Forecasting Economic Activity for Estonia

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INTRODUCTION

Of the many tasks economists undertake, forecasting is possibly one of the most relevant to decision makers in practice. Indeed, many of the other tasks like modelling, explaining and estimating economic relationships only become relevant to a wider public when the results are employed to the prediction of certain variables of interest. These variables in macroeconomic forecasting range from the development of sales and profits in certain product markets to price and inflation forecasting and forecasting of economic activity for individual regions, countries, groups of countries, or indeed the whole world. As policymakers and investors must rely on macroeconomic forecasts when making both short-term and long-term decisions, much effort and resources have been spent on the development and application of forecasting tools.

Since the beginning of the 20th century macroeconomic forecasts are increasingly derived from economic models and employ leading indicators as well as econometric and statistical methods (Clements and Hendry, 2000). With these, researchers try to fulfil various requirements made of forecasts, for instance:[1]

- Accuracy: Forecasts should be quantitative and accurately predict the forecasted variable as well as stating the expected forecasting error
- Timeliness: Forecasts should take account of the most up-to-date information and not be subject to revisions later on
- Stability: The forecasting model's performance must be stable with respect to changes in the environment, such as economic regime shifts

Macroeconomic forecasting based on business cycle theory was founded by Burns and Mitchell (1946), who had also played a significant role in the founding of the first independent institutions which started to publish economic forecasts regularly. The National Bureau of Economic Research (NBER) in the United States was founded as early as 1920. One of the first popular leading indicators, the Harvard Barometer, was introduced in 1919, based among others on the work of Persons (1919). In Europe, pioneers of model based forecasting worked in the Netherlands, where Tinbergen's macroeconomic models started to be used in the 1930s, strengthened later by the works of Theil (1966). The variety of

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[1] Cf. Zarnowitz (1992)

published leading indicators worldwide has grown constantly since, with new developments in the conceptual and methodical frameworks, but also with the failings of established indicators in warning of imminent economic crises (indeed, the Harvard Barometer had failed to predict the great recession in 1929). In addition to econometrically derived indicators, survey-based indicators became more and more popular, such as the IFO Institute of Economic Research index in Germany, which is a survey of business sentiment among managers of a large and representative sample of firms of the economy. Today, a plethora of published leading and coincident indicators is available for every country, at least for the mature western economies.[2]

The object of the forecasting exercises in this work is the economy of Estonia. This small country, the northernmost of the three Baltic republics, declared independence from the Soviet Union in 1991. The second Estonian republic (the first independence had only lasted from 1918 till 1940) immediately made a rapid transition from the Soviet planned economy to a very liberal market economy. The successful transition process finally led to Estonia's accession to both NATO and the European Union in 2004. The economic catch-up process of Estonia can be divided into three phases. During the first phase, which began immediately after independence and the painful rupture with the old planned-economy system, economic growth accelerated quickly, supported by strictly laissez-faire policies of the government, a stable currency-board exchange rate regime and the proximity to and support of its Scandinavian neighbours. This positive development came to a sudden halt when the Russian economic crisis of the late 1990s hit Estonia, leading to a brief but marked recession in 1998/1999. This was the second economic phase. During this recession the last remains of Estonia's connections to the old Soviet area broke down and a firm orientation towards the Northern and Western European economies took place. The third phase started after the Russian crisis and its aftermath, with the new millennium. Economic growth picked up again quickly and stayed between 5% and 7% for the first half of the current decade. During this period, inflation remained relatively stable and low, and unemployment, which had been chronically high during the 1990s, steadily declined. In 2006 and 2007 economic growth attained double-digits once again. This, in conjunction with other indicators such as a very high current account deficit, rising inflation and very high property prices signalled

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[2] It should be mentioned that the discussion of whether economic forecasts are possible and, if so, successful, is as old as the development of the methods itself, starting with Morgenstern (1928).

overheating in the Estonian economy. The current discussion in Estonian economic circles is about whether or not Estonia can avoid a "hard landing". However, most indicators and the most recent (spring 2008) forecasts of the Bank of Estonia point towards exactly this unwelcome development.[3]

The focus of the studies assembled in this paper is the application of different unobserved common factor models to the forecasting of economic activity in Estonia. In the first two papers, common factor methodologies are used to extract leading indicators from large panels of macroeconomic data. The resulting leading indicators are then used to forecast economic activity. The third paper focuses on the growth potential of the Estonian economy and employs common factor methodology to extract a cyclical component in GDP from two equations: an output equation and a Phillips curve equation. This permits the calculation of the varying inflation non-accelerating growth rate of the economy, or its potential growth rate.

The first paper is entitled "Forecasting Economic Growth for Estonia: Application of Common Factor Methodologies" and presents the application of two different unobserved factor models to an Estonian data set: state-space modelling and static principal components. It thereby extends the methodologies currently used by the Bank of Estonia for short-term forecasting to include the use of common factor methodologies. State-space modelling was introduced to economic forecasting by Stock and Watson (1991). The idea is that a common dynamic trend is extracted from a small set of potentially leading variables, 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. Static principal components are widely used and have, for instance, been applied by Stock and Watson (2002) to 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. In the paper, first, the respective common factors are derived; second, the forecasts of real economic growth for Estonia are performed and, finally, evaluated against benchmark models for different estimation and forecasting periods. In-sample testing (Diebold and Mariano, 1995) and out-

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[3] The latest spring forecast 2008 of the Bank of Estonia can be found on its website at www.eestipank.info .

of-sample testing (Clark and McCracken, 2001) is employed. The results demonstrate that both methods show improvements over the benchmark model, but not for all forecasting periods. This paper was published as Working Paper 09/2007 in the Bank of Estonia Working Paper Series.

The second paper's title is "Forecasting Economic Activity for Estonia: Application of Dynamic Principal Components Analysis". In this paper, we apply a method developed by Forni, Hallin, Lippi and Reichlin (2000) to derive a short-term leading indicator for economic activity in Estonia. This method was initially developed for and applied to Euro zone data (Forni et al., 2001). There are three main advantages to the method: First, it 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. Second, the method permits the derivation of one or a 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. cleansed of their idiosyncratic components. And third, the method allows for discrimination between series as leading or lagging with respect to economic activity at relevant frequencies; dynamic principal components methodology lets us look at measures of coherence at relevant cycle lengths. In the paper 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 and pseudo out-of-sample testing indicate clear improvements over benchmark models.

The second paper pays additional attention to the correct specification of growth cycles in Estonia. We find that a particularly good way to do this is to use 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 shifted between periods of sustainable growth (particularly during 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). This paper was published as Working Paper 02/2008 in the Bank of Estonia Working Paper Series.

The third and final paper is entitled “Can Inflation Help in Determining Potential Output of the Estonian Economy?” and applies a common factor model developed by Kuttner (1994) to the identification of output gaps and the potential output of the Estonian economy. The central idea of the model is to combine a simple output equation and a Phillips curve equation for inflation, linking the two via a transitory or cyclical component of output. The assumption is that this cyclical component drives inflation, a result we would expect from a theoretical point of view (Okun, 1962). It can therefore be seen as a hybrid between purely statistical filtering methods such as the Hodrick-Prescott filter or bandpass filtering à la Baxter and King (1999) and models with strong theoretical foundations, such as the production function approach (Perry, 1977) used by the European commission. The model, originally developed for the U.S. economy, has to be adapted to the small and open Estonian economy and the catch-up process it has gone through. The paper presents alternative specifications for the Phillips curve and compares the results. Estimation results, diagnostics and sensivity tests show that a model which includes foreign direct investment as a weakly exogenous variable in the output equation and a traditional Phillips curve relationship with wage inflation (rather than consumer price inflation or the GDP deflator as in other applications) as the dependent variable provides the best results. The resulting series for potential growth shows marked differences from the other widely-used models for the identification of output gaps.[4] This stems from the development of inflation rates in Estonia over the sample period. Inflation rates were very high during the 1990s, particularly up until the Russian crisis. Similarly to more mature economies, inflation rates then fell to very low levels in the early 2000s before they started to rise strongly again from 2005 onwards. This results in high negative output gaps before the Russian crisis and low positive output gaps after it. The output gap grows as actual output growth remains below potential output growth for some years. Only at the very end of the sample do we observe negative output gaps again as inflation climbs. The paper shows that the resulting estimates outperform the Hodrick-Prescott filter in terms of pseudo real-time reliability, according to tests developed by Planas and Rossi (2004).

[4] Cf. Kattai and Vahter (2006)

Baxter, M. and King, R. G. (1999). Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series. *The Review of Economics and Statistics* 81 (4), 575-593.

Burns, A. F. and Mitchell, W. C. (1946). *Measuring Business Cycles.* New York: National Bureau of Economic Research.

Clark, T. E. and McCracken, M. W. (2001). Tests of Forecast Accuracy and Encompassing for Nested Models. *Journal of Econometrics* 105, 85-110.

Clements, M. P. and Hendry, D. F. (2000). *Forecasting Economic Time Series.* Cambridge: Cambridge University Press.

Diebold, F. X. and Mariano, R. S. (1995). Comparing Predictive Accuracy. *13Journal of Business & Economic Statistics*, 253-263.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2001). Coincident and Leading Indicators for the Euro Area. *The Economic Journal*, 62-85.

Forni, M., Lippi, M. and Reichlin, L. (2000). The Generalized Factor Model: Identification and Estimation. *The Review of Economics and Statistics* 82, 540-554.

Kattai, R. and Vahter, P. (2006). Kogutoodangu Lõhe ja Potentsiaalne SKP Eestis. *mimeo*.

Kuttner, K. N. (1994). Estimating Potential Output as a Latent Variable. *Journal of Business & Economic Statistics* 12, 361-368.

Morgenstern, O. (1928). *Wirtschaftsprognose: Eine Untersuchung ihrer Voraussetzungen und Möglichkeiten.* Wien: Springer.

Okun, A. (1962). Potential GNP: Its Measurement and Significance. In *Proceedings of the Business and Economic Statistics Section of the American Statistical Association.*

Perry, G. L. (1977). Potential Output: Recent Issues and Present Trends. In *U.S. Productive Capacity: Estimating the Utilization Gap.* Working Paper, Washington University: Center for the Study of American Business.

Persons, W. M. (1919). An Index of General Business Conditions. *The Review of Economic Statistics* 1(2), 111-205.

Planas, C. and Rossi, A. (2004). Can Inflation Data Improve the Real-Time Reliability of Output Gap Estimates? *Journal of Applied Econometrics* 19, 121-133.

Stock, J. H. and Watson, M. W. (1991). A Probability Model of the Coincident Economic indicators. In *Leading Indicators: New Approaches and Forecasting Records*(Eds, Lahiri, K. and Moore, G. H.). Cambridge, UK: Cambridge University Press, 63-89.

Stock, J. H. and Watson, M. W. (2002). Forecasting Using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association* 97, 147-162.

Theil, H. (1966). *Applied Economic Forecasting.* Amsterdam: North Holland Publ. Co.

Zarnowitz, V. (1992). *Business Cycles - Theory, History, Indicators and Forecasting.* Chicago: University of Chicago Press.

Eesti Pank
Bank of Estonia

Forecasting Economic Growth for Estonia: Application of Common Factor Methodologies

Christian Schulz

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9/2007

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Christian Schulz

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

Keywords: Estonia, forecasting, principal components, state-space model, 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 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

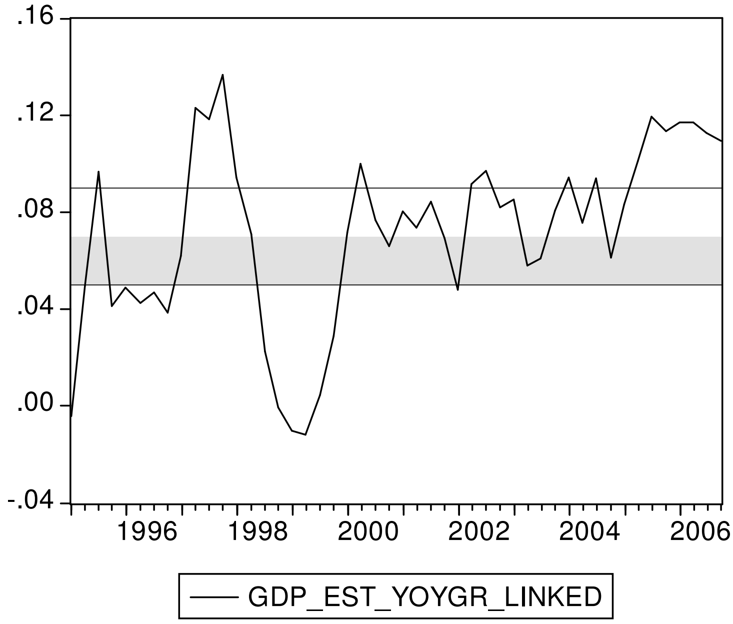


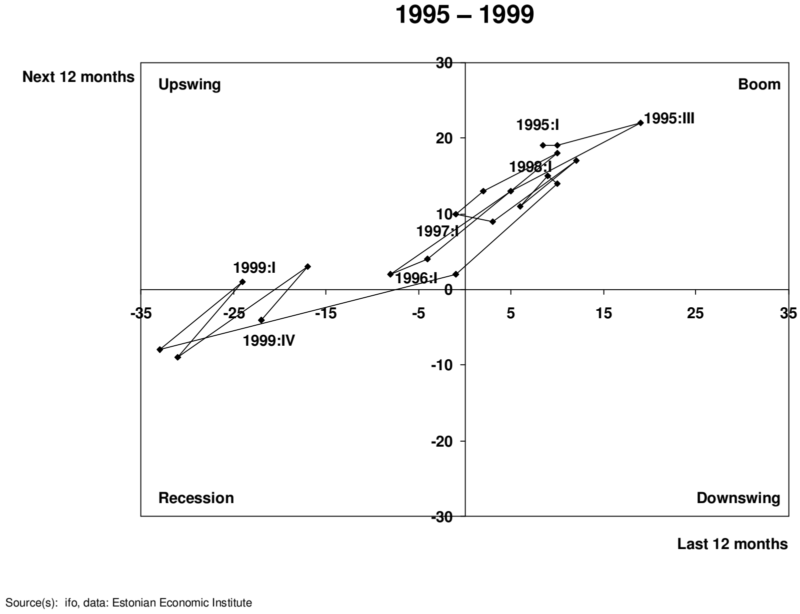
Figure 1: Real GDP Growth in Estonia (% yoy, constant 2000 prices)

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).



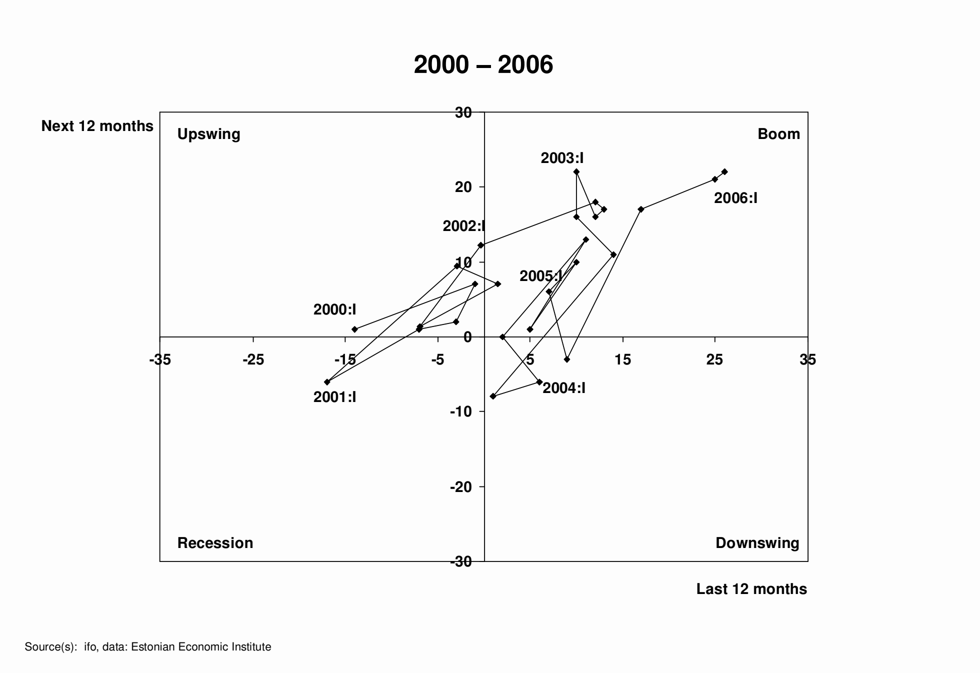


Figure 2: Economic clock — consumer perception of the general economic situation

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.

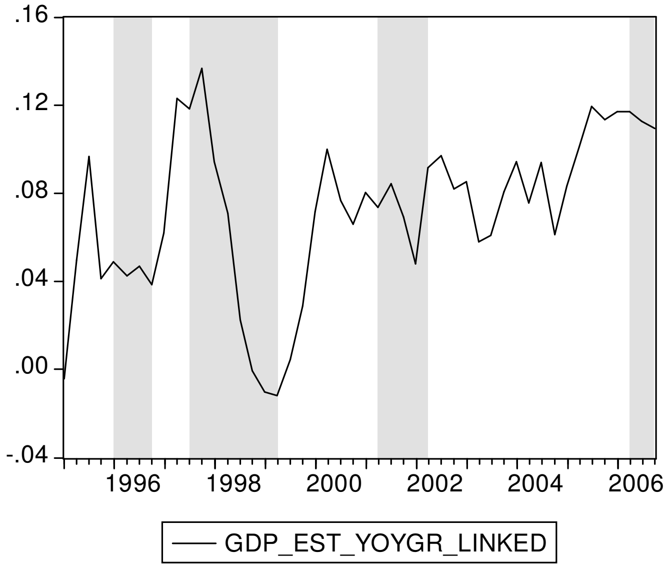


Figure 3: Growth cycle recessions in Estonia

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.

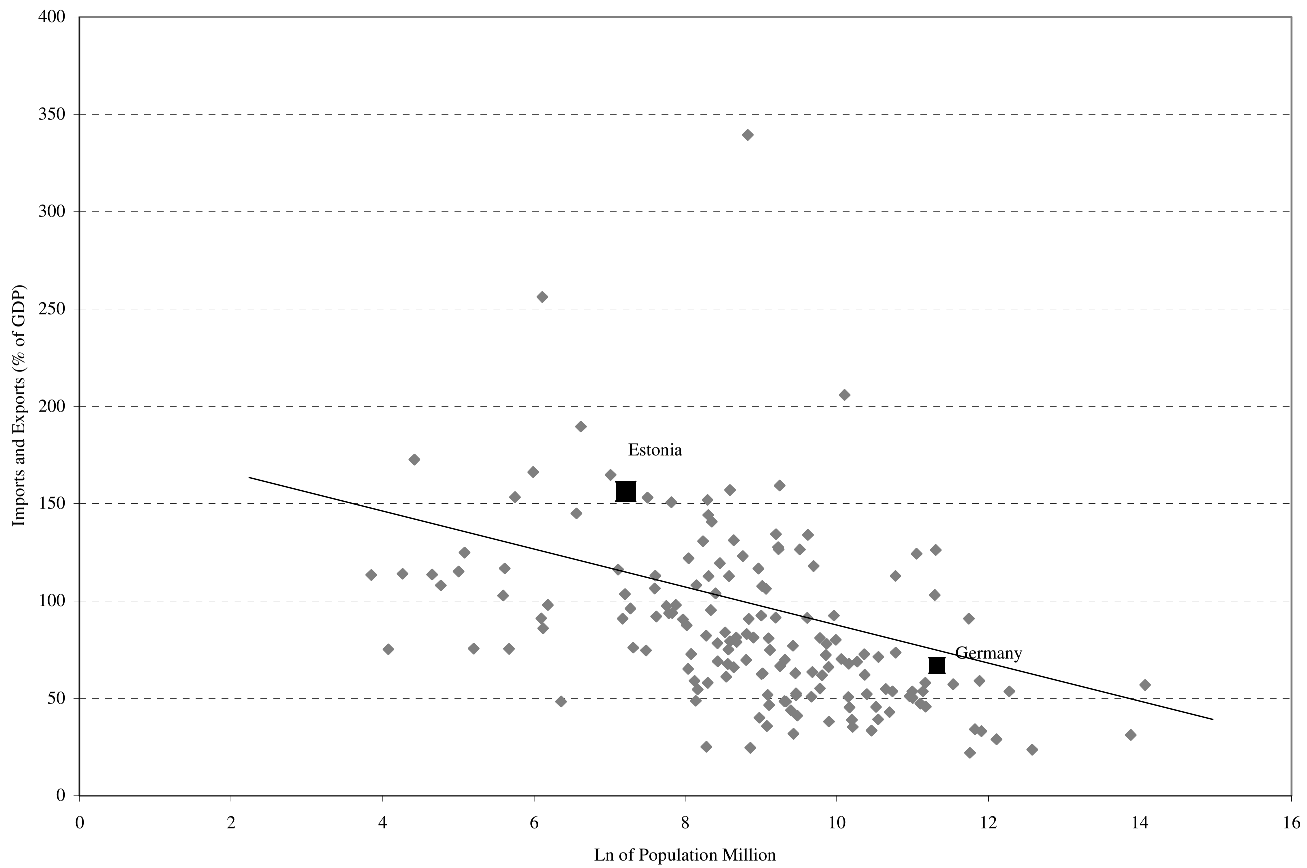


Figure 4: Openness versus Population

Source: Economist Intelligence Unit (EIU).

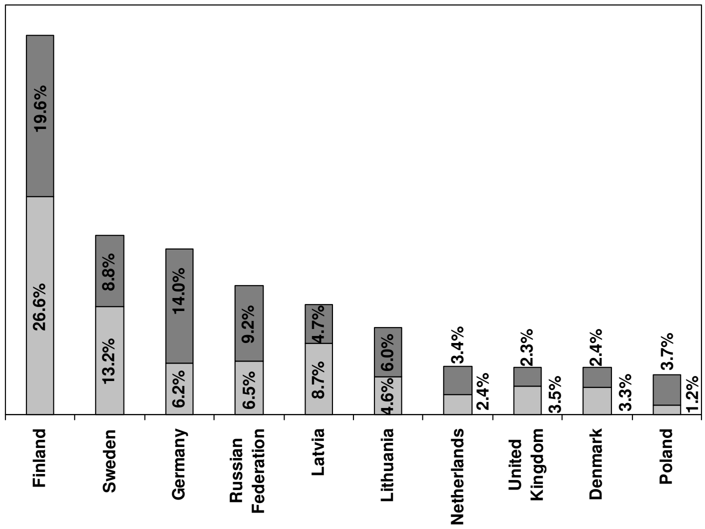


Figure 5: Trade partners of Estonia

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.

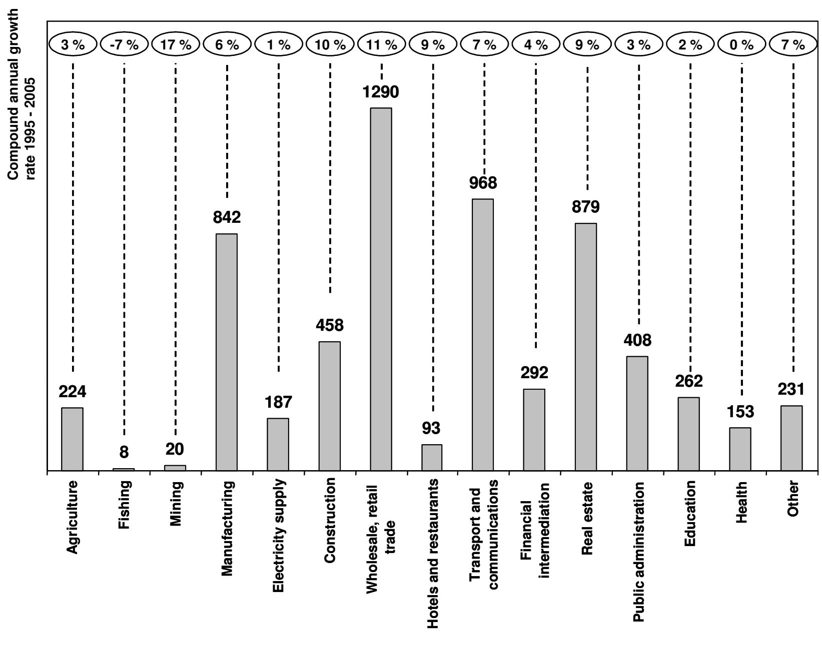


Figure 6: Estonian GDP by sectors

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.

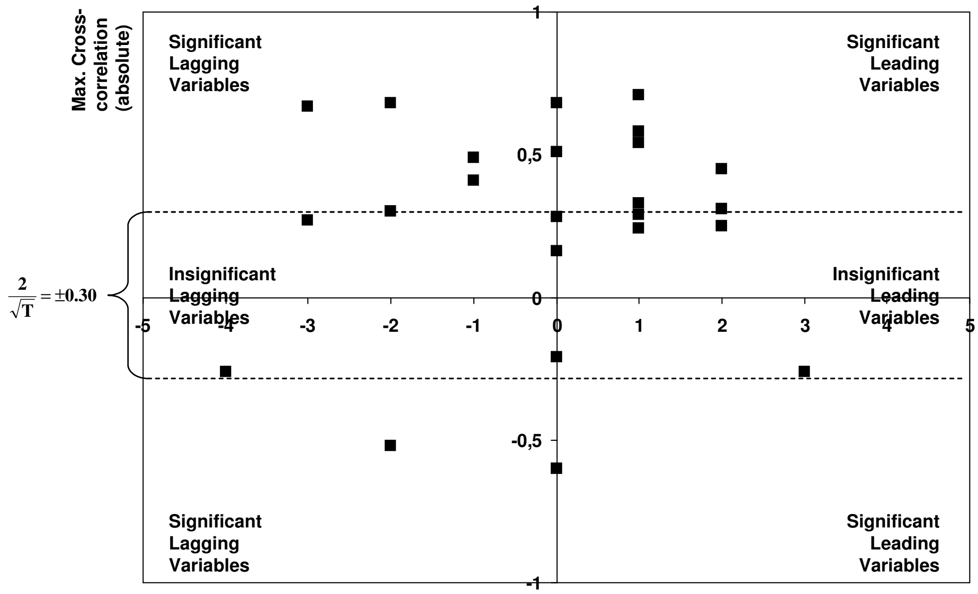


Figure 7: Cross-correlation characteristics of Financial Variables 1995–2006

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

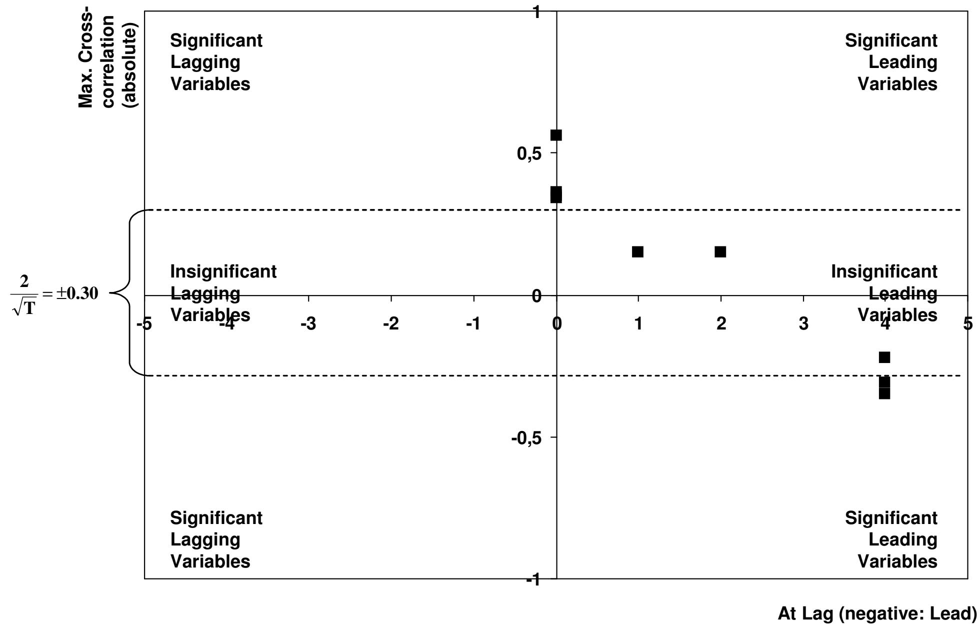


Figure 8: Cross-correlation characteristics of Trade Variables 1995–2006

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.

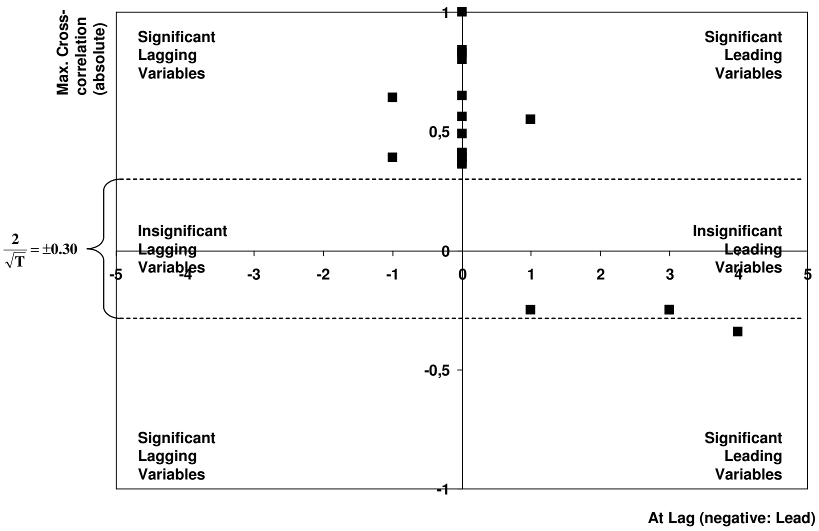


Figure 9: Cross-correlation characteristics of sectoral variables 1995–2006

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

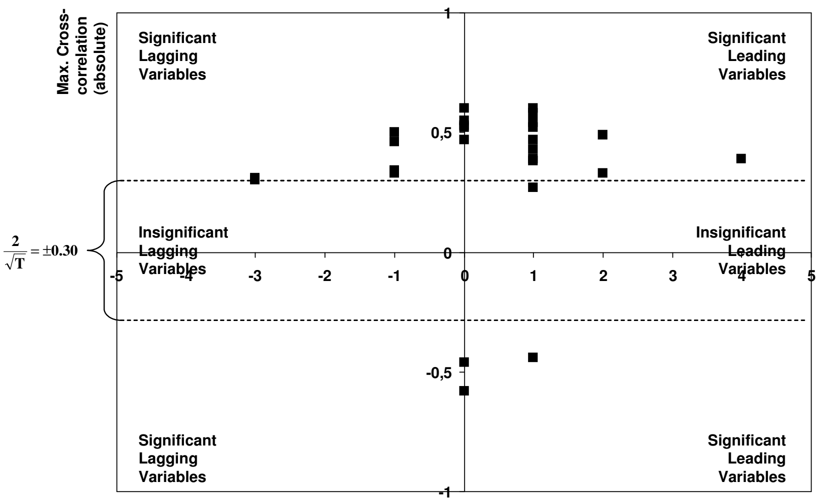


Figure 10: Cross-correlation characteristics of Survey-Type Variables 1995–2006

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.*

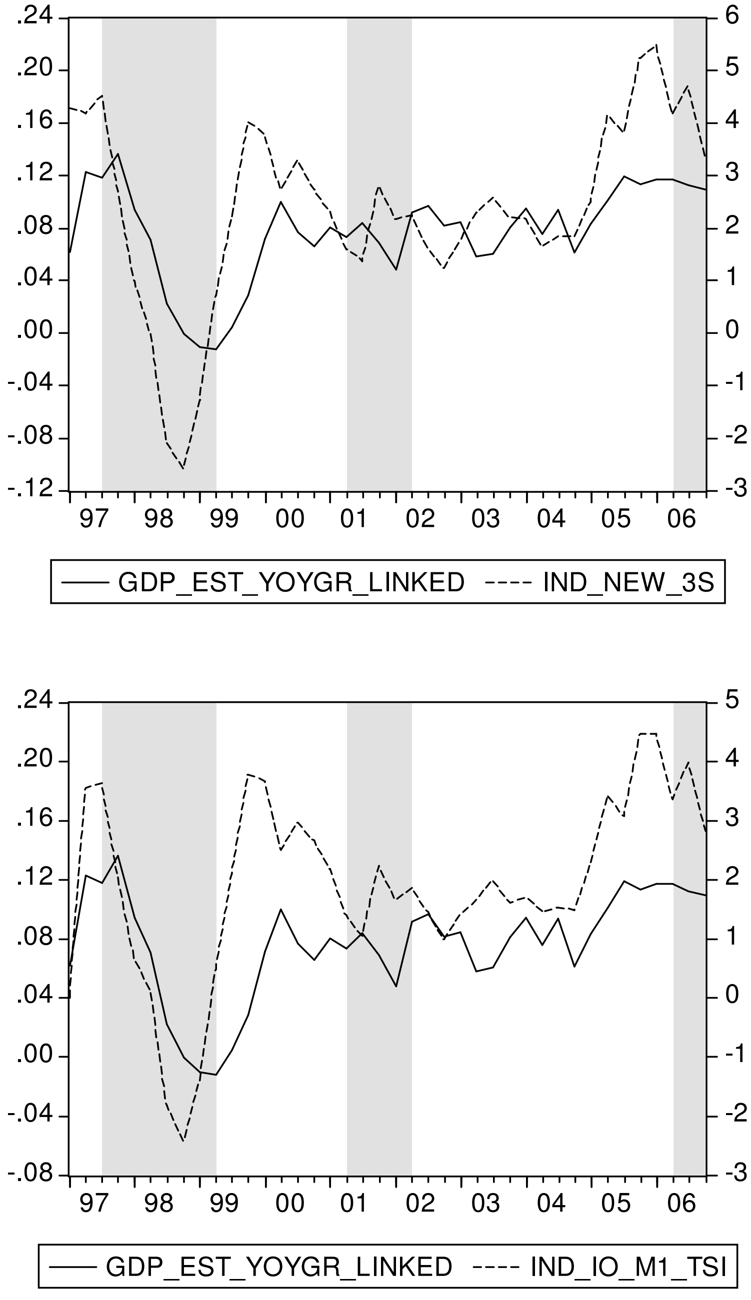


Figure 11: Resulting leading indicators from state-space-modelling

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).

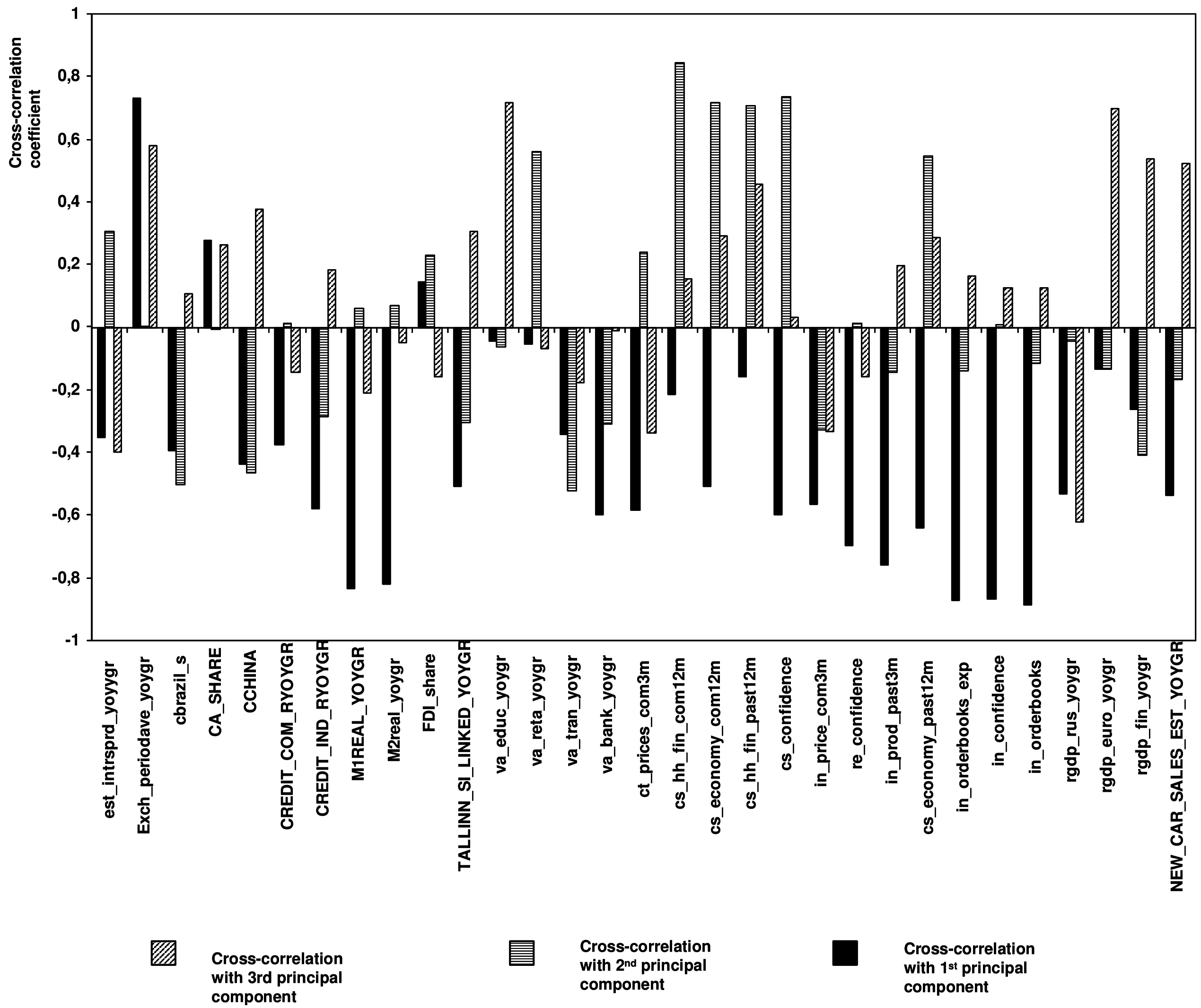


Figure 12: Principal components: correlations contemporaneous — contemporaneous

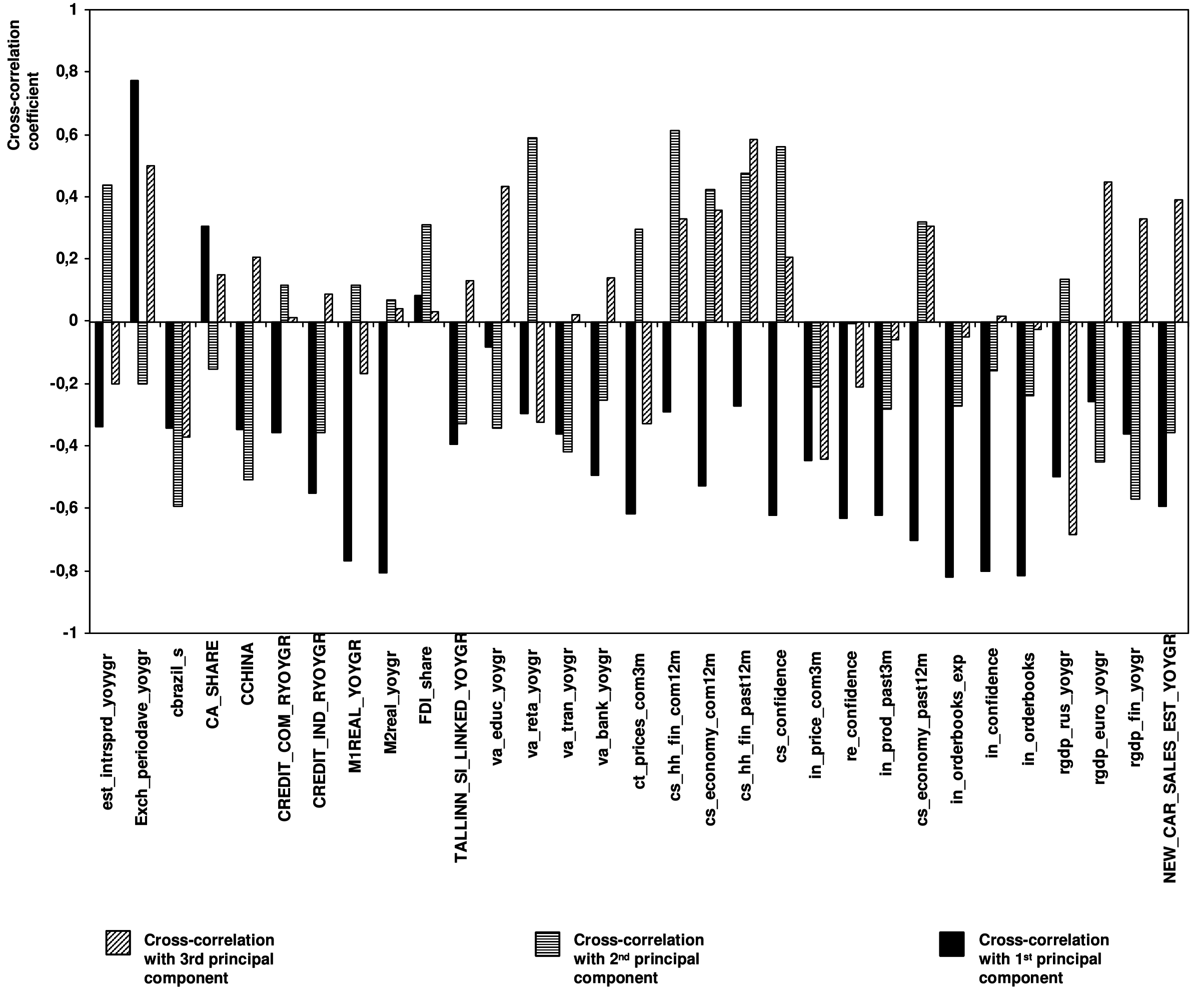


Figure 13: Principal components: correlations contemporaneous — stacked

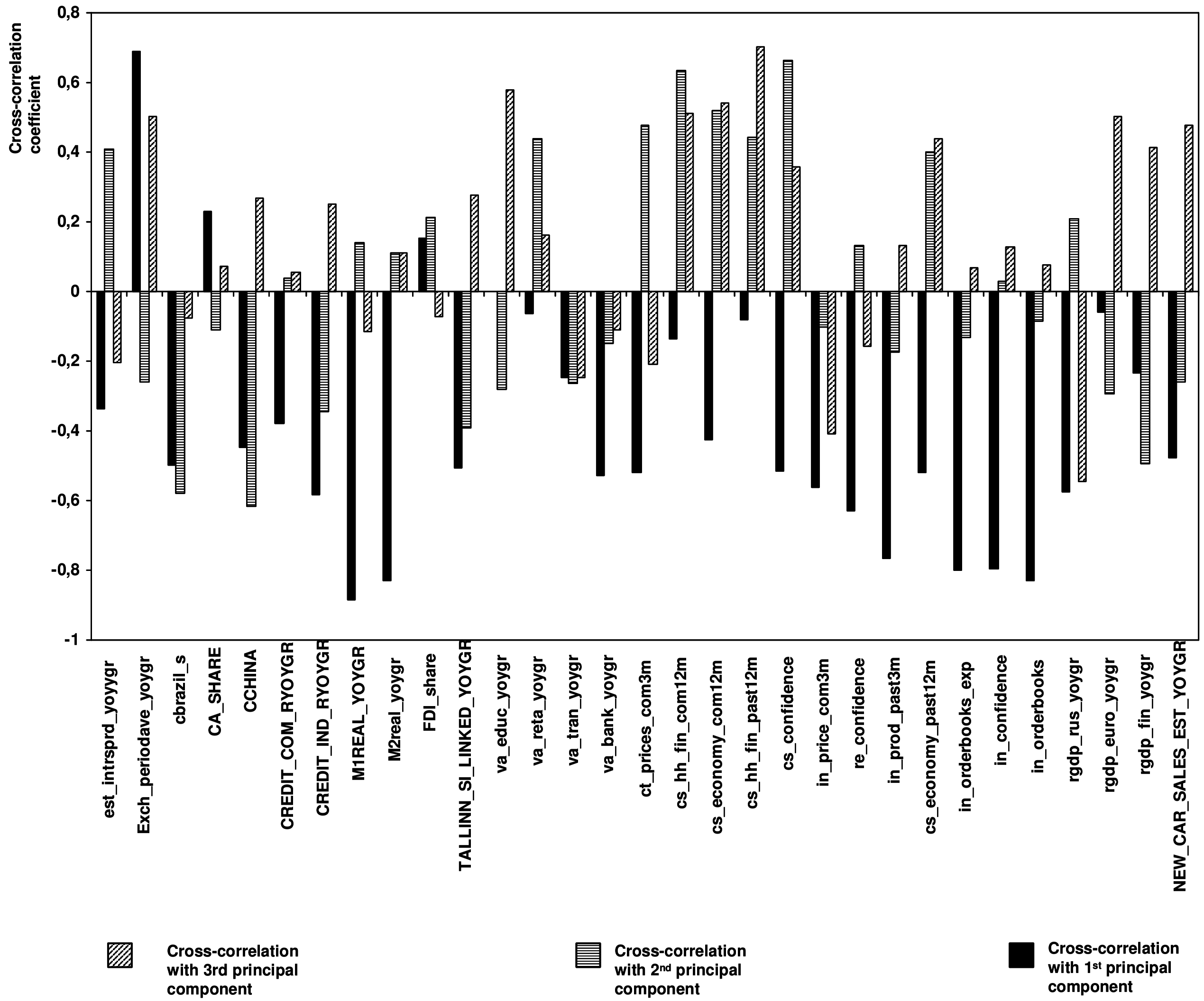


Figure 14: Principal components: correlations lagged — stacked

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.

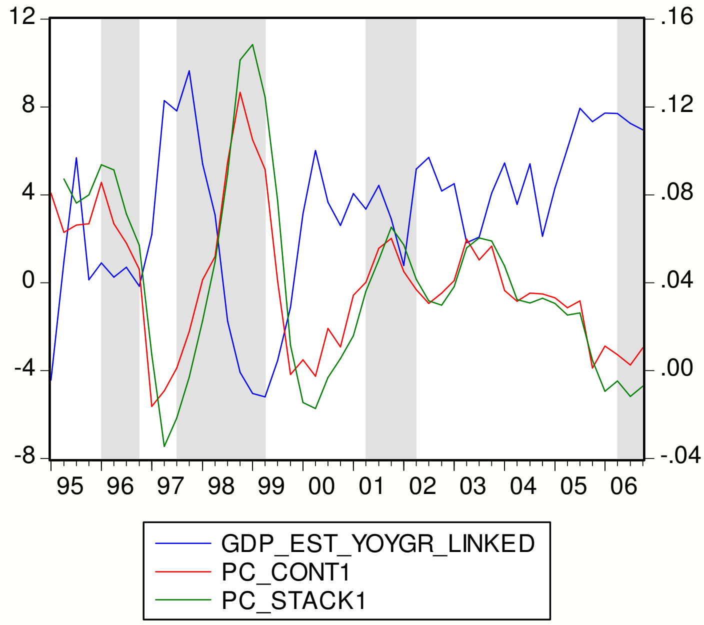


Figure 15: 1st Principal components and GDP growth

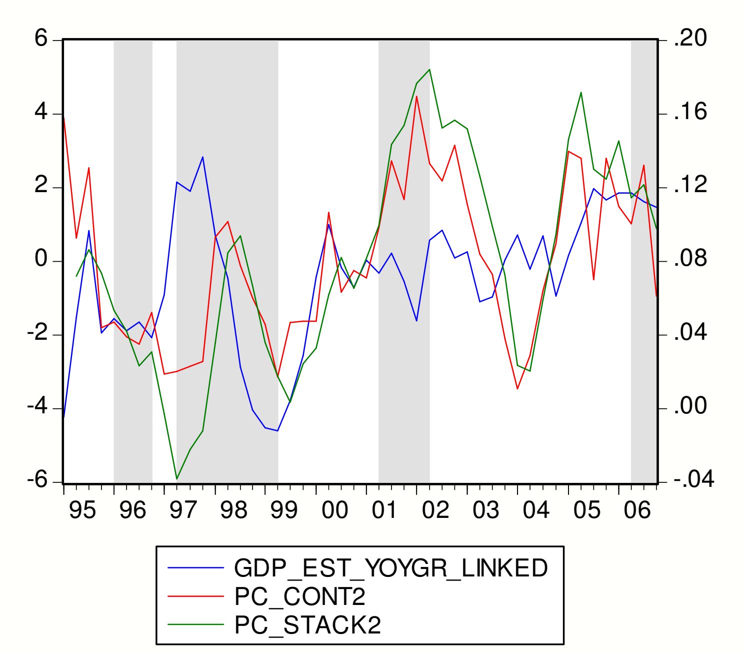


Figure 16: 2nd Principal components and GDP growth

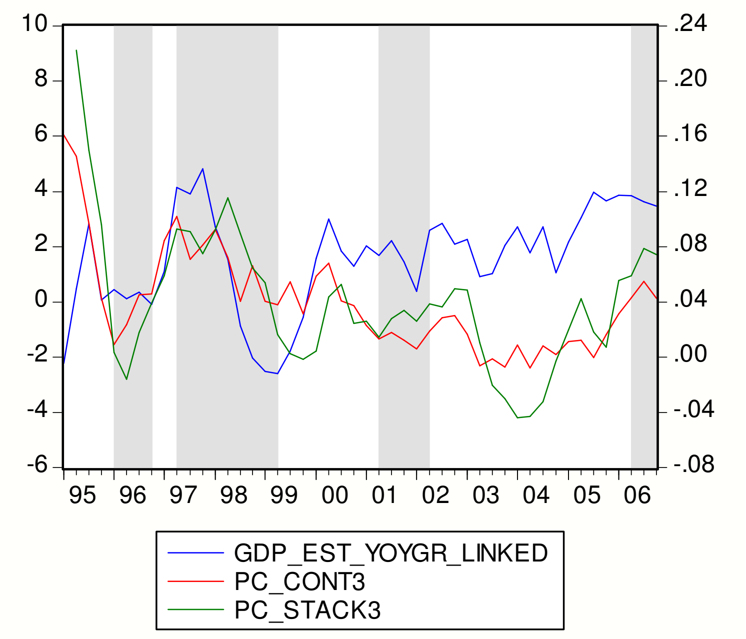


Figure 17: 3rd Principal components and GDP growth

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).

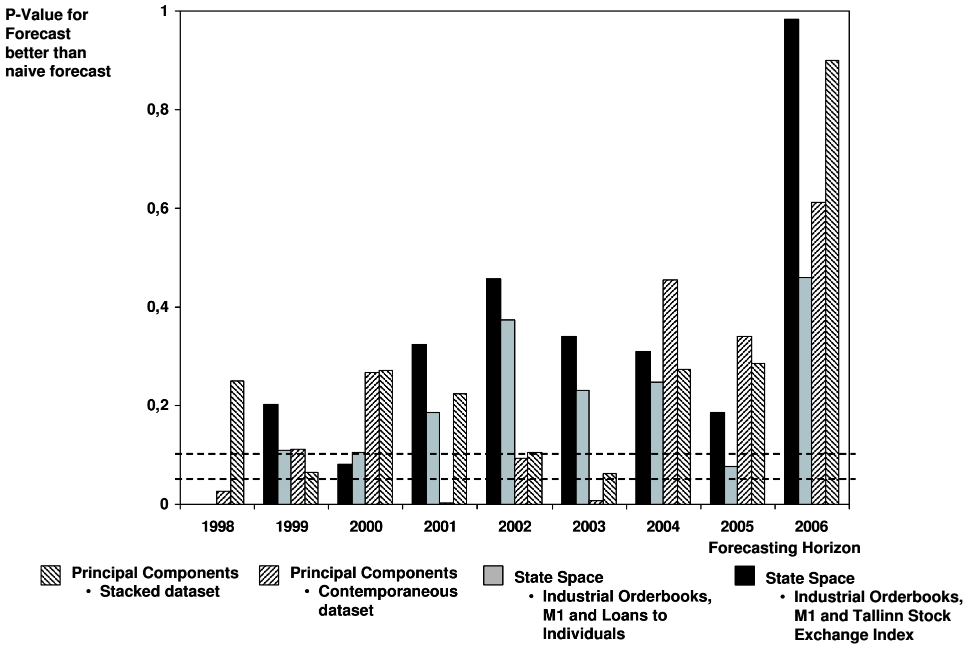


Figure 18: Forecasting Performance: DM-P-Values per period

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.

References

Altissimo, F., Bassanetti, A., Cristadoro, R., Forni, M., Hallin, M., Lippi, M. and Reichlin, L., 2001. EuroCOIN: a real time coincident indicator of the euro area business cycle. CEPR Working Paper 3108.

Artis, M., Banerjee, A. and Marcellino, M., 2001. Factor Forecasts for the UK. EUI Working Paper No. 2001/15.

Bai, J. and Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70:191–221.

Bandholz, H., 2004. Konjunkturelle Frühindikatoren für die Bundesrepublik Deutschland und die Freie und Hansestadt Hamburg. Frankfurt am Main: Peter Lang.

Bandholz, H. and Funke, M., 2003. In Search of Leading Indicators of Economic Activity in Germany. Journal of Forecasting 22:277–297.

Breitung, J. and Eickmeier, S., 2005. Dynamic factor models. Deutsche Bundesbank Discussion Paper.

Bry, G. and Boschan, C., 1971. Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. In National Bureau of Economic Research. New York.

CESIfo, 2007. World Economic Survey. Vol. 6. CESIfo, No. 4.

Chen, S.-S., 2005. A Note on In-Sample and Out-of-Sample Tests for Granger Causality. Journal of Forecasting, No. 24:453–464.

Clark, T. E. and McCracken, M. W., 2001. Tests of Forecast Accuracy and Encompassing for Nested Models. Journal of Econometrics, No. 105:85–110.

Curran, D. and Funke, M., 2006. Taking the temperature — forecasting GDP growth for mainland China. BOFIT Discussion Papers, No. 6.

D'Agostino, A. and Giannone, D., 2006. Comparing alternative predictors based on large-panel factor models. ECB Working Paper Series.

Diebold, F. X. and Mariano, R. S., 1995. Comparing predictive accuracy. Journal of Business Economic Statistics, No. 13:253–263.

Dreger, C. and Schuhmacher, C., 2004. Estimating Large-Scale Factor Models for Economic Activity in Germany: Do They Outperform Simpler Models? Jahrbücher für Nationalökonomie und Statistik, No. 224:731–750.

Eickmeier, S. and Breitung, J., 2005. How synchronized are Central and East European economies with the euro area? Evidence from a structural factor model. Bundesbank Discussion Paper Series 1: Economic Studies.

Estrella, A. and Mishkin, F. S., 1998. Predicting U.S. Recessions: Financial Variables as Leading Indicators. The Review of Economics and Statistics, No. 80:45–61.

Forni, M., Hallin, M. and Lippi, M., 2003. The Generalized Dynamic Factor Model one-sided estimation and forecasting. Journal of the American Statistical Association.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L., 2001. Coincident and leading indicators for the Euro area. The Economic Journal.

Forni, M., Lippi, M. and Reichlin, L., 2000. The Generalized Factor Model: Identification and Estimation. The Review of Economics and Statistics, No. 82:540–554.

Fritsche, U. and Stephan, S., 2000. Leading Indicators of German Business Cycles: an Assessment of Properties. Deutsches Institut für Wirtschaftsforschung (DIW), Berlin.

G. C. o. E. E. (Sachverständigenrat),(2005). Annual Report 2003/2004.

Gerlach, S. and Yiu, M. S., 2005. A dynamic factor model of economic activity in Hong Kong. Pacific Economic Review, No. 10:279–292.

Granger, C. W. J. and Newbold, P., 1977. Forecasting Economic Time Series. Orlando: Academic Press.

Harvey, D. I., Leybourne, S. J. and Newbold, P., 1998. Tests for Forecast Encompassing. Journal of Business Economic Statistics, No. 16:254–259.

Jolliffe, I. T., 2002. Principal Component Analysis. New York: Springer.

Kalman, R. E., 1960. A New Approach to Linear Filtering and Prediction Problems. Journal of Basic Engineering, Transactions of the ASME, Series D.

Kalman, R. E., 1963. New Methods in Wiener Filtering Theory. In Proceedings of the First Symposium of Engineering Applications of Random Function Theory and Probability. (Eds, Bogdanoff, J. L. and Kozin, F.). New York: Wiley, 270–388.

Kapetanios, G. and Marcellino, M., 2006. Impulse Response Functions from Structural Dynamic Factor Models: A Monte Carlo Evaluation. CEPR Discussion Paper, No. 5621.

Kim, C.-J., 1999. State-space models with regime switching: classical and Gibbs-sampling approaches with applications. Cambridge, Mass.: MIT Press.

Marcellino, M., Stock, J. H. and Watson, M. W., 2000. A dynamic factor analysis of EMU.

McCracken, M. W., 1999. Asymptotics for out-of-sample tests of causality. Louisiana State University.

Nerb, G., 2007. The Importance of Representative Surveys of Enterprises for Empirically Oriented Business Cycle Research. In Handbook of Survey-Based Business Cycle Analysis (Ed, Goldrian, G.). Cheltenham: Edward Elgar.

Stock, J. H. and Watson, M. W., 1991. A Probability Model of the Coincident Economic Indicators. In Leading Indicators: New Approaches and Forecasting Records (Eds, Lahiri, K. and Moore, G. H.). Cambridge, UK: Cambridge University Press, 63–89.

Stock, J. H. and Watson, M. W., 2002. Forecasting Using Principal Components from a Large Panel of Predictors. Journal of the American Statistical Association, No. 97:147–162.

Zanghieri, P., 2006. Current account dynamics in the new Member States. In The Central and Eastern European Countries and the European Union (Eds, Artis, M., Banerjee, A. and Marcellino, M.). Cambridge: Cambridge University Press, 245–273.

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_YOY GR	Trade

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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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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 $\mathbf{z}_t$.

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

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.

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

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

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

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

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.

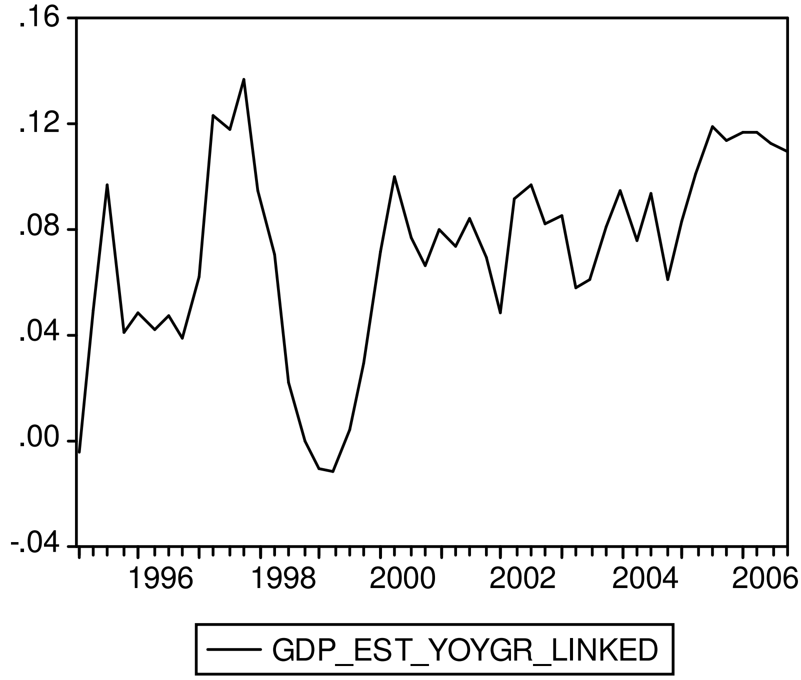

Figure 1: Real GDP Growth in Estonia (% yoy, constant 2000 prices)

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 $\mathbf{M}$, where $p_{12} = prob(s_t = 2\,|s_{t-1} = 1)$ etc. The rows of $\mathbf{M}$ 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.

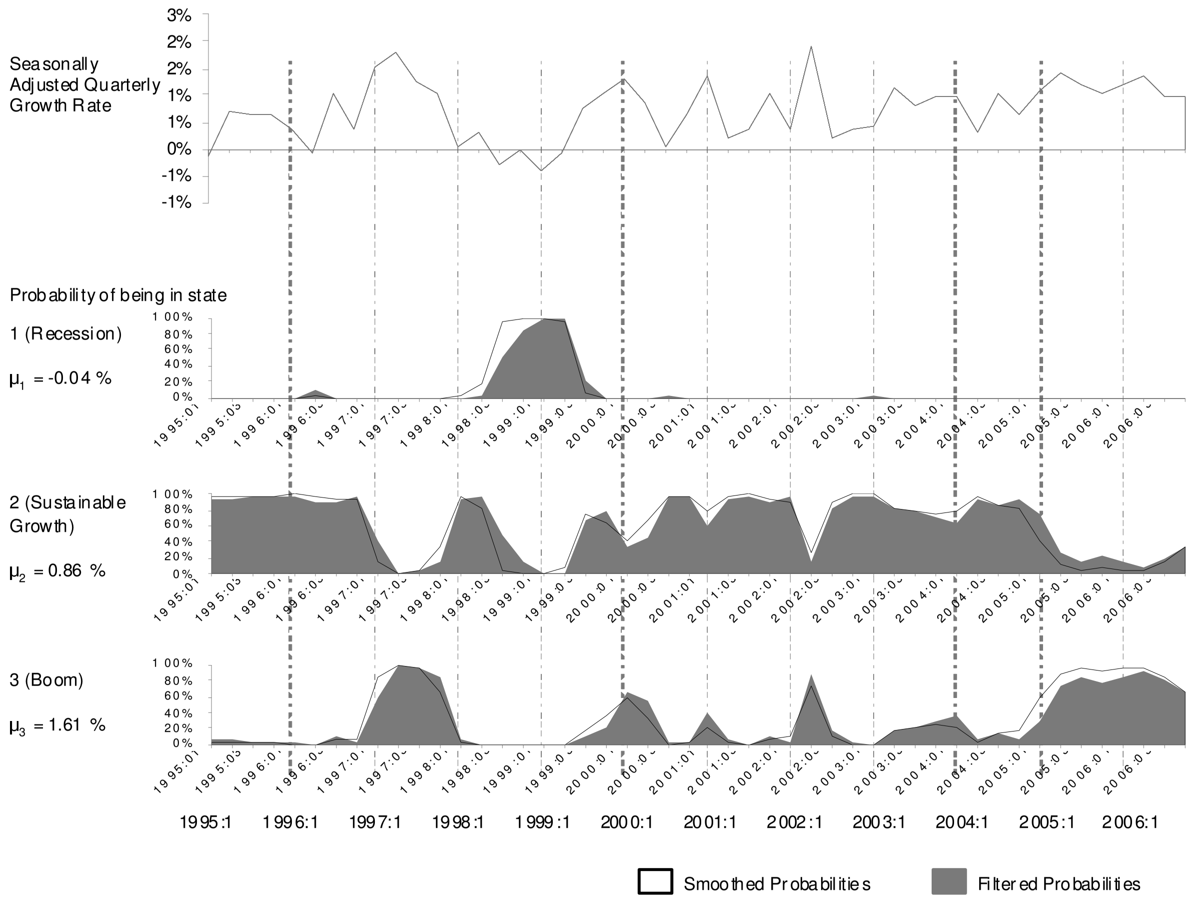

Figure 2: Markov-Switching State Probabilities for seasonally adjusted quarter-on-quarter growth rates

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.

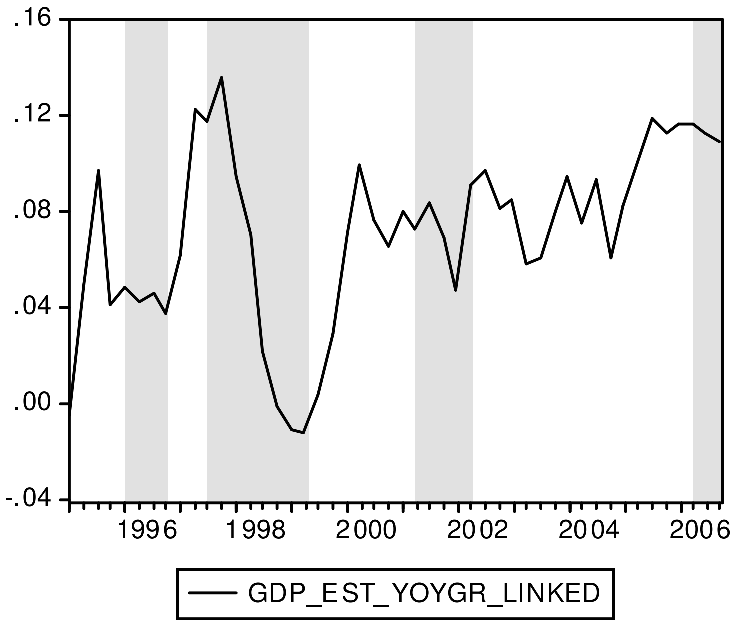

Figure 3: Growth Cycles of the Estonian Economy

[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.

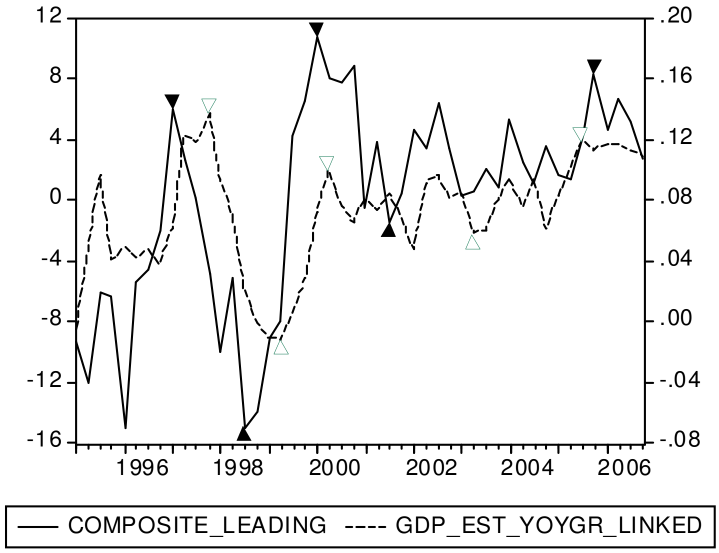

Figure 4: Reference Series and Indicator – Comparison and Turning Points

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.

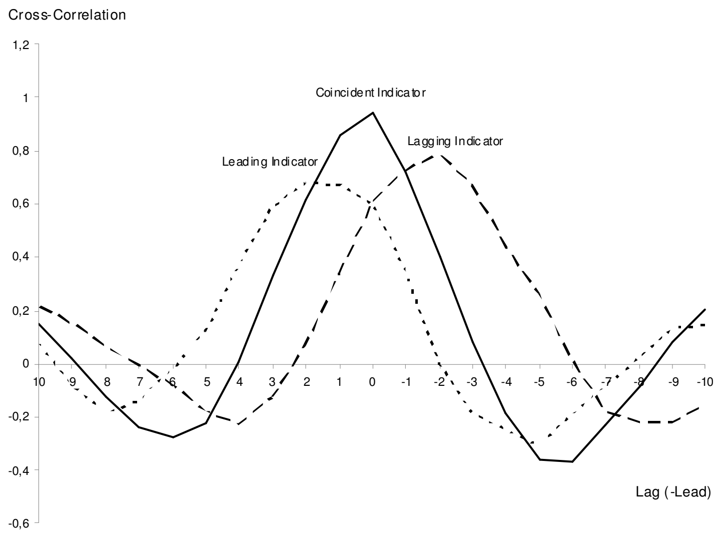

Figure 5: Phase-shifts between leading, coincident and lagging indicators

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.

References

Altissimo, F., Marchetti, D., Oneto, G. P., 1999. New Coincident and Leading Indicators for the Italian Economy. Bank of Italy. Mimeo.

Artis, M., Banerjee, A., Marcellino, M., 2001. Factor Forecasts for the UK. EUI Working Paper, No. 15.

Bai, J., Ng, S., 2002. Determining the Number of Factors in Approximate Factor Models. Econometrica, No. 70:191–221.

Bandholz, H., Funke, M., 2003. In Search of Leading Indicators of Economic Activity in Germany. Journal of Forecasting, No. 22:277–297.

Banerjee, A., Marcellino, M., Masten, I., 2006. Forecasting Macroeconomic Variables for the New Member States. In The Central and Eastern European Countries and the European Union (Eds, Artis, M., Banerjee, A. and Marcellino, M.). Cambridge: Cambridge University Press.

Boivin, J., Ng, S., 2005. Understanding and Comparing Factor-Based Forecasts. Mimeo.

Brillinger, D. R., 1981. Time Series Data Analysis and Theory. New York: Holt, Rinehart and Winston.

Bry, G., Boschan, C., 1971. Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. In National Bureau of Economic Research. New York.

Burns, A. F., Mitchell, W. C., 1946. Measuring Business Cycles. New York: National Bureau of Economic Research.

Chauvet, M., 1998. An Econometric Characterization of Business Cycle Dynamics with Factor Structure and Regime Switching. International Economic Review, No. 39:969–996.

Chin, D., Geweke, J., Miller, P., 2000. Predicting Turning Points. Technical Paper Series Congressional Budget Office.

Clark, T. E., McCracken, M. W., 2001. Tests of Forecast Accuracy and Encompassing for Nested Models. Journal of Econometrics, No. 105:85–110.

Croux, C. M., Forni, M., Reichlin, L., 2001. A Measure for Co-movement for Economic Variables: Theory and Empirics. The Review of Economics and Statistics, No. 83:231–241.

Curran, D., Funke, M., 2006. Taking the Temperature — Forecasting GDP Growth for Mainland China. BOFIT Discussion Papers, No. 6.

D'Agostino, A., Giannone, D., 2006. Comparing Alternative Predictors Based on Large-Panel Factor Models. ECB Working Paper Series.

Diebold, F. X., Mariano, R. S., 1995. Comparing Predictive Accuracy. Journal of Business & Economic Statistics, No. 13:253–263.

Diebold, F. X., Rudebusch, G. D., 1996. Measuring Business Cycles: A Modern Perspective. Review of Economics and Statistics, No. 78:67–77.

Eickmeier, S., Breitung, J., 2005. How Synchronized are Central and East European Economies with the Euro Area? Evidence from a Structural Factor Model. Bundesbank Discussion Paper Series 1: Economic Studies.

Emery, K. M., Koenig, E. F., 1992. Forecasting Turning Points: Is a Two-State Characterization of Business Cycles Appropriate? Economics Letters, No. 39:431–435.

Fiorentini, G., Planas, C., 2003. Busy Programme: Tools and Practices for Business Cycle Analysis in the European Union.

Forni, M., Giannone, D., Lippi, M., Reichlin, L., 2007. Opening the Black Box – Structural Factor Models with Large Cross-Sections. European Central Bank Working Paper Series.

Forni, M., Hallin, M., Lippi, M., 2003a. The Generalized Dynamic Factor Model: One-Sided Estimation and Forecasting. Journal of the American Statistical Association forthcoming.

Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2001. Coincident and Leading Indicators for the Euro Area. The Economic Journal.

Forni, M., Lippi, M., Reichlin, L., 2000. The Generalized Factor Model: Identification and Estimation. The Review of Economics and Statistics, No. 82:540–554.

Forni, M., Lippi, M., Reichlin, L., 2003b. Opening the Black Box: Structural Factor Models Versus Structural VARs. CEPR Discussion Paper.

Fuller, W. A., 1996. Introduction to Statistical Time Series. New York: John Wiley&Sons.

Gerlach, S., Yiu, M. S., 2005. A Dynamic Factor Model of Economic Activity in Hong Kong. Pacific Economic Review, No. 10:279–292.

Granger, C. W. J., Newbold, P., 1977. Forecasting Economic Time Series. Orlando: Academic Press.

Hamilton, J. D., 1989. A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica, No. 57:357–384.

Harvey, A., 1990. The Econometric Analysis of Time Series. Cambridge, Mass., MIT Press.

Harvey, D. I., Leybourne, S. J., Newbold, P., 1998. Tests for Forecast Encompassing. Journal of Business & Economic Statistics, No. 16:254–259.

Kapetanios, G., Marcellino, M., 2006. Impulse Response Functions from Structural Dynamic Factor Models: A Monte Carlo Evaluation. CEPR Discussion Paper, No. 5621.

Kholodilin, K. A., Yao, K. W., 2005. Measuring and Predicting Turning Points Using a Dynamic Bi-Factor Model. International Journal of Forecasting, No. 21:525–537.

Kim, C.-J., Nelson, C. R., 1999. State-space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications. Cambridge, Mass., MIT Press.

Lahiri, K., Wang, J. G., 1994. Predicting Cyclical Turning Points with Leading Index in a Markov Switching Model. Journal of Forecasting, No. 13:245–263.

McCracken, M. W., 1999. Asymptotics for Out-of-Sample Tests of Causality. Louisiana State University.

Neftci, S., 1984. Are Economic Time Series Asymmetric Over the Business Cycle? Journal of Political Economy, No. 92:307–328.

Schulz, C. H., 2007. Forecasting Economic Growth for Estonia: Application of Common Factor Methodologies. Bank of Estonia Working Paper Series.

Schumacher, C., 2005. Forecasting German GDP Using Alternative Factor Models Based on Large Data Sets. Deutsche Bundesbank Discussion Paper, No. 24.

Stock, J. H., Watson, M. W., 1991. A Probability Model of the Coincident Economic indicators. In Leading Indicators: New Approaches and Forecasting Records (Eds, Lahiri, K. and Moore, G. H.). Cambridge, UK: Cambridge University Press.

Stock, J. H., Watson, M. W., 2002. Forecasting Using Principal Components from a Large Number of Predictors. Journal of the American Statistical Association, No. 97:147–162.

Stock, J. H., Watson, M. W., 2002a. Macroeconomic Forecasting Using Diffusion Indexes. Journal of Business & Economic Statistics, No. 20:147–162.

Walter, N., Becker, W., Mühlberger, M., 2006. Estonia, Lithuania, Slovenia: Poised to adopt the Euro. In Deutsche Bank Research EU-Monitor.

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

Data Set and Sources

Shortname	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.

Can Inflation Help in Determining Potential Output of the Estonian Economy?

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May 2008

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Can Inflation Help in Determining Potential Output of the Estonian Economy?

Christian Schulz

Abstract

In this paper, we adapt a method developed by Kuttner (1994) for the identification of potential output to the case of the Estonian economy. We model output and inflation using a traditional Phillips curve relationship and link the two via an unobserved component, the cyclical component of output. The resulting series for potential output differs from the results of widely used techniques such as the Hodrick-Prescott filter. We show that this is driven by the development of inflation in Estonia. The introduction of economic theory to the estimation of potential output as opposed to pure filtering improves the real-time reliability of the estimates.

JEL-Codes: E3, C5

Keywords: Potential Output, Output Gap, Phillips Curve, Estonia, Unobserved Components

Table of Content:

1 INTRODUCTION

After the Russian crisis in the late nineties of the last century, the economic performance of Estonia in recent years has been spectacular. Persistent double-digit real GDP growth is more than even insiders had expected. However, many economists, for example at the International Monetary Fund (2007b), are warning that the current pace of expansion is not sustainable. In its latest 2008 spring forecast, the Bank of Estonia forecasts real growth to decelerate sharply in 2008, dropping to 2%.[1]

In 2007, several indicators began to signal an overheating of the Estonian economy. The current account deficit has been very high for years and although long-term foreign direct investment has financed a large part of this deficit, there were indications that this might not continue. The competitiveness of the Estonian economy compared to major investing economies such as the Nordic countries is decreasing as unit labour cost is rising fast. Credit growth financed by foreign banks, which own almost the entire financial sector, has accelerated. Inflation, driven by labour cost, has increased to more than 7% on an annual basis recently, further eroding the country's competitive position.

The instruments available to Estonian economic policy makers are limited. Monetary policy is not independent, as the exchange rate is governed by a strict currency board with the Euro, and therefore the European Central Bank's monetary policy is "imported". This arrangement has been very successful in the past, and abandoning it to realign the exchange rate is virtually no option, not least because of the consequences for consumers, as a large part of the private sector credit is denominated in foreign currency. However, the monetary authority Bank of Estonia (Eesti Pank), the Estonian central bank, advises the government on its fiscal stance and on its relationship with the current cyclical position of the economy. Prudent fiscal policy is the major lever in the hands of Estonian policy makers, and has been used to some extent by raising indirect taxes repeatedly.[2]

The Estonian economy has been growing at a high rate for the past 15 years, except for during of the Russian crisis. Therefore we do not observe the classic cycles of boom and recession as

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[1] The latest spring forecast 2008 of the Bank of Estonia can be found on its website at www.eestipank.info .

[2] This was commended by the International Monetary Fund in its 2007 country report (IMF, 2007a).

famously referred to in Burns and Mitchell (1946). Rather, we should detect cycles in GDP growth. In this paper, we apply an econometric technique for the identification of potential output and the output-growth gap to the Estonian case, in order to add to the available instruments for research on the potential output of the economy. Potential output is the permanent component of GDP growth, which in most applications is assumed to be stable at least in the short term. The transitory or cyclical component is often referred to as the "output-growth gap".[3] Clearly, a positive output-growth gap does not indicate a recession.

The remainder of this paper is structured as follows. Section 2 reviews some of the relevant literature, both from a theoretical point of view and in terms of relevant applications of the methodologies. In section 3, we lay out the empirical framework and the specifications. Section 4 presents the results of our estimation and compares them to the results of a simple Hodrick-Prescott filter application. Section 5 expands on the sensivity of our results with respect to changes in the estimation sample. Section 6 concludes. In the Appendix, we apply the same methodology to monthly data for comparison.

2 Literature Review

Potential output and the output gap are established concepts in economics. Their original definition stems from Okun (1962), who defined potential output as the maximum level of output the economy can produce without creating inflationary pressures. It has since become part of much of macroeconomic theory, for instance Phillips curves and business cycle theory (Lucas, 1972). As it is impossible to measure potential output directly, there is considerable literature on modelling and estimation procedures. Results are published and used by many organisations and institutions. For example, measures of the output gap are used by the Directorate General for Economic and Financial Affairs of the European Commission to calculate the cyclically adjusted budget balance of the member states, an important measure in the fiscal surveillance framework of the Stability and Growth Pact (Langedijk and Larch, 2007). In a monetary policy context, estimates of the output gap and potential output are used to derive reference values for money growth (ECB, 2004). The Organisation for Economic Co-operation and Development (OECD) regularly publishes estimates of the output gap for countries in its economic country surveys.[4]

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[3] See Langedijk and Larch (2007)

[4] Economic country surveys can be found on the OECD's website www.oecd.org .

Arguably the most popular method in practice to estimate potential output and the output gap is the Hodrick-Prescott (HP) filter. The use of such univariate methods is widespread and has been discussed exhaustively in Clark (1987) and Watson (1986). Although they are very convenient to use, one major problem which has been associated with these types of models is their weak performance at the ends of the sample. This can affect their real-time output gap measurement capacity (Planas and Rossi, 2004a). Other univariate methods include band-pass-filter techniques such as the Baxter-King filter (Christiano and Fitzgerald, 1999) and unobserved component models which were proposed, for example, in Watson (1986), Clark (1987) or in Harvey and Jaeger (1993). Multivariate filtering methods include the Beveridge-Nelson decomposition (Beveridge and Nelson, 1981). Structural VAR methodology has been adapted to the output gap analysis literature by Cooley and Dwyer (1998).[5] These methods have no end-of-sample bias, but they are strongly affected by the choice of variables and may therefore be somewhat awkward to use in routine analysis (Kichian, 1999). Markov-switching models, which do not estimate the output gap directly, have been used for example by Kress (2004) for Sweden with two states and by Schulz (2008) for Estonia with three states in the average growth rates.[6] Both studies find that estimates are highly dependent on the sample length, particularly on whether the period of the Russian crisis is included.

A rival method widely used in practice is a production function approach, which argues that the potential is mainly determined by the supply side of the economy, whereas the demand side leads to certain fluctuations. The supply side is assumed to be rather stable in the short term, while the demand side can vary significantly.[7] In the 1970s, this method attracted a lot of attention, as can be seen in the publications of Perry (1977), Clark (1979), or Perloff and Wachter (1979). It applies explicit economic reasoning to the decomposition into cycle and trend by determining what output should be, based on a more or less simple production function and the available numbers from statistics. The approach is therefore often referred to as "production function approach" or "growth accounting" and became the official methodology for the calculation of potential output by the European Commission in 2002. Recent work using this methodology includes, for example, Denis et al. (2006) and Proietti and Musso (2007). A lot of effort is being spent on the improvement of the input variables

[5] See also Funke (1997) who applies structural VAR modelling to output gap measuring for West German manufacturing.

[6] Other authors, like Bandholz and Funke (2003), use Markov-switching in combination with a small-scale unobserved common components model.

[7] See, for instance, Denis et al. (2006)

which measure capital and labour input. As determining the starting values for the stock of capital in an economy can pose serious problems, especially for countries where the starting point is rather recent (e. g. in Estonia), going from level estimates of potential output to estimates of potential growth is discussed in the literature. Kattai and Vahter (2006) made an attempt to adapt this method to the Estonian case, while Tsalinski (2007) applied it to Bulgaria.

The central piece of this paper is a methodology developed by Kuttner (1994) which combines the easy-to-use ad-hoc signal extraction filter analysis with a Phillips curve approximation which adds economic theory to the derivation of the output gap. The method has been used extensively, for instance by Kichian (1999) for the G7 countries and by Gerlach and Smets (1999) for the Euro Area. Tsalinski (2007) has applied the Kuttner methodology successfully to the Bulgarian case. Besides adding a component of economic theory to the estimation of the output gap, this bivariate technique can improve the real-time reliability of output gap estimates. This is found by Planas and Rossi (Planas and Rossi, 2004a). They find that their bivariate sample estimates for the United States, France and Italy need 30 – 50% less revision than comparable univariate estimates. This should also be looked at for the Estonian case.

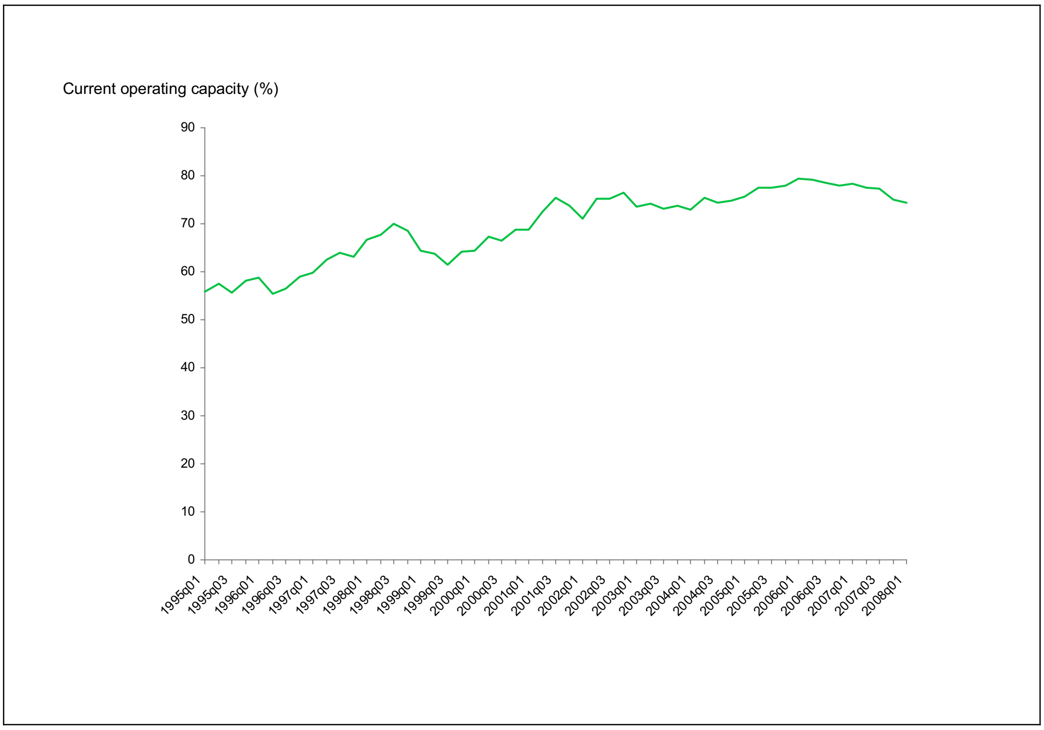
There are few publications on measures of the output gap for Estonia. A comprehensive study by Kattai and Vahter (2006) compares a linear trend, the HP-filter, the Baxter-King filter, a univariate (Watson (1986), Harvey (1989)) and bivariate unobserved components model (Kuttner (1994), Gerlach and Smets (1999)), as well as a production function approach. The authors find that differences between these essentially univariate methods are small and that real-time properties between the different methodologies are not significantly different. Our paper expands on the bivariate methods, which only combined measures of output and CPI-inflation, as we try to adapt them more specifically to the Estonian case.

Besides these statistical and econometric methods mentioned above, an alternative way of determining capacity utilisation is to survey economic enterprises. For Estonia, this is performed by the Estonian Institute of Economic Research (Konjuntuurinstituut).[8] As capacity utilisation is not an unambiguous concept in many branches of the economy, such as services and retail trade, only the industry survey includes an explicit question on the

[8] Website: www.ki.ee

percentage of capacity operating. The following graph displays the result of the survey question.

Figure 1: Survey on industry capacity utilisation



Source: Estonian Institute of Economic Research

Note: Deseasonalised

Capacity utilisation was low in the mid- and late 90s as compared to levels typical for mature economies. One explanation might be that capacities from Soviet times were still available but unused. These capacities, which probably were not sufficiently productive for modern Estonia's manufacturing, might have been abandoned or not considered in later surveys. In this case, the level of non-inflation-accelerating capacity utilisation might be rising in the beginning of the sample, as "old" capacity is replaced by new, more productive installations. After the Russian crisis, capacity utilisation levels rose to between 70% and 80%, dropping again towards the end of the sample. These levels are more characteristic of mature economies. The advantage of this data is its timely publication and that it is not subject to econometric modelling issues. However, the fact that it only reflects a rather small part of the economy can be criticised.[9] In addition, the numbers are hard to interpret with respect to inflationary pressures in the macro economy, as there is no evident threshold for when capacity is over-utilised. Indeed, if part of the unused capacity of the earlier part of the sample were rather unproductive Soviet-era installations, then room for expansion without inflationary pressures was probably not given at the time, as additional utilisation would immediately have decreased productivity and therefore increased inflationary pressures.

3 Empirical Framework and Model Specification

The Kuttner (1994) methodology introduces two interrelated equations for output and for inflation, respectively. Both equations include an unobservable common component, which is assumed to be the cyclical component of output. This system of equations can then be estimated in state-space form using maximum likelihood estimation and the Kalman filter.[10] In the following, we will describe the equations in general without reference to the actual data used further below in this section. The first equation for output, denoted as X_1, is specified as follows:

(1) $$X_{1t} = \sum_{i=1}^{M_1} \alpha_{1i} Z_{1it} + \widetilde{X}_{1t}$$

Z_{1it} is a vector of M_1 weakly exogenous variables and $\widetilde{X}_{1t}$ is the sum of a trend (T) component of output and a cyclical (C) component:

(2) $$\widetilde{X}_{1t} = X_{1t}^{T} + X_{1t}^{C}$$

In our specification, the short-term or cyclical component is assumed to follow an AR(2) process:

(3) $$X_{1t}^{C} = \phi_1 X_{1t-1}^{C} + \phi_2 X_{1t-2}^{C} + a_t^{C} \text{ or } \left(1 - \phi_1 L - \phi_2 L^2\right) X_{1t}^{C} = a_t^{C}$$

L is the lag operator and a_t^C is a white noise error term with variance $Var\left(a_t^C\right)$. The trend component is assumed to follow a second-order random walk:

(4) $$X_{1t}^{T} = \mu_{1t-1} + X_{1t-1}^{T} + a_t^{T} \text{ or } (1 - L)X_{1t}^{T} = \mu_{1t-1} + a_t^{T}$$

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[9] Value added in manufacturing accounted for about 20% of total value added in the Estonian economy on average from 2000 until 2006.

[10] We use software provided by the European Commission's Joint Research Centre in Ispra, Italy, called Program Gap, which can be found at http://eemc.jrc.ec.europa.eu/softwareGAP.htm.

In this specification, the slope of the trend component is:

(5) $$(1-L)\mu_{1t} = a_t^{\mu}$$

Both error terms are assumed to be white noise with variances $Var(a_t^T)$ and $Var(a_t^{\mu})$, respectively. If the slope were a constant, the data generating process of the trend component would be a first order random walk, an option we make extensive use of below.

Introducing a Phillips curve relationship, the second series X_2, a measure of inflation, is related to the first series as follows:

(6) $$X_{2t} = \mu_2 + \sum_{i=1}^{M_2}\alpha_{2i}Z_{2it} + \gamma(1-L)^d X_{1t-1} + \sum_{i=0}^{r}\beta_i X_{1t-i}^C + \sum_{i=1}^{p}\phi_i^* X_{2t-i} + \sum_{i=0}^{q}\theta_i a_{t-i}^{\pi}$$

The inflation measure X_2 depends upon an intercept μ_2, M_2 exogenous variables Z_{2it}, the first series X_1, which is integrated of order d, the short term or cyclical component of output with r lags, p autoregressive terms and q moving average terms.[11]

The estimation is performed in a state-space context using Kalman filtering. To give an example, in state-space form, a model with no exogenous variables would yield the following measurement equation:

(7) $$\begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta_1 & \beta_2 & \phi^* & \theta_1 & \theta_2 \end{bmatrix} \begin{bmatrix} X_t^T \\ X_t^C \\ X_{t-1}^C \\ X_{t-2}^C \\ X_{2,t-1} \\ a_t^{\pi} \\ a_{t-1}^{\pi} \end{bmatrix}$$

Accordingly, the transition equation would be:

(8) $$\begin{bmatrix} X_t^T \\ X_t^C \\ X_{t-1}^C \\ X_{t-2}^C \\ X_{2,t-1} \\ a_t^{\pi} \\ a_{t-1}^{\pi} \end{bmatrix} = \begin{bmatrix} \mu_T \\ 0 \\ 0 \\ 0 \\ \mu_{\pi} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta_1 & \beta_2 & \phi^* & \theta_1 & \theta_2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X_{t-1}^T \\ X_{t-1}^C \\ X_{t-2}^C \\ X_{t-3}^C \\ X_{2,t-2} \\ a_{t-1}^{\pi} \\ a_{t-2}^{\pi} \end{bmatrix} + \begin{bmatrix} a_t^T \\ a_t^C \\ 0 \\ 0 \\ 0 \\ a_t^{\pi} \\ 0 \end{bmatrix}$$

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[11] In practice, r is restricted to between 0 and 4, p to a maximum of 2 and q to a maximum of 3. The first moving average coefficient θ_0 is set unity.

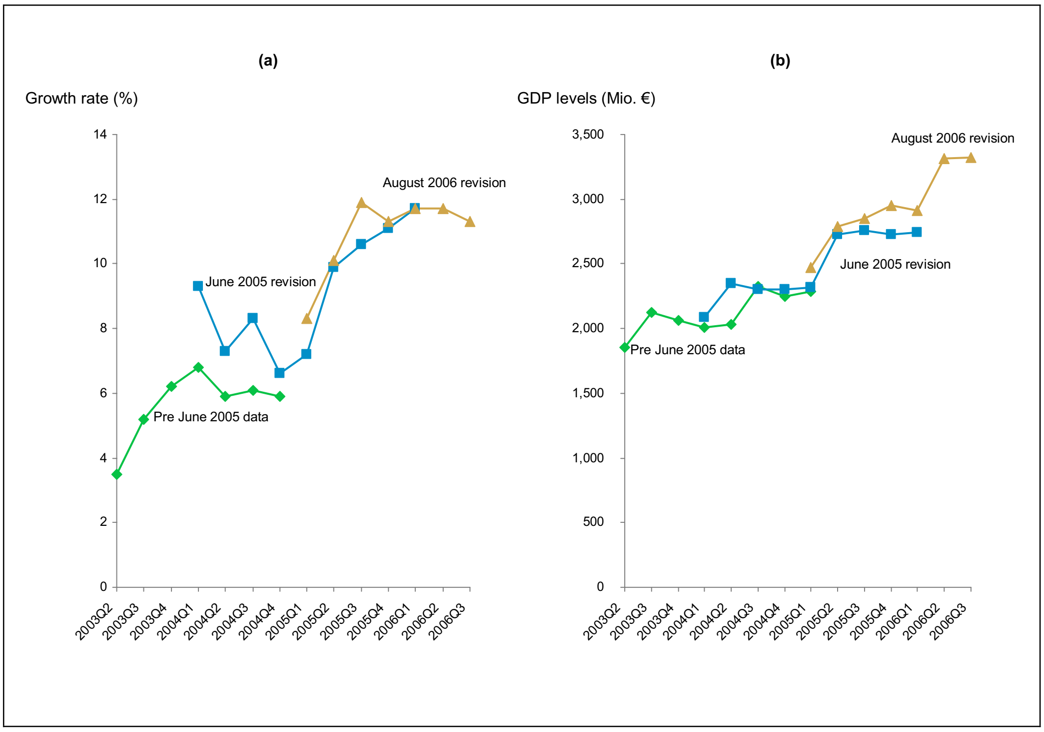
At the end of the estimation procedure, fixed-point smoothing described in Harvey (1989) is applied. Further below, we will provide both the smoothed results and the filtered results. For real-time estimation performance testing, i. e. pseudo-out-of-sample testing, only the filtered series will be relevant, because for each estimated data point, only data up to this point is used. The smoothed series reflects information from the entire data set for each estimated data point. A description of the software implementation can be found in Planas and Rossi (2004b).

Some of the literature applying the Kuttner (1994) methodology elaborates on the choice of the variables for the two equations. Naturally, different measures of output and inflation can be used in the two equations. In the remainder of this section, we will briefly discuss the model specification we use in order to adapt the Kuttner (1994) methodology to the Estonian case. Alternative specifications and results are reported in the Appendix.

All of the surveyed literature use GDP as the measure for which the output gap is estimated. Even though this need not necessarily be the case, it is a natural starting point for this paper as well. A point to be mentioned is that there have been frequent revisions of GDP data for Estonia in the past, usually due to changes of the methodology. Pre-revision data is subsequently deleted from the statistics office website, so that in order to check for their effects in the past, we have had to take recourse to the paper version of the Monthly Statistical Bulletin of the Statistical Office of Estonia. We sampled the 24 reports published in 2005 and 2006 and found two revisions. The effect of these revisions is depicted in the following graphs in terms of growth rates (a) and levels (b).[12]

[12] The effect of data revisions on the real-time performance of output gap estimations was analysed in Hughes Hallet et al. (Hughes Hallet et al., 2007) for some major OECD countries.

Figure 2: GDP revisions



Note: growth rates are year-on-year growth rates as published in the Statistic Office of Estonia's Monthly Statistical Bulletin, from 2005 till 2006

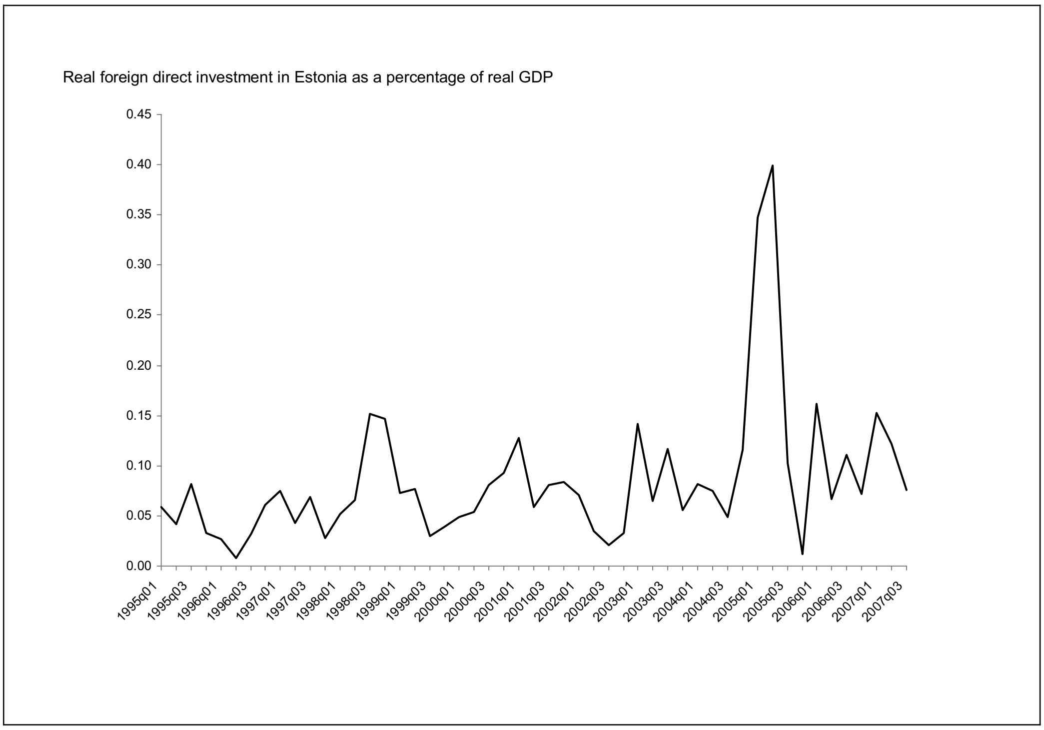
It can be seen that of the two revisions in this period, the one in June 2005 had the stronger effect in terms of growth rates as well as levels. Revisions are made irregularly and cannot be predicted. A case might be made for predicting the output gap using a measure other than GDP, such as the industrial production index, which is also available over a long time period and even timelier and at a higher frequency than GDP data. However, as we only make short term forecasts and as the manufacturing sector only represents a rather small part of the Estonian economy which might be driven by entirely different dynamics, we stick to GDP as a measure.[13]

As a small open economy with a currency board exchange rate regime, Estonia's output capacities are strongly influenced by foreign direct investment. Because of the currency board arrangement, both production capacity and money supply are increased. Consequently, while they have a strong influence on GDP growth, they might be inflation-neutral in the sense that growth due to FDI might not increase inflationary pressures. This shall be taken into account

[13] We use GDP data based on the 2006 revision, which was only recently re-calculated back until 1994. This differs from earlier papers, where this information was not yet available.

and is in line with the discussions of the European Commission report on the estimation of output gaps (EPC, 2004). The following figure displays the quarterly time series of foreign direct investment in Estonia as a percentage of real GDP. It is deflated using the (implicit) GDP deflator of the Estonian Statistical office.[14] The series is stationary; however, there is a major outlier in the beginning of 2005, which is probably due to the takeover of the Baltic states' largest bank, Estonia's Hansapank by the Swedbank of Sweden. We shall remove this outlier using the TRAMO/SEATS procedure.

Figure 3: Foreign direct investment in Estonia



Note: deflated with GDP deflator

Consequently, X_1 from equation (1) will be real GDP in constant 2000 prices in the following. We will use data in Estonian Kroons. In all models, the trend component will be modelled as integrated of order one, while the cyclical component will be assumed to follow an AR(2)-process. Foreign direct investment at constant 2000 prices as a percentage of GDP (FDI_t) will

[14] Other deflators than the GDP deflator, which is used in the national accounts, could be applied; data from before 1998 is only published for CPI, export prices and construction prices by the Statistical Office of Estonia.

be an exogenous variable in the output equation so that the specification of equation (1) amounts to the following expression:[15]

$$GDP_t = \alpha_{11k} FDI_t + G\widetilde{D}P_{kt} = \alpha_{11k} FDI_t + GDP_{kt}^T + GDP_{kt}^C \tag{9}$$
$$= \alpha_{11k} FDI_t + \left(\mu_k^T + GDP_{kt-1}^T + a_{kt}^T\right) + \left(\phi_{k1} GDP_{kt-1}^C + \phi_{k2} GDP_{kt-2}^C + a_{kt}^C\right)$$

The index k indicates the different model specifications, which will be described below. Within the estimation procedure, we will be using GDP in logs to obtain better comparable coefficients (*gdp*=*ln*(*GDP*)).[16]

$$gdp_{1t} = \alpha_{11k} FDI_t + g\widetilde{d}p_{k1t} = \alpha_{11k} FDI_t + gdp_{k1t}^T + gdp_{k1t}^C \tag{10}$$
$$= \alpha_{11k} FDI_t + \left(\mu_k^T + gdp_{k1t-1}^T + a_{kt}^T\right) + \left(\phi_{k1} gdp_{k1t-1}^C + \phi_{i2} gdp_{k1t-2}^C + a_{kt}^C\right)$$

The measure of inflation which will be used in the specification of the Phillips curve might have tremendous impact on the outcome of the estimation exercise. Therefore, some time and intellectual effort should be spent on the choice of the inflation variable. Kuttner, in his original 1994 paper, uses CPI inflation for the US. The paper by Kichian (1999) suggests using core inflation, as it is the actual target variable of the Canadian central bank.[17] Tsalinski (2007), in his paper on potential output in Bulgaria, tests three different measures: the consumer price index, the GDP deflator and labour cost. He finds the strongest and most explicable (in terms of significance and signs of the coefficients) relationship between the output gap and inflation for his measure of labour cost inflation.

For the case of Estonia, the fact that this very small economy is among the most open in the world has to be reflected in the inflation measure. We therefore suggest using two different measures of inflation: unadjusted consumer price inflation (model 1) which was used in Kuttner's original paper and wage inflation (model 2). The following figure displays the time series for CPI and wage inflation. The series are displayed as quarter-on-quarter growth rates and were seasonally adjusted using the X12 census method. A brief glance at the graphs shows that inflation rates were fluctuating wildly before 1998. After the Russian crisis, inflation rates were low and stable for some time, until particularly wage inflation started

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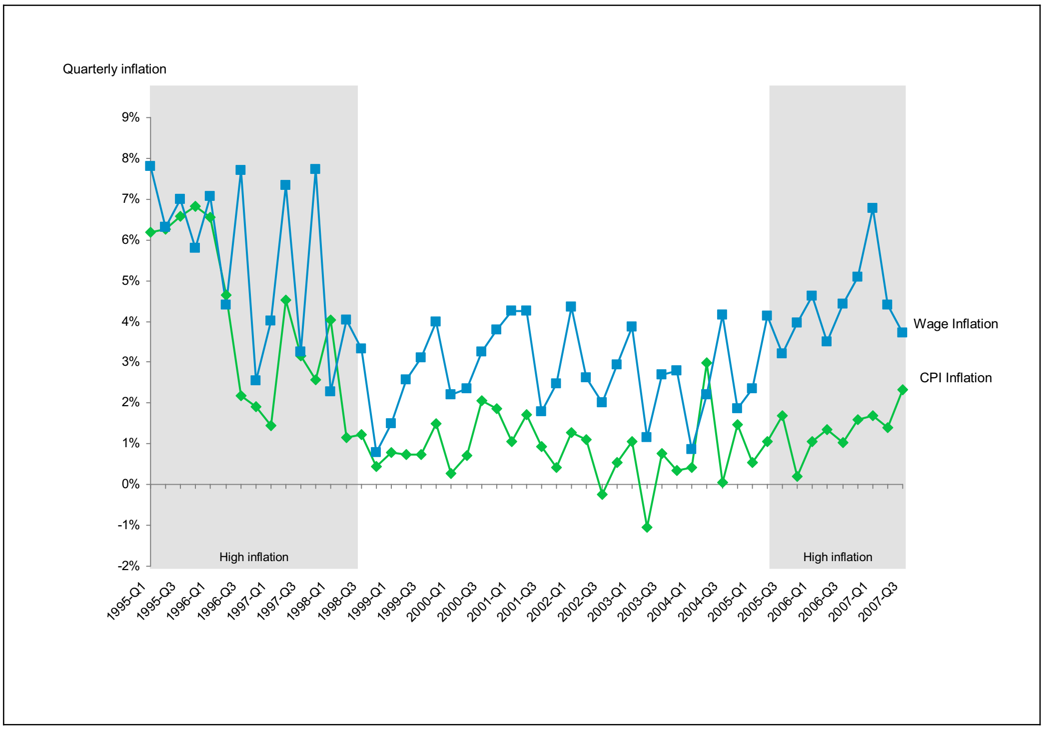
[15] We have tested for weak exogeneity of foreign direct investment with respect to log GDP using the Hausman-Wu test (Hausman, 1978). As instruments, we used the first two lags of FDI. When we add the resulting residual series from the IV equation to the structural equation, we find the coefficient of this residual series to be clearly insignificant, so we cannot reject the null-hypothesis of weak exogeneity of FDI.

[16] Lower-case letters indicate logs.

[17] He assumes that the consumer price index inflation is influenced by transitory effects of food and energy prices. In addition, changes in indirect taxes are assumed as transitory. Core inflation is then consumer price inflation "cleaned" of the influence of these three factors.

rising sharply. At the end of the sample, wage inflation started dropping again, albeit still at a high level. The two periods of high inflation are marked by the grey-shaded area in the figure below.

Figure 4: Inflation rates



Note: Series are given in quarter-on-quarter growth rates. De-seasonalisation was performed on each series using the X12 census method. Shaded areas mark periods of high quarterly inflation.

Further examination is required to determine whether the original Phillips curve specification with inflation in levels, or the modified Phillips curve with change in inflation as a dependent variable should be used.[18] A brief glance at classic Phillips curve representations with level inflation (first row of graphs) and changes in inflation (second row of graphs) depicted against the unemployment rate on the abcyss shows no stable relationship here for any of the models.[19] This is in line with the results of research by the Bank of Estonia, for instance in Dabusinskas and Kulikov (2007). As Phillips curves with change in inflation have been more pervasive for a long time, we use and compare both types of specifications.

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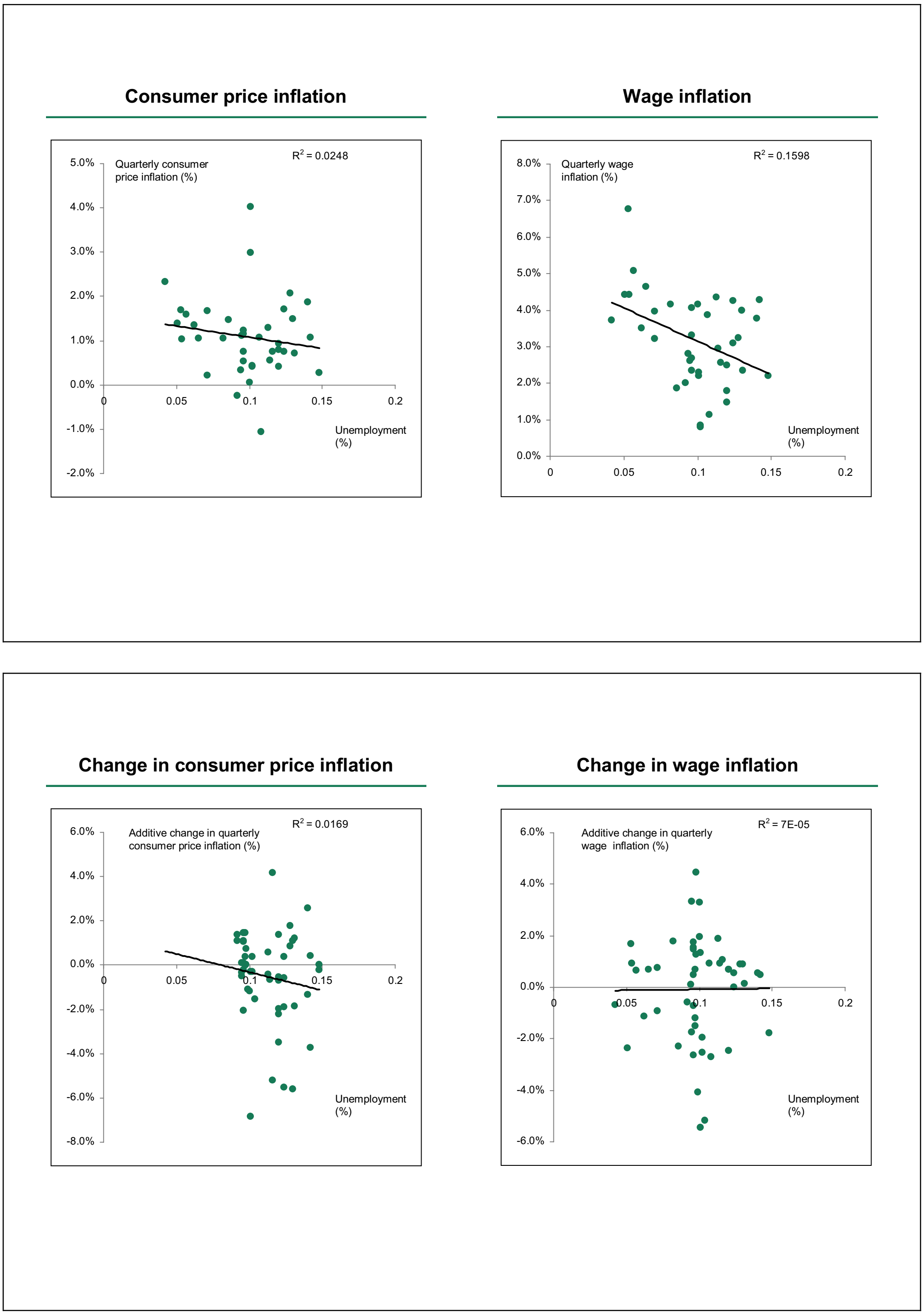
[18] We find both inflation series in levels and in differences to be stationary according to the results of augmented Dickey-Fuller testing (ADF) at the usual significance levels.

[19] Unemployment is another measure of the output gap or the output-growth gap, which is used in most textbook illustrations of the Phillips curve. We shall replace this measure with our derived output-growth gap below.

Figure 5: Different Phillips curves specifications



Notes: R-squared for linear regression, quarterly inflation rates and quarterly changes in inflation rates deseasonalised using X12 census.

In each specification of the Phillips curve, we will include different specifications of the autoregressive and moving average terms, due to different diagnostics. The first difference of GDP will be excluded as we found it to yield insignificant coefficients for γ in all models and specifications. We include the first lag of the cyclical component from the output equation while, again, the other lags as well as the contemporaneous value of the cyclical component were found to yield insignificant coefficients β_i for i>1 and i=0. If we denote quarter-on-quarter CPI inflation as π_{CPIt} and wage inflation as π_{Wt}, then the specification of the Phillips curve becomes:

(11a) Model 1a: $\pi_{CPIt} = \mu_1 + \beta_{11} gdp_{t-1}^{C} + \phi_{11}^{*} \pi_{CPI\,t-1} + a_t^{\pi_{CPI}}$

(11b) Model 2a: $\pi_{Wt} = \mu_2 + \beta_{21} gdp_{t-1}^{C} + \phi_{21}^{*} \pi_{W\,t-1} + \sum_{j=0}^{2} \theta_{2j} a_{t-j}^{\pi_W}$

The Phillips curve specifications with change in inflation rates as a dependent variable are the following, in the same order as above:

(12a) Model 1b: $\Delta\pi_{CPIt} = \mu_4 + \beta_{41} gdp_{t-1}^{C} + \phi_{41}^{*} \Delta\pi_{CPI\,t-1} + \sum_{j=0}^{2} \theta_{4j} a_{t-j}^{\pi_{CPI}}$

(12b) Model 2b: $\Delta\pi_{Wt} = \mu_5 + \beta_{51} gdp_{t-1}^{C} + \phi_{51}^{*} \Delta\pi_{W\,t-1} + \sum_{j=0}^{2} \theta_{5j} a_{t-j}^{\pi_W}$

The tables below summarise the models' specifications with respect to both equations. In the following section we will display and discuss the results of the estimation exercise.

Table 1: Model specifications overview

	MODEL 1A	MODEL 2A	MODEL 1B	MODEL 2B
Output Equation				
Dependent Variable	Ln GDP	Ln GDP	Ln GDP	Ln GDP
Trend:	Random walk plus drift	Random walk plus drift	Random walk plus drift	Random walk plus drift
Cycle AR order:	2	2	2	2
Exogenous variables	FDI as a percentage of GDP	FDI as a percentage of GDP	FDI as a percentage of GDP	FDI as a percentage of GDP
Phillips curve equation				
Dependent Variable	QoQ Consumer Price Inflation	QoQ Wage Inflation	Change in QoQ Consumer Price Inflation	Change in QoQ Wage Inflation
AR order:	1	1	2	2
MA order:	2	1	2	2
Endogenous Regressors	Cycle Lag 1-2	Cycle Lag 1-2	Cycle Lag 1	Cycle Lag 1
Exogenous Variable 1	None	None	None	None
Exogenous Variable 2	None	None	None	None

4 ESTIMATION RESULTS

All four specifications/models were estimated using the state-space framework and Kalman filtering. The following table displays the results of the estimation for each of the models, both traditional Phillips curves (models 1a and 2a) and modified Phillips curves (models 1b and 2b). The parameters are given on the left hand side and the columns display the results for each specification. Information on significance is revealed by p-values.

Table 2: Estimation results

	MODEL 1A		MODEL 2A		MODEL 1B		MODEL 2B	
Output Equation								
		p-value		p-value		p-value		p-value
μ_{1k}^{T}	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
ϕ_{k1}	1.84	0.00	1.71	0.00	1.63	0.00	1.58	0.00
ϕ_{k2}	-0.85	0.00	-0.75	0.00	-0.81	0.00	-0.77	0.00
$Var\left(a_{kt}^{T}\right)$	0.0001		0.0001		0.0001		0.0001	
$Var\left(a_{kt}^{C}\right)$	0.0000		0.0000		0.0000		0.0000	
Cross-Corr. Cycle – Infl.	-0.29		0.76		-0.16		0.32	
α_{11k}	0.04	0.01	0.04	0.00	0.02	0.40	0.01	0.47
Phillips Curve Equation								
μ_{2k}	0.01	0.04	0.02	0.00	1.13	0.41	0.38	0.00
β_{1k}	1.27	0.00	1.07	0.00	-56.58	0.52	-6.56	0.44
β_{2k}	-1.18	0.00	-0.95	0.00				
ϕ_{1k}^{*}	0.37	0.03	0.35	0.04	-0.28	0.73	-1.07	0.00
ϕ_{2k}^{*}					-0.13	0.79	-0.37	0.06
θ_{1k}	-0.22	0.35	-1.03	0.00	0.19	0.80	0.63	0.00
θ_{2k}	0.22	0.33		1.00	0.30	0.49	-0.33	0.10
$Var\left(a_{t}^{\pi}\right)$	0.00		0.00		19.68		0.21	

Notes: Likelihood function maximised by Newton-Raphson - E04UCF from NAG Mark 19; Standard errors computed using information matrix

Starting with the output equations, marked differences between the model specifications with traditional Phillips curves and the ones with modified curves can be observed. The coefficients on the AR-terms add up to close to unity, hinting at non-stationarity in the trend component. This is clearly not the case in the specifications with modified Phillips curves. The coefficient α_{11}, on the other hand, is strongly significant in the traditional case and insignificant in the modified case. It has the expected positive sign, so real foreign direct investment has a significant positive effect on real GDP, even in the presence of a strong cyclical component. The fact that the correlation between the cyclical component and inflation is not equal to unity is helpful, as otherwise the set-up in two equations could be questioned at this point.

The Phillips curves' estimation results lead us to conclude that modified Phillips curves are not helpful in determining potential output for the Estonian economy, given the present data set and the present model. The most important coefficients for our economic interpretation are obviously the coefficients on the cyclical component from the output equation, β. While these are strongly significant and carry the expected positive sign, at least on the first lag, in the case of the traditional Phillips curve specifications, they are insignificant and negative in the case of the modified Phillips curve specifications. In the case of model 1b, the magnitude of the coefficient β_1 is surprisingly large. In no case do we find indications for non-stationarity in the inflation rates. The AR-coefficients are non-unity, even when added. This positive picture of the estimation results continues when looking at the diagnostics in the following table:

Table 3: Diagnostics

	MODEL 1A	MODEL 2A	MODEL 1B	MODEL 2B
Output Equation				
Residuals autocorrelations				
r(1) =	0.1392	-0.0224	0.0107	0.0231
r(2) =	-0.0089	-0.0359	-0.0397	0.041
r(3) =	-0.08	-0.0054	0.0326	0.096
r(4) =	-0.1976	-0.1098	-0.01	0.0396
Approximated standard deviation	0.14	0.14	0.1414	0.1414
Ljung-Box test				
Q(4) =	3.5941	0.78	0.1533	0.7047
p-value =	0.4637	0.9411	0.9972	0.9508
Phillips Curve Equation				
Residuals autocorrelations				
r(1) =	-0.0965	-0.0032	0.0087	-0.014
r(2) =	-0.1107	-0.0834	0.0058	-0.0143
r(3) =	0.0247	-0.0713	0.0127	0.0387
r(4) =	-0.3817	-0.2285	-0.0468	0.066

Approximated standard deviation	0.14	0.14	0.1414	0.1414
Ljung-Box test				
Q(4) =	9.4277	3.6103	0.1361	0.344
p-value =	0.0513	0.4613	0.9978	0.9868
R-squared (uncentered) =	0.8462	0.8833	0.0656	0.3647

As the Ljung-Box Q-test on the fourth lag shows, weakly significant auto-correlation can only be found in the case of model 1a. The other three models seem to be well-specified on this account. The traditional Phillips curves exhibit much higher levels of R^2.

These numerical estimation results lead us to conclude that we should drop the modified Phillips curve specifications in favour of the traditional specifications. Among the two traditional specifications, the diagnostics slightly favour model 1b, which carries our economic theory explanations much better, because we would favour wage inflation ex ante as an indicator for inflation over consumer price inflation.

The following graphs depict the results for the selected specification 1b.[20] The first figure shows potential output growth as a year-on-year percentage. We present both the filtered series and the smoothed series, as indicated in section 3. For comparison, we also depict potential output growth as the HP-filter calculates it, as well as actual real growth of GDP. The second figure presents the resulting output gaps. For comparison, the results of a traditional application of the Hodrick-Prescott filter with an inverse signal-to-noise-ratio λ of 1.600 are also depicted as interrupted lines.[21]

[20] For comparison, we illustrate and comment on the results of model 1a in the appendix.

[21] The choice of an inverse signal-to-noise ratio of 1.600 is standard in the literature for quarterly data.

Figure 6: Potential output growth

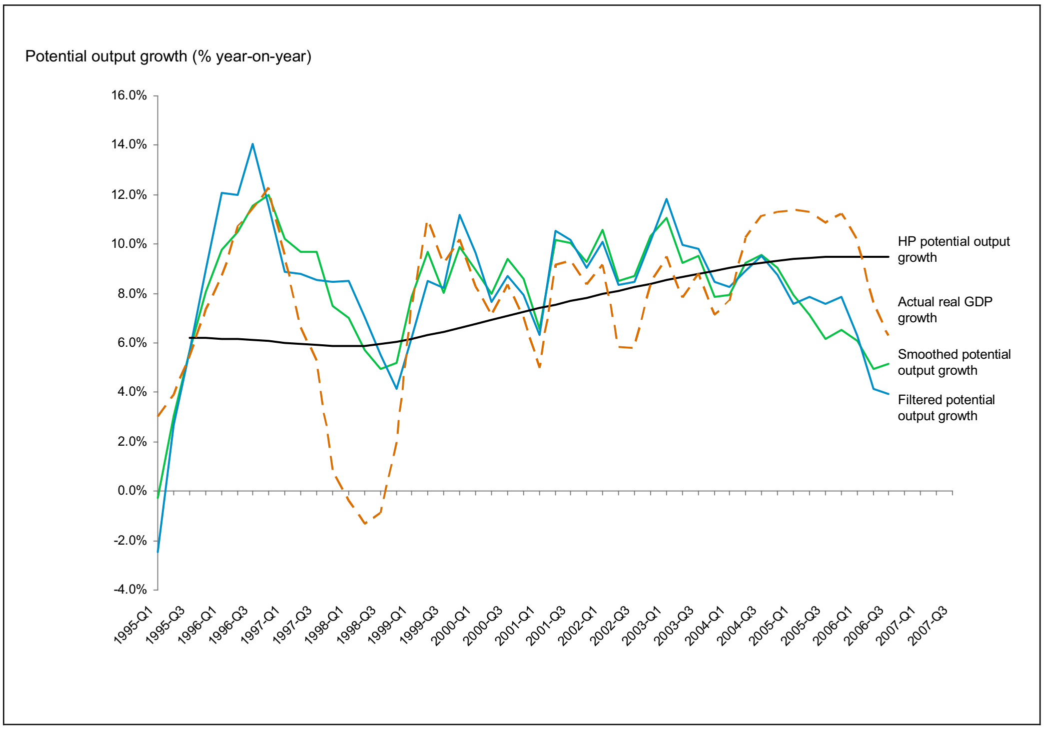
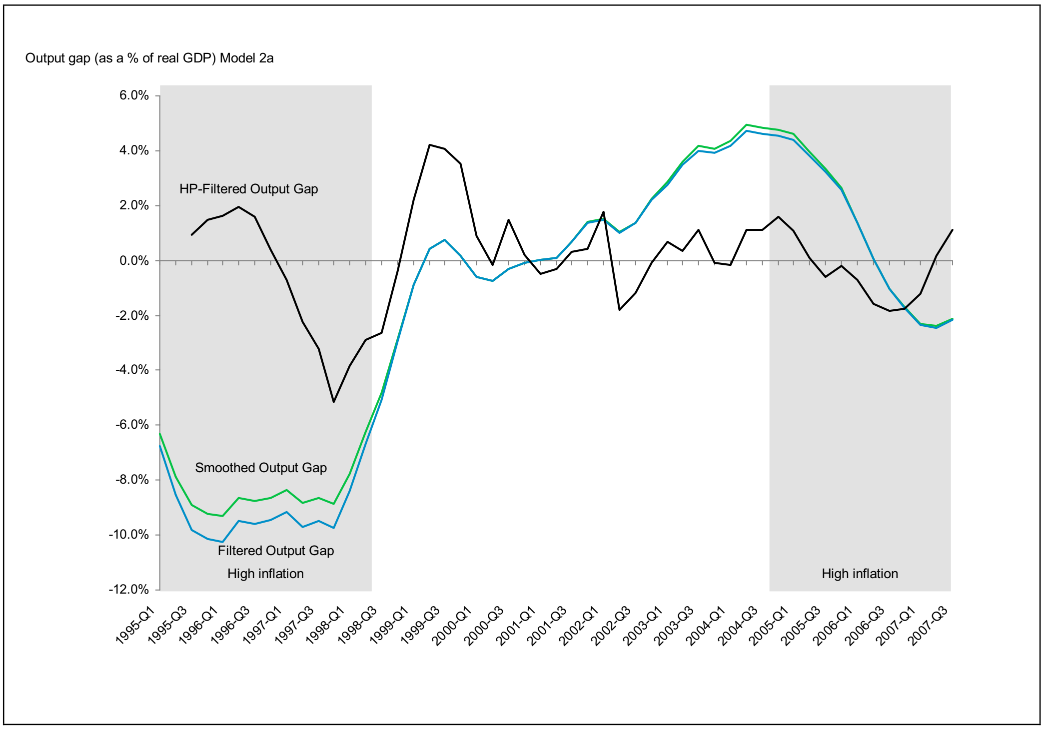


Figure 7: Output gap



Notes: Positive output gaps indicate actual output is below potential output (downward inflationary pressure); negative output gaps indicate actual is above potential output (upward inflationary pressure). Shaded areas mark periods of high inflation (see figure 4).

The Kuttner (1994) method yields less variation in potential output than actual real GDP growth. Actual real GDP growth variability is 3.40%, for the filtered potential output growth it is 2.76 %. For the smoothed series it is naturally lower, at 2.33%. However, potential output growth rate variability is much higher than when we use the HP-filter. The HP-filtered potential output growth rate's variability is only 1.38%. On the other hand, the output growth gap varies much less in our model than in the HP-filtered series.[22]

Actual real GDP growth deviates strongly from potential output growth as calculated by our model specifically in two periods. The first is during the Russian crisis, when potential output growth does not fall below 4% while actual real GDP growth briefly turns negative. The second is towards the end of the sample, when potential output growth drops much more quickly and steeply than actual real GDP growth. In between, the series are quite close.

The output gap graph looks very different in our model than in the HP-filtered series. At the start of the sample, our model indicates that potential output is far below actual output, i. e. the output growth gap is negative. This is due to very high inflation at the beginning of the sample, which in the sense of Okun (1962) indicates that potential output is below actual output. The shaded area in the figure above illustrates this. The Russian crisis leads to the closing of this gap. The same occurs in the HP-filtered series. However, while the HP-filtered series subsequently shows a little bit of overshooting (the output gap becomes positive for a short period) and then rather small and varying differences between actual and potential output, our model shows that actual output grows slower than potential output, which leads to a rising output gap between 2003 and 2005. This is because inflation was very low in the first half of the decade following the year 2000. Only at the very end of the sample, this trend is reversed, as inflation started to rise sharply again, illustrated by the shaded area on the right-hand side of the figure. At the very end, the HP-filter indicates that actual output is below potential, that is, the output gap becomes positive, while our model shows that potential output is below actual output, a negative output gap.[23] Referring back to the alternative measure of capacity utilisation from section 2, we calculate correlations between the different measures of the output gap and capacity utilisation. The expected sign is negative as a high output gap would indicate low capacity utilisation. For the HP-filtered output gap, we find no

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[22] This is in line with results presented in other papers using this methodology, including the original paper by Kuttner (1994), also see below.

[23] Most studies using this methodology analyse quarterly data, as GDP data is published at this frequency. In the appendix, we show that for Estonia the analysis of monthly data does not show sensible results.

significant correlation. For our model, the correlation between the resulting output gap series and capacity utilisation is strongly significant but positive. This would be implausible if it was not for the caution we already applied to the interpretation of the capacity utilisation series in section 2. There seem to be different driving processes in our output gap series, namely inflation) and the capacity utilisation series (namely replacement of old Soviet capacities by modern installations). We conclude that while the output gap series resulting from HP-filtering seems more plausible at first sight, the economic explanation of the output gap based on inflation, which is inherent to our model, is clearly reflected in our results.

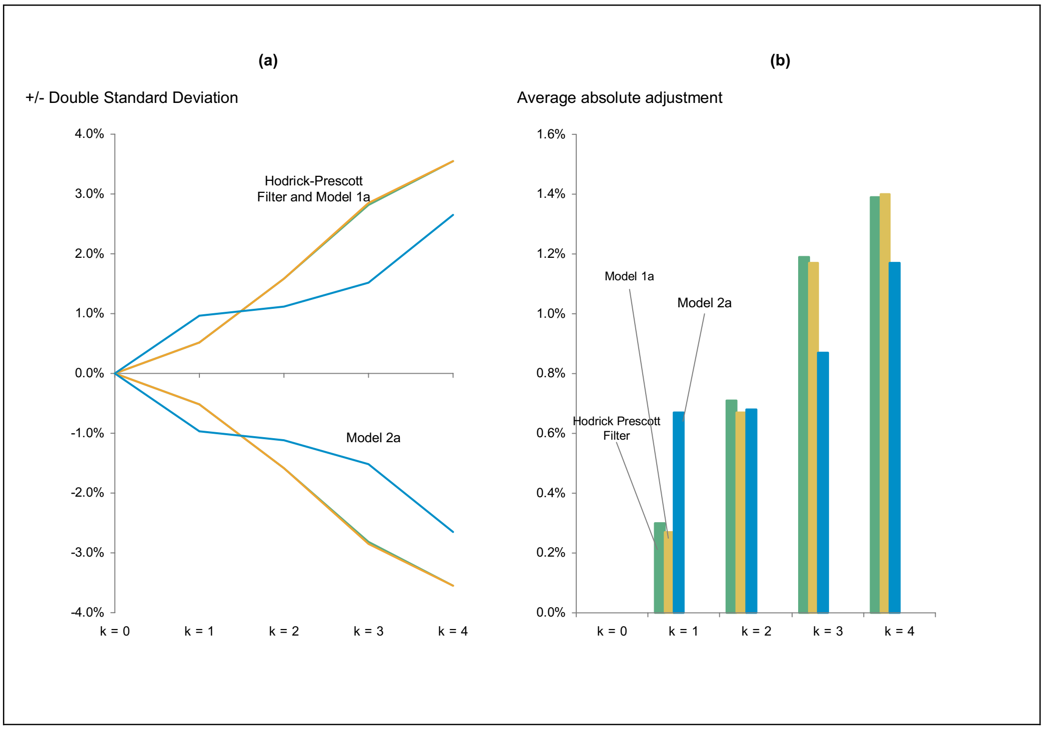
Our results are broadly in line with the results of other applications of the same methodology. Kuttner (1994) also finds potential GDP to vary significantly at low frequencies and reports persistent output gaps in excess of 5% for the United States, which leads us to believe that double digit deviations should be possible for Estonia. Tsalinski (2007) finds output gaps within the 1% range for Bulgaria, which also lead to potential output growth to follow actual output growth very closely, a rather implausible result. Kattai and Vahter (2006), who apply different methods to the Estonian output gap measurement, find patterns for the output gap similar to ours, as far as their sample period goes (until 2005), yet for most estimation methods, the absolute size of the deviations does not exceed 6% of real GDP. They do not report potential GDP growth rates but only potential GDP levels, which are hard to interpret graphically as variations are fairly low across different methods. In another application to a Nordic country, Cerra and Saxena (2000) also find output gaps up to double-digit levels for Sweden. Output gap estimates published by the European commission, which are based on the production function approach, range between plus and minus 4% over the period covered. It has to be noted, however, that these are annual numbers and therefore not directly comparable to our results.

5 SENSIVITY TESTING

As the estimation of the current output gap is an important policy instrument, the precision of this estimate is highly important. Unfortunately, most estimation methods rely on signal-extraction methods, which take account of the whole sample. At the ends of the sample this leads to uncertainty about the past at the beginning of the sample and about the future at the end of the sample. This is the case for both the Hodrick-Prescott filter as well as the estimation method used above. However, we expect the inclusion of the Phillips curve relationship to improve the real-time reliability of the output gap estimate, as we do not rely simply on signal extraction but also on economic theory. We employ the methodology developed in Planas and Rossi (2004a) to evaluate the real-time performance for the Hodrick-Prescott filter and our models 1a and 2a with the traditional Phillips curves.

For this exercise we estimate the models recursively, from 2003:1 onwards, by adding one quarter at the end of the sample each time.[24] Thereby we obtain a sequence of estimates for the output gap as a percentage of real GDP for each quarter, 17 different estimates for period 2003:1, 16 for 2003:2, and so on, until there is only one estimate for 2007:3. We then record the average absolute revisions after k = 1, 2, 3 and 4 quarters and the standard deviation of these, both in terms of the output gap as a percentage of GDP. The following graph displays the results with (a) 95%-confidence intervals between which revisions will lie and (b) the average absolute revisions.

Figure 8: Real-time revisions



24 We use the filtered estimates which only include information up to the last data point and not the smoothed estimates which reflect information over the whole sample. However, as we do use the final GDP data, this is not a “real-time” exercise in the strict sense. FDI data (international investment position data) is published with a three-month delay after the reference period, i. e. 3 weeks after GDP data (national accounts data). Thus, the timeliness of the estimates is somewhat affected by the choice of FDI as a weakly exogenous variable in the output equation.

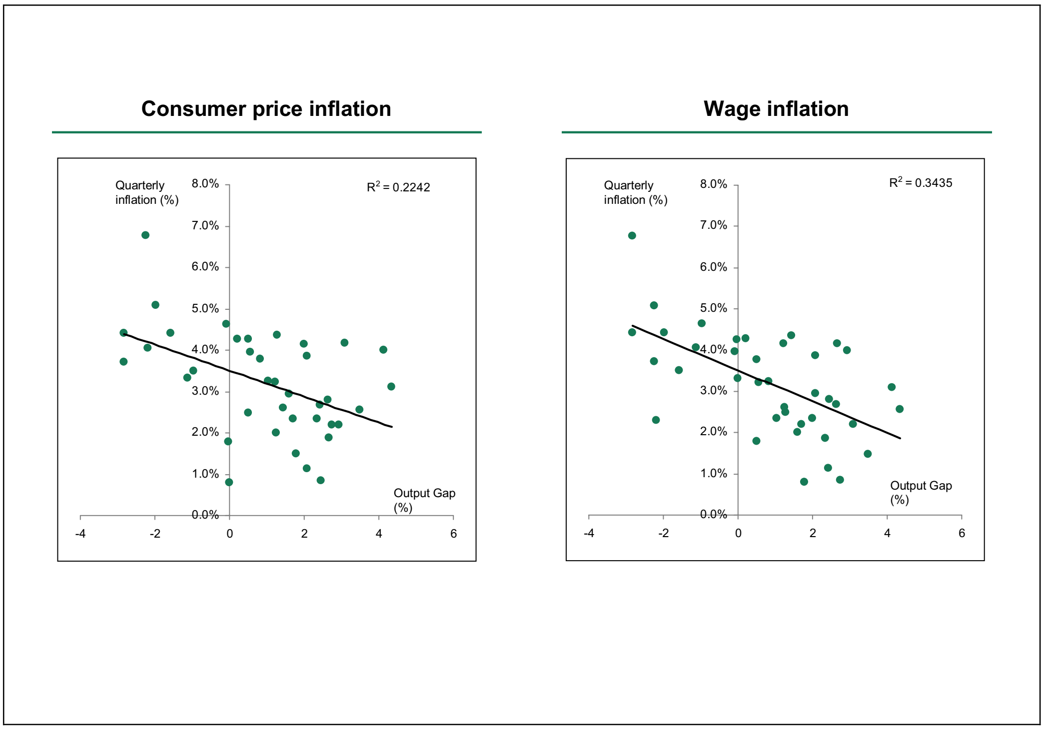
Model 1a with consumer price inflation as a dependent variable in the Phillips curve equation exhibits about the same amount of adjustment to the real-time estimates with 1, 2, 3 and 4 quarters delay as the HP-filter model. Model 2a, our preferred model, with wage inflation as a dependent variable in the Phillips curve equation shows stronger adjustments to the real-time estimate than the other two methods after one quarter, but significantly lower adjustments after 2, 3 and 4 quarters. In terms of average absolute adjustments, the picture is similar, of course. We conclude from this analysis that our model significantly improves the reliability of real-time estimates of potential output, potential output growth and the output gap.

6 Conclusion

In this paper we have shown that in certain specifications, the inclusion of measures of inflation via a Phillips curve can help when trying to estimate the output gap for Estonia. In any case, the results are different from the results of traditional estimation techniques like the HP-filter and lead to interesting economic observations. Initially, the measures of inflation used in studies on other countries had to be adapted to the Estonian case. As Estonia is a very small open economy, the effect of import price inflation has to be accounted for. We try to accomplish this by introducing wage inflation as the dependent variable in the Phillips curve specification. Different measures of inflation were found to yield less promising results. Secondly we discussed the Phillips curve specification, which could be traditional, with inflation as the dependent variable, or modified, with change in inflation as the dependent variable. As expected, the inclusion of some economic theory in the shape of the Phillips curve into the estimation of potential output enhances the real-time performance, which is superior to that of univariate methods such as the Hodrick-Prescott filter.

Finally, for comparison, we present the resulting Phillips curves in figure 9 in the same fashion as in section 3, however with unemployment replaced by the output gap from model 2a as an explanatory variable. This relationship shows the expected slope and is much more stable than the one with unemployment. Hence the results might also be used for further research involving Phillips curve relationships for Estonia.

Figure 9: Phillips curves: Output gap vs. quarterly inflation rates



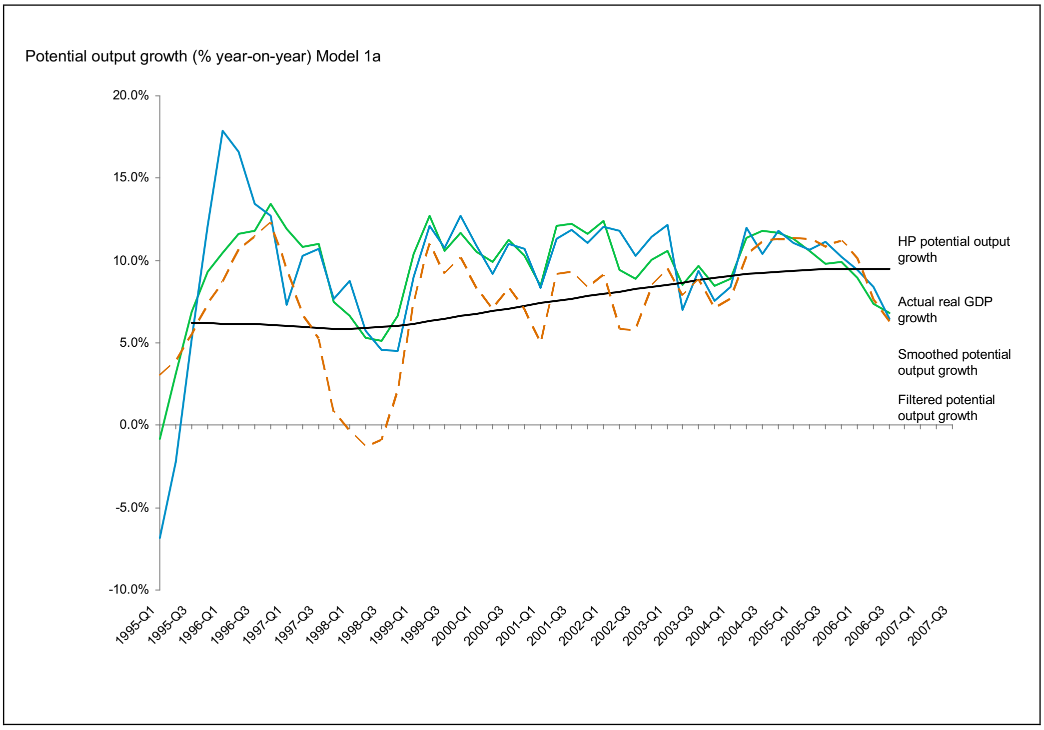
Notes: Output gap estimated using model 2a (wage inflation, FDI). Smoothed estimate as a percentage of real GDP.

7 APPENDIX

7.1 Graphical results of model 1a

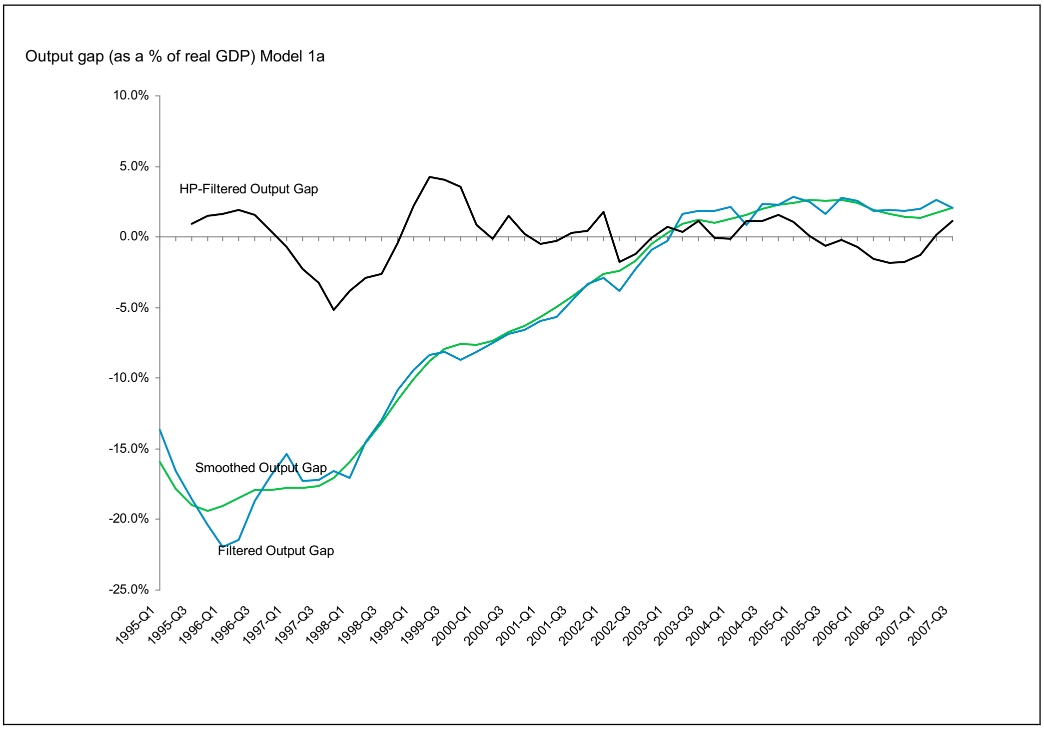
In this section we present the graphical results of model 1a as laid out in sections 3 and 4 of this paper. While the diagnostics of this model are very good and its sensitivity test results also impressive, particularly when compared to the results of the HP-filter exercise (see section 5), results for the path of potential growth rates and particularly for the output gap escape economic reasoning.

Figure 10: Potential growth rates for model 1a



Potential growth rates are variable and higher than actual growth rates for almost the entire sample period, except for the beginning and the very end of the sample. Again this is due to the path of consumer price inflation. This leads to a very negative output gap for most of the sample, starting as low as -20%, i. e. potential output is far below actual output. As potential output grows at higher rates than actual output for almost the entire sample, potential output slowly catches up with actual output so that in the last third of the sample we actually find a positive output gap.

Figure 11: Output gap for model 1a



Although one might argue that in a catch up process like the one most Eastern European countries went through potential output might indeed grow more quickly than actual output over a long period, in this case the levels of the output gap lead us to believe that model 1a does not yield results here which are reconcilable with economic theory.

7.2 The monthly perspective

Inflation data is available at a monthly frequency, and monthly data for output can also be obtained. As the available time series are necessarily short, we might increase the amount of information by raising the frequency of the data. In this section we will perform this analysis for models 1a and 2a with traditional Phillips curves.

As a first step, the disaggregation of the quarterly GDP series is performed using the Denton algorithm.[25] This approach employs a benchmark series, which is available at a higher frequency than the reference series, for temporal decomposition. Differently from simple pro-rata benchmarking, however, the method imposes that the sums of three-month periods of the

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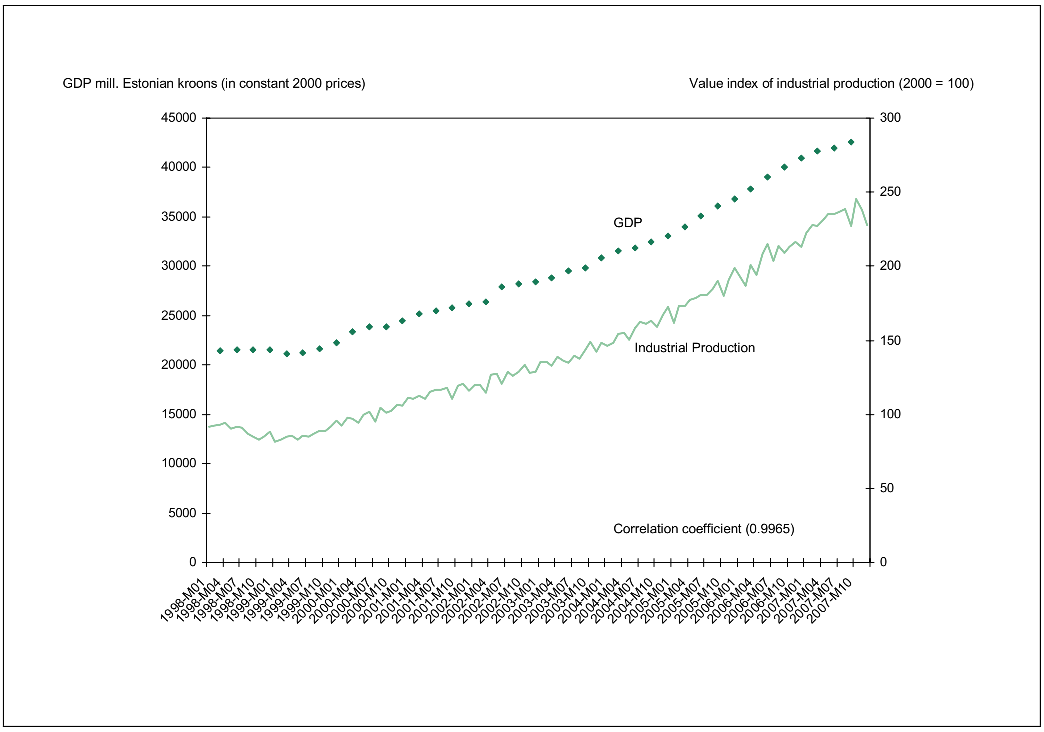
[25] The Denton method is recommended as "relatively simple, robust and well-suited for large-scale applications" by the IMF (Bloem et al., 2001). The method, developed by Denton (1971), is available as a RATS software procedure. It is also provided as part of the ECOTRIM software by Eurostat, see www.oecd.org/dataoecd/60/5/21781488.ppt .

benchmarked series equal the quarterly reference series' totals, and that the yearly aggregates of the reference series be observed. In many applications, the industrial production index is chosen as a benchmark series, for instance in Curran and Funke (2006). The figure below depicts quarterly seasonally adjusted real GDP and the monthly seasonally adjusted value index of industrial production in Estonia.[26]

Figure 12: GDP series and monthly value index of industrial production



Even though the industrial sector makes up only a relatively small share of total economic activity, we find that the value index of industrial production exhibits a very high correlation with GDP. As it is readily available in monthly frequency and is published with only one month delay, we can even use it to extend the reference series to the last quarter of 2007.

The consumer price index and the wage index for Estonia are available at monthly frequency from 1998 onwards. As in the quarterly analysis we use seasonally adjusted series and current inflation, i. e. in this case month-on-month inflation, as year-on-year data would reflect the development of the price indices over the whole year, when the change in the cycle and the

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[26] Seasonal adjustment was performed using the X12 census seasonal adjustment algorithm.

trend component of GDP do not.[27] The specifications of the monthly models are summarised in the table below.

Table 4: Model specifications for models 1a and 2a - monthly data

	MODEL 1A - MONTHLY	MODEL 2A - MONTHLY
Output Equation		
Dependent Variable	Ln monthly GDP	Ln monthly GDP
Trend:	Random walk plus drift	Random walk plus drift
Cycle AR order:	2	2
Exogenous variables	None	None
Phillips Curve Equation		
Dependent Variable	MoM Consumer Price Inflation	MoM Wage Inflation
AR order:	1	1
MA order:	2	2
Endogenous Regressors	Cycle Lag 1-2	Cycle Lag 1-2
Exogenous Variable 1	None	None
Exogenous Variable 2	None	None

The specifications of AR and MA terms were selected to improve significance levels and diagnostics. The results of the estimation are displayed in the table below.

Table 5: Estimation results for models 1a and 2a – monthly data

	MODEL 1A		MODEL 2B	
Output Equation				
		p-value		p-value
μ_{1k}^T	0.0057	0.00	0.0057	0.00
ϕ_{k1}	-0.5109	0.00	-0.5149	0.00
ϕ_{k2}	-0.4390	0.00	-0.4346	0.00
$Var\left(a_{kt}^T\right)$	0.0002		0.0002	
$Var\left(a_{kt}^C\right)$	0.0004		0.0004	
Phillips Curve Equation				
μ_{2k}	0.0037	0.04	0.0132	0.00

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[27] In addition, the use of year-on-year data would deprive us of one year of data, where as month-on-month data only shortens the sample by one month.

β_{1k}	0.0084	0.83	0.1696	0.07
β_{2k}	0.0202	0.55	0.1717	0.02
ϕ_{1k}^{*}	-0.0969	0.85	-0.6394	0.00
θ_{1k}	0.3375	0.51	0.6442	0.00
θ_{2k}	-0.0606	0.70	0.0480	0.58
$Var\left(a_t^{\pi}\right)$	0.0000		0.0001	

Notes: Likelihood function maximised by Newton-Raphson - E04UCF from NAG Mark 19. Standard errors computed using **information matrix**

The results for model 1a are not promising, as the most important coefficients from an economic point of view are insignificant. Overall, the Phillips curve relationship does not seem to hold. Model 2a shows better results, and the coefficients on the cyclical component of GDP in the Phillips curve equation have the expected positive signs. The diagnostics, displayed in the table below, do not indicate model misspecification.

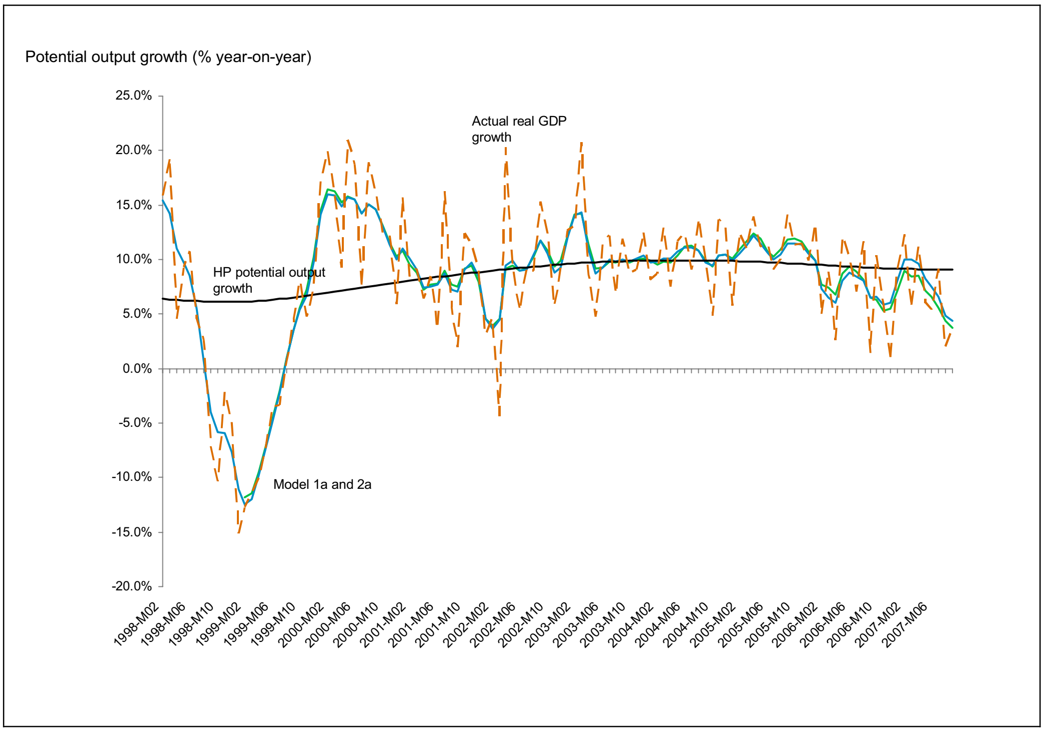
Table 6: Diagnostics for models 1a and 2a - monthly results

	MODEL 1B	MODEL 3B
Output equation		
Residuals autocorrelations		
r(1) =	0.0205	0.0257
r(2) =	-0.0699	-0.0759
r(3) =	0.0394	0.0594
r(4) =	0.0161	0.0428
Approximated standard deviation	0.0928	0.0928
Ljung-Box test		
Q(4) =	0.8488	1.4103
p-value =	0.9318	0.8424
Phillips curve equation		
Residuals autocorrelations		
r(1) =	-0.0159	-0.0079
r(2) =	-0.0127	0.0603
r(3) =	0.0694	0.1422
r(4) =	0.0988	0.1427
Approximated standard deviation	0.0928	0.0928
Ljung-Box test		
Q(4) =	1.8105	5.3388

p-value =	0.7706	0.2543
R-squared (uncentered) =	0.5039	0.3162

The graphical representations of potential output growth, and particularly of the output gap, show where the difficulties lie with monthly data: Even though the models do smooth potential output growth, a lot of high-frequency variation in the data remains, due to the mensualisation of GDP data. The HP-filter smoothes much more and shows a similar pattern as observed in the quarterly data. The output gap series for all models show the very high-frequency variation, which is implausible from the perspective of economic theory, as output gaps should be somewhat more persistent if they should explain inflation. This stylised fact is pervasive in the monetary policy literature.[28]

Figure 13: Potential growth rates for models 1a and 2a - monthly

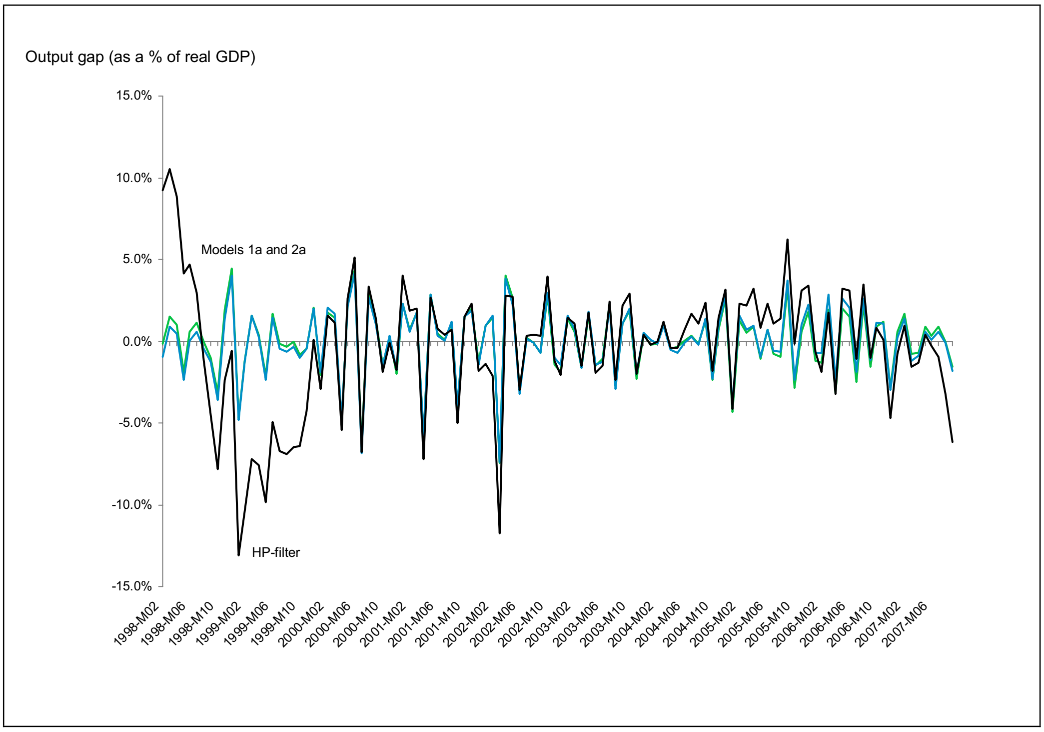


Notes: HP-filtered potential growth rates calculated based on signal-to-noise ratio of 104,035[29]

[28] See for instance Fuhrer and Moore (1995).

[29] Cf. Ravn and Uhlig (2002)

Figure 14: Output gap for models 1a and 2a - monthly



We conclude that monthly data does not seem to be helpful in determining potential output and the output gap using the Kuttner (1994) methodology. High-frequency variability of the output data leads to high variability in the output gap data, which in turn cannot be brought into an economically and statistically viable relationship with monthly inflation data.

References

Bandholz, H. and Funke, M. (2003). In Search of Leading Indicators of Economic Activity in Germany. *Journal of Forecasting* 22, 277-297.

Beveridge, S. and Nelson, C. R. (1981). A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to the Measurement of the Business Cycle. *Journal of Monetary Economics* 7, 151-174.

Bloem, A. M., Dippelsmann, R. J. and Maehle, N. O. (2001). Quarterly National Accounts Manual - Concepts, data sources, and compilation. *IMF Quarterly National Accounts*.

Burns, A. F. and Mitchell, W. C. (1946). *Measuring Business Cycles.* New York: National Bureau of Economic Research.

Cerra, V. and Saxena, S. C. (2000). Alternative Methods of Estimating Potential Output and the Output Gap: An Application to Sweden. *IMF Working Paper* 2000/59.

Christiano, L. J. and Fitzgerald, T. J. (1999). The Band Pass Filter. *NBER Working Paper Series* 7257.

Clark, P. K. (1979). Potential GNP in the United States, 1948-80. *The Review of Income and Wealth* 25, 141-166.

Clark, P. K. (1987). The Cyclical Component of U. S. Economic Activity. *Quarterly Journal of Economics* 797-814.

Cooley, T. F. and Dwyer, M. (1998). Business Cycle Analysis Without Much Theory. A Look at Structural VARs. *Journal of Econometrics* 83, 57-88.

Curran, D. and Funke, M. (2006). Taking the Temperature - Forecasting GDP Growth for Mainland China. *Bank of Finland BOFIT Discussion Papers* 6/2006.

Dabusinskas, A. and Kulikov, D. (2007). New Keynesian Phillips Curve for Estonia, Latvia and Lithuania. *Bank of Estonia Working Papers* 7/2007.

Denis, C., Grenouilleau, D., McMorrow, K. and Röger, W. (2006). Calculating Potential Growth Rates and Output Gaps - A Revised Production Function Approach. *European Economy Economic Papers* 247.

Denton, F. T. (1971). Adjustment of Monthly or Quarterly Series to Annual Totals: An Approach Based on Quadratic Minimization. *Journal of the American Statistical Association* 66, 99-102.

ECB (2004). The Monetary Policy of the ECB. (Ed, ECB).

EPC (2004). Economic Policy Committee Report on Potential Output and Output Gaps. (Ed, EPC/ECFIN). Brussels: European Commission.

Fuhrer, J. and Moore, G. (1995). Inflation Persistence. *Quarterly Journal of Economics* 110, 127-159.

Funke, M. (1997). Supply Potential and Output Gaps in Western German Manufacturing. *International Journal of Forecasting* 13, 211-222.

Gerlach, S. and Smets, F. (1999). Output Gap and Monetary Policy in the EMU Area. *European Economic Review* 43, 801-812.

Harvey, A. (1989). *Forecasting Structural Time Series Models and the Kalman Filter.* Cambridge: Cambridge University Press.

Harvey, A. and Jaeger, A. (1993). Detrending, Stylised Facts and the Business Cycles. *Journal of Applied Econometrics* 8, 231-247.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica* 46.

Hughes Hallet, A., Kattai, R. and Lewis, J. (2007). Early Warning or Just Wise After the Event? The Problem of Using Cyclically Adjusted Budget Deficits for Fiscal Surveillance. In *Estonian Economic Association Annual Conference.*

IMF (2007a). Estonia 2007 IMF Article IV Consultation. *IMF Country Report* 07/255.

IMF (2007b). World Economic Outlook. *International Monetary Fund*.

Kattai, R. and Vahter, P. (2006). Kogutoodangu Lõhe ja Potentsiaalne SKP Eestis. *mimeo*.

Kichian, M. (1999). Measuring Potential Output with a State-Space Framework. *Bank of Canada Working Papers* 9/1999.

Kress, M. (2004). Lending Cycles in Estonia. *Bank of Estonia Working Paper Series* 3/2004.

Kuttner, K. N. (1994). Estimating Potential Output as a Latent Variable. *Journal of Business & Economic Statistics* 12, 361-368.

Langedijk, S. and Larch, M. (2007). Testing the EU Fiscal Surveillance: How Sensitive is it to Variations in Output Gap Estimates? *European Economy Economic Papers* 285.

Lucas, R. E. (1972). Expectations and the Neutrality of Money. *Journal of Economic Theory* 4, 103-124.

Okun, A. (1962). Potential GNP: Its Measurement and Significance. In *Proceedings of the Business and Economic Statistics Section of the American Statistical Association.*

Perloff, J. M. and Wachter, M. L. (1979). A Production Function - Non Accelerating Inflation Approach to Potential Output: Is Measured Potential Output Too High? *Carnegie Rochester Conference Series on Public Policy* 10, 113-164.

Perry, G. L. (1977). Potential Output: Recent Issues and Present Trends. In *U.S. Productive Capacity: Estimating the Utilization Gap.* Working Paper, Washington University: Center for the Study of American Business.

Planas, C. and Rossi, A. (2004a). Can Inflation Data Improve the Real-Time Reliability of Output Gap Estimates? *Journal of Applied Econometrics* 19, 121-133.

Planas, C. and Rossi, A. (2004b). Program GAP: Technical Description and User-Manual. *European Commission Joint Research Centre*.

Proietti, T. and Musso, A. (2007). Growth Accounting for the Euro Area: A Structural Approach. *ECB Working Paper Series* 804 / August 2007.

Ravn, M. and Uhlig, H. (2002). On Adjusting the HP-Filter for the Frequency of Observations. *Review of Economics and Statistics* 84(2), 371-376.

Schulz, C. H. (2008). Forecasting Economic Activity for Estonia: the Application of Dynamic Principal Components Methodology. *Bank of Estonia Working Paper Series* 2/2008.

Tsalinski, T. (2007). Two Approaches to Estimating the Potential Output of Bulgaria. *Bulgarian National Bank Discussion Papers* 57.

Watson, M. W. (1986). Univariate Detrending Methods with Stochastic Trends. *Journal of Monetary Economics* 18, 49-75.