

Forecasting turning points of the business cycle: dynamic logit models for panel data

In this paper, I propose the methodology for forecasting turning points of the business cycle on the basis of the quarterly panel dataset comprising OECD countries and Russia over the 1980-2013 period. Contrasting to the previous studies, I combine data on OECD countries and Russia into a single dataset and develop universal models suitable for the entire sample with a quality of predictions comparable to the analogues of single-country models. On the basis of conventional dynamic discrete dependent variable framework I estimate the business cycle leading indicator models at different forecasting horizons (from one to four quarters). The results demonstrate that there is a trade-off between forecasting accuracy and the earliness of the recession signal. Best predictions are achieved for the model with one quarter lag (approximately 94% of the observations were correctly classified with a noise-to-signal ratio of 7%). However, even the model with the four quarter lags correctly predicts more than 80% of recessions with the noise-to-signal ratio of 25% can be useful for the policy analysis. I also reveal significant gains of accounting for the credit market variables when forecasting recessions at the long horizons (four quarter lag) as their use leads to a significant reduction of the noise-to-signal ratio of the model. I propose using the “optimal” cut-off threshold of the binary models based on the minimization of regulator loss function arising from different types of wrong classification. I show that this optimal threshold improves model forecasts as compared to other exogenous thresholds.

Keywords: business cycles, leading indicators, turning points, dynamic logit models, recession forecast.

JEL Classification: E32, E37.

¹ Center for Macroeconomic Analysis and Short-Term Forecasting (CMASF), Senior Expert; Institute of Economic Forecasting, Russian Academy of Sciences (IEF RAS), Research fellow; and National Research University Higher School of Economics (NRU-HSE), Research fellow. Email: annapestova@gmail.com.

1. Introduction

The problem of the early identification of business cycle turning points is of great practical interest for both the business community and policymakers. An ability to foresee the recession can prevent inefficient consumption and investment expenditures, as well as provide politicians with sufficient time to prepare the countercyclical measures. Since the 1946 study by Mitchell and Burns, in which the first comprehensive statistical analysis of business cycles was performed, the issue of "predicting the future" has been holding an important place in macroeconomic research.

At the end of the 1990s, following a decade of smooth macroeconomic dynamics in USA and other OECD countries, analysts and researchers proclaimed the "end of the business cycle" (Weber, 1997). In the academic literature, Stock and Watson (2002) provide strong evidence in favour of what they called "the great moderation" of the business cycle. The main factors behind the moderated volatility of macroeconomic indicators were supposed to be the growth of the service sector, technological shifts, financial innovations, improved monetary policy and "good luck" (a decrease in the volatility of exogenous shocks).

However, the great moderation did not imply a termination of recessions; on the contrary, despite the duration of expansion phase in USA had increased twice since 1984 (the year of structural break in the postwar U.S. real GDP growth, first documented by Kim and Nelson, 1999), the duration of recession remained constant². The recessions of early 1990s and 2000s were actually mild and short; however, the recent global crisis called "the great recession", which was the most severe recession in the post-war period, brought back the issue of predicting recessions into the focus of academic research and practical interest.

This study is aimed at contributing to the discussion on which indicators could early detect the approaching of recession. In this paper, I develop the leading indicators of business cycle phase using dynamic panel data models with discrete dependent variable reflecting the state of the business cycle.

Prior research has made a significant progress in predicting business cycle turning points. Starting from Estrella and Mishkin (1998) study, the research has documented that the slope of government bond yield curve has strong predictive power for the probability of US recessions. Subsequent works added dynamics into the static canonical specification of recession model (Kauppi and Saikkonen, 2008; Nyberg, 2010; Ng, 2012), tested yield curve predictions in the euro area countries (Moneta, 2005) and included a number of additional indicators (Ng, 2012; Christiansen et al. 2014).

Earlier studies use data for only one country – USA or euro area, without posing the question whether the same specification would be relevant for other countries. In this paper, I extend the previous literature by adopting panel data framework for recession forecasting. I exploit panel data set

² According to NBER official US recessions dates, in 1945-1983 the duration of expansion was on average 45 months compared to 95 months in the 1984-2010 period. The duration of recession during both 1945-1983 and 1984-2010 periods equaled 11 months.

on OECD countries and Russia with the aim of developing leading indicators of recession for the latter. The analysis of the Russian economy is severely constrained due to unavailability of comparable long series, thereby limiting the number of recessions. When combining different country statistics into a single panel, I assume that the determinants and leading indicators of the recessions are similar across countries experiencing cyclical ups and downs³. Thereby this approach allows developing a universal model suitable for the entire sample of OECD countries and Russia.

Most of previous research employed a quite limited list of variables which could potentially be the leading indicators of the business cycle. In particular, they omitted credit market variables as possible predictors, which – in the light of growing literature on macro-financial linkages – could account for a considerable part of macroeconomic fluctuations (see, for example, Cardarelli et al. (2011) and Claessens et al. (2012) for empirical findings on how financial disruptions affect depth and duration of recessions). Recent paper by Ng and Wright (2012) revealed significant differences between the post-1984 recessions and the earlier ones in the US. In particular, the authors claimed that the recent recessions were of financial origins, i.e. attributed to financial market disruptions. These recessions were characterized by pronounced leverage cycle, slow growth and low availability of credit at the outbreak of recovery. If this is true for other OECD countries, then omitting banking sector indicators and, particularly, credit market ones from the potential set of predictors could worsen the quality of models. This paper adds to the literature by showing that the indicator of credit market overheating is a significant predictor of recessions and its power is best revealed at the long horizon (up to four quarters).

The preceding literature is scarce on the choice of cut-off threshold splitting the predicted values of the dependent variable into “recession” states and “normal” states. This threshold is needed to compare predictions with the actual discrete set of business cycle phases. Earlier literature suggested to evaluate the quality of prediction using the exogenous threshold values equalled to either 0.5 or unconditional probability of recession – see Birchenhall et al. (1999); values of 0.25 and 0.5 in Nyberg (2010) and Ng (2012). Based on these thresholds, the authors calculated the percentage of correctly predicted recessions, but they stayed silent about the rate of noise associated with their predictions. In the recent papers of Berge and Jorda (2011) and Liu and Moench (2014), the authors propose the novel approach to evaluate the quality of business cycle phase classification. They suggest using receiver operating characteristic (ROC) curve that enables comparison of the discrete dependent variable models on the entire space of the thresholds. However, despite ROC curve is surely an effective method of model comparison because it is not influenced by the particular threshold, it does not address the issue of the interpretation of predicted recession probabilities, i.e. which of them are high enough to be considered as a warning of recession. In this paper, I fill this gap by introducing the regulator loss

³ Except for the transition crisis at the end of 1980s - beginning of 1990s in the post-soviet countries, which was excluded from the analysis

function borrowed from the literature on financial crises (e.g. Bussiere and Fratzscher, 2002; Lo Duca and Peltonen, 2013). I propose choosing the cut-off thresholds based on the explicit minimization of weighted sum of classification errors. I complement the regulator loss function analysis with the ROC curve computation demonstrating that there is no conflict between them; on the contrary, they complement each other.

The main results of the paper can be summarized as follows. In this study, I present the leading indicators of the business cycle that are uniformly developed for a panel of countries, and the quality of the predictions of these models is comparable to analogues of single-country models. I reveal that financial sector variables and, in particular, credit market ones are extremely important when studying the leading indicators of the business cycle at the long horizons (four quarters) as their use leads to a significant reduction of the percentage of incorrect predictions. When testing different forecasting horizons, I show that the predictive power of the models tends to improve when the time lag between the dependent and explanatory variables narrows. However, even the model with four quarter lags, which is the least precise compared to the models with shorter lags, correctly predicts more than 80% of recessions with the noise-to-signal ratio of 25% – can still be useful in the policy analysis. I also suggest using the “optimal” cut-off threshold (selected by minimizing regulator loss function arising from different types of wrong classification) and show that it improves model forecasts as compared to other thresholds.

The rest of the paper is organized as follows. Section 2 presents a literature review. Section 3 describes the model, the estimation methodology and the data used. In Section 4 estimation results are presented and discussed. Finally, Section 5 concludes the paper.

2. Literature review

In the literature, two main approaches to construct leading indicators of macroeconomic dynamics can be identified. First, models with a continuous dependent variable that predict output level or growth rates. These models are mostly represented by static and dynamic factor models (see Stock and Watson, 1989, 2006; Forni et al. 2001, etc.) and a non-model approach developed by OECD (OECD, 2008). Second, models with a discrete dependent variable that forecast the state of the economy. These models predict how likely a change from expansion to recession, - and vice versa, is. This study belongs to the second strand of the literature as it forecasts the business cycle phase, not the entire dynamics of GDP or some other variables.

Previous empirical studies on leading indicators of recessions employ a discrete dependent variable (Stock and Watson, 1992; Estrella and Mishkin, 1998; Moneta, 2005; Kauppi and Saikkonen, 2008; Ng, 2012, etc.). Most of these studies analyse the predictive power of the slope of the government bond yield curve in anticipation of recessions in the US and in other developed countries. In most cases, these papers exploit time series data for one or several countries.

Estrella and Mishkin (1998) study the predictive power of financial sector variables for recession forecasting in the US. The authors analyse interest rates and spreads between them, stock indexes, monetary aggregates, macroeconomic indicators and a composite leading index of macroeconomic dynamics as leading indicators. Estrella and Mishkin found high predictive power of two financial indicators: the slope of US government bond yield curve and stock index.

Kauppi and Saikkonen (2008) introduce dynamic binary models that enabled the analysis of the impact of the previous states of the business cycle on the next ones (the dynamic nature of the cycle was taken into account). Ng (2012) introduces more variables into dynamic binary business cycle models compared with the classical predictor set (stock indexes, slope of the yield curve). These variables characterize interest rates at the interbank market (TED-spread) and the price stability of housing market.

Castro (2010) studies the determinants of the business cycle phase duration on the panel data of 13 developed countries thus contrasting to the previous literature that predict recessions on single country data. Castro proposes additional variables that are likely to affect the duration of the business cycle phases: OECD leading indicators calculated for most OECD countries in a unified methodology, the dynamics of private investment and the US business cycle phase.

Christiansen et al. (2014) show that sentiment variables (business confidence and consumer sentiment) are the best US recessions predictors compared to classical ones. The authors use ROC curve and calculate area under it (AUC), which measure model ability to distinguish between recessions and expansions.

Considering the leading indicators of the business cycle designed for the Russian economy, models with a continuous dependent variable are largely presented: dynamic factor models in Demidov (2008) and Porshakov et al. (2015) and non-model based leading indicators constructed by OECD (2008) and Smirnov (2001). For the models of recession prediction, Pestova (2013) performs the preliminary analysis of recession determinants that was made on the basis of OECD yearly data within static panel framework.

3. Methodology and data

Dating the business cycle significantly depends on the concept of cycle. In the literature, there are three main approaches: (1) the classical business cycle; (2) the deviation, or growth, cycle; (3) the growth rate cycle.

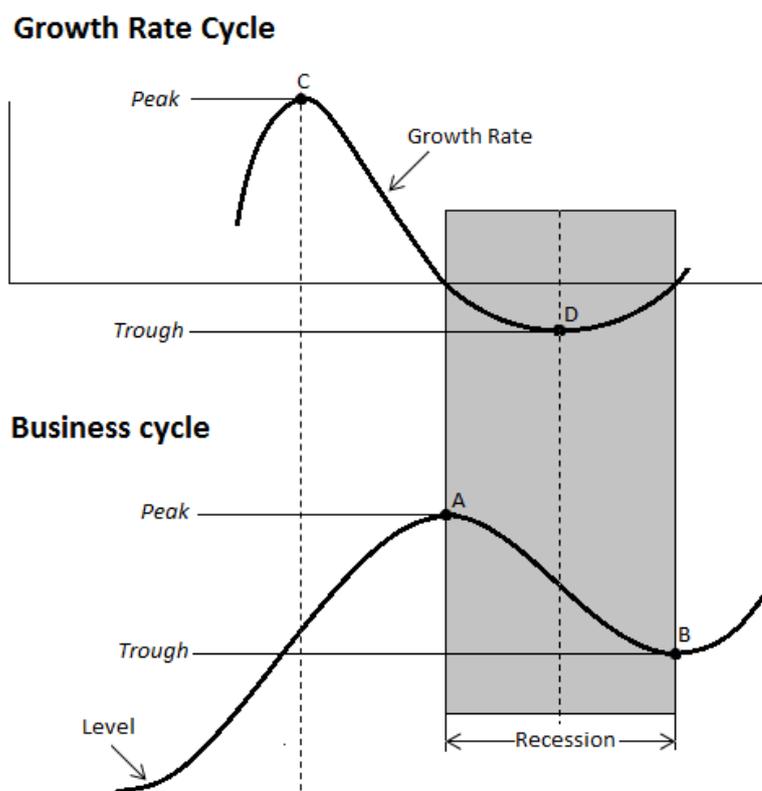
The National Bureau of Economic Research (NBER) has used the classical business cycle approach since the post-war period. The classical business cycle implies the identification of local minimum and maximum points of the index variable ("peak" and "trough", points A and B, see Chart 1). On this basis, it is determined whether the economy is in a recession or an expansion (a recession is defined as period between the peak and the trough; an expansion is a period between the trough and the next peak).

NBER has published announcements about the changing phases of the business cycle of US economy since 1980s (earlier data is also available, up to the mid-19th century) in line with the concept of the classical cycle. As for other countries, CEPR Business Cycle Dating Committee date recessions and expansions in the euro area as a whole from 1999 onwards. The Economic Cycle Research Institute (ECRI) dates recessions in line with US methodology in a number of developed and developing countries (totally 22 countries of which eight are European).

Under the deviation cycle approach, the deviation of economic activity from its long-term trend is considered. This way of thinking was introduced during the great moderation, when the frequency of recessions in terms of absolute volume of output contraction decreased. The deviation cycle methodology is used in the OECD studies for dating and forecasting business cycles in its member countries—see OECD (2008).

The third approach relies on the analysis of the growth rates of economic activity instead of its levels. The limitation of that method is the presence of noisy component in the growth rates over the short period (month, quarter). This problem could be addressed by, for example, taking year-over-year growth rates. In this case, the change of the sign of growth rates from positive to negative marks the onset of a recession (see Chart 1) and the return to the positive values marks its end.

Chart 1. Classical business cycle and growth rate cycle



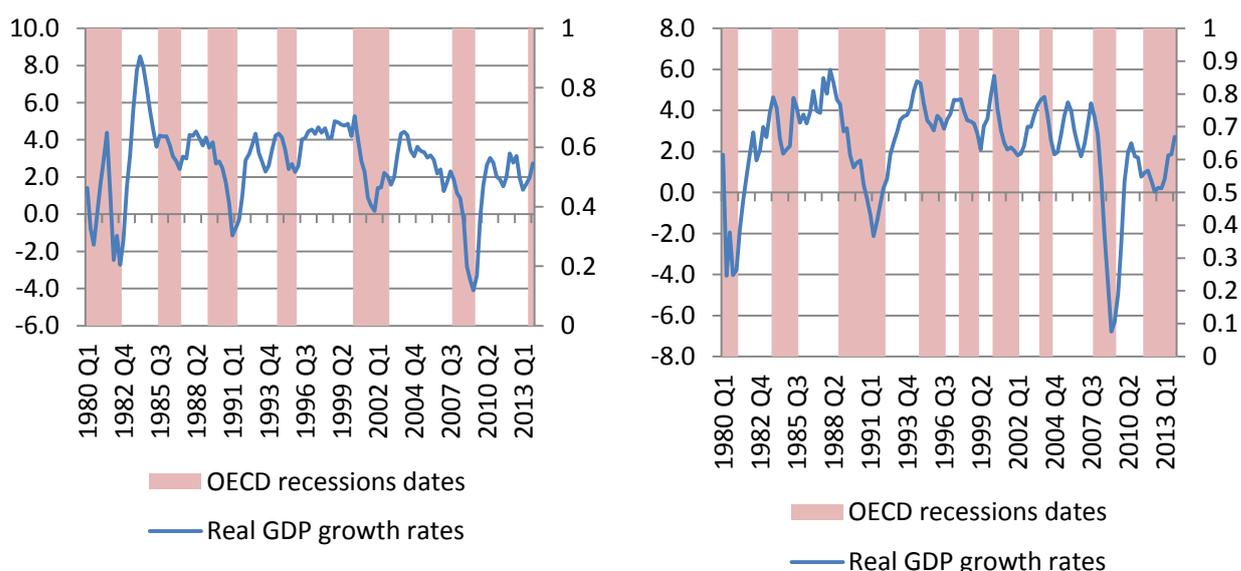
Source: Banerji and Dua (2011)

As the key indicator determining the business cycle phases I use real GDP annual growth rate as the most general and available economic activity indicator for all countries. Other types of variables, which reflect cyclical fluctuations are industrial production index, previously used by OECD, see OECD

(2008), synchronous indicators used by NBER and in most research on the US business cycles, see Estrella and Mishkin (1998), Kauppi and Saikkonen (2008), Ng (2012), and other composite synchronous indices, see Conference Board (2000), Stock and Watson (1989).

In this study, the dating of the phases of business cycles is based on the growth rate cycle approach. The explanation of that choice consists of the three following arguments: the unavailability or low validity of alternative dating and the simplicity of methodology and the clear identification of turning points. As previously noted, dating in the classical business cycle framework is not available for a representative sample of countries (the largest dataset is available on the ECRI website, however it has a very limited number of countries). The only available dating of the business cycles for a large sample of countries is the OECD one made with the deviation cycle approach. However, the latter seems unreasonable to exploit because this methodology identifies a large number of “false” recessions (when growth rates declined but stayed positive), see Chart 2.

Chart 2. OECD recession dates and actual real GDP growth rates (y-o-y) for USA (on the left) and UK (on the right)



Note. OECD recession dates are calculated as the periods between peaks and troughs.

The simplicity and comprehensibility of the growth rate cycle dating methodology arises from the easy rule of classifying the data: the times when GDP experienced a steady decline (GDP growth rate was negative) is classified as a recession, and when it grows – as an expansion, so that the binary dependent variable is defined as follows:

$$y_{it} = \begin{cases} 1 & \text{if } GDPgr < 0 \text{ (recession)} \\ 0 & \text{if } GDPgr > 0 \text{ (expansion)} \end{cases}$$

To avoid noise in the dependent variable (flashing business cycle phases) I adopted a more complex definition of a recession as compare to the technical one described above. In particular, I did not classify a one-quarter GDP decline as a recession. Instead, at least two negative quarters of GDP should be recorded to be qualified as a recession. The same logic was applied to a quarter of slight

positive growth surrounded by recessionary quarters both before and after it: this “positive” quarter was by design marked as a recession.

The specification of dynamic panel binary choice model is defined as:

$Pr\{y_{it} = 1 | \alpha_i, x_{it-k}, y_{it-k}\} = F(y_{it-k} \gamma + x'_{it-k} \beta + \alpha_i)$, where $Pr\{\cdot\}$ is a conditional probability of recession, $F(\cdot)$ is a logistic distribution function (logit model), x_{it-k} is a set of explanatory variables for country i in the quarter $(t - 1)$, β is a vector of parameters associated with x , γ is a state dependence parameter, k is the quarter lag.

The dynamic specification of the model (previously used in Kauppi and Saikkonen, 2008; Nyberg, 2010 and Ng, 2012) implies that the previous state of the business cycle influences the current one (lagged dependent variable is included). The dynamic specification of the recession model is explained by the high persistence of business cycle phases. For example, Berge and Jorda (2011) showed that the state of the economy up to 8 months ago predicts the current state better than uninformative predictor (coin-toss).

I include the component of unobservable country-specific heterogeneity into the model, which stands for the exogenous differences between countries in their probability of recession. Accounting for unobservable country-specific effects is necessary to distinguish between true state dependence (coefficient γ) from spurious one (driven by the persistence of country-specific effect).

I use a quarterly dataset on 22 OECD countries and Russia⁴ over the period 1980-2013⁵. Initially it consisted of a full set of about 30 OECD countries, but due to data unavailability on explanatory variables for some OECD countries it decreased significantly. Taking these data, I treat the cross-country heterogeneity component α_i as fixed effect⁶ because the sample appears to be restricted.

Under the fixed effects methodology the so called “incidental parameter problem” is unlikely to arise because in case of this study the number of countries (N) does not grow to infinity, it is fixed instead, as is the number of quarters (T). Besides, taking into account the specificity of models I develop – leading indicator models – one can see that the explanatory variables taken with lags would be exogenous to the dependent variable. That is why using an ordinary logistic regression with country-specific dummy variables and a fixed effects conditional maximum likelihood estimator should yield unbiased estimates. Fixed effects regressions are run only if the test on the joint significance of the country-specific dummy variables shows that these variables are significant.

In line with the empirical and theoretical literature on the determinants and the leading indicators of the business cycle, I study the following set of indicators, which could predict business cycle phase

⁴ Country dataset: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Portugal, Russia, Slovak Republic, Spain, Switzerland, UK, USA.

⁵ A period of the transition crisis (recession) experienced by the post-soviet countries after abandoning planned economy and transition to the market economy was excluded from the analysis.

⁶ Candelon et al. (2014) develop dynamic early warning system for currency crises on a panel of 16 emerging countries. The authors treat the permanent unobserved heterogeneity between countries as parameters to estimate, thus using dynamic fixed effects binary choice model.

changes: (1) macroeconomic variables; (2) consumer and business expectations; (3) external sector variables and (4) financial sector variables.

Macroeconomic variables include lagged GDP growth (previously used in Estrella, Mishkin, 1998) and investment expenditures (Stock and Watson, 1993; Birchenhall et al., 1999; Ozildirim et al., 2010, Castro, 2010). The role of the investment in generating fluctuations of aggregate output is emphasized in the majority of early business cycle theories (dating back to the first half of the 20th century, see review in Zarnowitz, 1996), and in the modern real business cycle theories (investment-specific technological change - see survey in Rebelo, 2005). Additionally, I examine the predictive power of the country GDP leading indicator in the OECD methodology (other papers where composite leading indices were used are Stock and Watson, 1989, 1992; Birchenhall et al., 1999; Ng, 2012; Castro, 2010).

Consumer and business expectation variables. In the theoretical dynamic general equilibrium models of macroeconomic fluctuations with rational expectations, under specific conditions several equilibria exist (see surveys in Mankiw, 2006; Zarnowitz, 1996). Switching between "favorable" and "unfavorable" equilibrium path occurs because of a sharp change in the expectations (confidence in the future positive macroeconomic dynamics). These expectations can easily become self-fulfilling. One possible mechanism is that agents adjust returns from investments based on the expectations of future profits. If agents are able to forecast worsening of economic situation, they will cut current costs (including investment ones) that will cause a decrease in output. Keynes first described this logic in 1936 in his "General theory of employment, interest, and money" suggesting the speculative profit expectations as one of the attributes of investment. Confidence indicators are exploited in the empirical literature, see Estrella and Mishkin (1998), Birchenhall et al. (1999), Ozildirim et al. (2010) and Christiansen et al. (2014). In this study I use the OECD standardised consumer and business confidence indicators which are available for most of the member countries and several non-member economies.

External sector variables are the US business cycle phase (previously used in Castro, 2010), the current account balance to GDP ratio, and real effective exchange rate index (REER). Nominal effective exchange rate index (NEER) was included in recession equation in Estrella, Mishkin (1998). The current account balance to GDP ratio and REER measure country's external trade and currency balance, which, if violated, could provoke a recession. Empirical evidence documents an increase in business cycles synchronization across major countries of the global economy over the past decades (Stock, Watson, 1999; Zarnowitz, 1996). The main reason is a deepening of countries integration into the global economy thereby leading towards an increased dependence of the economies on one another, as well as to an increase of vulnerability to the global shocks. This explains the need to account for the external sector variables in business cycle models.

Financial sector variables include those previously used in the literature: interest rates and spreads⁷ (Estrella and Mishkin, 1998; Kauppi and Saikkonen, 2008; Ng, 2012; Ozildirim et al., 2010; Castro, 2010), stock market indices (Estrella and Mishkin, 1998; Stock and Watson, 1992; Birchenhall et al., 1999; Ng, 2012; Ozildirim et al., 2010; Castro, 2010), as well as those proposed in this paper: bank lending and interest rates on loans. The omission of these variables in modern empirical studies is remarkable in light of the early business cycle theories by Hawtrey and Hayek, who claimed that bank lending instability is a source of cyclical fluctuations in the economy (Zarnowitz, 1996). In these theories, the interest rate on loans is considered as a transmission mechanism that connects financial and real sector variables through the availability of financial resources to investment.

4. Estimation results

I start the estimation of dynamic recession models from the analysis of predictive power of each individual indicator. To do that, I run univariate regressions of the dependent variables on each indicator separately. The quality of prediction is assessed by calculating the difference between pseudo-R² obtained from the dynamic model and the corresponding indicator in the simple autoregressive business cycle model (if only the lag of the dependent variable is included), as well as the significance of the corresponding coefficients. The results are presented in Table A2 in Appendix. The descriptive statistics of the dependent and explanatory variables are reported in Table A1 in Appendix.

The analysis have shown that country GDP leading indicator in the OECD methodology is the most informative individual predictors (with the exception of three- and four-quarter lag). In addition to this, an extremely high level of explanatory power is demonstrated by the consumer and business confidence indicators (except for deep lags again). Investment dynamics are also an important predictor of switching between the business cycle phases but that is true only for the one-quarter lag. A slowdown of real GDP growth is a good predictor of a recession for the same lag. US GDP leading indicator makes sense with one to three quarter lags. The current account balance to GDP ratio, REER and the stock price index reveal significant effects in models with all time lags considered. Spreads between interest rates are also important for all but fourth lags, whereas the predictive power of loans to GDP ratio increases with lag growth. Based on the preliminary analysis of individual indicators, I then estimate multivariate models with the most informative individual predictors as explanatory variables.

The estimation of multivariate recession models was carried out in four steps. First, I estimated the dynamic models where the only explanatory variable was the country GDP leading indicator in the OECD methodology. I was interested in whether this single indicator can predict the state of an economy most precisely; so that if it turned out to be the best predictor, then specifying and using other models would be unnecessary. Secondly, I estimated the dynamic models with the real sector variables

⁷ The most frequently used leading indicator of the recessions – the slope of the government bond yield curve – is not used in this study because it is not available for a wide range of countries.

but without the OECD GDP leading indicator. The following indicators were included in the block of real sector variables (only those indicators that have demonstrated the greatest predictive power in the univariate models): the consumer confidence indicator, investment dynamics, GDP growth rates, the US GDP leading indicators in OECD methodology, REER index, and the current account balance to GDP ratio. Third, I added financial sector variables to the models with the real sector variables, in order to estimate whether considering them would lead to an increase in the predictive power of the models. The block of financial sector variables includes stock market indices, spreads between interest rates and bank loans to GDP ratio. At the fourth step, I dropped the lagged dependent variable from the models with real and financial sector variables to learn whether accounting for inertia in the business cycle phases makes sense. These four types of models were estimated for a one, two and four quarter lag of all of the explanatory variables. Additionally, in order not to restrict the models by such rigid lag selection, I also estimated models with “best” lags, that is, those lags for which the predictive power was largest in the univariate models. All the sixteen resulted models are presented in Appendix in Tables A3-A6.

Discussion of the results

In general, most of the variables are significant in the estimated equations with the expected coefficient signs. The lag of the dependent variable is significant in one and two-quarter lag specifications and becomes insignificant at longer horizons. This can indicate a damping of inertia with increasing lag. The estimated coefficients are robust to the change of specification (the addition of variables) and variation of the quarter lags. This indicates that the obtained results seem to reveal the underlying relationships between business cycle phases and their leading indicators.

More specifically, I obtained a negative sign of the coefficient before the country GDP leading indicator in the OECD methodology meaning that an increase in the value of this indicator lowers the probability of a recession with one to four quarter lag. An increase in consumer confidence indicates an increased propensity to consume preventing thus an economy from a recession. The US leading indicator significantly influences business cycle phase of the other countries, however the significance disappears for more than the two-quarter lag. The risk of recession increases during the slowdown of GDP growth rates which are important for short lags (up to two quarters). A weakening of the country's external balance (a decrease in the current account surplus or its shift to negative values) is a factor increasing the probability of negative output growth rates with only a four-quarter lag. An increase in the interbank market rate spread predicts a crisis with a one or two quarter lag (via a credit crunch mechanism) whereas a rise in the interest rates on loans anticipates a recession with a year lag (due to borrower adverse selection and the possible rise of defaults on loans). Substantial growths of the loans to GDP ratio may imply that significant credit risks have been accumulated that are not compatible with continued expansion. This indicator is significant with a four-quarter lag only, meaning that a credit overheating peak occurs one year before a recession.

Based on the pseudo- R^2 measure, the preliminary analysis of predictive power of estimated models shows that those models with only the real sector indicators are worse as compared to the models with both real and financial sector variables. This demonstrates that it is crucial to include the latter into the explanatory variables set. However, the result is less evident when the model with only the GDP leading indicators in OECD methodology is compared to the model with both real and financial sector variables by the pseudo- R^2 measure. Though, for a one-quarter lag the latter outperform the former, for a two-quarter the relationship is reversed. Thus, an additional analysis of the model's predictive power is needed.

According to the tests on the significance of individual effects (country dummy variables), for two and four-quarter lag models, country-specific constants are jointly significant (Tables A4-A5 in Appendix). For the one-quarter lag model, a pooled specification is more preferable. For models with various lags, the result depends on the specification. For the specification with both real and financial sector variables, individual effects are marginally significant (at 10% level only, Table A6 in Appendix). Taking into account these results, I have reestimated those specifications for which the presence of individual effects was proven. The method I employed is the conditional fixed-effects logit estimator. The obtained results revealed no sharp differences between the dummy variables and the fixed effects estimator (Table A7 in Appendix). The values of most of the coefficients remained almost unchanged; they also preserved their respective signs and significance. Thus, if the estimation on the pooled sample provides almost the same results, it is unlikely to be biased as compared to the fixed effects model.

Next, in order to evaluate the predictive power of the models, I discuss and implement the procedure of choosing a cut-off threshold that separates the "crisis" values predicted by the models from all the others, i.e. "non-crisis", or normal states. This raises a question about the rule, according to which a continuous series of model-based recession probability values should be converted to a discrete scale (to compare with the actual values). A naive cut-off threshold could be chosen at the value of 0.5 (equally distances from "0" and "1"), however, there are modifications of this rule in the existing studies.

Birchenhall et al. (1999) addresses the issue of choosing a threshold for recession probability models, exceeding which is treated as a "signal" of recession. The authors suggest that the unconditional probability of an analysed event can be used as threshold. They consider the probability range between 0.5 to the unconditional probability as an ambiguous area.

The literature on financial crisis leading indicators (e.g. Bussiere and Fratzscher, 2006; Lo Duca and Peltonen, 2013) suggests choosing the optimal threshold by minimizing the regulator loss function. Such function is obtained from balancing between type 1 errors (missed event) and type 2 errors (false signal): $L(\theta) = \theta \frac{C}{A+C} + (1 - \theta) \frac{B}{B+D}$, where A, B, C and D are calculated according to the classification presented in the Table 1 below; θ is the regulator sensitivity to the type 1 errors as compared to the type 2 errors.

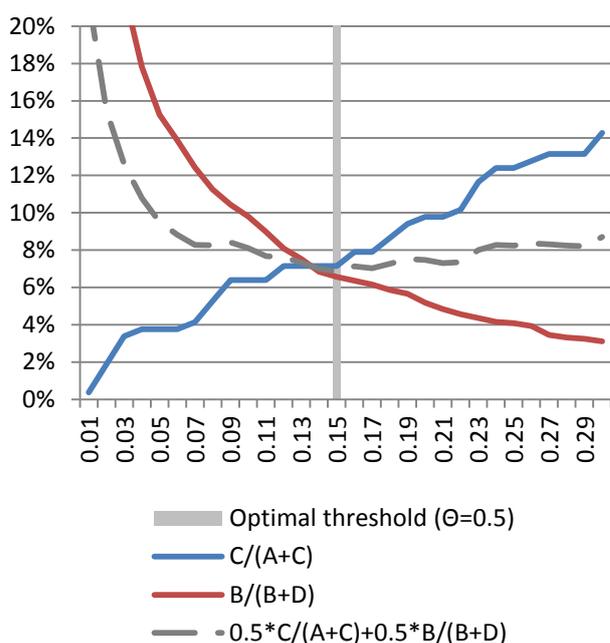
Table 1. Classification of the events of interest and the signals

	$Y = 1$ The event occurs in the following k quarters	$Y = 0$ The event does not occur in the following k quarters
$S = 1$ indicator issues a signal (exceed threshold)	A	B (type 2 error)
$S = 0$ indicator does not issue a signal (do not exceed threshold)	C (type 1 error)	D

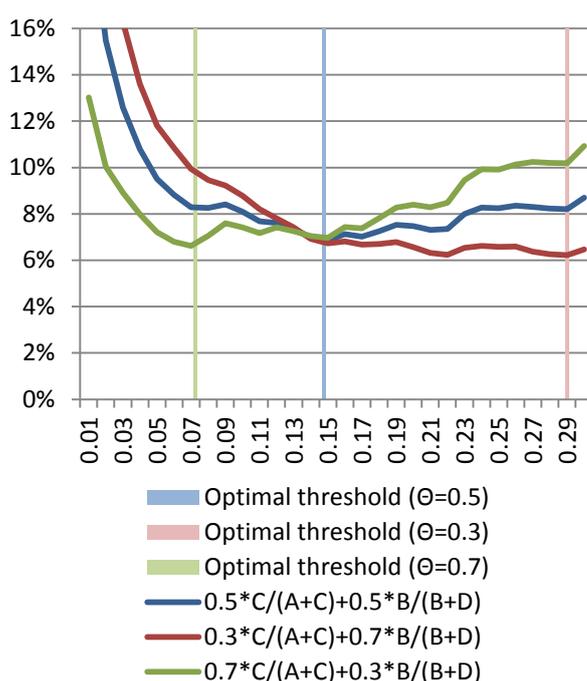
For any value of parameter θ , the function $L(\theta)$ will have a minimum point, since the ratio of type 1 errors $C/(A+C)$ grows with an increase in threshold values, whereas at the same time the ratio of type 2 errors $B/(B+D)$ drops (Chart 3a).

Chart 3. Choosing an optimal threshold for the business cycle phase model with OECD GDP leading indicator (lag = 1 quarter)⁸

a) Type 1 and type 2 errors and their weighted sum as the functions of cut-off threshold



b) The choice of optimal threshold depending on a parameter of regulator loss function



However, the result of the optimization depends on a choice of parameter θ . That is why I considered several values of such a parameter: 0.5, 0.3, and 0.7. As depicted on the Chart 3b, the choice of optimal threshold depends on θ : the higher the parameter (regulator sensitivity with respect to missing events), the lower the optimal threshold.

⁸ Estimation results are presented in the Table A3 in Appendix, the first column.

In Table 2, I present a set of indicators characterizing the predictive power of models as a function of parameter θ . These models were estimated using the OECD leading indicators only. For the sake of comparison, I also show the model quality characteristics for the thresholds used in previous studies, which are equal to the unconditional probability of the event (in our case 0.11) and the value of 0.5.

As it is shown in the Table 2, using the threshold of 0.5 leads to a drop in a noise-to-signal ratio to negligibly low levels (2.5%). However, in this case the quality of prediction also decreases: the ratio of correctly predicted events drops below 80% (see the last column of Table 2). At the same time, the threshold, which is equal to the unconditional probability of the event, lies close to its "optimal" value calculated with $\theta = 0.5$. This means that the unconditional threshold could be treated as useful alongside with the optimal one. However, when comparing different models, I apply another rule to choose the optimal threshold. This rule is based on the regulator loss function with 0.5 sensitivity value to the missed crises, since this threshold lies close to the unconditional probability of recession (and thus could be considered as reasonable). At the same time, this value is obtained through the optimization of loss function calculated in a specific way. The value of 0.5 is treated as exogenous as it is unknown what this value actually is.

Table 2. A set of indicators reflecting the quality of business cycle phase model with OECD leading indicators only (lag = 1 quarter), depending on the cut-off threshold, %

Parameter of regulator loss function (Θ)	$\Theta = 0.7$	$\Theta = 0.5$	$\Theta = 0.3$	$P(Y = 1) =$	0.5
Optimal threshold	0.07	0.15	0.29	= 0.16	
<i>Full Sample (22 countries)</i>					
Noise-to-signal ratio	13.0%	7.1%	3.7%	7.0%	2.5%
Recessions correctly predicted	95.9%	92.9%	86.8%	92.5%	78.6%
Absence of recessions correctly predicted	87.6%	93.4%	96.8%	93.5%	98.0%
<i>Russia</i>					
Noise-to-signal ratio	0.0%	0.0%	0.0%	0.0%	0.0%
Recessions correctly predicted	100.0%	100.0%	100.0%	100.0%	100.0%
Absence of recessions correctly predicted	100.0%	100.0%	100.0%	100.0%	100.0%

Note. The first three columns ($\Theta = 0.7, 0.5$ and 0.3) show the quality indicators for different regulator sensitivity to the type 1 errors compared to type 2 ones. The fourth column presents the same indicators for the unconditional threshold (calculated as the percentage of recessionary quarters in the sample). The last column provides the results for the 0.5 threshold.

I proceed with the analysis of predictive power of all the four types of models estimated with the regulator loss function parameter $\Theta = 0.5$ and 1, 2 and 4 quarter lags for all explanatory variables (Table 3 and 4). Obtained results clearly demonstrate that the model with a real sector indicators predicts the recessions worse and with a higher noise-to-signal ratio as compared to the model with OECD GDP leading indicator only. At the same time, the model with both real and financial indicators forecasts recessions more precisely than the model with only the OECD GDP leading indicator; the noise-to-signal

ratios are the same in these specifications (Table 3). For the models with two-quarter lags the optimal threshold provides ambiguous result concerning the comparison of the model with only the OECD GDP leading indicator and the model with both real and financial indicators (Table A8 in Appendix). For the latter both the ratio of correctly predicted recessions and the noise-to-signal ratio are lower. However, if an additional analysis of weighted type 1 and type 2 errors is performed, one can see that for most of the thresholds the regulator loss function is lower for the model with real and financial sector variables when compared to the model with only the OECD GDP leading indicator (Chart 4a). This finding is also supported by a ROC curve. For the model with real and financial sector variables the curve lies in the upper left part of the Chart 4b compared with other models (lower type 2 errors together with higher correct classification rate). For the models with four-quarter lag, the set of real and financial sector variables clearly outperforms the OECD GDP leading indicator in terms of both higher rate of correctly predicted recessions and lower noise-to-signal ratio. The OECD GDP leading indicator loses its forecasting power at this and longer horizons. These findings confirm the usefulness of models based not only on the existing leading indicators (the OECD GDP leading indicator), but also on a selected set of predictors of both real and financial sector variables.

When the models with both real and financial sector variables are compared to the models with only real sector variables, the choice will be in favour of the formers (Table 3 and Tables A8-A10 in Appendix). This becomes more pronounced at long horizon; in the models with four-quarter lag, the inclusion of financial sector variables improves the accuracy of the model, that is, reducing noise-to-signal ratio by 10 percentage points. Thus, my calculations provide strong support to the idea that the periods of recession could be better predicted if financial sector variables are considered alongside with the real sector indicators.

As for the comparison of static and dynamic recession models, I found that the latter are more accurate than the former in various lag specifications because taking inertia into account yields both a higher quality of recession prediction and a lower noise rate – see Table 3 and Tables A8-A10 in Appendix. This means that accounting for the dynamic nature of the business cycle not just helps to avoid misspecification of the business cycle phase model, but also improves its forecasting accuracy.

Testing uniform specifications (with real and financial sector variables) among different forecasting horizons demonstrates that the larger the time lag between the dependent and explanatory variables, the worse the results in terms of the predictive power of models (Table 4). Therefore, there is a trade-off between forecasting accuracy and the earliness of the recession signal. With the precision increase, the lead-time of the models drops and vice versa. However, despite the prediction results with four-quarter lag are being the least precise, this model could still be viewed as useful as it correctly predicts more than 80% of recessions with a noise-to-signal ratio of 25%.

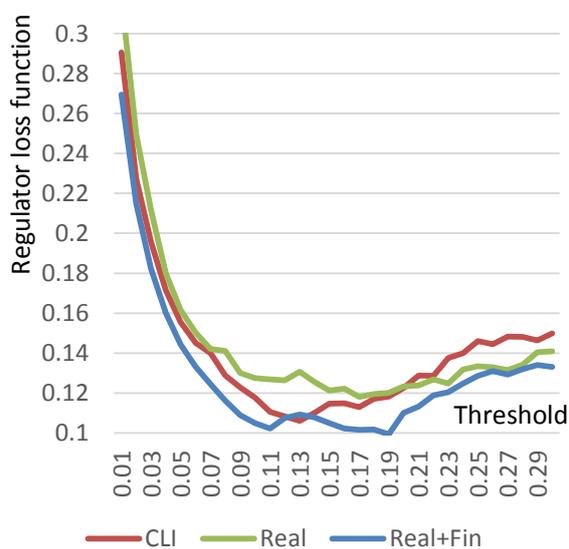
Table 3. The quality of prediction of the business cycle models, lag=1 quarter

	Dynamic model with OECD GDP leading indicator only (1)	Dynamic model with real sector variables only (2)	Dynamic model with real and financial sector variables (3)	Static model with real and financial sector variables (4)
Optimal threshold	0.15	0.12	0.15	0.15
<i>Full Sample (22 countries)</i>				
Noise-to-signal ratio	7.1%	8.6%	7.1%	8.7%
Recessions correctly predicted	92.9%	94.7%	94.7%	94.0%
Absence of recessions correctly predicted	93.4%	91.9%	93.2%	91.9%
<i>Russia</i>				
Noise-to-signal ratio	0.0%	15.6%	7.8%	7.8%
Recessions correctly predicted	100.0%	80.0%	80.0%	80.0%
Absence of recessions correctly predicted	100.0%	87.5%	93.8%	93.8%

Note. Optimal threshold is calculated based on the regulator loss function minimization with $\theta = 0.5$, where θ is the regulator sensitivity to the type 1 errors as compared to the type 2 errors.

Chart 4. The quality of prediction of the business cycle models, lag=2 quarters

a) Regulator loss function depending on the threshold of the business cycle models



b) ROC-curve, the dependence between fraction of correctly predicted recessions and type 2 errors

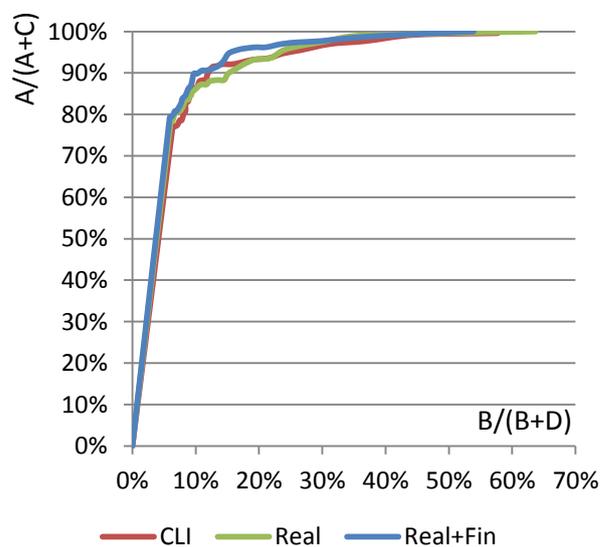


Table 4. The quality of prediction of business cycle models, dynamic models with real and financial sector variables

	1Q lag	2Q lag	4Q lag	Various lag
Optimal threshold	0.15	0.19	0.15	0.15
<i>Full Sample (22 countries)</i>				
Noise-to-signal ratio	7.1%	10.8%	25.1%	6.9%
Recessions correctly predicted	94.7%	89.8%	81.2%	94.4%
Absence of recessions correctly predicted	93.2%	90.3%	79.6%	93.5%
<i>Russia</i>				
Noise-to-signal ratio	7.8%	15.6%	23.4%	7.8%
Recessions correctly predicted	80.0%	80.0%	80.0%	80.0%
Absence of recessions correctly predicted	93.8%	87.5%	81.3%	93.8%

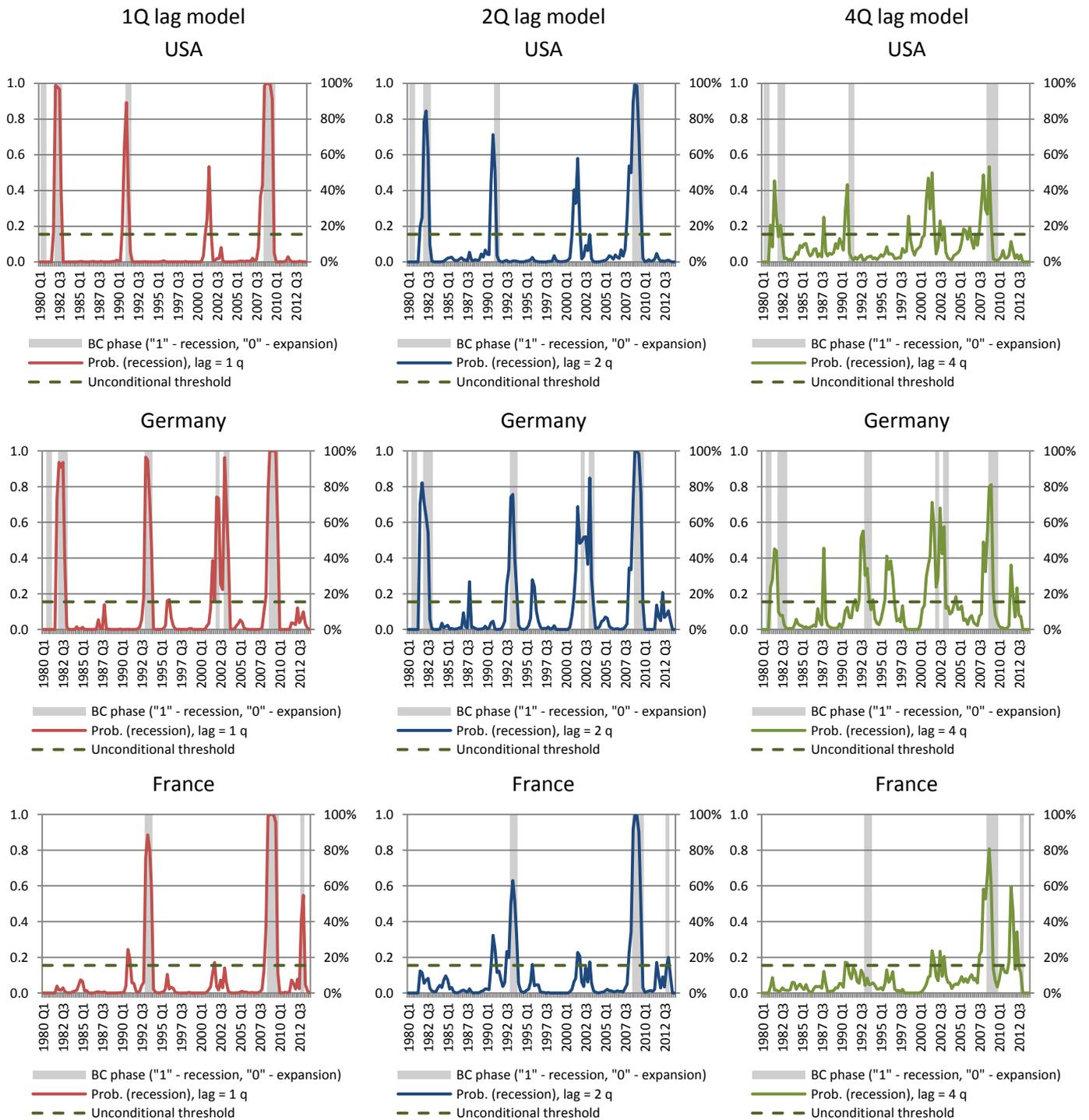
Note. Optimal threshold is calculated based on regulator loss function minimization with $\theta = 0.5$, where θ is the regulator sensitivity to the type 1 errors as compared to the type 2 errors.

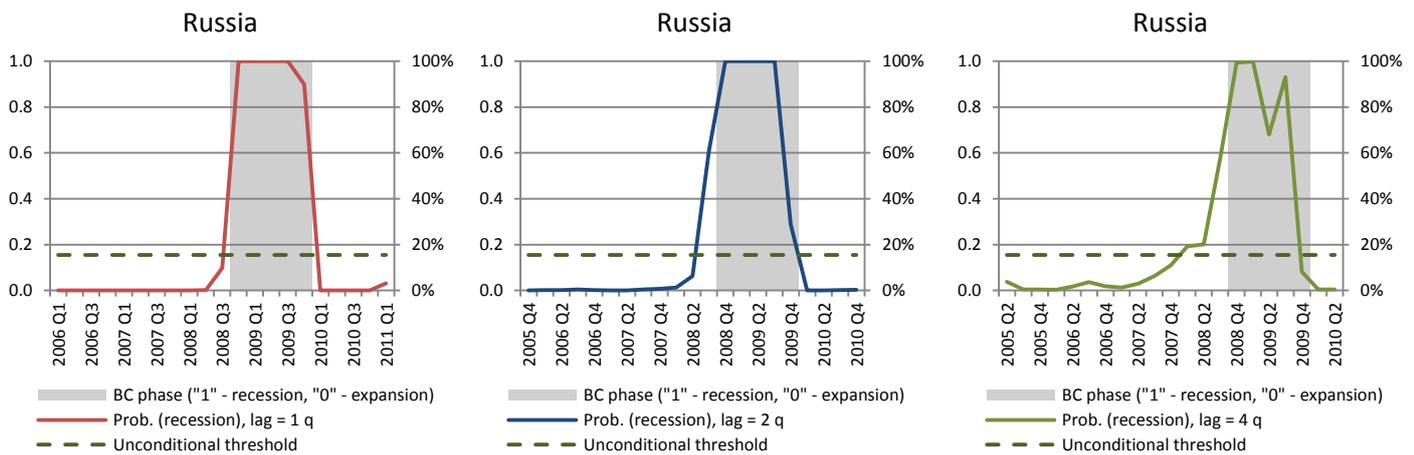
The analysis of the predictive power of models suggests that the model with various lags turns out to be the best among models with the same time lag of the explanatory variables (Table 4, the last column). In particular, this model slightly overrides the one-quarter lag model. The estimated various-lag model mostly consists of one-quarter lags of the explanatory variables (which are better than other lags in the univariate models, see Table A2 in Appendix) and also includes some financial sector variables that performed better at deeper lags (the estimation results are reported in Table A6 in Appendix). These financial sector variables, when included with long lags, are responsible for an increase in the predictive power of various-lag models when they are compared to the one-quarter lag analogues.

In Chart 5, I provide examples – for some major OECD countries – demonstrating the trade-off between the precision of forecasting recessions and the lead time when the signal of forthcoming crisis is issued. For USA, Germany and France, the recession model with one-quarter lag (first column of the chart) clearly gets actual dating. For the model with two-quarter lag, the noise ratio is higher; however, the predicted probability rises earlier than that in the model with one-quarter lag. When the model with four-quarter lag is considered, one can see that the prediction of recessions becomes quite noisy; but at the same time the time lag turns out to be long enough to implement appropriate policy measures.

As for Russia, the model with one-quarter lag fails to predict the 2008 recession in advance; despite the model issues a signal in a quarter before the beginning of macroeconomic downturn, the strength of the signal is insufficient. On the contrary, the models with two and four quarter lags are more successful since they break the threshold from one to three quarters before the recession actually started.

Chart 5. The actual and predicted probabilities of recession in USA, Germany, France and Russia in the models with real and financial sector variables with different lags





5. Conclusions

In this paper, I develop the leading indicators of the business cycle phases exploiting the quarterly panel dataset comprising OECD countries and Russia over the 1980-2013 period. Using a dynamic specification of the business cycle model, I show that the existing leading indicators in the OECD methodology are less precise in recession forecasting as compared to the models developed here. In particular, models with the following two sets of explanatory variables were estimated: with the real sector variables only and with both the real and financial sector variables. The estimation results clearly demonstrate that the adding financial sector variables leads to a significant increase in the quality of the models; this, in turn, causes a substantial growth of predictive power and a significant decline in the noise-to-signal ratio as compared to the models with the real sector variables only.

I apply an advanced analysis of cut-off thresholds for leading indicator models based on the optimization of regulator loss function. This method is widely used in the literature on financial crises, and was for the first time considered with regard to the leading indicator models of business cycle turning points.

I estimate the business cycle leading indicator models at different forecasting horizons (from one to four quarters). The results demonstrate that there is a trade-off between forecasting accuracy and the earliness of the recession signal. Best predictions are achieved for the one-quarter lag model (approximately 94% of the observations were correctly classified with a noise-to-signal ratio of 7%). The prediction results of the four-quarter lag model are the least precise (about 80% of recessions were predicted with a noise-to-signal ratio of 25%). However, the latter model can still be useful because the longer the forecasting horizon, the more time the regulators possess to prevent recessions and develop appropriate set of policy measures.

6. References

- Banerji, A. and Dua, P. (2011). Predicting Recessions and Slowdowns: A Robust Approach Working Paper No. 202. Centre for Development Economics, Delhi School of Economics.
- Berge, T. and Jorda, O. (2011). Evaluating the Classification of Economic Activity into Recessions and Expansions. *American Economic Journal: Macroeconomics*, 3(2), pp.246-277.
- Birchenhall, C., Jessen, H., Osborn, D. and Simpson P. (1999). Predicting U.S. Business-Cycle Regimes. *Journal of Business & Economic Statistics*, 17(3), pp. 313–323
- Bussiere, M. and Fratzscher, M. (2006). Towards a new early warning system of financial crises. *Journal of International Money and Finance*, 25(6), pp.953-973.
- Candelon, B., Dumitrescu, E. and Hurlin, C. (2014). Currency crisis early warning systems: Why they should be dynamic. *International Journal of Forecasting*, 30(4), pp.1016-1029.
- Cardarelli, R., Elekdag, S. and Lall, S. (2011). Financial stress and economic contractions. *Journal of Financial Stability*, 7(2), pp.78-97.
- Castro, V. (2010). The duration of economic expansions and recessions: More than duration dependence. *Journal of Macroeconomics*, 32(1), pp.347-365.
- Christiansen, C., Eriksen, J. and Moller, S. (2014). Forecasting US recessions: The role of sentiment. *Journal of Banking & Finance*, 49, pp.459-468.
- Claessens, S., Kose, M. and Terrones, M. (2012). How do business and financial cycles interact? *Journal of International Economics*, 87(1), pp.178-190.
- Conference Board (2000). Business Cycle Indicators Handbook.
- Demidov O. (2008). Different indexes for forecasting economic activity in Russia. *Quantile*, 5, pp. 83-102.
- Estrella, A. and Mishkin, F. (1998). Predicting U.S. Recessions: Financial Variables as Leading Indicators. *Review of Economics and Statistics*, 80(1), pp.45-61.
- Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2001). Coincident and Leading Indicators for the Euro Area. *Economic Journal*, 111(471), pp.62-85.
- Kauppi, H. and Saikkonen, P. (2008). Predicting U.S. Recessions with Dynamic Binary Response Models. *Review of Economics and Statistics*, 90(4), pp.777-791.
- Kim, C. and Nelson, C. (1999). Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle. *Review of Economics and Statistics*, 81(4), pp.608-616.
- Liu, W. and Moench, E. (2014). What Predicts U.S. Recessions? Federal Reserve Bank of New York Staff Report No. 691.
- Lo Duca, M. and Peltonen, T. (2013). Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance*, 37(7), pp.2183-2195.
- Mankiw, N. (2006). The Macroeconomist as Scientist and Engineer. *Journal of Economic Perspectives*, 20(4), pp.29-46.

- Mitchell, W., Burns, A. (1946). Measuring Business Cycles. NBER Studies in Business Cycles, No 2.
- Moneta, F. (2005). Does the Yield Spread Predict Recessions in the Euro Area? *International Finance*, 8(2), pp.263-301.
- Ng, E. (2012). Forecasting US recessions with various risk factors and dynamic probit models. *Journal of Macroeconomics*, 34(1), pp.112-125.
- Nyberg, H. (2010). Dynamic probit models and financial variables in recession forecasting. *Journal of Forecasting*, 29(1-2), pp.215-230.
- OECD (2008). OECD System of Composite Leading Indicators.
- Ozyildirim, A., Schaitkin, B. and Zarnowitz, V. (2010). Business cycles in the euro area defined with coincident economic indicators and predicted with leading economic indicators. *Journal of Forecasting*, 29(1-2), pp.6-28.
- Pestova, A. (2013). Predicting Turning Points of the Business Cycle: Do Financial Sector Variables Help? *Voprosy ekonomiki*, 7, pp.63-81.
- Porshakov, A., Deryugina, E., Ponomarenko, A. and Sinyakov A. (2015). The short-term estimation and forecasting Russia's GDP using dynamic factor model. The Bank of Russia series of reports on economic research No. 2
- Rebelo, S. (2005). Real Business Cycle Models: Past, Present and Future. *Scandinavian Journal of Economics*, 107(2), pp.217-238.
- Smirnov, S. (2001). The system of leading indicators for Russia. *Voprosy ekonomiki*, 3, pp.23-42.
- Stock, J. and Watson, M. (1992). A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience. NBER Working Paper Series. No 4014.
- Stock, J. and Watson, M. (2006). Forecasting with many predictors. In: Elliott, G., Granger, and Timmermann, A. (Eds.), *Handbook of Economic Forecasting*, 1, pp. 515-554 Amsterdam: Elsevier North-Holland.
- Stock, J., Watson M. (1999). Business cycle fluctuations in US macroeconomic time series. In: Taylor, J. and Woodford, M. (ed.), *Handbook of Macroeconomics*, 1(1), pp. 3-64. Amsterdam: North-Holland
- Stock, J. and Watson, M. (1989). New Indexes of Coincident and Leading Economic Indicators. *NBER Macroeconomics Annual*, 4, p.351.
- Stock, J. and Watson, M. (2002). Forecasting Using Principal Components From a Large Number of Predictors. *Journal of the American Statistical Association*, 97(460), pp.1167-1179.
- Weber, S. (1997). The End of the Business Cycle? *Foreign Affairs*, 76(4), pp.65-82.
- Zarnowitz V. (1996). Business Cycles: Theory, History, Indicators and Forecasting. Chicago: University of Chicago Press.
- Zarnowitz, V. (1985). Recent Work on Business Cycles in Historical Perspective: A Review of Theories and Evidence. *Journal of Economic Literature*, 23(2), pp.523-580.

Appendix – Additional empirical results

Table A1. Descriptive statistics of indicators used in the business cycle phase change models

Variable name	Number of obs.	Mean	Stand. dev.	Min.	Max
Phase of the business cycle (1 - recession, 0 - absence of recession*)	2621	0.15	0.36	0	1
GDP growth rates, over corresponding quarter of the previous year, %	3034	2.6	3.2	-18.6	34.6
Consumption, growth rate over corresponding quarter of the previous year, %	3002	2.7	3.9	-27.9	42.0
Investment in fixed capital, growth rate over corresponding quarter of the previous year, %	2986	2.3	9.8	-55.0	87.9
Inventories to GDP ratio, growth over corresponding quarter of the previous year, perc. points	3135	0.0	1.8	-9.0	8.4
Country GDP leading indicator, in OECD methodology, in annual terms, %	2492	2.3	2.6	-12.8	16.4
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year, %	2226	0.0	1.5	-11.3	9.0
Business confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year, %	2075	0.0	1.9	-8.3	8.3
US GDP leading indicator, in OECD methodology, in annual terms, %	3135	2.7	2.3	-6.0	9.0
Current account balance to GDP ratio, %	2848	-0.8	5.6	-27.0	17.5
REER index, 2005=100	3135	101.0	13.6	59.9	176.2
Stock price index, growth rate per quarter, %	2789	2.4	10.1	-57.2	54.3
Spread between interest rate on loans and government bonds interest rate, perc. points	3135	1.9	2.6	-5.8	14.6
Spread between money market interest rate and government bonds interest rate, perc. points	3053	-1.1	2.3	-12.6	33.8
Bank loans to GDP ratio, %	3036	81.4	57.6	5.7	346.2

Note: * – 1 corresponds to the quarters of recession (at least 2 quarters of negative GDP growth rates, over corresponding quarter of the previous year), 0 - all remaining observations

Table A2. The predictive power of individual leading indicators of the business cycle phase change

Dependent variable: phase of the business cycle (1 - recession, 0 - absence of recession)	Lag = 1 quarter		Lag =2 quarters		Lag =3 quarters		Lag =4 quarters	
	Coef-t	Pseudo R ²						
<i>Macroeconomic variables</i>								
GDP growth rates, over corresponding quarter of the previous year	-0.560***	0.046	-0.047	0.001	0.074***	0.004	0.118***	0.010
Investment in fixed capital, growth rate over corresponding quarter of the previous year	-0.084***	0.017	-0.013	-0.001	0.021***	-0.002	0.026***	0.003
Country GDP leading indicator, in OECD methodology, in annual terms	-1.028***	0.171	-0.837***	0.107	-0.348***	0.022	-0.067	-0.003
<i>Consumer and business expectations</i>								
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year	-0.984***	0.083	-0.813***	0.048	-0.527***	0.011	-0.190**	-0.008
Business confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year	-0.765***	0.065	-0.468***	0.012	-0.122**	-0.020	0.080	-0.019
<i>External sector variables</i>								
US GDP leading indicator, in OECD methodology, in annual terms	-0.571***	0.076	-0.366***	0.036	-0.145***	0.007	-0.002	0.000
Current account balance to GDP ratio	-0.098***	0.001	-0.103***	0.004	-0.120***	0.004	-0.131***	0.003
REER index, 2005=100	0.040***	0.009	0.037***	0.008	0.033***	0.006	0.034***	0.007
<i>Financial sector variables</i>								
Stock price index, growth rate per quarter	-0.086***	0.049	-0.072***	0.039	-0.083***	0.049	-0.037***	0.017
Spread between interest rate on loans and government bonds interest rate	0.119***	0.008	0.150***	0.011	0.157***	0.009	0.112**	0.008
Spread between money market interest rate and government bonds interest rate	0.170***	0.013	0.208***	0.015	0.211***	0.015	0.085	0.004
Bank loans to GDP ratio	0.009***	0.003	0.010***	0.006	0.011***	0.007	0.012***	0.010

Notes. * – significant at 10%; ** – significant at 5%; *** – significant at 1%. Pseudo R² is provided in differences from the corresponding indicator in the simple autoregressive business cycle model (only lag of the dependent variable is used as the explanatory variable). Negative values in Pseudo R² column mean that R² in autoregressive model is larger than in the model with additional explanatory variable.

Table A3. Estimation results of business cycle phase models (lag of all explanatory variables - 1 quarter)

Dependent variable: phase of the business cycle (1 - recession, 0 - absence of recession)	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
<i>Explanatory variables</i>				
Dependent variable (lag = 1 quarter)	4.591*** (16.25)	2.408*** (5.67)	2.683*** (5.74)	
Country GDP leading indicator, in OECD methodology, in annual terms	-1.027*** (-10.52)			
Investment in fixed capital, growth rate over corresponding quarter of the previous year		-0.087*** (-2.82)	-0.080** (-2.55)	-0.104*** (-2.97)
GDP growth rates, over corresponding quarter of the previous year		-0.632*** (-4.44)	-0.748*** (-5.02)	-1.258*** (-8.31)
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year		-0.780*** (-7.18)	-0.674*** (-5.62)	-0.646*** (-5.19)
US GDP leading indicator, in OECD methodology, in annual terms		-0.482*** (-5.42)	-0.418*** (-4.50)	-0.365*** (-4.49)
REER index, 2005=100		0.032*** (2.67)	0.028** (2.20)	0.028** (2.23)
Stock price index, growth rate per quarter			-0.070*** (-4.15)	-0.053*** (-3.60)
Spread between money market interest rate and government bonds interest rate			0.242*** (2.96)	0.256*** (3.44)
Constant	-1.692*** (-3.84)	-5.407*** (-3.96)	-4.582*** (-3.14)	-3.608** (-2.44)
Number of observations	1941	1941	1941	1941
Pseudo R-sq	0.699	0.710	0.729	0.701
Log pseudolikelihood	-242.4	-233.5	-218.7	-241.2
LR-test, significance of equation as a whole (P-value)	365.5 0.000	328.9 0.000	317.5 0.000	254.3 0.000
Number of countries	22	22	22	22
LR-test, absence of fixed effects (P-value)	0.286	0.318	0.462	0.097

Notes. t-statistics are in parentheses. * – significant at 10%; ** – significant at 5%; *** – significant at 1%

Table A4. Estimation results of business cycle phase models (lag of all explanatory variables - 2 quarters)

Dependent variable: phase of the business cycle (1 - recession, 0 - absence of recession)	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
<i>Explanatory variables</i>				
Dependent variable (lag = 2 quarters)	1.608*** (6.88)	0.855** (2.54)	0.931** (2.55)	
Country GDP leading indicator, in OECD methodology, in annual terms	-1.075*** (-14.72)			
Investment in fixed capital, growth rate over corresponding quarter of the previous year		-0.132*** (-5.37)	-0.136*** (-5.26)	-0.143*** (-5.52)
GDP growth rates, over corresponding quarter of the previous year		-0.084 (-0.81)	-0.167 (-1.47)	-0.305*** (-3.13)
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year		-0.796*** (-7.82)	-0.667*** (-6.05)	-0.667*** (-6.14)
US GDP leading indicator, in OECD methodology, in annual terms		-0.404*** (-6.92)	-0.317*** (-4.85)	-0.307*** (-4.72)
REER index, 2005=100		0.041*** (4.48)	0.032*** (3.03)	0.032*** (3.00)
Stock price index, growth rate per quarter			-0.059*** (-3.68)	-0.056*** (-3.60)
Spread between money market interest rate and government bonds interest rate			0.326*** (5.26)	0.343*** (5.31)
Bank loans to GDP ratio			0.012*** (3.31)	0.012*** (3.23)
Constant	-0.885** (-2.30)	-6.503*** (-6.06)	-5.251*** (-4.48)	-4.923*** (-4.21)
Number of observations	1881	1881	1881	1881
Pseudo R-sq	0.545	0.505	0.543	0.538
Log pseudolikelihood	-359.6	-390.5	-360.8	-364.8
LR-test, significance of equation as a whole (P-value)	399.2 0.000	303.0 0.000	297.6 0.000	279.0 0.000
Number of countries	22	22	22	22
LR-test, absence of fixed effects (P-value)	0.042	0.007	0.002	0.000

Notes. t-statistics are in parentheses. * – significant at 10%; ** – significant at 5%; *** – significant at 1%

Table A5. Estimation results of business cycle phase models (lag of all explanatory variables - 4 quarters)

Dependent variable: phase of the business cycle (1 - recession, 0 - absence of recession)	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
<i>Explanatory variables</i>				
Dependent variable (lag = 4 quarters)	-1.211*** (-4.40)	-0.315 (-1.13)	-0.476 (-1.46)	
Country GDP leading indicator, in OECD methodology, in annual terms	-0.703*** (-11.13)			
Investment in fixed capital, growth rate over corresponding quarter of the previous year		-0.033** (-2.03)	-0.030* (-1.74)	-0.014 (-1.05)
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year		-0.716*** (-7.71)	-0.511*** (-6.18)	-0.490*** (-6.03)
REER index, 2005=100		0.037*** (5.00)	0.025*** (2.92)	0.024*** (2.85)
Current account balance to GDP ratio		-0.126*** (-3.48)	-0.125*** (-3.22)	-0.126*** (-3.25)
Stock price index, growth rate per quarter			-0.077*** (-8.49)	-0.077*** (-8.47)
Spread between interest rate on loans and government bonds interest rate			0.356*** (4.82)	0.356*** (4.89)
Bank loans to GDP ratio			0.025*** (5.75)	0.024*** (5.79)
Constant	-0.743** (-2.01)	-6.253*** (-7.12)	-5.942*** (-6.37)	-5.923*** (-6.35)
Number of observations	1690	1690	1690	1690
Pseudo R-sq	0.285	0.216	0.323	0.321
Log pseudolikelihood	-513.8	-563.4	-486.7	-488.1
LR-test, significance of equation as a whole (P-value)	187.3 0.000	189.4 0.000	274.9 0.000	265.0 0.000
Number of countries	22	22	22	22
LR-test, absence of fixed effects (P-value)	0.023	0.000	0.000	0.000

Notes. t-statistics are in parentheses. * – significant at 10%; ** – significant at 5%; *** – significant at 1%

Table A6. Estimation results of business cycle phase models (various lags of explanatory variables)

Dependent variable: phase of the business cycle (1 - recession, 0 - absence of recession)	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
<i>Explanatory variables</i>				
Dependent variable (lag = 1 quarter)	4.566*** (15.14)	2.307*** (5.12)	2.649*** (5.13)	
Country GDP leading indicator, in OECD methodology, in annual terms (lag = 1 quarter)	-1.048*** (-9.68)			
Investment in fixed capital, growth rate over corresponding quarter of the previous year (lag = 1 quarter)		-0.071** (-2.37)	-0.065** (-2.04)	-0.077** (-2.14)
GDP growth rates, over corresponding quarter of the previous year (lag = 1 quarter)		-0.705*** (-4.59)	-0.803*** (-4.64)	-1.322*** (-7.86)
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year (lag = 1 quarter)		-0.831*** (-6.83)	-0.760*** (-5.81)	-0.731*** (-5.28)
US GDP leading indicator, in OECD methodology, in annual terms (lag = 1 quarter)		-0.496*** (-4.93)	-0.366*** (-3.38)	-0.323*** (-3.32)
Stock price index, growth rate per quarter (lag = 1 quarter)			-0.076*** (-4.46)	-0.055*** (-3.58)
Spread between money market interest rate and government bonds interest rate (lag = 3 quarters)			0.323*** (3.49)	0.362*** (4.04)
Bank loans to GDP ratio (lag = 4 quarters)			0.012** (2.50)	0.014*** (2.93)
Constant	-1.625*** (-3.66)	-2.102*** (-3.73)	-2.353*** (-4.16)	-1.437** (-2.36)
Number of observations	1686	1686	1686	1686
Pseudo R-sq	0.702	0.713	0.736	0.711
Log pseudolikelihood	-213.7	-206.4	-189.4	-207.7
LR-test, significance of equation as a whole (P-value)	324.4 0.000	269.4 0.000	238.6 0.000	192.1 0.000
Number of countries	22	22	22	22
LR-test, absence of fixed effects (P-value)	0.266	0.195	0.096	0.004

Notes. t-statistics are in parentheses. * – significant at 10%; ** – significant at 5%; *** – significant at 1%

Table A7. Dynamic business cycle phase models with real and financial sector variables, logit with dummy variables (DV) and fixed effects (FE) logit estimates

Dependent variable: phase of the business cycle (1 - recession, 0 - absence of recession)	2 lags model		4 lags model		lag	Various lags model	
	Logit with DV	Logit with FE	Logit with DV	Logit with FE		Logit with DV	Logit with FE
<i>Explanatory variables</i>							
Dependent variable (lag = k quarters)	1.035*** (2.63)	0.906*** (2.78)	-0.489 (-1.51)	-0.468* (-1.67)	1 q	2.649*** (5.13)	2.550*** (5.64)
Investment in fixed capital, growth rate over corresponding quarter of the previous year	-0.138*** (-4.86)	-0.131*** (-4.94)	-0.031* (-1.76)	-0.030* (-1.86)	1 q	-0.065** (-2.04)	-0.064* (-1.90)
GDP growth rates, over corresponding quarter of the previous year	-0.150 (-1.23)	-0.162* (-1.80)			1 q	-0.803*** (-4.64)	-0.751*** (-5.03)
Consumer confidence indicator, in OECD methodology, growth rate over corresponding quarter of the previous year	-0.670*** (-5.58)	-0.651*** (-7.43)	-0.513*** (-6.17)	-0.496*** (-7.33)	1 q	-0.760*** (-5.81)	-0.722*** (-5.89)
US GDP leading indicator, in OECD methodology, in annual terms	-0.326*** (-4.64)	-0.305*** (-5.46)			1 q	-0.366*** (-3.38)	-0.346*** (-4.14)
REER index, 2005=100	0.031*** (2.73)	0.031*** (2.79)	0.025*** (2.97)	0.024*** (2.74)			
Stock price index, growth rate per quarter	-0.074*** (-5.74)	-0.057*** (-5.11)	-0.077*** (-8.43)	-0.075*** (-8.30)	1 q	-0.076*** (-4.46)	-0.073*** (-4.46)
Spread between money market interest rate and government bonds interest rate	0.328*** (4.62)	0.314*** (5.11)	0.358*** (4.84)	0.348*** (5.86)	3 q	0.323*** (3.49)	0.308*** (3.40)
Bank loans to GDP ratio	0.015*** (3.99)	0.011*** (3.52)	0.025*** (5.76)	0.024*** (7.29)	4 q	0.012** (2.50)	0.011** (2.31)
Current account balance to GDP ratio			-0.126*** (-3.23)	-0.123*** (-3.46)			
Constant	-5.231*** (-4.15)		-5.992*** (-6.40)			-2.353*** (-4.16)	
Number of observations	1686	1881	1686	1690		1686	1686
Pseudo R-sq	0.557	0.542	0.323	0.308		0.736	0.749
Log (pseudo)likelihood	-317.8	-326.4	-485.8	-448.7		-189.4	-162.5
LR-test, significance of equation as a whole (P-value)	270.6 0.000	772.4 0.000	273.4 0.000	398.9 0.000		238.6 0.000	970.1 0.000
Number of countries	22	22	22	22		22	22

Notes. t-statistics are in parentheses. * – significant at 10%; ** – significant at 5%; *** – significant at 1%

Table A8. The quality of prediction of business cycle phase models, lag of all explanatory variables - 2 quarters

	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
Optimal threshold	0.13	0.17	0.19	0.16
<i>Full Sample</i>				
Noise-to-signal ratio	13.8%	12.4%	10.8%	12.4%
Recessions correctly predicted	91.4%	87.2%	89.8%	91.0%
Absence of recessions correctly predicted	87.4%	89.2%	90.3%	88.7%
<i>Russia</i>				
Noise-to-signal ratio	6.3%	12.5%	15.6%	15.6%
Recessions correctly predicted	100.0%	100.0%	80.0%	80.0%
Absence of recessions correctly predicted	93.8%	87.5%	87.5%	87.5%

Note. Optimal threshold is calculated based on regulator loss function minimization with $\theta = 0.5$, where θ is the regulator sensitivity to the type 1 errors as compared to the type 2 errors.

Table A9. Quality of prediction of business cycle phase models lag of all explanatory variables - 4 quarters

	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
Optimal threshold	0.19	0.14	0.19	0.15
<i>Full Sample</i>				
Noise-to-signal ratio	21.8%	35.2%	25.1%	25.3%
Recessions correctly predicted	73.7%	79.7%	81.2%	82.0%
Absence of recessions correctly predicted	83.9%	72.0%	79.6%	79.3%
<i>Russia</i>				
Noise-to-signal ratio	31.3%	41.7%	23.4%	23.4%
Recessions correctly predicted	60.0%	60.0%	80.0%	80.0%
Absence of recessions correctly predicted	81.3%	75.0%	81.3%	81.3%

Note. Optimal threshold is calculated based on regulator loss function minimization with $\theta = 0.5$, where θ is the regulator sensitivity to the type 1 errors as compared to the type 2 errors.

Table A10. Quality of prediction of recession models, various lags of explanatory variables

	Dynamic model with OECD GDP leading indicator only	Dynamic model with real sector variables only	Dynamic model with real and financial sector variables	Static model with real and financial sector variables
Optimal threshold	0.15	0.09	0.15	0.19
<i>Full Sample</i>				
Noise-to-signal ratio	7.1%	11.4%	6.9%	7.3%
Recessions correctly predicted	92.9%	96.2%	94.4%	93.2%
Absence of recessions correctly predicted	93.4%	89.0%	93.5%	93.2%
<i>Russia</i>				
Noise-to-signal ratio	0.0%	15.6%	7.8%	7.8%
Recessions correctly predicted	100.0%	80.0%	80.0%	80.0%
Absence of recessions correctly predicted	100.0%	87.5%	93.8%	93.8%

Note. Optimal threshold is calculated based on regulator loss function minimization with $\theta = 0.5$, where θ is the regulator sensitivity to the type 1 errors as compared to the type 2 errors.

Anna Pestova, Center for Macroeconomic Analysis and Short-Term Forecasting (CMASF), Institute of Economic Forecasting, Russian Academy of Sciences; and National Research University «Higher School of Economics», Moscow, Russia.

Email: annapestova@gmail.com

© Pestova, 2015