2000), and Altissimo et al. (2001), who all find a range between 32% and 55%. Correlations between derived principal components and the input series can be seen in the following three figures. Figure 12 displays correlation coefficients between the input data series and the principal components derived from the contemporaneous data set (specification 1). Figure 13 displays correlation coefficients between the contemporaneous input data series and principal components derived from the stacked data set (specification 2), and Figure 14 displays correlation coefficients between the lagged input data series and principal components derived from the stacked data set (specification 2). A similar representation is used by Stock and Watson (2002).

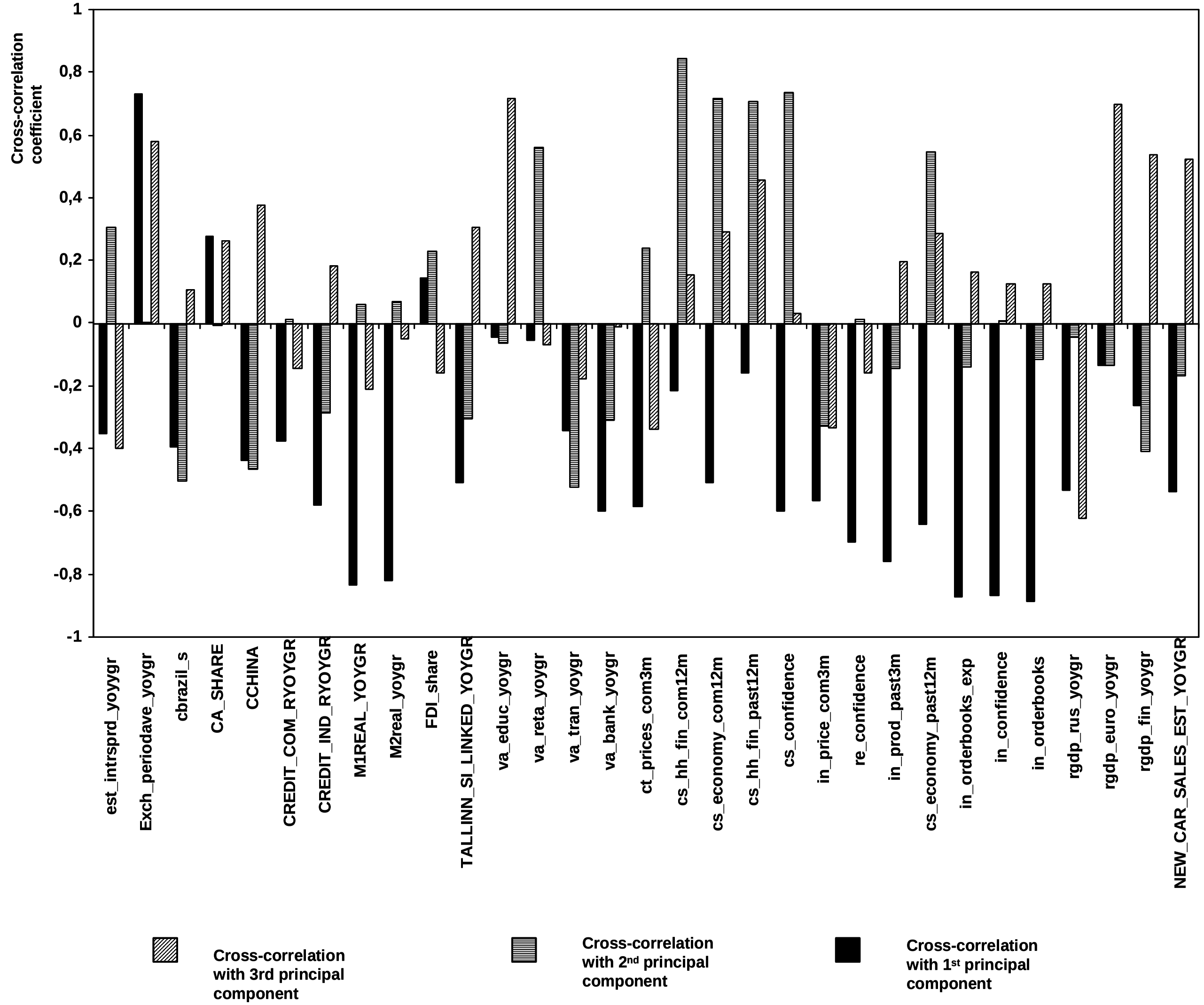


Figure 12: Principal components: correlations contemporaneous — contemporaneous

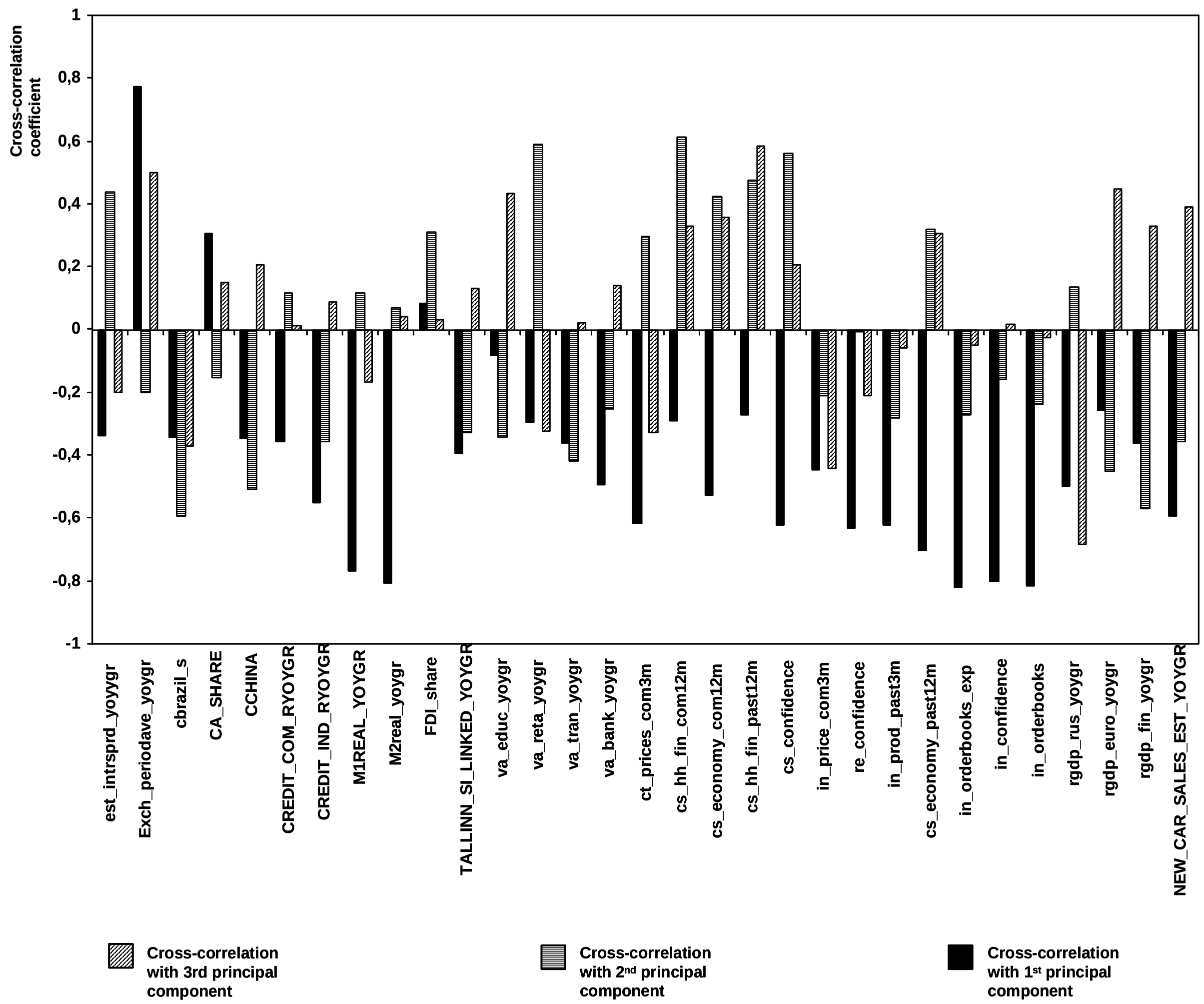


Figure 13: Principal components: correlations contemporaneous — stacked

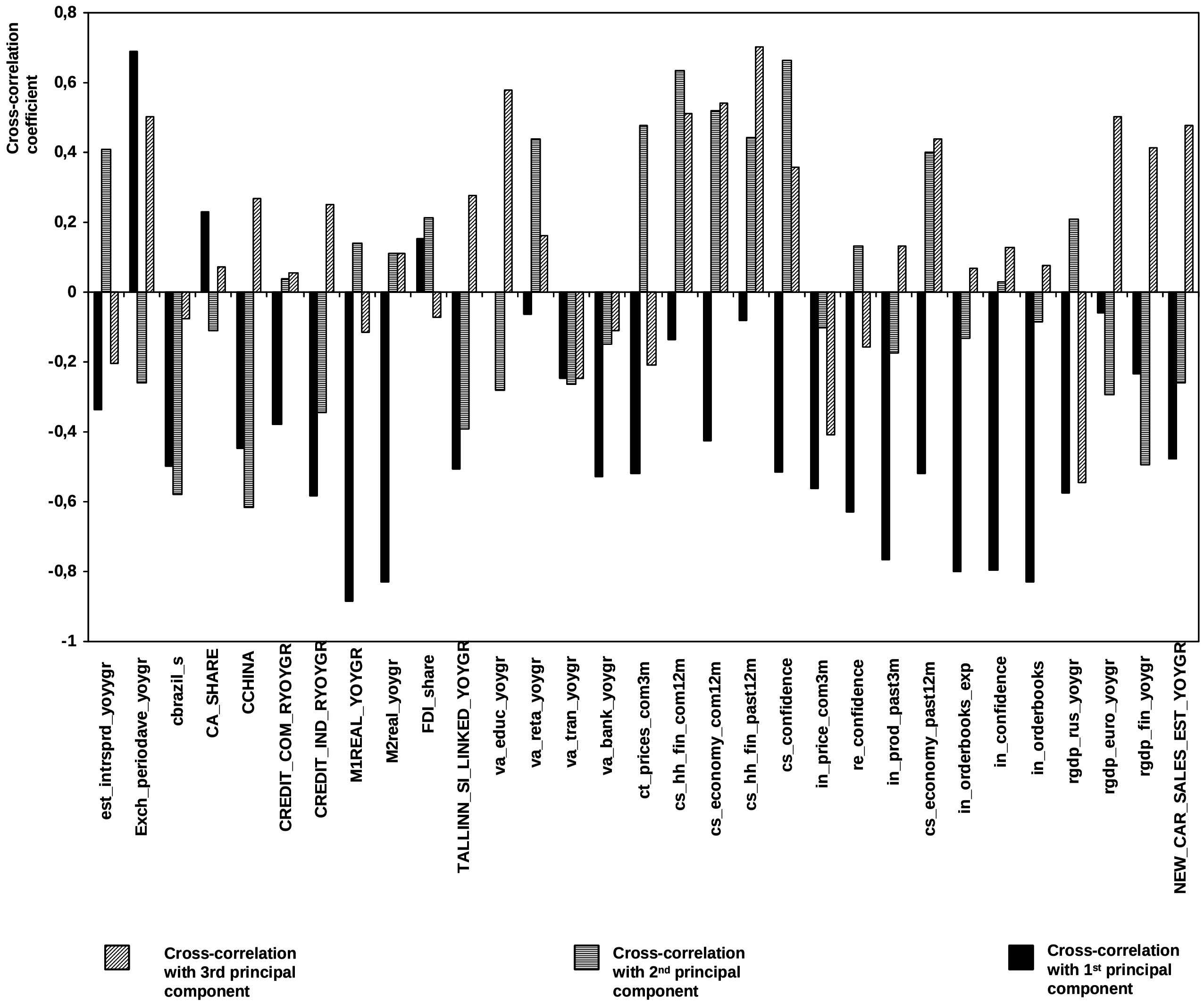


Figure 14: Principal components: correlations lagged — stacked

The following figures (15–17) display the resulting principal components as time series. It can be seen that the first principal component has a negative correlation with the reference series. The first principal components both have very high contemporaneous cross-correlations with real GDP growth. However, it can be seen that the most recent spike in economic growth to double-digit figures in 2005/2006 was not anticipated by the first principal components. This spike, on the other hand, was clearly anticipated by the second principal components, which other than that, show very little correlation with the reference series. For both the first and second principal components, the contemporaneous and stacked data set show quite similar results. They differ from the third principal component, however. Both third principal components show little predictive power in the earlier part of the sample: However, the third principal components derived from the stacked data set show the clearest indication of the most recent spike in growth of all the indicators and it remains at a very high level. This is in line with reality.

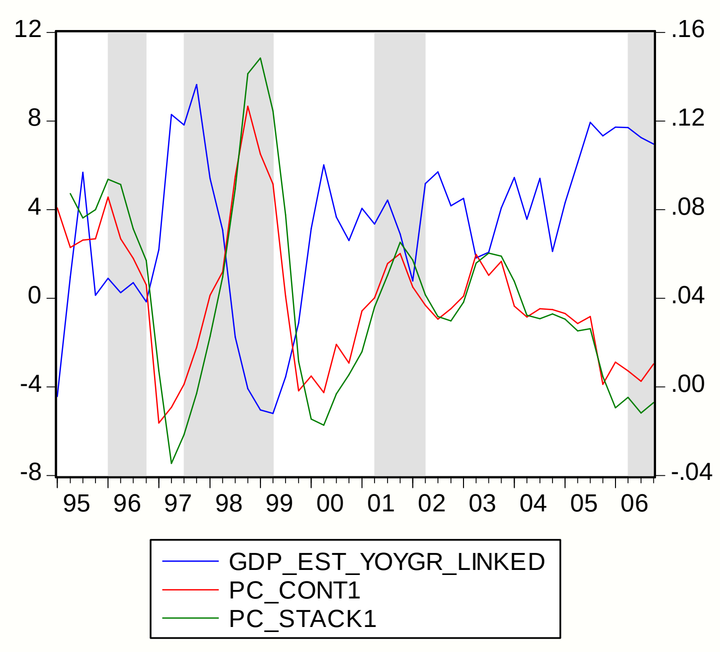


Figure 15: 1st Principal components and GDP growth

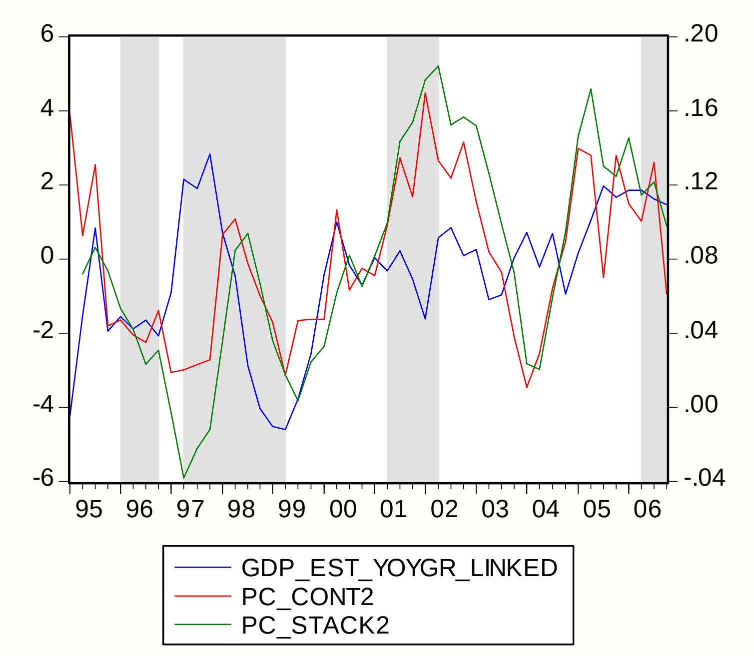


Figure 16: 2nd Principal components and GDP growth

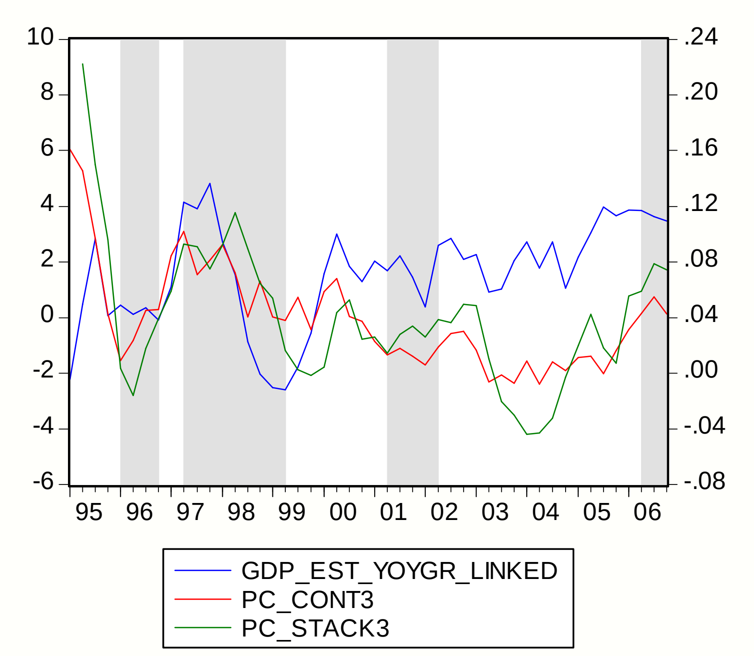


Figure 17: 3rd Principal components and GDP growth

It remains to be answered which principal components should be included when trying to forecast economic growth. An often used criterion for determining the optimal number of factors is the test developed by Bai and Ng (2002), which was explicitly developed for this kind of approximate common factor model using static principal components and relying upon the variance-covariance matrix of the data set[10]. Another possibility would be to simply compare the forecasting performance of the models[11]. As the number of time series is rather limited here, we will not consider more than three principal-components-based common factors for each data set and will follow the forecast evaluation approach. We estimated the regressions of the reference series on all possible combinations of the principal components derived from the contemporaneous data set and the stacked data set, respectively. The fitted coefficients were used to run forecasts over the whole sample period 1995:1 to 2006:1 and estimate the root mean squared forecasting error (RMSFE), defined as follows:

$$RMSFE = \sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / h} \tag{19}$$

It turns out that for both cases, the inclusion of all three principal components yields the best forecast, even though the inclusion of only the first two is only slightly worse. When we go on to compare state-space modelling and principal components in the next section, we will keep two principal components based models:

- Three principal components derived from the contemporaneous data set.
- Three principal components derived from the stacked data set.

5. Forecast comparison

In the following section we use tests developed by Diebold and Mariano (1995) and Clark and McCracken (2001) to carry out comparisons of the in-sample and out-of-sample performances of the developed indicators, respectively. For a discussion of the merits of different tests and methods see Chen (2005).

One simple way of in-sample performance testing is to compare the F-tests from regressing the reference series on different specifications involving

[10] See Breitung and Eickmeier (2005).
[11] See Stock and Watson (2002).

the various leading indicators. However, this will not permit any statement as to whether the difference between the two forecasting models is actually significant. Diebold and Mariano (1995) have developed a method that does exactly that — they simply regress the difference between the absolute forecast errors of both series on a constant using robust standard errors and check the t-value of the constant.

We will compare five specifications, of which the naïve AR(1) model of real GDP growth (20) 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. The naïve model is defined as follows:

$$gdp_t = c_{naive} + b_{naive} \cdot gdp_{t-1} + e_{naive} \tag{20}$$

We include the lagged dependent variable in the two different specifications of the state-space-model-forecasts as well:

$$gdp_t = c_{ind\,3\,S} + b_{ind\,3\,S} \cdot gdp_{t-1} + b_{ind\,3\,S} \cdot i_{ind\,3\,S,t-1} + e_{ind\,3\,S} \tag{21}$$

$$gdp_t = c_{i0\ m1\ tsi} + b_{i0\ m1\ tsi} \cdot gdp_{t-1} + b_{i0\ m1\ tsi} \cdot i_{i0\ m1\ tsi,t-1} + e_{i0\ m1\ tsi} \tag{22}$$

Finally, as mentioned in the section above, we use the first three principal components derived from the contemporaneous data set and the stacked data set, respectively. Again, we include lagged values of the dependent variable and use static forecasting.

$$\begin{aligned} gdp_t = c_{PC,Cont} + b_{PC1,Cont} \cdot gdp_{t-1} + b_{PC1,Cont} \cdot PC_{1,Cont,t-1} + \\ + b_{PC2,Cont} \cdot PC_{2,Cont,t-1} + b_{PC3,Cont} \cdot PC_{3,Cont,t-1} + e_{PC,Cont} \end{aligned} \tag{23}$$

$$\begin{aligned} gdp_t = c_{PC,Stack} + b_{PC1,Stack} \cdot gdp_{t-1} + b_{PC1,Stack} \cdot PC_{1,Stack,t-1} + \\ + b_{PC2,Stack} \cdot PC_{2,Stack,t-1} + b_{PC3,Stack} \cdot PC_{3,Stack,t-1} + e_{PC,Stack} \end{aligned} \tag{24}$$

The RATS-procedure we used to implement the Diebold and Mariano test reports 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 following table reports the p-values for different specifications and periods.

Table 6: DM-P-values for different specifications and forecasting samples

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

It can be clearly seen that all derived indicators perform much better than the naïve forecast over the entire sample. For more recent periods, the picture is not as good. Only the state-space model based on industrial order books, M1 and stock exchange data seems to perform significantly better than the naïve forecast. Indeed, for 2006, none of the specifications are significantly better. Three specifications are worse than the naïve forecast, two even significantly so. To shed some light on this we display the performances of the specifications in terms of DM-P-values per yearly period in Figure 18.

While all specifications seem to perform very well in the beginning of the sample, particularly during the Russian crisis, the performance improvement becomes, in many cases, insignificant in the latter periods, and in 2006 it gets even worse than the naïve forecast. There are marked differences, however. For instance, the principal components based indicator specifications perform very well in 2002 and 2003, while the state-space-models are much better in 2000 and in 2005. These results indicate that more testing of potential leading variables needs to be done, with particular weight laid upon performance in the latter periods of the sample.

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[12]. In out-of-sample testing, the forecasting

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

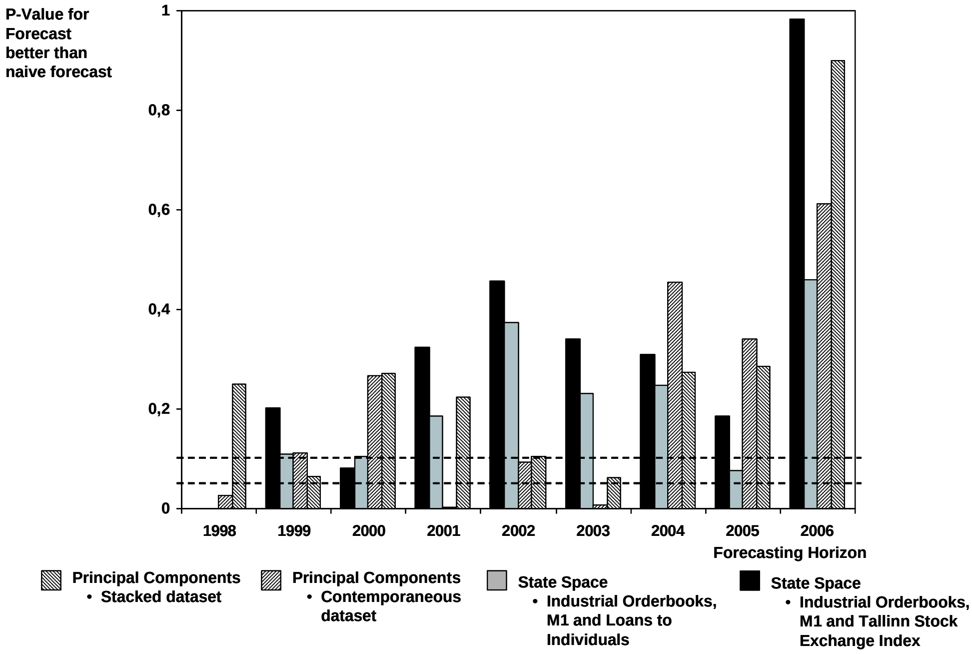


Figure 18: Forecasting Performance: DM-P-Values per period

model is estimated for a sub-sample of the entire available sample and then forecasts for the remaining sample are evaluated with respect to the actual values. We perform test procedures used by Clark and McCracken (2001) using the same nested forecasting model specifications as in (20) through (24), with (20) 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.

Again, the results are mixed (see Table 7). We will not pay much attention to the equal MSE-tests, as they only confirm what has already been shown by the in-sample tests; namely, that 2006 was a particularly bad year for all the different forecasting models compared to the naïve model. However, except for the principal-components-based model based on the stacked data set, for almost all other forecasting horizons, the indicators do reveal additional information: that is, they are not already encompassed by the naïve model.

Table 7: Clark and McCracken Test results (one-sided critical values)

Indicator	Sample	MSE-f	MSE-t	ENC-f	ENC-T
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***
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**
Principal Components 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
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

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

6. Conclusions

The search for leading indicators has revealed several interesting results. Many data series are available for forecasting economic growth in Estonia, even though the length of the available period is not very long and one should be cautioned against making comparisons with mature Western countries with longer data histories. However, some trends with respect to forecasting can be identified: Financial variables, particularly the growth of monetary aggregates, have the best predictive power, followed by the variables of investment and some survey-type data, such as industrial order books. Surveys of confidence, which are broadly public in mature economies, seem to be less suited to the pattern of Estonia's economic trajectory. Another result from this analysis is that classical business cycles with booms and recessions cannot be found in the Estonian data. If anything, only certain growth cycles can be identified.

The state-space model may be easier to interpret, as only a few variables enter the construction of the common factor and these are carefully selected. However, it is computationally much more cumbersome than the static principal components approach and, at least in our examples, seems to yield little or no forecasting performance improvement. Principal components analysis is, on the other hand, not only an interesting way to create a weighted average of many time series, but also provides an interesting insight into the correlations between different series, which can be seen using a component-wise correlation analysis. The indicators constructed using state-space modelling and static principal components both clearly outperform the benchmark naïve

AR(1) model in in-sample testing. However, this seems to be due to a very strong performance in the earlier part of the sample, particularly during the Russian crisis. The performance in the latter part of the sample, particularly in 2006, seems to be rather poor, which is confirmed by out-of-sample testing. This might be due to a systemic change; that is, factors other than the financial variables we identified might have taken over the driving of economic development in Estonia. However, this could also be a temporary break.

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Appendix 1. Data set and cross correlations

No.	Name of Series	Transformation	ADF (p-value)	Max X-corr	at lag (-lead)
1	Assets with BIS-reporting banks	YOY change	0.00	0.16	0
2	Brazilian Stock Market Index	YOY change	0.01	0.45	2
3	Chinese Stock Market Index	YOY change	0.22	-0.26	-4
4	Commercial banks' foreign assets	YOY change	0.00	0.31	2
5	Commercial banks' foreign liabilities	YOY change	0.33	0.24	1
6	Construction building activity over the past 3 months	YOY change	0.00	0.43	1
7	Construction confidence indicator	YOY change	0.00	0.46	-1
8	Construction employment over the next 3 months	YOY change	0.01	0.39	1
9	Construction factors limiting building activity ** insufficient demand	YOY change	0.01	-0.44	1
10	Construction factors limiting building activity ** weather conditions	YOY change	0.00	0.33	2
11	Construction order books	YOY change	0.17	0.50	-1
12	Construction prices over the next 3 months	YOY change	0.18	0.53	0
13	Consumer confidence Indicator	YOY change	0.11	0.55	0
14	Consumer financial situation of households over next 12 months	YOY change	0.01	0.34	-1
15	Consumer financial situation of households over past 12 months	YOY change	0.00	0.31	-3
16	Consumer major purchases over next 12 months	YOY change	0.01	0.33	-1
17	Consumer perception of change in unemployment	YOY change	0.11	-0.58	0
18	Consumer perception of general economic situation over next 12 months	YOY change	0.01	0.38	1
19	Consumer perception of general economic situation over past 12 months	YOY change	0.00	0.52	1
20	Consumer price index (av)	YOY change	0.01	-0.26	3
21	Consumer price Index at end of period	YOY change	0.00	-0.21	0
22	Current Account share of GDP	Levels, de-seasonalised	0.00	-0.52	-2
23	Current-Account balance	YOY change	0.00	0.33	1
24	Deposit interest rate	YOY change	0.00	0.68	-2
25	Economic sentiment indicator	YOY change	0.20	0.60	0
26	Estonian interest rate spread	YOY change	0.00	0.28	0
27	Euro zone real GDP	YOY change	0.05	-0.35	4
29	FDI as share of GDP	Levels	0.00	0.27	-3
30	Finnish exports	YOY change	0.38	-0.22	4

No.	Name of Series	Transformation	ADF (p-value)	Max X-corr	at lag (-lead)
31	Finnish imports	YOY change	0.14	0.15	2
32	Finnish Real GDP	YOY change	0.00	-0.31	4
33	Foreign direct investment Change yoy	YOY change	0.00	0.25	2
34	Foreign-exchange reserves	YOY change	0.05	0.30	-2
35	Estonian Real GDP change	YOY change	0.06	1.00	0
36	Gold, national valuation	YOY change	0.87	0.29	1
37	Industrial confidence indicator	YOY change	0.03	0.58	1
38	Industrial current export order books	YOY change	0.00	0.54	1
39	Industrial current overall order books	YOY change	0.00	0.60	1
40	Industrial current stock of finished products	YOY change	0.00	-0.46	0
41	Industrial production index	YOY change	0.00	0.84	0
42	Industrial production over the past 3 months	YOY change	0.02	0.49	2
43	Industrial production will over the next 3 months	YOY change	0.00	0.27	1
44	Industrial selling prices will over the next 3 months	YOY change	0.01	0.39	4
45	International reserves	YOY change	0.05	0.30	-2
46	Lending interest rate (%)	YOY change	0.00	0.67	-3
47	Liabilities with BIS-reporting banks	YOY change	0.37	0.41	-1
48	Loan Stock granted to commercial undertakings	YOY real change	0.40	0.51	0
49	Loan Stock granted to individuals	YOY real change	0.14	0.58	1
50	Money market interest rate (%)	YOY change	0.11	0.49	-1
51	Net taxes on products	YOY change	0.02	0.80	0
52	New Car Registrations	YOY change	0.02	0.56	0
53	Real effective exchange rate of the kroon	YOY change	0.01	-0.60	0
54	Retail Confidence indicator	YOY change	0.00	0.47	1
55	Retail Employment over the next 3 months	YOY change	0.00	0.52	0
56	Retail orders placed with suppliers during the next 3 months	YOY change	0.00	0.47	0
57	Retail Stocks	YOY change	0.00	0.30	-3
58	Russian GDP	YOY real change	0.01	0.35	0
59	Stock of money M1	YOY real change	0.02	0.71	1
60	Stock of money M2	YOY real change	0.01	0.68	0

No.	Name of Series	Transformation	ADF (p-value)	Max X-corr	at lag (-lead)
61	Tallinn Stock Market Index	YOY real change	0.06	0.54	1
62	Total exports fob Change yoy	YOY change	0.04	0.36	0
63	Total imports cif Change yoy	YOY change	0.02	0.34	0
64	Trade balance (fob-cif basis)	YOY change	0.08	0.15	1
65	Value Added in Agriculture, Hunting	YOY real change	0.00	0.37	0
66	Value Added in Construction	YOY real change	0.00	0.64	-1
67	Value Added in Education	YOY real change	0.00	-0.25	3
68	Value Added in Electricity, Gas and Water Supply	YOY real change	0.00	0.36	0
69	Value Added in Financial Intermediation	YOY real change	0.17	0.55	1
70	Value Added in Fishing	YOY real change	0.03	0.41	0
71	Value Added in Forestry	YOY real change	0.07	-0.25	3
72	Value Added in Health and Social Work	YOY real change	0.00	-0.25	1
73	Value Added in Hotels, Restaurants	YOY real change	0.00	0.39	0
74	Value Added in Manufacturing	YOY real change	0.02	0.83	0
75	Value Added in Mining, Quarrying	YOY real change	0.02	0.65	0
76	Value Added in Other community, social and personal service activities	YOY real change	0.01	0.49	0
77	Value added in Public Administration and Defence; compulsory social security	YOY real change	0.01	-0.34	4
78	Value Added in Real Estate, Renting and Business Activities	YOY real change	0.00	0.56	0
79	Value Added in Transport, Storage, Communication	YOY real change	0.00	0.41	0
80	Value Added in Wholesale and Retail Trade	YOY real change	0.00	0.39	-1

Appendix 2. Principal components: time series included

No.	Series Name	Short name	Type
1	Interest rate spread (long-term minus short-term)	est_intrsprd_yoygr	Finance
2	Effective exchange rate	Exch_periodave_yoygr	Finance
3	Brazilian stock exchange	cbrazil_s	Finance
4	Current account as share of GDP	CA_SHARE	Finance
5	Chinese stock exchange	CCHINA	Finance
6	Loans to Commercial Customers	CREDIT_COM_RYOYGR	Finance
7	Loans to Individuals	CREDIT_IND_RYOYGR	Finance
8	Real Money Supply M1	M1REAL_YOYGR	Finance
9	Real Money Supply M2	M2REAL_YOYGR	Finance
10	Foreign Direct Investment (% of GDP)	FDI_share	Finance
11	Tallinn stock exchange	TALLINN_SI_LINKED_YOYGR	Finance
12	Value added in Education	va_educ_yoygr	Sector
13	Value added in retail and wholesale trade	va_reta_yoygr	Sector
14	Value added in Transportation, etc.	va_tran_yoygr	Sector
15	Value added in Financial Intermediation	va_bank_yoygr	Sector
16	Construction Prices over next three months	ct_prices_com3m	Survey
17	Households' financial situation over next twelve months	cs_hh_fin_com12m	Survey
18	Households' expectations of the state of the economy over next twelve months	cs_economy_com12m	Survey
19	Households' financial situation over last twelve months	cs_hh_fin_past12m	Survey
20	Consumer confidence	cs_confidence	Survey
21	Manufacturing Prices over next twelve months	in_price_com3m	Survey
22	Retail trade confidence	re_confidence	Survey
23	Industrial production over last three months	in_prod_past3m	Survey
24	Consumers' perception of the state of the economy over last twelve months	cs_economy_past12m	Survey
25	Industrial order books, exports	in_orderbooks_exp	Survey
26	Industrial confidence	in_confidence	Survey
27	Industrial order books, overall	in_orderbooks	Survey
28	Russian real GDP	rgdp_rus_yoygr	Trade
29	Euro zone real GDP	rgdp_euro_yoygr	Trade
30	Finnish real GDP	rgdp_fin_yoygr	Trade
31	New car sales	NEW_CAR_SALES_EST_YOYGR	Trade