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Liudmila Kitrar, Tamara Lipkind, Georgy Ostapkovich

THE PERFORMANCE OF BUSINESS AND CONSUMER SENTIMENT FOR EARLY ESTIMATES OF GDP GROWTH: OLD TURNING POINTS AND NEW CHALLENGES OF THE CORONA CRISIS

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Liudmila Kitrar[1]*, Tamara Lipkind*[2]*, Georgy Ostapkovich*[3]

THE PERFORMANCE OF BUSINESS AND CONSUMER SENTIMENT FOR EARLY ESTIMATES OF GDP GROWTH: OLD TURNING POINTS AND NEW CHALLENGES OF THE CORONA CRISIS[4]

This study proves the efficiency of the results of business and consumer surveys for the first early estimates of GDP growth in Russia. For the expert community, the use of this alternative information, which is not revised over time and covers major economic activities, is essential when up-to-date traditional statistical information are not available, are often revised, and published with a delay.

The main hypothesis of the joint cyclical sensitivity of flash estimates of aggregate entrepreneurial behaviour and reference statistics on GDP growth is tested. For this purpose, the authors calculate the composite economic sentiment indicator (ESI), which combines 18 indicators based on the results of surveys of approximately 24,000 entrepreneurs in all main economic activities and 5,100 consumers. The empirical patterns, cyclical movement, the correspondence of turning points in GDP growth and ESI dynamics, and GDP expected estimates are identified through the joint testing of the analysed series. The authors present the results of cross-correlations, Hodrick-Prescott statistical filtering, a long-term interrelation, and a two-dimensional vector autoregression model.

Statistically significant test results and the pattern of the impulse response function allow us to evaluate the quarterly nowcasts of GDP growth with the maximum predictive period of four quarters. Three scenarios of expected impulses in the dynamics of aggregate economic sentiments, different in strength and duration of their impact on further economic growth, are formed; these impulses include new crisis shocks for the Russian economy, which have been growing since March 2020. The resulting options of assessments reflect the possible amplitude of the decline in GDP growth from mid-2020, after COVID-19 containment measures and the collapse of oil prices. According to the results, the first signs of a recovery in low economic growth rates are possible only by mid-2021.

Keywords: business and consumer surveys, economic sentiment indicator, business confidence, composite indicators of business cycle, leading indicators, economic growth, GDP growth, growth cycles.

JEL: C81, C82, E32, O47.

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[1] National Research University Higher School of Economics, Russian Federation. Institute for Statistical Studies and Economics of Knowledge, Centre for Business Tendency Studies. Deputy Director, lkitrar@hse.ru, ORCID: 0000-0002-6383-9562

[2] National Research University Higher School of Economics, Russian Federation. Institute for Statistical Studies and Economics of Knowledge, Centre for Business Tendency Studies, leading expert, tlipkind@hse.ru, ORCID: 0000-0003-2632-9026

[3] National Research University Higher School of Economics, Russian Federation. Institute for Statistical Studies and Economics of Knowledge, Centre for Business Tendency Studies. Director, gostapkovich@hse.ru, ORCID 0000-0003-2793-0446

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Introduction

Expectations of economic growth until the end of 2020 are becoming more pessimistic for the Russian economy, with a high probability of a noticeable drop into the negative zone. According to the forecasts of leading international organizations, the real GDP in Russia will decrease by 5.5-6% in 2020 (World Bank, 2020; IMF, 2020). The process that began in the economy at the end of the 1st quarter and is associated with the quarantine shutdowns of economic activity during the outbreak of the coronavirus, inevitably undermines the demand and supply from all economic agents – enterprises, households, and financial organizations.

To overcome the economic and social consequences of such a negative external impulse, public resources are being redistributed to control the epidemic and prevent sectoral recessions. Financial assets earmarked to achieve the development priorities are inevitably reduced, while income from economic activities, especially from the export of primary goods, are insufficient to cover all expenses including contingencies. Specifically, in April 2020, the expenditures of federal budget for social purposes increased by 54.4% y-o-y (16.6% of GDP) and for the "General State Issues" by 64.9% y-o-y (3.4% of GDP) due to the measures to mitigate the COVID-19 consequences, including benefits for unemployed and families with children, additional payments to medical personnel, and medical equipment. Budget expenditures will continue to grow rapidly, as funding for measures to support the economy will increase. At the same time, oil and gas revenues to the budget decreased significantly – by 69.7% y-o-y (6.1% of GDP) in April 2020 due to the fall in commodity prices on the global market. Budget revenues are also negatively affected by the decline in tax revenues caused by the pandemic-driven contraction of economic activity (Bank of Russia, 2020). Sectoral events related to the closure of enterprises, delays in the resumption of trade and production activities, and, as a result, breaks in production and supply chains aggravate the situation with budget cuts.

The sudden weakening of the financial security of entrepreneurs and households, when the former are increasingly unable to make investment decisions, while the latter significantly limit consumption, is becoming a considerable challenge. The prospects for overcoming sectoral negative developments and a subsequent rapid V-shaped recovery are becoming more distant (World Bank, 2020).

The growing uncertainty of economic prospects, the new challenges for the economy and society, and the risks of o deteriorating situation compared with preliminary "here and now" estimates over-complicate the flash quantitative measurements of current and expected economic development. In particular, the complexity of measurements is affected by the indirect nature of the damage caused to the economy by the sharp contraction of business confidence, very restrained intentions and negative expectations.

We expect that such uncertainty exacerbated by the sudden changes for the worse, if it persists (even for one-two quarters) will have a strong negative effect on aggregate demand. In order to more reliably assess the expected progress of Russia towards achieving its Sustainable Development Goal, especially in the new economic situation, and to increase the effectiveness of the relevant statistical monitoring, we consider it advisable to focus on information from business and consumers based on regular large-scale surveys by Federal State Statistic Service (Rosstat). For this reason, within the joint study of the cyclical dynamics of GDP growth and aggregate entrepreneurial behaviour, the key question is how effective for the Russian practice of the early assessments of macroeconomic development are the quantified and combined opinions of economic agents, especially with sudden short-term impulses in sectoral evolution.

As a special case for quarterly nowcasts of GDP growth using the results of Rosstat business and consumer surveys (BCS), we examine the impulses in the dynamics of the composite survey indicator from the beginning of 2020 in the context of a possible new cyclical reversal and subsequent recession.

We test the following two hypotheses:

- Short-term economic cycles are caused not only by shocks in the aggregated dynamics of economic events but also by impulses that are generated in the business environment in response and which spread backward to the economic system, and affect the fluctuations of sectoral and macro indicators;
- The opinions, intentions, expectations, uncertainty, and confidence of entrepreneurs and consumers are considered as both outcomes of the ongoing economic events and warning factors, the basis for making current and future economic decisions that affect real-time aggregate economic activity.

Besides these hypotheses, there are practical considerations about the relevance of timely and non-revised information on entrepreneurial behaviour in the cyclical analysis of the Russian economy. These so-called “soft” statistics are often 3-4 months ahead of the official release of quantitative “hard” statistics. These practical considerations include the quality of traditional hard statistics, the coverage of the observed phenomena, the number and timing of information revisions, the lack of necessary short-term data at every moment and the possibility of replacing or replenishing missing data with relevant survey-based information (UN 2015, UNECE 2019, OECD 2003, 2012, EC 2019a). The problems of the collecting and treatment of quantitative statistics are compounded when sudden shocks, challenges, new risks, and uncertain sectoral consequences put pressure on the economy.

Business and consumer surveys as a measurement method and source of information

Literature review

The composite indicators of sentiment based on BCS results are widely used in international practice for the early estimated of economic growth. (e.g. the European Commission's harmonized confidence indicators[5], the OECD's Composite Leading Indicators[6], the Purchasing Managers’ Index (PMI) by IHS Markit[7], the Eurocoin[8], the EUROFRAME Euro Growth Indicator[9], ifo Business Climate Index[10] and the ZEW Indicator of Economic Sentiment[11] for Germany, the French business climate indicator[12] and the KOF Economic Barometer for the Swiss economy[13]). These indicators, obtained by aggregating individual measures that reflect the perceptions or expectations of respondents, evaluate multidimensional phenomena, which are not covered by traditional statistics. Over the past decade, composite sentiment indicators are in high demand; they become official statistical short-term indicators and are used in various areas of economic analysis, including business cycles analysis, measuring well-being, sentiments,

[5] The Directorate-General Financial and Economic Affairs of the European Commission, https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en.

[6] Organisation for Economic Co-operation and Development, https://www.oecd.org/sdd/leading-indicators/.

[7] IHS Markit, https://ihsmarkit.com/products/pmi-faq.html

[8] Centre for Economic Policy Research & Banca D’Italia, https://eurocoin.cepr.org/

[9] EUROFRAME, https://www.euroframe.org/Indicator.html

[10] Ifo Institute, https://www.ifo.de/en/survey/ifo-business-climate-index

[11] ZEW – Leibniz Centre for European Economic Research, https://www.zew.de/en/publikationen/zew-gutachten-und-forschungsberichte/forschungsberichte/konjunktur/zew-finanzmarktreport/

[12] INSEE – Insititut national de la statistique et des etudes economiques, https://www.insee.fr/en/statistiques/4498169

[13] KOF Swiss Economic Institute, https://kof.ethz.ch/en/news-and-events/media/press-releases/2020/05/kof-economic-barometer-historical-low-reached.html

confidence and expectations of businesses and households, as well as in international comparisons (UNECE 2019).

In particular, the economic sentiment indicator (ESI) is widespread in European countries; ESI is calculated and published monthly by the European Commission (EC) for Member States, European Union (EU) and euro-area within the Joint Harmonized EU Programme of BCS. The economic rationale and the algorithm for ESI calculation are presented in the basic methodological recommendations by the Directorate-General for Economic and Financial Affairs (DG ECFIN) EC (EC 2019a).

ESI is a coinciding composite indicator of business activity, as it changes synchronously with the dynamics of the reference statistic: GDP growth. However, ESI, which uses simple questionnaires and short data processing, is published much earlier than GDP, thus providing early signals of changes in economic activity. Timeliness and a high synchronous correlation with the reference statistic are the key ESI advantages (UNECE 2019, EC 2019a, Lipkind et al, 2019).

A broad consensus has been reached regarding the coincident properties of BCS indicators; there is also evidence of their ability to predict the evolution of economic growth (Cesaroni 2011). Recent studies investigate the performance of survey-based composite indicators, including ESI, during recessions and crises at both European and country levels. Biau and D'Elia (2011) give evidence of a change in the relationship between ESI and GDP growth in European countries before and after the 2009 crisis and conclude that the further study of this relationship is necessary. A number of papers examine the possible change in correlations between quantitative (hard) statistics and qualitative (soft) survey-based indicators after the European Great Recession of 2008-2012 (EC 2016a, Gayer and Marc 2018). The studies confirm the hypothesis of a level shift or ‘new modesty’, according to which the survey indicators rose to values that did not correspond to the post-crisis levels of the reference indicators (GDP growth, industrial production, etc.). This shift must be taken into account when interpreting survey results and formulating regression-based conclusions about economic activity.

Nonetheless, the BCS indicators are still an important tool in economic analysis and forecasting. European studies (EC 2017q2) prove that the post-crisis ESI dynamic demonstrates an even higher correlation with annual GDP growth. Astolfi et al. (2016) confirm the leading nature of dated turning points based on OECD composite indicators compared to those based on national accounts during the Great Recession. Cesaroni and Iezzi (2017) note the high statistical ability of survey-based indicators to predict macroeconomic changes in the short term.

The seminal papers on nowcasting economic growth (Runstler and Cedillot, 2003; Banbura and Runstler, 2007; Giannone et al., 2005; Angelini et al., 2008) investigate the role of high frequency indicators, both quantitative and qualitative, and find that they provide useful information for predicting GDP. The empirical results of further studies show that adding flash BCS data to the set of indicators can improve nowcast and forecast accuracy (Darracq Paries and Maurin, 2008; Drechsel and Maurin, 2011; Girardi, 2014; Girardi et al., 2015).

For the early estimates of economic growth using BCS indicators various econometric methods are applied. Lehmann and Wohlrabe (2013) develop an autoregressive distributed lag (ADL) model with hard and soft statistics for forecasting GDP in German regions. D´Amato et al. (2015) exercise nowcasting of Argentinian GDP growth using bridge equations and a dynamic factor model (DFM) with consumer surveys data. DFM models, which include survey information, are also used to forecast GDP for euro area (Banbura and Runstler, 2007; Basselier et al., 2017) and for France, Germany, Italy, Japan, United Kingdom and the United States (Ollivaud et al., 2016). Galli et al. (2019) apply DFM and a mixed frequency data sampling (MIDAS) regression models to monitor short-term economic developments in Switzerland. The nowcasting performance of MIDAS regression model for euro area GDP in a pseudo real-time setting is evaluated in the EC paper (EC, 20181q).

A vector autoregressive (VAR) models based on BCS data or combined hard and soft statistics are developed in Hansson et al. (2003), Erkel-Rousse and Minodier (2009), Mattos et al (2016) and in EC studies (EC, 2014). The researchers conclude that VAR forecasting accuracy often outperforms the alternatives procedures including DFM.

Data source

All our research, which reflects the assessments, intentions, and expectations of economic agents in the context of the “economic growth – business and consumers confidence” model, is based on the results of surveys conducted by the Federal state statistics service (Rosstat) in all 85 regions of Russia and six basic sectors of the economy, according to the methodology proposed by the HSE[14] Center for Business Tendency Studies (CBTS). In recent years, a stratified sample of regular and pilot surveys covered more than 53,000 observations: 3,100 manufacturing and 500 mining firms (monthly), 6,000 construction organizations (quarterly), 4,000 retail and 4,000 wholesale firms (quarterly), 6,000 services organisations (quarterly), 5,100 consumers (quarterly). The annual survey of investment activity covers more than 23,000 industrial enterprises[15]. The pilot survey collects data from about 1000 industrial enterprises, 700 retail organizations, 600 ICT organizations and 1,000 investment-active industrial enterprises. The surveys were gradually introduced into state statistical practice from 1998, first by the Centre for Economic Analysis under the TACIS program, and then, from 2009, by the CBTS in collaboration with Rosstat. All the series of survey-based indicators are accumulated in the CBTS database and distributed to external users, including the OECD database.

These surveys contain qualitative assessments and expectations: all respondents are asked about the current level, recent and expected changes in their business. The answers are aggregated in the form of balances, which are constructed as the difference between the percentages of positive and negative replies, that is, an "increase" and "decrease" in the indicator compared to the previous period or the indicator level "above normal" and "below normal" in the surveyed period (EC 2019a). The series of balances are used to build various composite indicators, as possible harmonized with the recommendations of the DG ECFIN and OECD (EC 2019a, OECD 2003) for cross-country comparative analysis. The quantified results of the surveys mainly reflect early measurements of current and expected business tendencies in various sectors of the economy. All primary questions and indicators are developed taking into account the specifics of the Russian economy.

The approach to data aggregation

The regular publication of ESI, which summarizes the all BCS results about entrepreneurial and consumer confidence in the current and expected economic situation, is a key area of our research related to the survey methodology. The practical relevance of regular ESI

[14] National Research University Higher School of Economics.

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calculations is determined by the rapid indexation of sectoral confidence and aggregate sentiment indicators as early estimates that highly correlate with national GDP growth. This is essential under in the format of the “new modesty” of the sluggish economic growth in Russia in recent years, interrupted by sudden stressful situations, when the expert community needs any relevant short-term information to quickly respond to possible cyclical fluctuations in macro and sectoral development.

We calculate ESI by integrating the opinions and expectations of 29,000 economic agents, according to the results of surveys in six sectors of the economy and households. A significant part of the information coming from the business environment is compressed, minimizing the problem of data dimensionality for subsequent analysis. In addition, this indicator is unique because it covers the largest number of respondents and economic activities in Russia and can be compared with international indicators both in terms of information coverage and cyclical sensitivity. For the ESI calculation, we use 18 indicators from regular BCS by Rosstat that promptly reflect the short-term fluctuations in entrepreneurial and consumer estimates of business tendencies in the Russian economy in 1998-2018. These indicators include the following:

- The level of demand, expected changes in output and the level of stocks of finished goods in mining and manufacturing;
- The level of orders book and expected changes in employment in construction;
- Current and expected changes in the economic situation of organizations and the level of stocks in retail;
- Current and expected changes in the economic situation of organizations and the level of stocks in wholesale;
- Current and expected changes in demand for services and current changes in the economic situation of services organizations;
- Consumer confidence indicator.

Methodologically, the ESI consists of the harmonized set of components recommended by EC, which was expanded by including three wholesale components and dividing industrial activities into mining and manufacturing. Because wholesale trade is a significant part of the Russian economy and its share is almost 10% of total gross value added, the ESI expansion allows us to summarize the survey results in economic activities with a total contribution to GDP of up to 70%. The breakdown of confidence indicators by kinds of industrial activities makes it possible to more accurately track short-term fluctuations in the combined information. The ESI calculation algorithm includes seasonal adjustment and the standardization of components; their weighting according to their shares in GDP; and summing up the components and normalizing the result with an average value of 100 and a standard deviation of 10.

For the ESI calculation, all individual components are standardized to make them comparable in terms of their average level and variation (in this study, we use a sample for the period 1998-2019, or 88 quarters):

$$Y_{1,t} = \frac{X_{1,t} - \overline{X1}}{S_1} \tag{1}$$

where $S_1 = \sqrt{\frac{1}{87}\sum_{t-1}^{88}\left(X_{1,t} - \bar{X}_1\right)^2}$, $\bar{X}_1 = \frac{1}{87}\sum_{t-1}^{88} X_{1,t}$

At the second iteration, all standardized series are weighted according to their sectoral weights. The sum of weights for each component $j = \overline{1,18}$ is determined at each time moment *t*; the weights are the shares of each sector in GDP for each quarter of all years:

$$\left(\sum_j w_j\right)_t \text{, where } j = \overline{1,18} \tag{2}$$

The weighted sum is divided by the sum of the assigned weights:

$$Z_t = \frac{\sum_j w_j * Y_{j,t}}{\left(\sum_j w_j\right)_t} \tag{3}$$

As a result, the time series $Z(t)$ is determined.

At the third iteration, the calculated weighted average values are scaled to have an average value over a long period of 100 and a standard deviation of 10.

$$\bar{Z} = \frac{1}{87}\sum_{t=1}^{88} Z_1 \tag{4}$$

$$S_Z = \sqrt{\frac{1}{87}\sum_{t-1}^{88}(Z_t - \bar{Z})^2} \tag{5}$$

$$ESI_t = \left(\frac{Z_t - Z}{S_Z}\right) * 10 + 100 \tag{6}$$

According to the logic of the ESI construction, the deviations of its values from the long-term average level of 100 identify the deviations of economic activity from a neutral situation. The growth of ESI above 100 reflects high economic activity and an increase (even a boom, overheating) of entrepreneurial optimism; a close approach to 100 indicates uncertain activity, slowing positive trends and confidence growth; and values significantly below 100 mark an increase in recessionary events (crisis) and depressive sentiments.

In the study, the ESI series are iteratively tested for sensitivity to a short-term cyclical profile in the dynamics of GDP growth. The algorithm for such a joint decomposition of quantitative and qualitative indicators is based on the two-fold linear Hodrick-Prescott (HP) statistical filter (Hodrick and Prescott 1997; Nilsson and Gyomai, 2011). The HP filter calculates the smoothed series s_t of the time series y_t through the minimization of the dispersion of the s_t elements around y_t:

$$\sum_{t=1}^{T}(y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1}\left((s_{t+1} - s_t) - (s_t - s_{t-1})\right)^2 \rightarrow min \qquad (7)$$

where s_t is the smoothed series of the time series y_t.

The smoothing parameter λ is calculated as:

$$\lambda = \left(2 * \left(\frac{\pi}{cut\text{-}off\ frequency}\right)\right)^{-4} \qquad (8)$$

where the *cut-off frequency* parameter is determined by the smoothing period.

This algorithm allows us to extract unobservable cyclic components with a smoothed amplitude. According to our previous studies, a double pass of the HP filter should be applied for the decomposition of ESI dynamic, if the pessimism/optimism accumulated at certain time intervals technically breaks the inherent stationarity of the analysed time series. In this case, the first HP pass at low frequencies (with $\lambda = 8330.69$) neutralizes the influence of a long-term stable component (15 years), and the second pass (with $\lambda = 6.885$) extracts a growth cycle smoothing out fluctuations with an amplitude of less than 30 months. For stationary time series, only one pass of the HP filter at high frequencies is used. The logic of this calculation and the periods of smoothing were previously established empirically (Kitrar et al. 2015).

The empirical measurement of economic growth in Russia is a difficult task, primarily due to the lack of long-term time series, especially at the industry-disaggregated level. In addition, frequent revisions of statistical information and weights, different denominators, and the low comparability of sectoral performance indicators complicate the interpretation of the results of large-scale nonlinear models. In this situation, we consider it acceptable to focus on relatively simple model specifications consisting of a minimum number of equations that reflect a single theoretical macroeconomic relationship and, consequently, the most significant determinants of the modelled process. In that regard, we use an approach to modelling the cyclical relationship of indicators based on "empirical facts about business cycles" and by constructing vector autoregressions, initially allowing the recommended number of parameters of the standard VAR model no more than 7-8 (for example, Bernanke et al., 2005). The model representation may differ significantly. For example, it can reflect a priori taken theoretical macroeconomic ratio (Korhonen and Mehrotra, 2010; Mehrotra and Ponomarenko, 2010). In (Korhonen and Mehrotra, 2009), economic shocks are identified based on a theory-driven identification scheme. In (Granville and Mallick, 2010; Mallick and Sousa, 2013), sign restrictions are imposed on the response impulse functions or they are considered as the most important determinants of the modelled process (Rautava, 2013). Bayesian VAR (BVAR) models are aimed at overcoming the "curse of dimensionality"; they allow obtaining valid results of scenario forecasts and simulation analysis when simultaneously modelling a large number of economic variables. The "compression" of the number of estimated parameters is based on the researcher's a priori ideas about the possible distribution of the covariance matrix, for example, by the Minnesota prior introduction (Litterman, 1986). In the case of a large number of diverse time series with "jagged edges" and frequent revisions, the BVAR models are very effective in terms of their ability to cover large-dimensional information matrices and have empirically based parameterization, for example, for the development of monetary policy, which is standard practice of many Central banks (De Mol et al., 2008; Banbura et al., 2010; Giannone et al., 2012; Banbura et al., 2014).

In our case, the statistical relationship between the ESI dynamics and the quantitative reference indicator (GDP growth) is confirmed in the study using a two-dimensional vector autoregression model (VAR), when the behaviour of each variable depends on the past values of both the variable itself and other series included in the model (Mayr and Ulbricht, 2007; Lütkepohl, 2011). Hence, each of the equations of such a model assumes the functional dependence of one of the endogenous variables on the lag values of all the variables in the model. Using a basic universal specification for two economic dynamics, such as GDP growth and ESI, we mainly wish to demonstrate that the relationship under consideration for most sectoral events with a high probability reflects a situation where the aggregate decisions of managers and households affect (significantly and ahead of) the total economic activity in the current and future periods. Therefore, when choosing the strategies for economic development, it is necessary to focus not only on the current behaviour of economic agents, but also on the expected economic growth in the short term, as a result of most current business actions and intentions.

Taking into account these basic assumptions for the specification, the proposed model includes two jointly dependent macro-variables: X_t and Y_t where t is quarters for the period 2008-2020. Accordingly, we use a second-order VAR model of two equations, each of which (separately for X_t and Y_t) includes autoregressive components of the second-order: X_{t-1}, X_{t-2}, Y_{t-1}, Y_{t-2}.

$$X_t = \alpha_1 + \beta_{11}^{(1)} X_{t-1} + \beta_{11}^{(2)} X_{t-2} + \beta_{12}^{(1)} Y_{t-1} + \beta_{12}^{(2)} Y_{t-2} + \varepsilon_{1t} \quad (9)$$

$$Y_t = \alpha_2 + \beta_{21}^{(1)} X_{t-1} + \beta_{21}^{(2)} X_{t-2} + \beta_{22}^{(1)} Y_{t-1} + \beta_{22}^{(2)} Y_{t-2} + \varepsilon_{2t} \quad (10)$$

where α_1, $\beta_{11}^{(i)}$, $\beta_{12}^{(i)}$, α_2, $\beta_{21}^{(i)}$, $\beta_{22}^{(i)}$ are estimated model parameters, $i(1,2)$.

The random residuals in the equations are denoted as ε_{1t} and ε_{2t} and are white noise processes with the following distribution parameters:

$$E(\varepsilon_{1t}) = 0, Var(\varepsilon_{1t}) = \sigma^2 \quad (11)$$

$$E(\varepsilon_{2t}) = 0, Var(\varepsilon_{2t}) = \sigma^2 \quad (12)$$

The initial time series for the period of 2005-2019 are preliminary tested for stationarity using the Augmented Dickey-Fuller test. The asymptotic p-values is 0.0004 for GDP growth and 0.0001 for ESI allow the rejection of the hypothesis of the time series non-stationarity for the period of 2005-2020, which confirms the feasibility of VAR modelling. We also prove the optimal lag number of two (quarters), based on the fact the smallest values of the Akaike, Schwartz, and Hennan-Quinn information criteria (9.042, 9.331 and 9.158, respectively) are defined for a model with two lags.

Note that in the VAR model used, variables are defined within the system and are endogenous. The presence of delayed relationships for 2 quarters allows us to classify this model as dynamic. The universality and simplicity of the proposed model is one of the main advantages that we were guided by, limiting its specification according to the goal of the study.

We first interpret the results of VAR simulation through impulse response functions (IRF), when a shock (equal to one standard deviation for the entire analysed period) that could have an effect on the analysed series, has artificially introduced in the dynamics of each variables on the right end of the studied interval. Thus, we determine the time of the return of one endogenous variable to the equilibrium trajectory after a single shock of another variable. For the calculation, we used the EViews 10 software package.

The use of IRF allows us to clarify the relationship between the series included in the model, to estimate the strength and direction of the shock, and the duration of the estimated series adjustment. The impulse response reflects the statistically significant relationship between the model variables that were used to calculate scenario expectations for GDP growth with three possible options for the gaps of ESI in mid-2020 relative to its long-term average level.

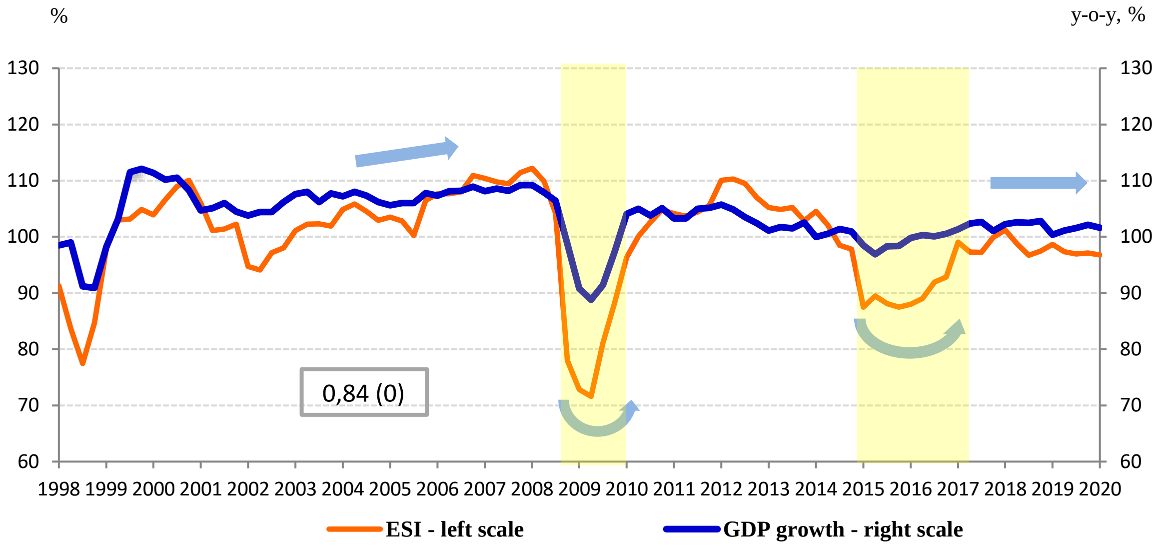
In addition, we confirmed the quality of the obtained forecast values by comparing the forecast values of GDP growth calculated sequentially according to the proposed model, with GDP growth real values, for example, for the period from Q1 2015 to Q4 2019. In this selected in-sample period, the validity of the model for the quarterly forecast is confirmed based of the obtained parameters of forecast accuracy: R-squared = 1.86, standard error of equation = 1.79, root-mean-square error (RMSE) = 1.74, mean error (ME) = -0.0000056, mean absolute error (MAE) = 1.26, mean absolute percentage error (MAPE) = 1.2%.

Based on the selected model specification (9, 10), we evaluate quarterly GDP growth for one year ahead. This evaluation is based on the IRF as a projection of GDP growth on a given pool of impulses in the ESI dynamics in Q2 2020 and its own lag values.

The proposed method of analysis is largely an illustration of the use of an empirical approach, which is available to researchers and is flexible and convenient for solving more complex problems that require the introduction of additional indicators and complicating the specification.

Results of comparing the ESI and GDP growth dynamics: visualization, cross-correlation and dispersion diagram

We observe the longest cyclic phase in the last decade of economic development in Russia since 2013, when economic growth clearly turned towards gradual deceleration and increasing stagnation for the first time. Since mid-2014, GDP began to fall, gradually falling into a recession and a large-scale aggravation of systemic crisis phenomena. The lower turning point of the cyclic phase was overcome by mid-2015, followed by a long period of an uneven sluggish slowdown in recession (UNIDO 2017); a slow and fragile recovery eventually began in 2017 in the context of the "new modesty" of economic development and continued in the beginning of 2020. Fig. 1 presents the joint movement of the ESI and GDP growth dynamics in 1998-2020.



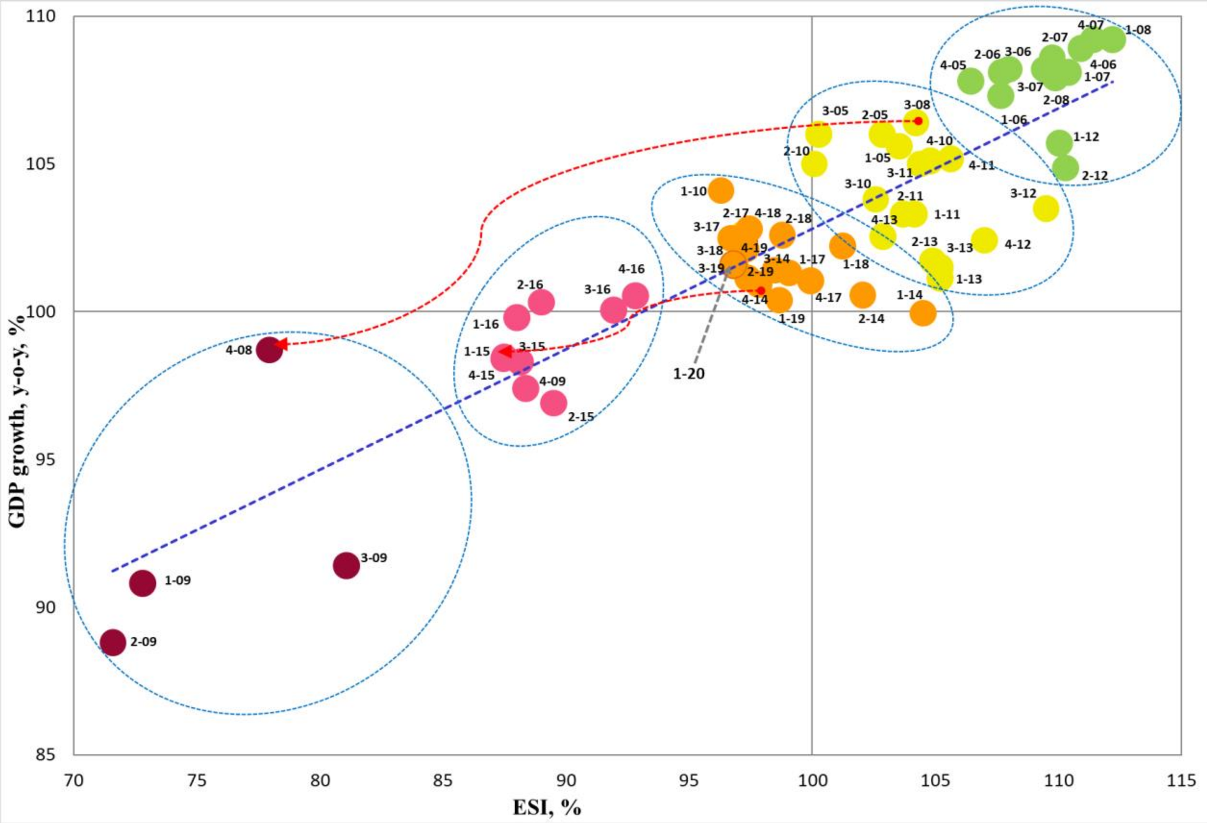
Note: The marker indicates the correlation coefficient between the ESI and GDP series, which shows the strength of the connection and its synchronous nature.
Source: Rosstat, Center for Business Tendency Studies, authors' calculations.

Figure 1. ESI and GDP growth dynamics

At the beginning of 2019, the annual GDP growth rate decreased almost to the level of Q4 2017, and more optimistic estimates of its dynamics until the end of 2019 indicated a decrease in the impact of vulnerability factors. However, noticeable changes in the ESI dynamics have not occurred as of the beginning of 2020. The uncertainty of opinions and expectations, close to pessimism, remained in the economy. Nevertheless, the stabilization of the national economy under the secondary effects of external challenges and internal shocks was largely caused by the high adaptation of the activity of economic agents to the counter-recession actions of regulators. This resulted in the limited extent of the economic slowdown compared to the previous recessions in Russia after 1998. In Q1 2020, the COVID-19 shocks, in the absence of restrictive measures in Russia, had almost no impact on the national economy.

The prompt calculation of ESI, which is almost two months ahead of the first quantitative estimate of GDP growth, and the stable synchronous correlation [0.84] between these series are the first evidence of the feasibility of using ESI as an early estimate of possible changes in the national economic growth.

A scatter graph enhances the primary visualization of the correspondence between the ESI and GDP growth (see Fig. 2).



Source: Rosstat, authors' calculations

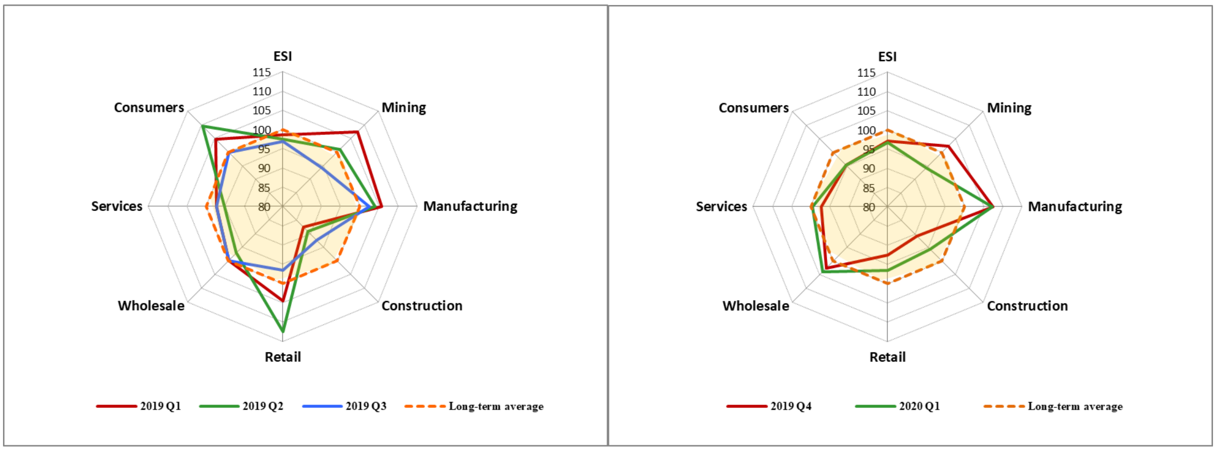
Note: Green markers indicate periods of the boom of optimism and highest GDP growth with quarters of economy overheating at the intersection of the highest values; yellow markers – high ESI values and high GDP growth; orange markers – neutral ESI values and low GDP growth; pink markers – low ESI values and moderate GDP decline; burgundy markers – extremely low ESI values and recessions of economic growth with crisis quarters at the intersection of the lowest values.

Figure 2. Scatter chart of GDP growth and ESI in 2005-2019

According to this representation, a pronounced long-term pattern in the dynamics of the two indicators is observed over the past 15 years: with an increase/decrease in ESI values, GDP changes in the same direction and (mainly) more intensively. However, in different episodes of cyclic development, the relationships between the levels of these time series differ. In the range of the highest values, which correspond to the periods of the most successful economic development, and especially during economic overheating, the ESI grows faster than GDP, and therefore, we can consider such fast-growing optimism as the most important trigger of GDP growth. In the range of extremely low values, we observe an inverse dependence. A slowdown in overall economic growth leads to a more intense increase in pessimism. As economic development stabilizes, entrepreneurial opinions and intentions become more restrained compared to GDP growth rates; however, even a slight fluctuation in entrepreneurial confidence is a noticeable signal of an improving economic situation in the country. In recent years, after the recession of 2014-2016, the aggregate confidence expanded on a smaller scale relative to the intensity of GDP growth. Nevertheless, our main conclusion is consistent with the initial idea: for successful and fast-growing economic development, a favourable business environment and sufficient entrepreneurial confidence are necessary, while a turn towards weakening positive trends is highly likely to be accompanied by a faster deterioration of the business environment compared to the slowdown in GDP growth. Thus, the obtained empirical result of the joint assessment of the two macro indicators shows that at the upper and lower turns of cyclical economic development, ESI reacts more strongly and corresponds to upcoming economic events more clearly, becoming their precursor, while stabilization periods correspond to more restrained intentions of economic entities with the prevailing uncertainty of estimates.

Decomposition of the ESI sectoral structure and cross-countries comparisons

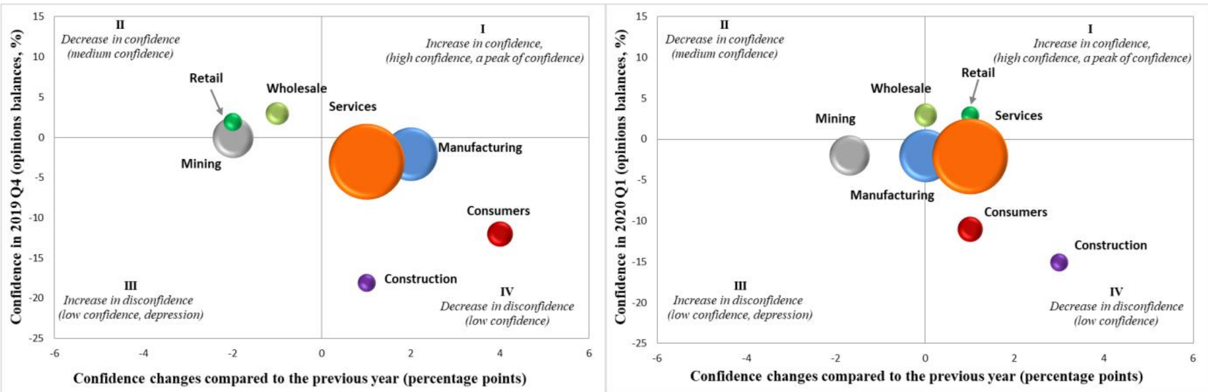
Current trends in the annual ESI dynamics are determined by the potential and growth of its sectoral components – entrepreneurial and consumer confidence. We use so-called radar charts to analyse the quarterly deviations of each confidence indicator from its long-term average value; this simplifies comparing the impacts of sectoral confidence components on ESI (see Fig. 3). All values are standardized in accordance with the EC recommendations (EC 2016b); the long-term average level of all indicators for 2012-2019 is defined as 100.



Note: Deviation from the radar center shows an improvement in the confidence indicator (the larger, the more confident economic growth). Time series are normalized to 100 with a standard deviation of 10, the long-term average for 2012-2019 is defined as 100.
Source: Center for Business Tendency Studies, authors' calculations.

Figure 3. Radar charts of ESI and its sectoral components

Fig. 4 presents the ESI sectoral decomposition at a point in time according to the current level and annual growth of ESI components. The four quadrants of the chart characterize the direction of changes in sectoral confidence indicators, which are aggregated in ESI. The main hypothesis is that industries that not only have a high level of trust, but also expand more intensively, have significantly greater potential for entrepreneurial confidence. Other industries, even those with a high level confidence, but growing at a slower pace or stagnating, are defined as 'catching up' in terms of the development of aggregate optimism.



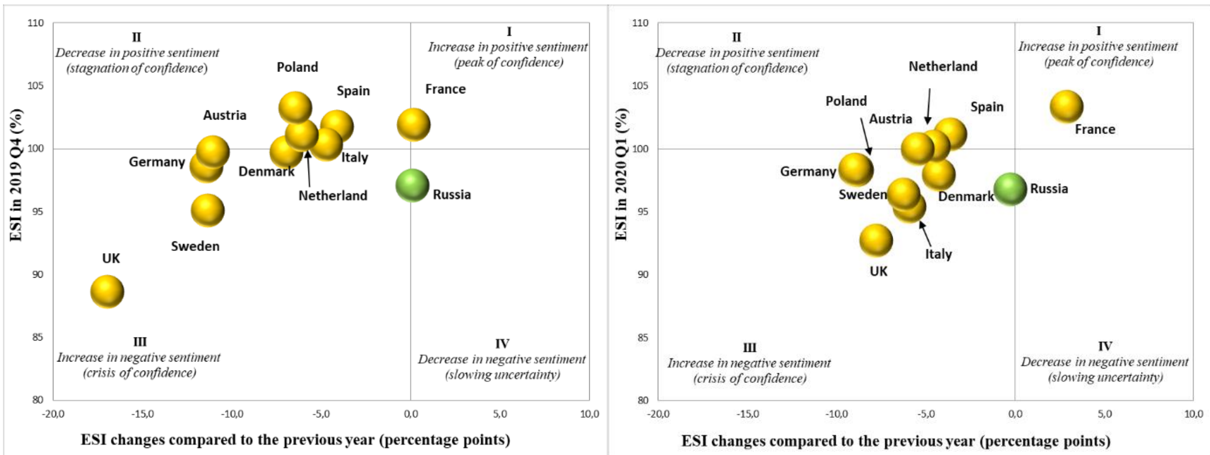
Notes: The highest values in quadrant I imply a boom, an increase in optimism; the lowest values in quadrant III – crisis sentiment. The shares of each sector in the ESI structure determine the bubbles size.
Source: Center for Business Tendency Studies, authors' calculations.

Figure 4. The ESI decomposition: levels and annual growth of sectoral components/confidence indicators

In the end of 2019, the entrepreneurial confidence in mining, retail and, to a lesser extent, in wholesale creates the main negative impulses for the annual change of ESI. In construction, we observe the stagnation of confidence at a very low level. In consumer sector, economic sentiment improves at the fastest pace, but confidence remains far from quadrant I because of its still low level. In manufacturing and services, indicators are close to the border with the cyclical phase of increasing confidence. In Q1 2020, negative expectations about possible coronavirus associated challenges were mainly reflected in industrial business sentiment.

Comparison of the Russian ESI with similar information in the EU is also included in the testing procedure. First of all, it evidences that the high harmonization of Russian and European surveys in terms of questions, data treatment and aggregation methods allows for a comparative analysis of composite sentiment indicators across countries including Russia. In addition, the joint visualization indirectly reflects the short-term expected fluctuations in the countries' GDP growth, based on the statistically significant correlation between ESI and macro-referent, and identifies the place of each economy in the coordinate system of the level and changes in economic activity.

The results of this analysis of economic sentiment in large European countries and Russia are presented in Fig. 5, which shows the position of each country in a particular quadrant of ESI changes.



Note: The highest values in quadrant I imply a boom, an increase in optimism; the lowest values in quadrant III – crisis sentiment.
Source: European Commission, authors' calculations.

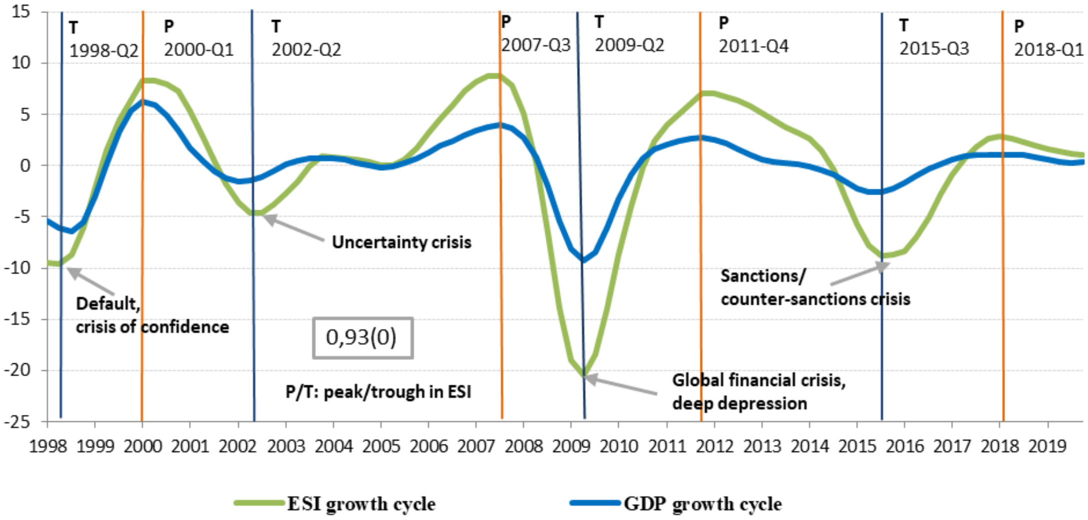
Figure 5. Economic sentiment in large European countries and Russia

The specific of the period considered in the diagram (before the coronavirus attack in Europe in early 2020) is the gap between the estimates of economic sentiment in several countries and the agglomeration of these estimates in other European countries. In the end of 2019, the United Kingdom with a clear gap from the other European countries was in the extreme position both in terms of the scale of negative sentiments and the rate of their growth; this position was very close to falling into depression. Russia and France overcame the crisis of confidence; however, Russia was still on the border of low estimates of economic sentiment due to the lack of growth potential. Austria and, to a lesser extent, Germany were characterized by growing stagnant problems that could lead these countries to a crisis of confidence in the longer term. Among the other countries, negative sentiments clearly intensified in Sweden.

In Q1 2020 the significant annual losses were recorded in Germany, Poland, the UK, Sweden, and Italy. The indicators did not reflect the full impact of the corona crisis because most of the survey information in March was collected before significant containment measures in European countries. In Russia, these restrictions were introduced later and had little effect on the survey results.

Joint cyclical testing of the ESI and GPD growth dynamics

The next important stage of the study is testing ESI dynamics for statistical sensitivity to short-term cycles in GDP growth. The results of the time series decomposition – the smoothed growth cycles in the dynamics of ESI and GDP growth in 1998-2019 are presented in Fig. 6.



Note: The marker indicates the coefficient of synchronous correlation between the ESI and GDP growth cycles.
Source: Center for Business Tendency Studies, the HP filter double pass, authors' calculations.

Figure 6. Short-term cycles in the ESI and GDP growth dynamics

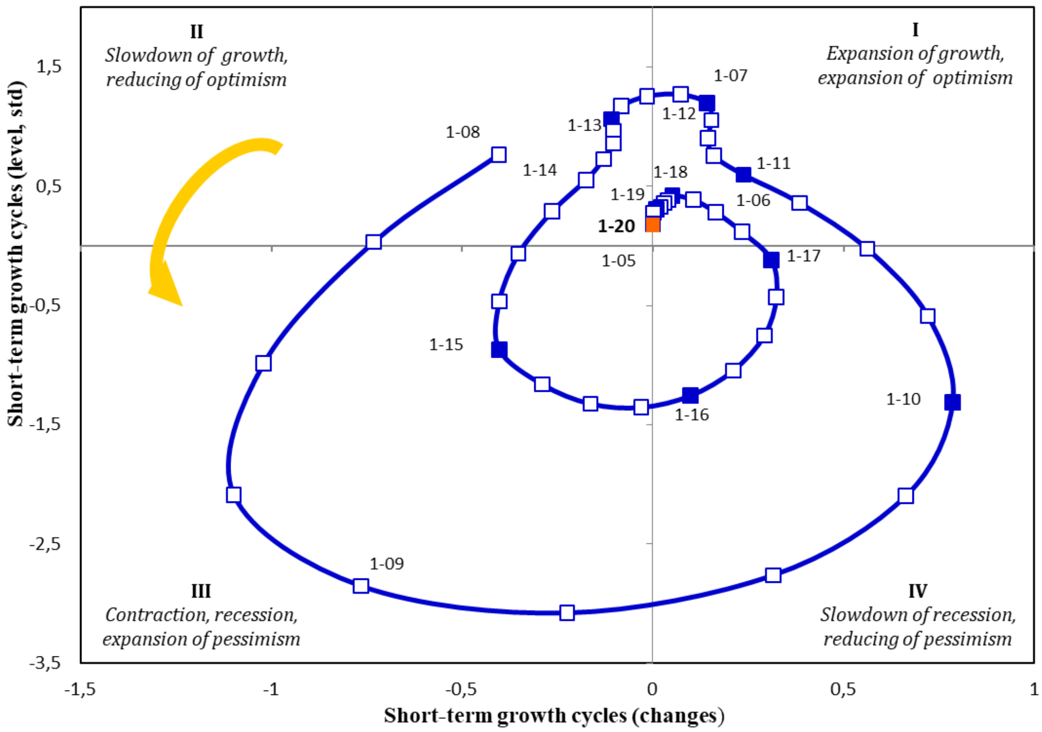
According to the results of joint graphical visualization and the cross-correlation analysis of the smoothed cyclic dynamics of ESI and GDP growth, a stable synchronous correlation of growth cycles in these time series is confirmed (0.94). The turning points in the growth cycles identified through the Bry-Boshan procedure (Bry and Boschan 1971) are almost identical.

We empirically identified the dominant three- and four-year growth cycles in the dynamics of the two indicators from the beginning of 1998 to the end of 2011. The last cycle began in 2012 after the period of economic overheating and the most optimistic sentiment of business entities. Because of a clear reversal to the stagnation phase, this cycle has become the longest in the history of the cyclical analysis of modern economic dynamics in Russia and continues to this day. From mid-2014 to Q3 2015, the economy remained in the phase of recession, crisis events, and depressed economic sentiment; after passing the cyclical trough, there was a slowdown of recession and a contraction of pessimism. Since the end of 2017, the recovery phase of the growth cycle has strengthened. However, for the final confirmation of the signs of accelerated growth we need additional empirical information because this new rise is too insignificant and unstable in terms of its potential and fluctuations.

Thus, the joint decomposition of the ESI and GDP growth time series with the extraction of statistically significant, mainly synchronous (smoothed with an amplitude of 30 months) growth cycles and the dating of cyclic turning points confirm the initial hypothesis about the almost synchronous cyclic compliance of the analysed indicators. We believe that the ESI by its nature has leading capabilities; the timeliness of its calculation allows it to be published much earlier compared to quantitative statistics on GDP growth. The hypothesis of all our previous measurements is confirmed again: the aggregate assessments of entrepreneurial and consumer sentiments are effective and reliable as early warning information on national economic growth due to their ability to correspond to all phases and turning points of real cyclical development.

The visualization of the cyclical movement of economic sentiments for the period of 2008-2020 is achieved through a tracer, which is based on the EC concept in terms of the diagram quadrants and the direction of the tracer movement (EC 2019b, Gayer 2008). However, the ESI time series for this period are non-stationary according to the results of ADF testing. For this reason, we construct the tracer (unlike the EU approach) after converting the ESI time series to a stationary form by filtering the influence of a medium-term 15-year cycle (trend), which corresponds at low frequencies to the accumulated optimism/pessimism of entrepreneurs and consumers. In the tracer, we use the residual of the unobservable dynamics after the second pass of the HP filter, smoothing the high frequencies fluctuations with an amplitude of at least 30 months (Kitrar et al. 2015) (see Fig. 7).

The tracer clearly shows all growth cycles in the ESI dynamics from Q1 2008 and the phase of extremely weak recovery in the last growth cycle, which began at the end of 2017. The contraction of optimism became apparent after the last cyclical peak in mid-2012, when the indicator entered the phase of growth slowdown. Since mid-2014, while recessionary events and the pre-crisis scenario in the national economy developed, the ESI cyclical growth remained in the phase of recession and increasing pessimism. The tracer passed a cyclic trough in the second half of 2015, when the aggregate economic sentiments reached its lowest level over the past seven years. The transition of the tracer to the quadrant of recession slowdown and pessimism contraction in Q4 2015 reflected the beginning of the cyclical recovery in ESI growth. The phase of strengthening weak growth was recorded from Q4 2017 to Q1 2020; all tracer values are concentrated in the lower part of the first quadrant.

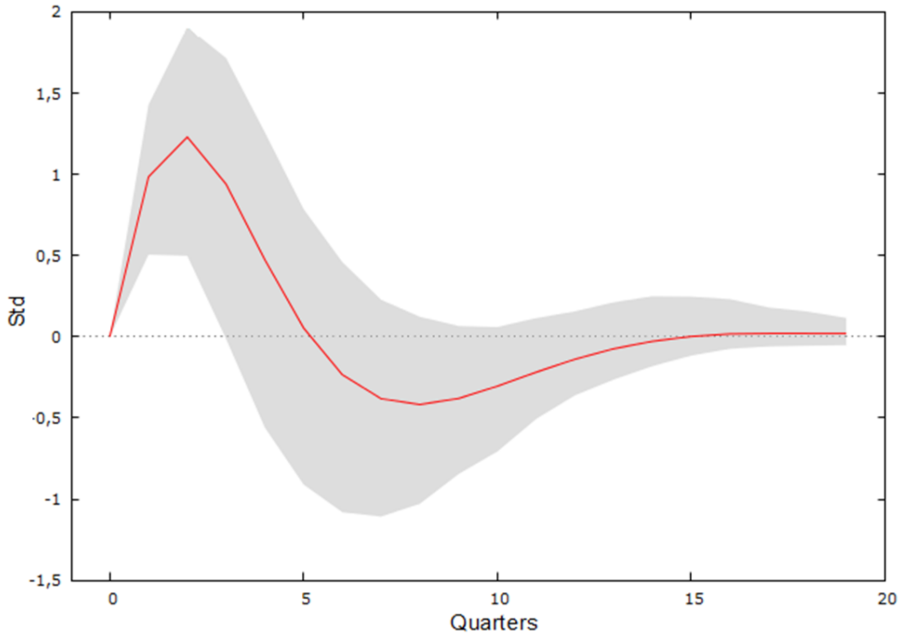


Source: Center for Business Tendency Studies, EC concept, the HP filter double pass, authors' calculations.
Note: The upper and lower values located within the central vertical line indicate the turning points of the growth cycles of economic sentiment: the peaks of overheating (optimism) and the troughs of crisis (depression). Values grouped around zero are more likely to correspond to uncertain sentiments.

Figure 7. Tracer of cyclic profile in the ESI dynamics in 2005-2019

The early estimates of quarterly GDP growth based on VAR simulating results

Visualization of the results of the VAR simulation through IRF (see Fig. 8) allows us to estimate the strength and direction of the impact of an artificial shock (equal to one standard deviation) in the ESI series on GDP growth since 2005 and the duration of the GDP growth adjustment to the shock. The results confirm a significant positive and unidirectional relationship between these two indicators and a non-linear pattern, when each upsurge (by one standard deviation) in the aggregate sentiment of economic agents (ESI) has more than twice the upward impact on economic growth (GDP) increasing then slightly over the next two quarters. After that, the response of the reference indicator to the impulse in the survey indicator fades for at least five quarters, and then the reference indicator gradually stabilizes at the initial level for eight consecutive quarters.

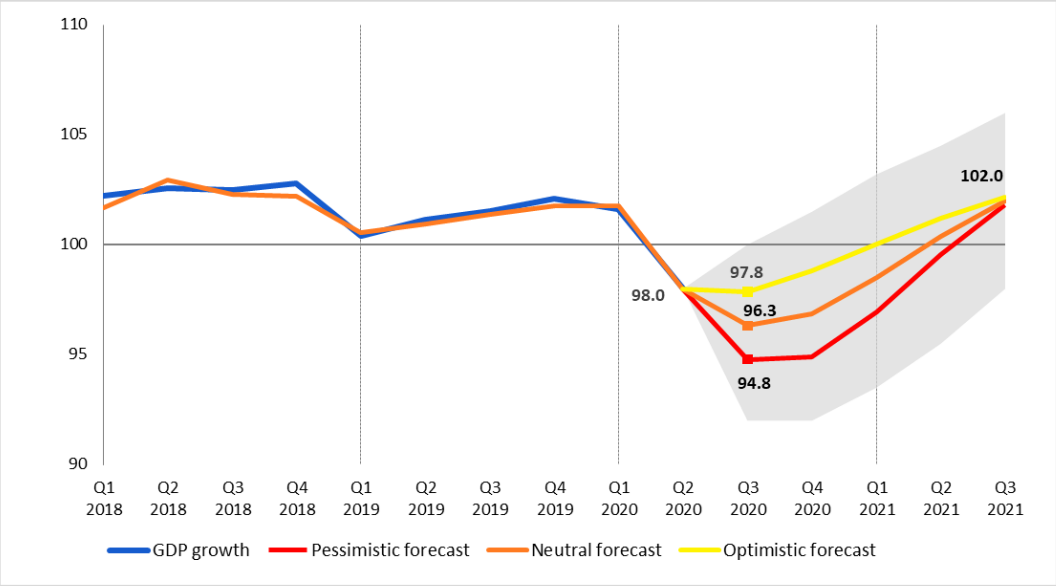


Source: Center for Business Tendency Studies, authors' calculations.

Figure 8. The response of the GDP growth to the impulse in ESI: the degree and direction of impact

We use the identified empirical pattern for early estimation of GDP growth as a response to the actual and potential shocks in the dynamics of aggregate economic sentiment in Russia. As an example, we have calculated three scenario estimates of GDP growth till the mid-2021 based on an expert-defined range of possible ESI values in Q2 2020, which sequentially deviate down from the long-term average value of this indicator's dynamics (100) by 0,5 standard deviation. The impulses we have introduced into the ESI dynamics vary, depending on the strength and duration of the impact of new crisis shocks (which have been increasing since March 2020) on the aggregate economic sentiment. These shocks are mainly related to COVID-19 containment measures, the collapse of oil prices, and the expected depth of the coronavirus impact on various economic activities.

The first scenario estimate of GDP growth (yellow line) is associated with a milder and optimistic version of an ESI decline in the Q2 2020 by 5 points (0.5 standard deviation) relative to its long-term average 100, or by 2 points relative to its value in Q1 2020, before coronavirus containment measures and the drop in oil prices. The second moderate assessment (orange line) is calculated based on ESI falling by 1 standard deviation (10 points relative to its the long-term average); the third, most pessimistic scenario (red line) is obtained after a shock of 1.5 standard deviations (15 points) relative to the long-term average (see Fig. 9).



Source: Rosstat, authors' calculations.
Note: For the period from Q1 2018 to Q4 2019, the orange line denoted in-sample forecast, from Q2 2020 to Q3 2021 it denoted the neutral out-of-sample forecast.

Figure 9. Forecasts of GDP growth through a two-dimensional VAR model

The early estimates based on the obtained non-linear relationship between two series with the response of GDP growth to the given impulses in the ESI dynamics, as a possible reaction of the business environment to new sectoral events in Q2 2020, indicate a clear reversal of the sluggish GDP growth towards a falling path. The rate of this fall, caused initially by expert-defined impulses in the ESI dynamics, differs between the extreme values of GDP growth by only three percentage points. In Q3 2020, even under the most optimistic scenario, GDP growth can be at the level below the trough of the last Russian sanctions/counter-sanctions crisis in 2015. Under the same scenario, without taking into account the aggravating effect of negative shocks on the national economic growth, we expect that GDP growth can recover to the approximate level of Q4 2019 in Q3 2021 only.

Conclusions

The main empirical results of this study allow us to make a conclusion about the sensitivity of Russian business confidence/sentiment indicators to GDP growth, their significant relevance for measuring sectoral drivers, cyclical phases, and the effectiveness of joint testing of business trends and economic dynamics in the context of achieving the goals of sustainable economic development in the country.

We focused on evaluating the reliability of survey-based indicators in the analysis of short-term growth cycles. This made it possible to assess when and to what extent the collapse of confidence of economic agents becomes an important factor and a harbinger of changing cyclical phases in Russia, and the economic sentiment indicator becomes the most useful measure in the system of predictive assessments of economic dynamics. The joint decomposition of the ESI and GDP growth time series with extracting short-term growth cycles and identifying cyclic turning points confirms our hypothesis about an almost synchronous cyclic conformity of the analyzed dynamics and the statistically significant predictive effectiveness of the composite survey-based indicator. Moreover, ESI is released much earlier than quantitative statistics on GDP growth.

The early estimates of GDP in 2020-2021 using a two-dimensional VAR model consider the expected impact of the new corona crisis on the aggregate economic sentiment in Russia. They show a decline in GDP dynamics in mid-2020, after coronavirus containment measures and a collapse of oil prices, then a slow and unstable recovery in GDP growth then a slow and unstable recovery in GDP growth in the second half of 2021 to the level of the end of 2019.

This study confirms the reliability of long-term BCS results in Russia conducted by Rosstat as early warning information on economic growth due to its high measuring ability to reflect all phases and turning points of real cyclical development.

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Liudmila Kitrar

National Research University Higher School of Economics, Russian Federation. Institute for Statistical Studies and Economics of Knowledge, Centre for Business Tendency Studies. Deputy Director.: lkitrar@hse.ru