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Niko Korte

Predictive power of confidence indicators for the Russian economy

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BOFIT Discussion Papers
Editor-in-Chief Laura Solanko

BOFIT Discussion Papers 15/2012
12.7.2012

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ISBN 978-952-462-746-7
ISSN 1456-5889
(online)

Suomen Pankki
Helsinki 2012

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Abstract

This study examines the forecasting power of confidence indicators for the Russian economy. ARX models are fitted to the six confidence or composite indicators, which were then compared to a simple benchmark AR-model. The study used the output of the five main branches as the reference series. Empirical evidence suggests that confidence indicators do have forecasting power. The power is strongly influenced by the way which the indicator is constructed from the component series. The HSBC Purchasing Managers' Index (PMI), the OECD Composite Leading Indicator (CLI) and the OECD Business Confidence Indicator (BCI) were the best performers in terms of both the information criterion and forecasting accuracy.

Keywords: confidence indicators, forecasting, Russia
JEL Codes: E37, P27

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This is a shortened version of my Masters thesis for Turku School of Economics. I'd like to thank Heikki Kauppi and Matti Virén from the Department of Economics as well as Laura Solanko and Vesa Korhonen from BOFIT for giving central insights and helping with finding the data.

1 Introduction

The efficacy of an econometric methodology is often sensitive to the associated data. According to Clements and Hendry (1998) the most important cause of systematic estimation error is the inability of the model to take into account changes in the Data Generating Processes (DGP), such as changes in measurement processes, legislation or technology. The transition of the Russian economy from planned to market economy over the past two decades can be seen as such a change not only in the data but also the process by which it is generated.

Confidence indicators can inform us of the conceptions and expectations of the market as to conditions in the broad economy or in a particular sector. Surveys are used to aggregate subjective perceptions into indicators which, subject to certain conditions, provide objective information on present and future economic conditions. The aim of this paper is to study the predictive ability of such indicators for the Russian economy.

The research question addressed is: Does including confidence indicator variables in econometric forecasting models improve their forecasting power in respect of the Russian economy? We also examine whether adding confidence indicator variables reduces the amount of forecasting error induced by changes in the DGP. The author has no knowledge of previous research on the forecasting power of economic indicators for the Russian economy based on econometric methods.

The methodology of this study consists of autoregressive (AR) models, autoregressive exogenous input (ARX) models and the comparison of such models. The model used for comparison is an AR model of the Russian economy where the dependent variable is the output of five major branches. The model is then altered to include lags of confidence indicator variables as exogenous explanatory variables. The models are then compared using information criteria and root mean squared errors of forecasts generated by the models. Due to an observed structural break, the models are estimated for two separate samples, so that we are also able to compare results for the two samples.

In order to increase the usefulness of the study, we will focus on changes at the monthly level. Monthly data have greater practical value than eg quarterly data, which may be outdated - as regards planning for the future - already on the day of release.

The second section introduces indicators in general and discusses their classification. The third section lays down the criteria used for selecting indicators and introduces

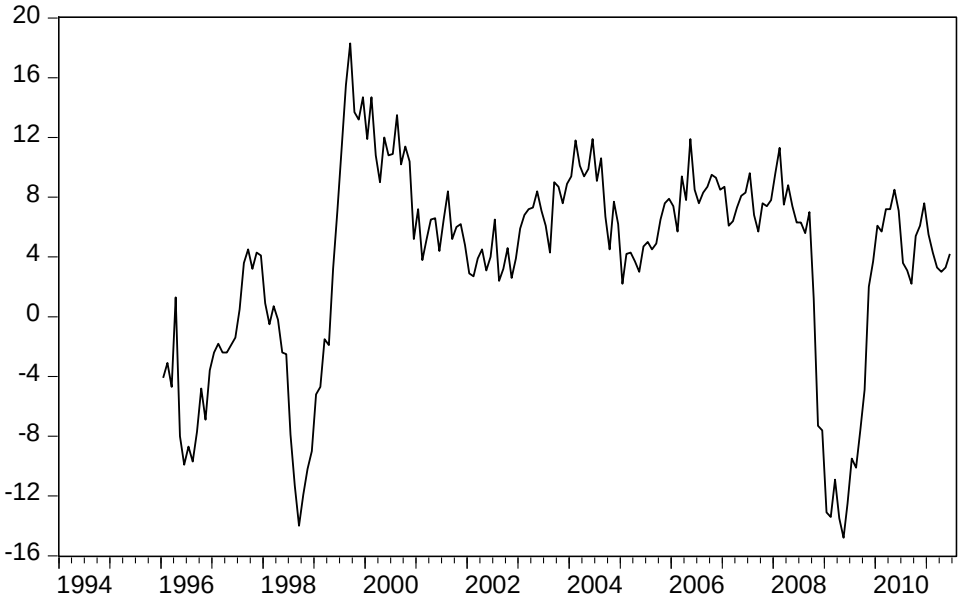
the indicators thusly selected. In the fourth section we discuss the empirical methodology more thoroughly, and the fifth section reports the empirical results. The sixth section interprets these results and the final section summarizes the study and draws some conclusions.

2 Data

2.1 Reference series

The subject of interest in this study is the changes in economic activity in Russia. A natural approach to this topic would be to study changes in GDP, but Russian GDP is only reported on a quarterly basis. We are now interested in monthly data, and so we must choose a reference series which mimics monthly changes in GDP. The combined output of the five main branches was chosen as the reference series, the five branches being industry, agriculture, construction, transportation and trade. An alternative reference series would be the indicator of the volume of industrial output, which is a reference series used for example by OECD. But numerous revisions have been made to this series, and its reliability has thus declined (Smirnov 2006).

Figure 1 Graph of the five main branches of the Russian Economy 1996-2011, depicted as y-o-y percentage changes.



Source of data: BOFIT/Rosstat

Figure 1 illustrates monthly y-o-y changes in the Russian economy in the years 1996 to 2011. It gives a good overall picture on the development of output and economy. The reference series is used as an explanatory variable in the empirical analysis of section 6.

Two recessions occurred during the sample period, the first being caused by the crisis of 1998 and the second by the 2008 crisis. The first peak is observed in autumn 1997, when the Asian financial crisis began to affect the Russian economy. The RTS stock market index plummets during September and October 1997 (RTS 2011). Yet the low point is seen only in September of 1998, as decision-making is hindered by political uncertainty. The sharpness of the turning point is caused by the ruble's devaluation, the default of the Federation's domestic debt and freezing of payments to abroad, announced on August 17th 1998 (Åslund 2007)

The second peak in the series occurs in February 2008. The decline only becomes steep in September, as oil prices continue to rise until July (Neste Oil 2011). The RTS share index crash begins in May 2008 and accelerates by the beginning of the 2008 South Ossetia war in August (RTS 2011, Desai 2011). In July the oil prices begin to fall rapidly as a consequence of the global crisis, which causes a significant shock to the real economy. The decline is further accelerated in September by the fall of Lehman Brothers in the US. Oil prices touch bottom at the end of December 2008, and in June 2009 Urals oil sells at 70 dollars per barrel (Neste Oil 2011). The reference series turns upward again in May 2009.

2.2 Confidence indicators

Although the classification of indicators in the literature is somewhat desultory, one can make a broad distinction between confidence indicators and real-economy indicators. The latter indicators signal changes in real-economy quantities, such as the value of order books or the supply of money, either directly or via calculations. Confidence indicators, as well as sentiment, climate and tendency indicators, are based on various types of surveys (Mehrotra and Rautava 2007). These surveys reflect the conceptions, expectations and beliefs of economic agents regarding the state of the economy and its future and recent history. The scope of a survey may be an entire economy or an individual sector. These surveys are answered by agents with hands-on knowledge, such as corporate managers and

purchasing managers. Consumer confidence is measured by a different category of indicators and is not a topic of this study.

A confidence indicator is often expressed simply as a percentage of respondents who anticipate a certain change, whereas a diffusion index gives a measure of the extent to which a certain change is already noticeable.

The most common type of indicator is the composite indicator, which usually combines real-economy indicators with confidence indicators. A composite indicator may also be composed of survey results or real-economy data. The objective of a composite indicator is to paint a general picture of the economy. As every economic crisis has distinctive features and causes, composite indicators entail a greater likelihood of foreseeing a turning point than do single (non-combined) indicators. The flipside of the composite indicator is that it may perform worse when comparing the overall cross-correlations to reference series. Single indicators may perform well during a certain time period (when for instance a change in the reference series is caused by a change in the variable measured by that indicator), and then fail during another.

While confidence indicators for the Russian economy abound, most are based on methods which make them unsuitable for statistical analysis. Another common shortcoming is their fragmentary availability over time, and some of them are accessible only on payment of a fee. Thus it was necessary to set criteria for selecting indicators for the study.

The criteria generally resemble the Composite Leading Indicator (CLI) preselection criteria used by the OECD (Nilsson and Brunet 2006). The criteria are divided into three groups: *economic relevance, cyclical behavior and practical considerations.*

1. To be useful, an indicator must be economically *relevant*. This means that an observed dependency relationship or lag structure between the indicator and the reference series must have an economic explanation. For example, crude oil price can be considered a leading indicator in the case of Russia, as it affects Russia's macro economy directly through the current account and Federal budget and indirectly via exchange rates. Series which widely describe an area of interest are also favored. The relevance of confidence indicators has been justified in the prior section.
2. *Cyclical behavior*. A good indicator will follow and lead the movements of the reference series with a certain lag, which preferably remains constant dur-

ing the entire observation period. A reverse relation is also acceptable. It is important that an indicator observe turning points efficiently and not generate extra cycles. The smoothness of the series makes it easier to separate turning points from ordinary fluctuations.

3. *Practical considerations.* For a good series a high, continuous and exact update frequency and a minimal number of revisions are a necessity. This is the reason why this study only considers monthly data. Naturally, we must also have access to the data. Documentation on both the methods used and possible statistical corrections made in collecting and transforming the data is also highly important. Raw data are preferred over processed data. Unfortunately, raw data on the Russian economy are in scarce in supply. The same applies to real time data for making simulated forecasts.

Based on these pre-selection criteria, seven confidence indicators were chosen to be tested in the econometric framework (see Table 1).

Table 1 The Selected indicators

Name	**Description**	**Periodicity**	**Data span**	**Publisher**
Output of five main branches	Percentage change y-o-y	monthly	M1/1996-M6/2011	Rosstat
REB order book	Diffusion index of order book levels, survey-based, forward- looking 3 months	monthly	M4/1994-M7/2011	Center for Economic Sociology
REB manufacturing	Diffusion index of manufacturing output, survey-based, forward- looking 3 months.	monthly	M7/1992-M7/2011	Center for Economic Sociology
PMI - Purchasing Manager's Index	Survey-based purchasing manager index, five components, seasonally adjusted	monthly	M9/1997-M6/2011	VTB Capital-Markit Economics/HSBC
OECD CLI (amplitude adjusted)	Composite indicator, six components, both survey-based and real data, percentage change y-o-y	monthly	M1/1995-M7/2011	OECD
OECD BCI	Sentiment indicator with three components, percentage change y-o-y	monthly	M1/1995-M8/2011	OECD
DC CLI	Composite indicator, seven components, of which two are survey-based, percentage change y-o-y	monthly	M1/1996-M6/2011	HSE/Development Center

2.2.1 PMI

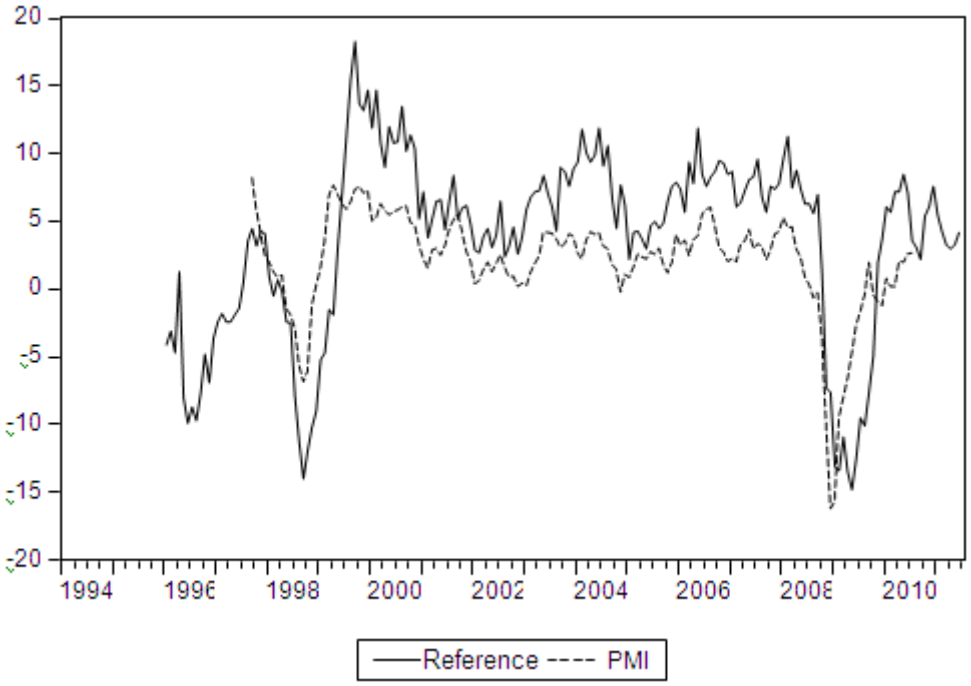
The Purchasing Managers' Index (HSBC Manufacturing PMI) published by the HSBC[1] is based on approximately 300 monthly interviews. The aggregation method is the same for 26 countries and regions. Respondents are asked to assess their conceptions compared to the previous interview. The indicator components and their respective weights are listed below (Smirnov 2010):

1. new orders (30 %)
2. production (25 %)
3. employment (20 %)
4. volume weighted delivery times, inversed (15 %)
5. stock levels (10 %)

The respondents answer either "improved", "worsened" or "no change". Based on the responses, diffusion indices are calculated as $D \quad = [(A_t + 0.5B_t)/\ N_t] * 100\ \%$, where D_t is the value of the index at the time of interview, t; A_t is the number of "improved" answers; B_t is the number of "no change" answers; and N_t is the total number of answers. The five component series calculated in this way are seasonally adjusted and aggregated to a confidence indicator using the above-mentioned weights. The index gets the value 100 if all respondents answer "improved" and zero if they all express a negative outlook. Thus indicator is scaled $[0,100]$, and fluctuates around 50 (Smirnov 2010).

[1] Before summer 2010 the index was sponsored by VTB bank - thus the previous name was VTB PMI (Smirnov 2010).

Figure 2 The reference series plotted against the HSBC PMI 1996-2011.



Data sources: BOFIT and Rosstat

2.2.2 REB

Russian Economic Barometer, published by The Institute of World Economy and International Relations (IMEMO) under the Academy of Science of Russia, is a wide survey that incorporates over 100 indicators from different branches of the economy, mainly manufacturing, banking and agriculture. In manufacturing 500 companies, on average, are interviewed, and the response rate is between 30 and 40 per cent. The majority of companies are, by Russian standards, medium-scale, with 150–2000 employees. The sample is representative both geographically and in terms of industry sectors (REB 2004).

The turnover of participating companies has been quite rapid, especially during the years 1994-1998 because of the rapid pace of transition, and this could bias the results. In this study the following REB indicators are used:

- REB order book - a diffusion index of order books that anticipates conditions over 3-month spans.
- REB manufacturing - a diffusion index of industrial production that anticipates conditions over 3-month spans.

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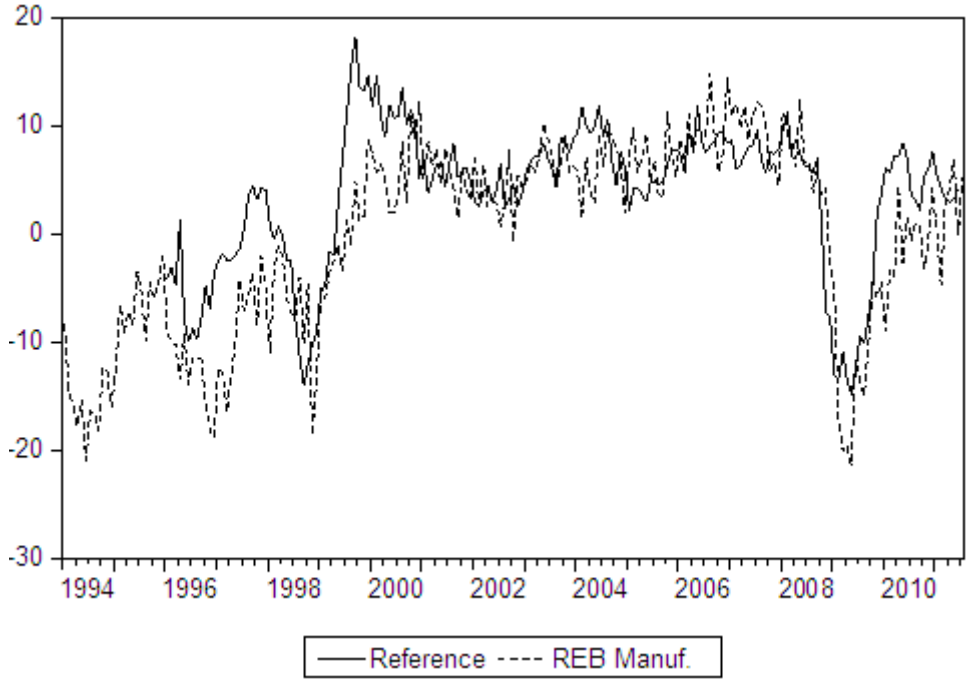
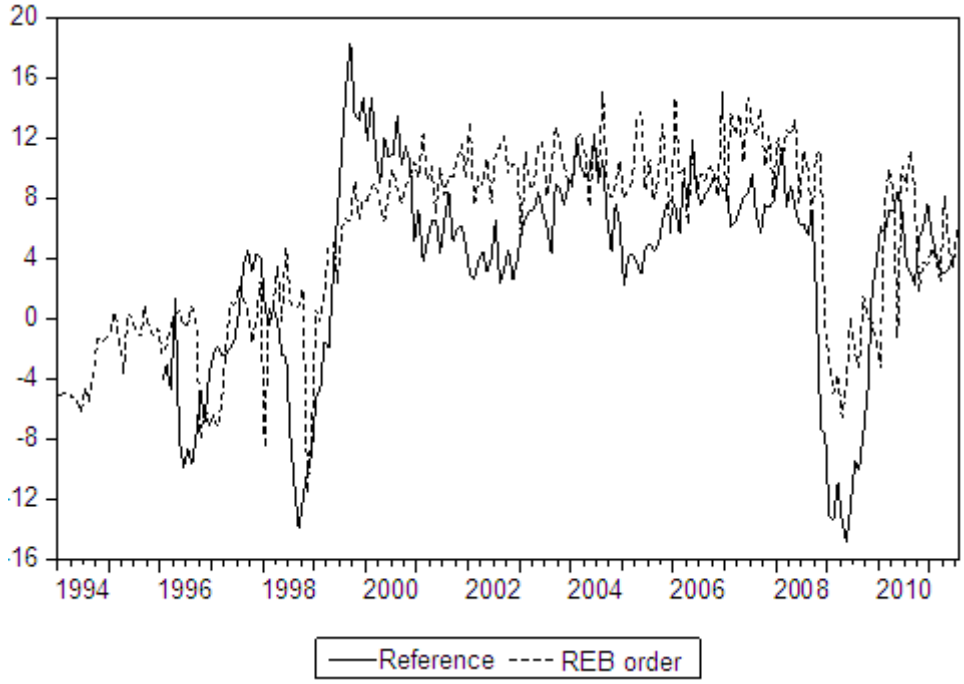
Figure 3 The reference series plotted against REB Manufacturing. The latter is seasonally adjusted via Tramo/Seats, except in the final time series analysis where seasonal difference is used instead.



Data sources: BOFIT and Rosstat.

Figure 4 The reference series plotted against REB order book. The latter is seasonally adjusted via Tramo/Seats, except in the final time series analysis where seasonal difference is used instead.



Data sources: BOFIT and Rosstat.

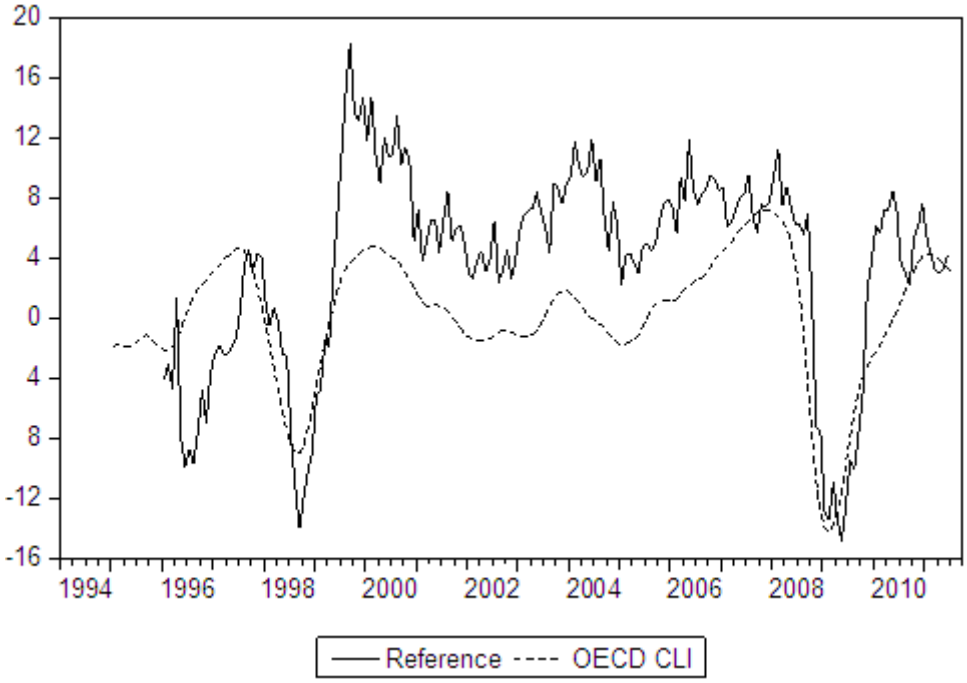
2.2.3 OECD CLI

The Composite Leading Indicator (CLI), published by OECD for seven regions and 35 countries, is probably the best known leading indicator in the world and thus a natural choice for this study. The purpose of the indicator is to spot cyclical turning points. The first CLIs were published in 1981 based on data from the 1960s. Usually, as in the case of Russia, the reference series used to construct the indicator is domestic industrial production. The Russian CLI has been published regularly on monthly basis since 2006, so the earlier figures had to be calculated backwards (OECD website, OECD 2010a, Nilsson and Brunet 2006). The CLI methodology is the same for all countries and regions although the set component series varies according to the fundamentals of each economy. The component series for the Russian CLI are listed below, the first three being survey-based:

1. The production trend observed in the most recent month (Institute for the Economy in Transition, IET)
2. Order books (IET)
3. Assessment of export order books (IET)
4. World market price of crude oil (Hamburg Institute of International Economics, HWWA)
5. Share prices (RTS index, Central Bank of Russian Federation)
6. US imports from Russia, inverted (Bureau of Labour, US Department)

The components are given equal weights in aggregating the indicator. There were major revisions to the CLI in 2008 and 2010[2]. In 2008 the reason was a regular methodology update, and in 2010 the OECD changed three component series and IET replaced the Centre for Economic Analysis (CEA) as supplier of survey data (Smirnov 2010, Gyomai and Guidetti 2008, OECD 2010a). In 2010 the average lead time of the CLI was three months with standard deviation of 2.7 months.

Figure 5 Reference series plotted against the OECD's CLI (amplitude adjusted).



Data sources: BOFIT and OECD.

2.2.4 OECD BCI

The Business Confidence Indicator (BCI) published by the OECD relies totally on survey-based confidence indicator data. The monthly survey covers 1150 companies in the manufacturing sector covering all Russian regions the response rate being 65-70%. The questionnaire is in line with the harmonising recommendation of the OECD and EU. Surveys are conducted by the Gaidar Institute for Economic Policy (IEP or IET) (OECD 2011). The components of the BCI are:

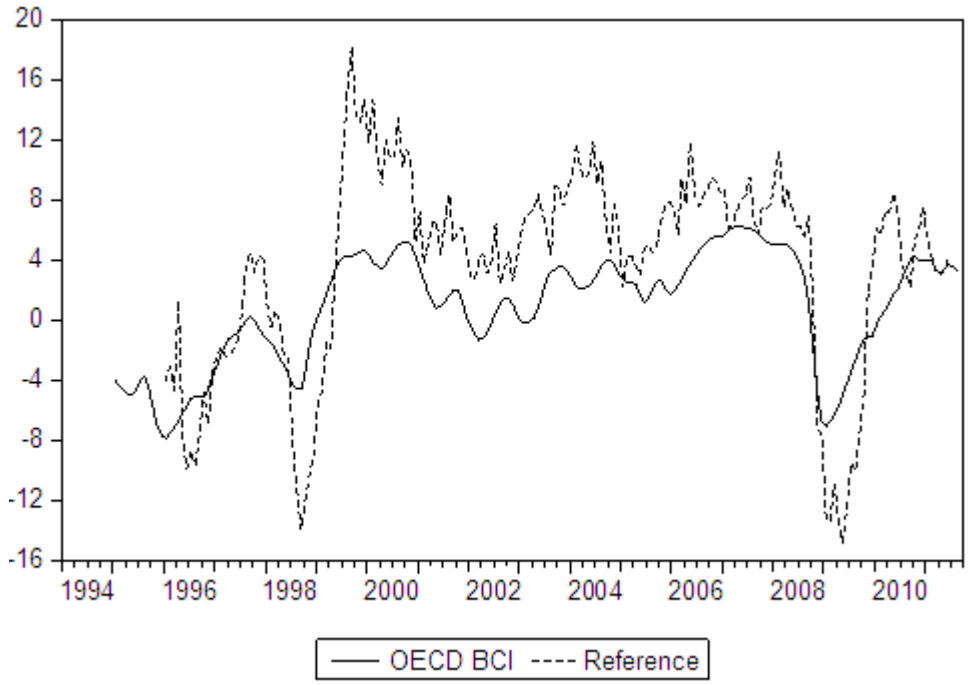
1. The future tendency of production
2. The stock levels of finished products, inverted
3. Order books

BCI is calculated as the average of these variables. OECD smoothens the series via the Hodrick-Prescott filter and makes seasonal adjustments. The series are scaled and normal-

[2] For the earlier stages of the Russian CLI, see Kitrar, Pogosova and Nilsson (2003) and Nilsson and Brunet (2006).

ised[3]. The same procedure holds for OECD's CLI. (OECD 2010b, OECD 2011)[4]. The promised lead times are shorter for the BCI than for the CLI. On the other hand the BCI lead times are more stable. Furthermore, the BCI has been less subject to revisions than the CLI (OECD 2006).

Figure 6 Reference series plotted against OECD BCI.



Data sources: BOFIT and OECD.

2.2.5 DC CLI

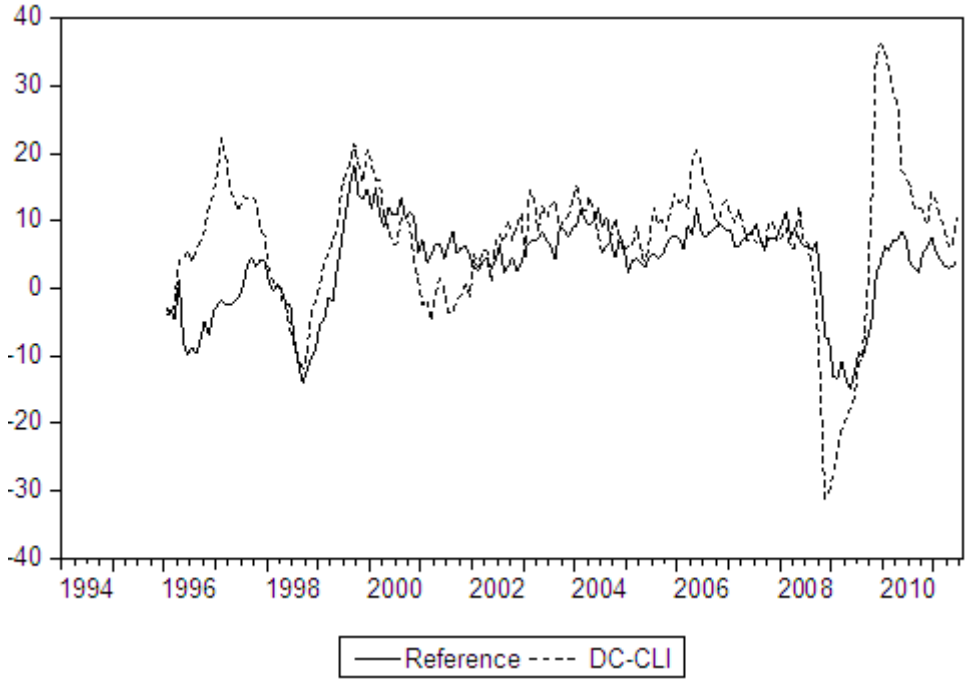
The Development Center unit of the Higher School of Economics in Moscow publishes its own CLI for the Russian economy. The DC CLI has been published since 2006. After that one component variable is removed and two are replaced[5]. CLI is published monthly with a publication lag of 10-15 days. The indicator includes the following components (Smirnov 2010):

[3] When normalising the series is reduced by its own average and divided by its standard deviation.
[4] OECD Handbook (2003) and OECD (2010) and OECD (2006) offer detailed information on the BCI methodology.
[5] For the stages of DC CLI see Smirnov 2000, 2006 and 2010b

1. The REER index of the ruble, inverted (Central Bank of Russian Federation)
2. The ratio of enterprises facing increased or stable domestic demand (IET)
3. The share of enterprises that do not have excessive inventories of finished products (IET)
4. Nominal M2
5. The RTS index
6. The interbank interest rate (MIACR overnight)
7. The average monthly price of urals oil.

The DC CLI is the weighted average of y-o-y percentage changes in the component series (Smirnov 2010). This indicator was selected for study also because it produced a good lead into the 2008 crisis (figures 7 and 9)

Figure 7 The reference series plotted against DC CLI.



Data source: BOFIT and HSE.

3 Methodology

When the data generating process (DGP) changes, forecasting with an econometric model becomes prone to error. Clements and Hendry (1998) state that the main reason for systematic forecasting errors is the inability of the model to take into account changes in the data generating processes.

A change in the data generating process may occur as a result of a change in legislation, technology or statistical measurement and compilation techniques. This weakens the stability of the parameters of a forecasting model. An economic crisis is a possible cause for the types of changes mentioned. The Russian crisis in 1998, for example, induced a structural change in which budget deficits and the unfruitful crediting of state owned companies were reduced and barter limited in order to stimulate the economy.

The above-mentioned issue can be mitigated via two approaches. The first has to do with data selection and the second with the research methodology. Emphasis in data selection can be given to survey-based time series which reveal the conceptions and expectations of economic actors, instead of to real economic variables. Economic crises start out in different sectors of the economy, which is in itself a good reason to include multiple variables in the forecasting model. In addition, it is interesting to study whether using confidence indicators makes it easier to overcome structural change when forecasting. This hypothesis will be partly tested in the context of this study. The detailed analysis of structural changes is, however, left to future studies.

Another means of controlling the problem is selecting a forecasting method with limited memory (Giacomini and White 2006) or selecting a sample that does not include structural changes. Time series analysis usually utilizes the longest periods of time possible, so as to reduce the bias in the results. Short memory models give emphasis to recent information, which reduces the variance in the series. Giacomini and White (2006) have developed a test for comparing forecasts, in which the scope of the test is widened from the forecasting model to the whole forecasting method, so that the data selection is also reflected in the test results. The Giacomini and White method could be practicable in the study of a transition economy.

In this study, though, we shall stay with the more traditional methods. The structural change during the 1998 crisis will be discussed in section 5. As a result, a sample is chosen so that the first observation occurs after the crisis. The models created using this

data will then be compared to models based on the entire dataset. This enables us to examine the contribution of confidence indicators when a structural break occurs.

Next we introduce the models that are used to create the forecasts. Later, we introduce the methodology for comparing the models.

3.1 ARX models

The Autoregressive Exogenous Input (ARX) model is an AR model that includes an exogenous explanatory variable, in this case a confidence indicator. The ARX model is defined as:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \psi_1 x_{t-1} + \psi_2 x_{t-2} + \cdots + \psi_k x_{t-k} + \varepsilon_t, \quad (1)$$

where the coefficients $\phi_1 \ldots \phi_p$ are AR coefficients for the lags of the dependent variable, p is the degree of the model, coefficients $\psi_1 \ldots \psi_k$ are the coefficients of the exogenous variables, and k is the number of exogenous variables. The lags of the AR variables and exogenous variables need not be consecutive. A two variable ARX model is estimated for each pair of dependent and indicator variables.

In order to limit the number of parameters in the final model, the maximum AR-order is set at 5. There is no need to limit the lags of the exogenous variables, because surveys use varying time frames, which entails the possibility of distant lags also having explanatory power. Nevertheless, the number of exogenous parameters is limited to 3. The lags with most explanatory power are initially screened with a cross autocorrelation graph, after which the final selection is made using the Schwarz information criterion.

The reason for using information criteria to choose models is to favor models with few parameters. Increasing the number of parameters does of course increase the fit of a model, but it is relevant only when trying to explain past events. When making forecasts, models with fewer parameters have usually performed better, as each additional parameter includes a potential source of error when estimating models (Stock and Watson 2011). The Schwarz information criterion, SC , was chosen as it penalizes models with a high number of parameters more than alternative criteria, such as the AIC.

3.2 Model comparison and diagnostics

Indicators are compared in three ways. In the *first stage* each ARX model is compared to AR models using the SC. In order to make the criteria for choosing models comparable between models, the parameters are estimated for the time frame 1996:12-2011:6[6], so that neither the observations which are lost after differentiation nor the number of previous observations required by different lags affect the SC value.

In the *second stage* pseudo out-of-sample forecasts are made with the models, and the models are compared using the relative root mean squared errors of the forecasts. In other words the root mean squared errors of the forecasts of each ARX model are compared to the root mean squared errors of the forecast of the AR model. A value smaller than 1 for the relative $RMSE_{i,0}$ incidates that the model i is more accurate than the AR model (0) . Due to a structural change to be observed data (see sub-section 5.3), this procedure is first conducted using data from the period 1996:12-2011:6 (sample 1) and then from the period 1999:5-2011:6 (sample 2). Thus the *third* means of comparison involves the results between the two samples.

The parameters are estimated recursively. At first each ARX model is used to simulate pseudo out-of-sample forecasts. The forecast period was set to 2008:2-2011:6, which enables us to analyze the forecasting power of the confidence indicators in the context of the 2008 crisis. In other words we first make a one period forecast, $h = 1$, for period 2008:3, using data from the period 1996:12-2008:2. After this, the same model is used to forecast the period 2008:4 using data from the period 1996:12-2008:3. This procedure is repeated to the end of the data, with the observation window expanding in step.

An alternative approach would be to make the estimates using a so-called rolling window, which differs from our approach in that the length of the time estimation window is fixed, which means that the lower bound of the window moves when estimating recursively. Thus each set of parameters is estimated using the same number of observations, but from different parts of the sample. Therefore using a rolling window limits the significance of the early observations, as the final forecasts are made without using them. This method seeks to overcome problems caused by structural changes. The data used in this

[6] The notation 1996:12 refers to December 1996. All dates in this work are notated as above, in order to increase the ease of reading.

study have already been divided into two samples based on structural changes, which removes the need to use a rolling window (see sub-section 5.3).

The models were also tested for autocorrelation of the residuals. For a good model, there is no excessive autocorrelation in the residuals, i.e. the residuals are "white noise". If that is not the case, it is possible that the model does not include the correct explanatory variables. In this study, the autocorrelation of residuals is tested using the LM test (Breusch-Godfrey Lagrange Multiplier Test). The number of lags was chosen to be five, based on the nature of autocorrelation of the dependent variable.

Chow's and Quandt-Andrews' tests were used for structural break identification.

4 Empirical study

This section presents the empirical findings of the study. First the series are made stationary, a benchmark model is created and structural changes are examined. After this, the models are fitted and simulated forecasts are made.

4.1 Model specification – stationarity

The analytical methods used in this study require data from a stationary process, which is why the time series must be made stationary prior to actual time-series analysis. In this study weak stationarity, or covariance stationarity, is deemed acceptable.

Because of the reasons related to the data availability, many of the series were already seasonally adjusted. For example the reference series data were acquired as seasonally adjusted year-on-year change. This is clearly a shortcoming as regards the predictive ability of the series also because, by definition, the values of y-o-y changes are affected by what happened in the previous year.

The stationarity of the series was studied with autocorrelation functions and the Augmented Dickey-Fuller (ADF) test. The null hypothesis in the ADF test is that the series has a unit root, which suggests that the series is nonstationary. The test statistic follows a non-standard distribution. Table 2 lists the ADF test results for the final transformed series used in the time series analysis.

Table 2 ADF test results for final time series

Series	**Lag length (used information criterion)**	**Value and significance of the test statistic**
Output of five main branches	0 (SC) 12 (AIC)	-2.14** -1.74*
PMI	1(SC) 5(AIC)	-3.92*** -2.74***
DC-CLI, first difference	11(SC) 12(AIC)	-7.30*** -5.76***
REB order book, seasonal difference	12(SC) 13(AIC)	-4.24*** -3.53***
REB manufacturing, seasonal difference	12(SC, AIC)	-3.32***
OECD CLI, first difference	4(SC) 5(AIC)	-5.13*** -4.54***
OECD BCI, first difference	1(SC) 2(AIC)	-7.57*** -5.68***

The ADF test statistic is significant at the *10% significance level, **5% significance level and *** 1% significance level compared to the critical values of the MacKinnon (1996) criteria. The regressions do not include deterministic terms. The lag lengths were determined using the criteria in question, by testing from the maximum lag length downward. The maximum lag length is determined based on the number of observation from the formula: $p_{max} = \left[\min\left(\frac{T}{3}, 12\right) * \left(\frac{T}{100}\right)^{1/4}\right]$, where T is the number of observations (EViews 7 Guide).

Based on the ADF test results we can assume the series are stationary after the above mentioned transformations, which allows us to continue the analysis.

4.2 Benchmark model and structural breaks

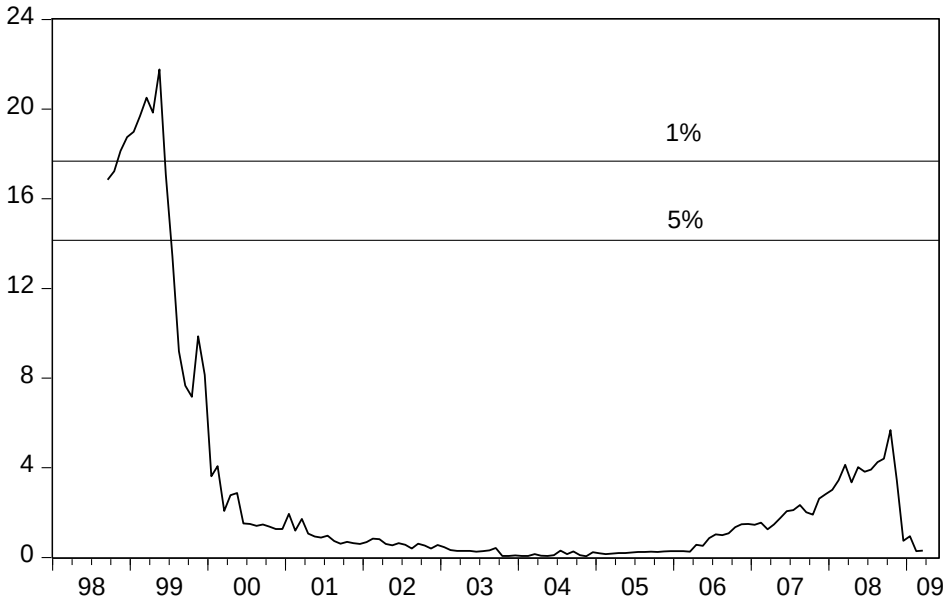
For us to be able to compare forecasts, we need a benchmark model. In this study the reference model will be the best AR model of the reference series, chosen by minimising the number of parameters, the autocorrelation of residuals, and most importantly the Schwarz

Information Sriterion (SIC). An AR($|1||4|$)[7] model was selected as the benchmark model since it minimised the Schwarz criterion. Making this selection for the benchmark model puts the forthcoming indicator models under the most rigorous assessment since they are also compared with the SIC.

In order to be able to conduct tests on structural changes, the benchmark model with a constant was estimated for the output of five main branches between 1996:5 and 2011:6. Wald's F-test statistic in the Quandt-Andrews test peaks in 5:1999, in line with the Russian economic reforms that took place after the 1998 crisis. The test statistic is significant at the 1% significance level (Figure 8), which suggests a structural change. The LR test statistic peaks in 1998:10, but is insignificant.

When a single Chow's test is conducted on 1999:5, indicated by Wald's F-test, we may say with increased certainty that a structural change has occurred, as Chow's F-test statistic is significant at the 5% significance level (Table 3). It is now necessary to estimate the model using both the time frame 1996:12-2011:6 and the shorter time frame 1999:5-2011:6, because we want to study the performance of the confidence indicators during periods of structural change.

Figure 8 Wald's F-test statistic as a function of time in the Quandt-Andrews test for structural change, during the time frame 1996:5-2011:6. Andrews' (1993) 1% and 5% signify cance levels are depicted with horizontal lines.



[7] Notation refers to an AR model which includes the 1st and 4th lags but excludes the 2nd and 3rd.

The test results suggest that a structural change occurred in 1999:5, which is why we will now estimate and the AR model for the latter part of the time frame, namely 1999:5-2011:6. The AR (|1||4|) model appears to remain the best choice for benchmark model. The Quandt-Andrews test now suggests a structural change in 2008:10 (Table 3). This seems natural, as it was in the fall of 2008 that the financial crisis erupted, and the declining price of oil as well as international economic conditions began to affect the Russian economy. It should be noted that the structural change was caused mainly by exogenous factors, and since the crisis Russia has not notably restructured its economy so as to reduce the oil dependency and other vulnerabilities. However, the important factor is that a structural change was observed, which enable us to study how confidence indicators behave in such situations.

Table 3 Summary of test results for structural breaks

Data	$\max(LR\ F)$	$\max(Wald\ F)$	**Chow's F**
1996:5-2011:6	3.08 (1998:10)	21.77*** (1999:5)	2.94** (1999:5)
1999:5-2011:6	5.74** (2008:10)	17.51** (2008:10)	5.74*** (2008:10)

Summary of test results for structural break. The table reports test statistic values from the Quandt-Andrews test and Chow's F-test, dates included in brackets. The test statistics are significant at the ***1% significance level, **5% significance level and *10% significance level.

4.3 Empirical results

Based on examination of the structural changes we observe two cases. When the models are estimated using the entire data 1996:12-1999:5, the data include a clear structural change during the 1998 crisis. The shorter sample (1999:5-2011:6) does not include this change, as the 2008 crisis is in the forecast period (Table 7). ARX–models are fitted for each pair of dependant variable and confidence indicator by minimizing the Schwarz information criteria. Table 4 summarizes the ARX-models estimated using the full data.

Table 4 ARX-models fitted in the full sample (sample 1)

Model	AR-order	indicator lag(s)	SC	LM**	$Adj\ R^2$
Benchmark	1,4	-	4.462	0.347	0.89
Five branches, PMI	1,4	-2,-5,-9	4.427*	0.702	0.89
Five branches, DC CLI	1,4	-9	4.472*	0.204	0.89
Five branches REB manufacturing	1,4	-5	4.463	0.426	0.89
Five branches, REB order book	1,4	-9	4.462	0.523	0.89
Five branches, OECD CLI	1,3	-1,-2,-9	4.289	0.345	0.91
Five branches, OECD BCI	1,3,4	-2, -9	4.432	0.462	0.90

*due to data availability issues, the PMI-model has been fitted for the time frame 1998:3-2011:6 and the DC CLI for 1997:3-2011:6. Due to the differences in time frames, the information criteria from these models cannot be compared with the other indicator models.
** The p-value of the Lagrange Multiplier (LM)-test including five lags. If p>0.05, the residuals do not show a statistically significant autocorrelation at the 5% significance level.

The selected model does not minimize the SIC[8] for the OECD CLI or PMI, because the minimising model would have included the simultaneous effect (i.e. lag 0) of the confidence indicator. This might be appropriate for a theoretical model, but in this study the forecasts used to calculate the RMSE are done so as to simulate the actual forecasting conditions as closely as possible. Therefore, when forecasting the variable *five branches*$_{t+1|T}$, we would need observation x_{t+1} of the confidence indicator x, which is not available when the actual forecast is made. The simultaneous effect could naturally be used when forecasting the realized-but-not-observed variable *five branches*, as x_t is observed earlier than the

[8] The SIC of the OECD CLI is minimized by a model where the explanatory lags of the confidence indicator are 0,-1 and -9. The SIC of the PMI is minimized by a model, where the AR-degree is 1 and the confidence indicator lags are 0,-2 and -5. These models are not used for making forecasts.

variable *five branches*, due to the delay in reporting. Forecasting backward is not, however, practical for economic decision makers using confidence indicators. Also, the decision to leave out of consideration the simultaneous effects subjects the confidence indicators to a stricter assessment with regard to the reference model, which should increase the credibility of the study.

As regards the information criteria, the results suggest that OECD CLI and OECD BCI clearly offer value-added. The REB indicators render roughly the same SIC as the benchmark model. Thus in a real-life forecasting exercise it would be better to leave these indicators out, to reduce the number of parameters to be estimated an thus minimise the forecasting error due to errors in parameter estimation. On the other hand one can say that as SIC already includes a penalty function for additional parameters the REB indicators must contain some useful information. In any case this information is very weak. For PMI and DC CLI it was not possible to conduct the comparison for this sample due to the aforementioned data availability problem.

As a structural break was observed for the reference series, the ARX models were also estimated over a shorter sample 1999:5-2011:6 (Sample 2). In this sub-sample the SICs are comparable across all models. For all models except the model for REB order book, the indicators outperform the benchmark (Table 5). The best performer is once again OECD CLI, the second being the PMI. Poor performance of DC CLI was somewhat surprising, as even REB manufacturing does marginally better, for reasons discussed in section 6.

Table 5 ARX-models fitted in sample 2

Model	**AR-order**	**Indicator lag(s)**	**SC**	**LM***	$Adj\ R^2$
Benchmark	1,4	-	4.506	0.457	0.85
Five branches, PMI	1,4	-2,-5	4.412	0.582	0.87
Five branches, DC CLI	1,4	-9	4.500	0.429	0.86
Five branches, REB manufacturing	1,4	-5	4.497	0.368	0.86
Five branches, REB order book	1,4	-9	4.506	0.644	0.86
Five branches, OECD CLI	1,3	-1,-3,-9	4.339	0.699	0.86
Five branches, OECD BCI	1,3,4	-2, -9	4.472	0.277	0.87

* The p-value of the Lagrange Multiplier (LM)-test including five lags. If p>0.05, the residuals do not have statistically significant autocorrelation at the 5% significance level.

Tables A1 and A2 (in the appendix) report the estimated coefficients from both samples. The coefficients were estimated from the equation:

$$y_t = \mu + z_t + \hat{\psi}_1 x_{t-1} + \hat{\psi}_2 x_{t-2} + \cdots + \hat{\psi}_k x_{t-k} + e_t, \qquad (2)$$

where $z_t = \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 y_{t-2} + \cdots + \hat{\phi}_p y_{t-p} + u_t$ Therefore in order to have the same presentation as in the equation (1) the models must be reparametrised:

$$y_t = c + \hat{\phi}_1 y_{t-1} + \hat{\phi}_2 y_{t-2} + \cdots + \hat{\phi}_p y_{t-p} + \hat{\psi}_1 x_{t-1} + \hat{\psi}_2 x_{t-2} + \cdots + \hat{\psi}_k x_{t-k} + \varepsilon_t \qquad (3)$$

The coefficients estimated from the full sample are mostly significant at either the 1% or 5% significance level. The sole insignificant coefficient is the coefficient of the AR(4) term of the PMI model. In the case of the OECD CLI and the PMI, adding the confidence indicator to the model decreased the coefficient of the AR(1) term. For the CLI, this may

be a result of the AR(3) term, which is added to the model along with the confidence indicator. The model with the highest information criteria (the DC CLI and REB models) had coefficients for the AR terms very similar to those in the reference model. The coefficients of the lagged indicators were larger for those models which had small information criteria (the CLI, BCI and PMI) and small for other models. The estimates based on sample two had more insignificant coefficients, though the relative magnitudes of the coefficients were similar to those estimated from the full sample.

After fitting the models, simulated forecasts could be made. The one-step pseudo out-of-sample forecasts were calculated for the time frame 2008:2-2011:6 using both samples, which enables us to evaluate the performance of the confidence indicators during the entire financial crisis of 2008. The number of forecasted observations amounted to 23% and 28% of the total number of observations for samples 1 and 2 respectively. Table 6 below presents the absolute and relative RMSEs for the simulated forecasts.

Table 6 Summary of results of simulated forecasts

Model	**rel. RMSE, sample 2**	**abs. RMSE, sample 2**	**rel. RMSE, full sample**	**abs. RMSE, full sample**
Benchmark	1,000	2,855	1,000	2,553
PMI	0,889	2,539	0,978	2,498
OECD CLI	0,955	2,727	0,896	2,286
OECD BCI	0,973	2,778	0,923	2,356
DC CLI	1,008	2,879	1,010	2,578
REB manufacturing	1,041	2,973	1,006	2,569
REB order book	1,133	2,875	1,014	2,590

Absolute and relative RMSEs for forecasts from the models for time frame 2008:2-2011:6. An RMSE smaller than 1 indicates that the model outperforms the benchmark model. The parameters of the models were estimated recursively.

The best performer, by a wide margin, in the simulated forecasts in Sample 2 was the PMI model. Both OECD indicators also added remarkable value for forecasting. The remainder of the models did not add value. The REB Order book actually reduced the forecasting

power. The bad performance of the REB indicators did not come as a surprise, as the statistical characteristics of the data were unsatisfactory to begin with. The other indicators used series on same quantities, such as order-books or production expectations from detached surveys, mainly those conducted by the IET (Smirnov 2010, OECD 2011), and by so doing were able to achieve remarkably better results. In addition, the REB indicators each include only one component series per indicator, which weakens their ability to detect signals from various branches of the economy. One way of resolving this issue might have been to combine the REB indicators into a composite indicator, to which additional components might have been added.

The situation is different when the RMSEs are calculated for forecasts based on the full data. The best performer is now the OECD CLI, followed by OECD BCI. These results may have been affected by the unavailability of observations for the PMI and DC CLI for the early tail of the reference series, which limits the memory of those series. Consequently, the PMI was estimated using the time frame 1998:3-2011:6 and the DC CLI using the frame 1997:3-2011:6. Other models were estimated using data starting in 1996:12, but with negligible effects on the results.

Another significant difference is the drastic improvement on performance of REB manufacturing, though it still has a relative RMSE greater than 1. In general, the absolute RMSEs fell when the full data were used, which is somewhat surprising in light on the dramatic structural change that occurred after the 1998 crisis.

Based on the simulated forecasts we can generalize by saying that the confidence indicators do have forecasting power for the Russian economy, but that the choices of both indicator and its components are of great importance. Comparison of the forecasts made from the full data and from the data subsequent to the 1998 crisis underlines the capacity of the confidence indicators, as in both cases the same indicators produced better results than the AR model.

5 On the predictive power of confidence indicators

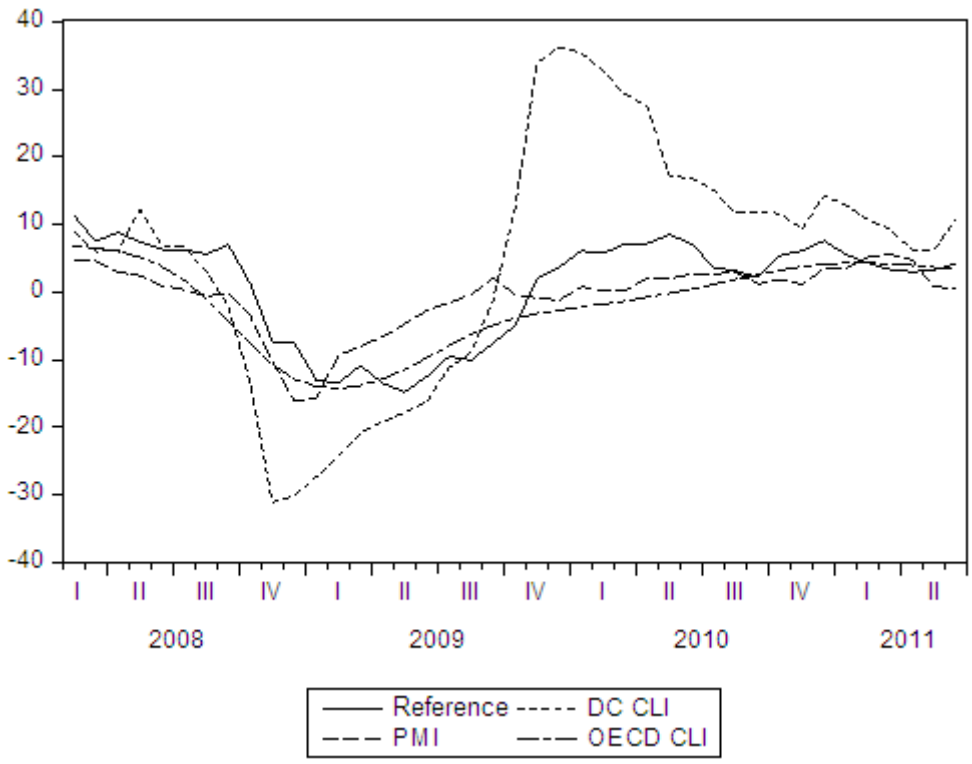
This section discusses the usefulness of the confidence indicators in predicting Russian economic developments. First, a general impression of the empirical results is given, and the effect of the selection of different components of indicators on forecast accuracy is as-

sessed. Next, the effect of the structural change on the forecasts is studied. Finally, the estimation results are critically evaluated.

5.1 The best performing indicators

Broadly, one can say that the confidence indicators do have forecasting power for the Russian economy. The OECD CLI, the OECD BCI and the HSBC PMI displayed the best predictive ability. These three were the best indicators measured by both the information criterion and the simulated forecasts. Neither of the Russian Economic Barometer variables added value to the forecasts - the effect was even negative at times. The absolute size of the coefficients also affects the forecasts. The empirical results show that the OECD models and the PMI decreased the AR coefficients compared to the benchmark, while the lag coefficients of the indicators were large.

Figure 9 The trajectory of the three best confidence indicators and the output of the five main branches during the 2008 crisis.



One surprise was the poor performance of the DC CLI. The indicator added practically no value to the econometric forecasts in the light of this study. There are many possible reasons for the poor performance. The DC CLI questionnaire does not give emphasis to changes in the magnitude of orders received, which is a quantity that predicts production and is a component in the best performing OECD indicators and in the PMI. The DC CLI uses the change in the M2 monetary aggregate as its component series. This may be a poor predictor of the Russian economy, as the volatile incomes from oil make monetary policy a game of balancing the domestic and exchange value of the ruble. Now that dollarization in the economy has decreased and the traditional impact channels of monetary policy have gained effectiveness, it is to be seen that the Bank of Russia is shifting its focus to the domestic value of the ruble and inflation targeting (Korhonen 2011). Such a transition may reduce the usefulness of the M2 monetary aggregate, at least temporarily. A more in-depth analysis would require testing of the component series for structural change, which lies outside the field of this study. The OECD also expressed skepticism toward the M2 component series, when it removed it from the CLI indicator due to unsatisfactory statistical attributes (OECD 2010a).

On the other hand Smirnov (2010) points out that among other cyclical indicators DC CLI has been developed specifically to foresee cyclical turning points, which impairs its usefulness in econometric forecasting. Figure 9 supports this argument, as we see that the DC CLI clearly predicts the drop already in August, when production began to fall only in October. When the publication delay is taken into account, the performance is to be considered good. The reaction is very dramatic with regard to both the drop in production and its recovery. The PMI only predicted the drop in October, so the lead time was just the difference in publication dates between PMI and reference series regarding the figures for the same month. The early reaction of the OECD CLI is not genuine, as the data were revised after the crisis. (Smirnov 2010, Gyömai and Guidetti 2008).

The strong reaction of the DC CLI to the changes in the component series suggests that there might be a nonlinear relationship between the indicator and the dependent variable. The ARX model used in this study naturally gives an approximation for this relationship. It is important to note that in both samples the DC CLI model uses only the ninth lag of the indicator variable and the coefficients are very small (tables 6 and 7); hence, if there is a nonlinear effect, the approximation is poor. Further studies should take this possible nonlinearity into account.

Lead times

The lead times given in the product specifications[9] of the indicators hold true only in the case of the OECD CLI. The selected lags 1,2 and 3 correspond to the average lead of three months with standard deviation of 2.7 months announced by the OECD. Naturally, the ninth lag is not included in this frame. The questions used in the REB indicators aim at a three-month-ahead outlook, yet the REB manufacturing uses the 5th lag and the REB order-book the 9th. In the case of the PMI, for example, it is difficult to estimate the accuracy of reported lead times, as the questions aim to map the changes in magnitude of orders and production, employment, delivery times and inventories of the previous month. Thus the lead time is roughly the time that it takes from the moment an order is placed to the time the product is completed. The actual reaction time is naturally affected by inventory levels. The PMI is explained with the lags 2 and 5, which apparently reflect the time it takes for different branches to adapt production to changes in demand.

Confidence variables vs. real economic variables

Of the best performing series in this study, the PMI and OECD BCI are strictly confidence based indicators, whereas the OECD CLI includes real economy time series as components. This observation further highlights the point that confidence indicators, in particular, are relevant. However, we can deduce very little from this information, as the OECD CLI, which includes real economy variables as components, outperformed the BCI. This is likely to have been caused by the CLI components such as price of oil and the value of the RTS stock index, of which at least the latter may be deemed to reflect future expectations. The price of oil is known to have a powerful direct effect on the economy. This is interesting because these same series, the price of oil and the RTS index, are also components of the DC CLI, which performed poorly. The difference likely lies in the aggregating methods: the OECD gives equal weights to the component series, whereas DC weighs each component series separately (Nilsson 2000 and Smirnov 2010,). The normalization methods for the series also differ.

[9] Specific information on lead time promises was only available for the OECD CLI and the REB indicators.

5.2 Forecasting structural changes

This study is also concerned with the usefulness of confidence indicators when a structural change occurs in the reference series. The results send cautiously positive, but contradicting, signals regarding the hypothesis that confidence indicators can decrease the forecasting error caused by structural changes. For both samples, some of the confidence indicator models received lower information criteria than the reference model. This supports the hypothesis, as there are two observable structural changes in sample 1 and one in sample 2.

Observing structural changes becomes very interesting in the case of simulated forecasts, as in the case of model 1 the parameters are estimated based on data that include a structural change, whereas the data used for model 2 do not. However, there is a structural change in the forecasting periods of both models (Table 7).

Table 7 Summary of relationships between simulated forecasts and structural changes.

	Data used to identify models	**Structural break-point according to QA-test**	**Pseudo out-of-sample forecasts between:**	**Structural break**
Full sample (sample 1)	1996:12-2011:6	1999:5, (2008:10)	2008:2-2011:6	Affects both parameter estimates and forecasts
Sample 2	1995:12-2011:6	2008:10	2008:2 2011:6	Affects only forecasts

The simulated forecasts use recursively estimated parameters. This means e.g. that for sample 2 the first simulated forecast uses data from the period 1999:5-2008:2 and the second from the period 1999:5-2008:3, and so forth. Hence the crisis of 2008 does not affect the estimates of the first parameters, i.e. the data are free of structural change. The analysis based on the full sample (Sample 1), in contrast, uses the period 1996:12–2008:2 to make the first simulated forecast, which means that the 1998 crisis affects the estimates of the parameters.

The results from the simulated forecasts are quite contradictory with regard to the structural change hypothesis. On one hand, both samples include confidence indicators that

perform significantly better than the reference model, as measured by relative RMSE. Also, the best performing indicators were the same for both samples (OECD indicators and PMI). On the other hand, the absolute RMSEs were smaller for all models for the full sample. This suggests that more observations would lead to better forecasts, even when a structural change has taken place for the dependent variable in sample 1. A simple AR model for sample 1 outperformed all models for sample 2 in the simulated forecasting. This signifies that a confidence indicator does not override the significance of a long history for a time series. This does nothing to alter the finding that confidence indicators provide useful information for improving the accuracy of forecasts.

A third way to study the behavior of confidence indicators in times of structural change is to study the recursive estimates of the parameters. The addition of confidence indicators to models did not stabilize the coefficients of the AR terms, though for instance the coefficients of the PMI changed less rapidly than those of the reference model. The coefficients for confidence-indicator lags were unstable in both OECD indicator models, while those of the PMI were more stable. Although the coefficients of the poorly performing REB and DC CLI models were stable during the 2008 crisis, this did little to improve the forecasting accuracy, as the coefficients were very small and in some cases statistically insignificant.

5.3 Critical assessment of the results

No study is perfect. The choice of methods and data is ultimately subjective, especially when the objective is to make forecasts. The results of the study are assessed critically below. However, none of the factors to be presented jeopardize the overall credibility of this study.

First, it is important to note that all of the forecasts here are based on simulations, which means that real-time data were not used, nor would it have been possible to obtain such data. This fact positively affects, as discussed previously, especially the results for the OECD indicators, albeit not conclusively.

The reference series used to construct the OECD indicators is the change in industrial production, whereas the reference series of this study is the output of the five main branches. Thus the OECD CLI might have given even better results if the reference series

was changed. In either case the use of the output of the five main branches as a reference series is well justified .

Secondly, it was found that with the DC CLI and the REB indicators the data were not entirely applicable for forecasting, as regards the statistical properties. Also, the possible nonlinear relationship between indicator and dependent variable was not examined. As regards the REB indicators, this was because the series included a structural change, apparently caused by the questionnaire or other methodology of the indicator being changed, and which led to heteroscedasticity and seasonal variations in a part of the data. For the DC CLI the methods used for aggregating the component series have led to the series foreseeing turning points aggressively (Figure 9), but have also rendered the series unsuitable for econometric forecasting as such. In other words the poor performance of the DC CLI in this study does not mean that it is not at all useful.

Issues concerning the quality and features of the data caused the ARX-models for REB and DC CLI to reach their information criterion minima when only the ninth lag was used. The use of the ninth lag as the sole exogenous lag is difficult to justify economically in the case of monthly data. An alternative approach to the study would have been to estimate models which would have used the first, second or third lag, or a combination of them, for the aforementioned indicators. However, this would have been inconsistent with the manner of choosing and comparing the other models. Also, as mentioned before, the poor explanatory power of the small lags is a result in itself. Also worth noting, is that the ninth lag was also present in both the OECD models, which performed very well.

Finally, many of the time series used were borderline cases with regard to stationarity. Both of the OECD indicators and the DC CLI were differentiated for that reason. Differentiation always carries the risk of losing information. Nonetheless, the OECD indicators achieved good results with regard to both the information criterion and forecasting errors.

6 Conclusions

This study examined the forecasting power of confidence indicators for the Russian economy. ARX models were fitted to the six confidence or composite indicators, which were then compared to a simple benchmark AR-model. The study used the output of the five main branches as the reference series. The models were compared using the Schwarz information criterion and the root mean squared errors of simulated pseudo out-of-sample forecasts. The models were estimated using two different samples, to enable comparison of results between samples.

The research question of this study can be split into two separate questions. Firstly, do confidence indicators have forecasting power? Secondly, how do confidence indicators affect the forecasting accuracy in times of structural change?

Empirical evidence suggests that confidence indicators do have forecasting power. The power is strongly influenced by the choice of indicator as regards the indicator's components and how it is constructed from the component series. The HSBC Purchasing Managers' Index (PMI), the OECD Composite Leading Indicator (CLI) and the OECD Business Confidence Indicator (BCI) were the best performers in terms of both the information criterion and forecasting accuracy.

With regard to the structural changes, cases were studied in which the sample used to estimate the parameters included a structural change (sample 1) and in which a structural change took place during the forecasting period (samples 1 and 2). It was found that confidence indicators decreased the relative forecasting errors in both cases. Confidence indicators cannot, however, replace the significance of the history of a dependent variable, because the forecasts made with the AR model from larger sample (1) were more accurate than all the forecasts made using confidence indicators from the smaller sample (2). This obtained despite the fact that the parameters of the AR models were estimated from data that included a structural change. It was also found that including confidence indicators in a model did not stabilize the coefficients of the AR terms.

It is noteworthy that using indicators for forecasting based on econometric methods and monitoring the indicators to foresee e.g. turning points are two different matters and require different data properties. Thus the results of this study cannot be directly generalized beyond the realm of econometric forecasting.

Three separate topics for further studies took shape in the course of this project. Firstly, the significance of the choice of indicators should be highlighted. Indicators that included only one component series did not perform as well as indicators based on information on numerous features of the economy. Thus the best way to making good use of indicators in making forecasts is to build a composite indicator out of confidence indicators that reflect a multitude of economic aspects as well as real economic quantities. In addition to the choice of components, the effects on the results of weighting, normalization and other alterations would also require more precise study. In this context it is also imperative to study the nonlinear relationships between dependent variable and indicator.

A second topic for further study has to do with the frontier between economics and psychology, which is reflected by confidence indicators. The study should be broadened to the area of psychology and models, making use of collective intelligence. There is also the question of survey methodology. Presently, confidence indicators are based solely on the expectations of economic professionals. It would be interesting to study, for instance, how the results of a consumer survey could be linked to the models. Finally, the relationship between structural changes in confidence indicators needs to be studied further, as the matter is far from unambiguous. The theoretical foundation of this field is still young and thin, but time is sure to correct the shortcoming.

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Appendix: Estimated coefficients

Table A1 The coefficient estimates of the ARX-models in the full sample (1996:12-2011:6)

	Constant	AR-part	ar(1)	ar(3)	ar(4)	Indicator lags	-1	-2	-3	-5	-9
Benchmark	4.62*** (1.67)		1.05*** (0.04)	-	-0.15*** (0.04)		-	-	-	-	-
PMI	2.55*** (0.76)		0.78*** (0.06)	-	-0.05 (0.06)		-	0.55*** (0.12)	-	0.53*** (0.13)	0.25** (0.11)
OECD CLI	4.73*** (1.29)		0.69*** (0.06)	0.19*** (0.06)	-		-5.08*** (1.21)	7.15*** (1.18)	-	-	4.43*** (0.53)
OECD BCI	4.51*** (1.63)		0.95*** (0.05)	0.22** (0.09)	-0.27*** (0.07)		-	1.29*** (0.45)	-	-	1.60*** (0.46)
DC CLI	4.57*** (1.73)		1.06*** (0.04)	-	-0.16*** (0.04)		-	-	-	-	-0.08** (0.03)
REB order book	4.69*** (1.72)		1.05*** (0.04)	-	-0.15*** (0.04)		-	-	-	-	-0.06** (0.03)
REB manufacturing	4.54*** (1.61)		1.05*** (0.04)	-	-0.15*** (0.04)		-	-	-	0.05** (0.02)	-

Estimated coefficients of ARX models in Sample 1. The coefficient is significant at the ***1%, **5% and *10% significance level. The standard error for each coefficient is in brackets.

Table A2 Coefficient estimates for ARX-models in 1999:5-2011:6 (Sample 2)

	Constant	AR-part	ar(1)	ar(3)	ar(4)	Indicator lags	-1	-2	-3	-5	-9
Benchmark	5.84*** (1.53)		1.03*** (0.05)	-	-0.15** (0.05)		-	-	-	-	-
PMI	2.47*** (0.51)		0.71*** (0.07)	-	-0.13* (0.07)			0.69*** (0.11)		0.69*** (0.11)	
OECD CLI	5.35*** (1.28)		0.67*** (0.07)	0.21*** (0.07)	-		-0.98 (0.78)	-	3.72*** (0.72)	-	4.32*** (0.59)
OECD BCI	5.70*** (1.40)		0.91*** (0.06)	0.25*** (0.10)	-0.28*** (0.08)		-	1.41*** (0.50)	-	-	1.54*** (0.48)
DC CLI	5.85*** (1.53)		1.04*** (0.05)	-	-0.16*** (0.05)		-	-	-	-	-0.09** (0.04)
REB orderbook	5.89*** (1.61)		1.03*** (0.05)	-	-0.14*** (0.05)		-	-	-	-	-0.06** (0.03)
REB manufacturing	5.71*** (1.42)		1.02*** (0.05)	-	-0.15*** (0.05)		-	-	-	0.07** (0.03)	-

Estimated coefficients for ARX models in Sample 2. Coefficient is significant at the ***1%, **5% and *10% significance level. The standard error for each coefficient is in brackets.

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