NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Liudmila Kitrar, Tamara Lipkind

ASSESSMENT OF GDP GROWTH AFTER THE CORONA CRISIS USING THE RESULTS OF BUSINESS AND CONSUMER SURVEYS

BASIC RESEARCH PROGRAM
WORKING PAPERS

SERIES: SCIENCE, TECHNOLOGY AND INNOVATION

WP BRP 118/STI/2021

Liudmila Kitrar[1], *Tamara Lipkind*[2]

ASSESSMENT OF GDP GROWTH AFTER THE CORONA CRISIS USING THE RESULTS OF BUSINESS AND CONSUMER SURVEYS[3]

The article analyses the short-term effects of aggregate economic sentiment on the expected GDP growth in Russia based on the results of regular large-scale surveys of business activity of the Federal State Statistics Service of the Russian Federation for the period 1998-2020. The main purpose of the study is to substantiate the predictive value of the opinions of economic agents in expanding macroeconomic information, including in crisis periods. The authors calculate a composite economic sentiment indicator (ESI), which combines quarterly information for the analysed period on 18 indicators of surveys with a sample of about 24,000 organizations of all size in basic kinds of economic activity, and 5,000 consumers in all Russian regions. The authors prove the possibility of using a vector autoregression model (VAR) with dummy variables to measure the relationship between GDP growth and ESI time series. Scenario estimates of GDP growth until the end of 2021 are based on the expected impulses in the ESI dynamics at the end of 2020, which differ in the amplitude and duration of their impact on economic growth, primarily due to the coronavirus effect. According to the results, under all possible scenarios for the development of business trends, national economic growth can exceed the level of the end of 2019, starting from the third quarter of 2021.

Keywords: business and consumer surveys, economic sentiment indicator, composite business cycle indicators, growth cycles, GDP growth, economic growth, VAR model with dummy variables

JEL: C53, E32, E37, O47.

[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] The paper was prepared within the framework of the Basic Research Program at the National Research University Higher School of Economics

Introduction

Measuring the dynamism and growth prospects of the national economy has become significantly complicated under the new challenges imposed by the COVID-19 crisis. This is mainly due to worsened disparities of countries, and the increasing uncertainty of further global development. Furthermore an unfavorable pricing situation has developed on the commodity markets and there has been a significant redistribution of global value added chains and the vectors of globalization. In addition a tangible loss of industries liquidity and the aggregate demand occurred. Given the high risk and vulnerability of many kinds of the economy's activities, the recovery of economic growth in Russia has increasingly become dependent on the effectiveness of domestic government policy measures and adaptation of entrepreneurs and households to them.

In 2020, the spread of the coronavirus (Covid-19) pandemic has led to a slowdown in global economic development. According to short-term forecasts of the International Monetary Fund, formed in October 2020, the annual growth of the world economy will be -4.4 percent. This last for 2020 scenario of global economic development is the most optimistic, because it is based on the dynamics of world GDP in the second and third quarters. The forecast takes into account the situation when, after the weakening of lockdowns in May and June, economic activity began to recover at a faster pace than previously expected. However, a moderate downward trend is still in line with expectations of maintaining social distancing at least until the end of 2020. This implies only limited progress toward catching up to the path of economic development for the period from 2020 to 2025 projected before the pandemic.[4] These tendencies will be especially pronounced if uncertainty persists for a long time or new crisis events arise[5]. According to the latest IMF forecast[6], the global economy is projected to grow 5.5% in 2021; however, this recovery follows a severe collapse in 2020. The global growth contraction for 2020 is estimated at -3.5%, 0.9 percentage point higher than projected in the previous forecast (reflecting stronger-than-expected momentum in the second half of 2020). The strength of the recovery is predicted to vary significantly across countries, depending on access to medicine, effectiveness of policy support, and structural characteristics entering the crisis. For Russia, what is becoming more obvious is the prospect for overcoming negative sectoral developments according to the scenario of a W-shaped recovery of economic growth.[7]

---

[4] International Monetary Fund. World Economic Outlook, October 2020: A Long and Difficult Ascent. https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020.

[5] OECD. Economic Outlook, December 2020. http://oecd.org/economic-outlook?utm_source=Adestra&utm_medium=email&utm_content=digital-report&utm_campaign=ecooutlookdec2020&utm_term=eco.

[6] International Monetary Fund. World Economic Outlook Update, January 2021. https://www.imf.org/en/Publications/WEO/Issues/2021/01/26/2021-world-economic-outlook-update.

[7] Cental Bank of the Russian Federation. What trends are talking about. Macroeconomics and Markets. Research and Forecasting Department Bulletin, November 2020. https://cbr.ru/Collection/Collection/File/31429/bulletin_20-07.pdf.

Large-scale short-term data obtained on the basis of the opinions and expectations of economic agents, are essential to reliably measure national progress and effectiveness of new growth models. Aggregate opinions and expectations provide timely additional information on various events and phenomena, including those that are not fully or untimely covered by official statistical observations. Therefore, composite indicators of business and consumer surveys (BCS) increase the efficiency of statistical monitoring in the new economic situation and become an important part of the early response to short-term changes in macroeconomic dynamics.

We study the dynamics of GDP growth and the aggregate results of surveys among managers and consumers by the Federal State Statistics Service of the Russian Federation (Rosstat) – i.e. the economic sentiment indicator (ESI) – for the period of 1998–2020. Important advantages of ESI are its significant correlation with the quarterly GDP growth (as a year-on-year percentage) for 1998 - 2020 and harmonisation with the composite index used by the European Commission to aggregate BCS results in European countries. Also, the ESI is not revised over time and are published timely (quarterly or monthly).

The key question of the study is to assess the effectiveness of using categorical survey data, aggregated into a composite indicator, to measure the prospects for GDP growth in the face of sudden and recurring crisis impulses that negatively and with varying degrees of intensity affected the sectoral development in 2020. Therefore, as a special case for flash quarterly estimates of GDP growth, we examine the sharp negative shock in the dynamics of the composite survey-based indicator – caused by the coronavirus attack – in the context of a possible new cyclical reversal and subsequent recession.

We use a universal model specification for the case of two economic dynamics – the GDP growth and ESI – determined by the *main goal of the study*: to substantiate the empirical and predictive value of aggregated results of business and consumer surveys (BCS) for expanding current and expected short-term information about economic growth in Russia. Such information is useful for decision-makers and the expert community, especially during rapid negative changes.

The main research objective is a statistical analysis of the time series, including determining the order of integrability with testing the indicators for stationarity and causality. The interrelation of indicators is analysed using the extended specification of the universal VAR model, which includes dummy variables that record episodes of strong fluctuations in the time series. Evaluation of the statistical efficiency of predicted values by using the proposed modification of the VAR model and the response function of the reference macroeconomic indicator to the impulse in the ESI dynamic is also an important task of the study.

According to the goal, the main thesis of the research and its scientific hypothesis have been determined.

The main thesis of the research is: the compatibility of cyclical dynamics of aggregate economic sentiment and GDP growth makes it possible to use ESI for early estimates of economic growth, especially taking into account its timely publications.

The *hypothesis* (H) is based on a quantitative assessment of the response of GDP growth to the impulse in the ESI dynamics: each clear short-term surge in the aggregate economic sentiment synchronously contributes to the expansion of economic growth; then, the expansion continues for six months, but with a noticeably lower intensity.

This paper is structured as follows. First, we provide a literature review on approaches to using survey-based indicators in economic analysis. Then, we describe the data and methodology used. Next, we calculate scenario forecasts for GDP growth until the end of 2021 by using a VAR model with dummy variables. The concluding section discusses the main results and possible areas for future investigation.

Literature review

All issues that are considered in the study are discussed in the scientific and expert literature. This concerns methodological and empirical problems of using the results of surveys of economic agents and survey-based composite indicators in macroeconomic analysis forecasting. Publications devoted to econometric forecasting methods are also very important.

In the international practice of studying the opinions and expectations of business and consumers, the ESI belongs to a group of coincident composite indicators of business activity, as it changes synchronously with the dynamics of reference statistic: the GDP growth. However, the ESI uses simple questionnaires and short data processing, and it 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 (EC, 2020; Kitrar et al., 2014; Kitrar & Lipkind, 2020; Lipkind et al., 2019; UNECE, 2019).

A review of the literature on the use of composite BCS indicators in forecasting economic activity reflects a broad consensus regarding their predictive capabilities. In particular, Cesaroni (2011) gives evidence of high predictive ability of business tendencies and the possibility of using them in high-frequency forecasting of the evolution of economic growth. Cesaroni and Iezzi (2017) note the effectiveness of 'soft' statistics in predicting short-term macroeconomic dynamics.

Most studies devoted to the economic consequences of the Covid-19 pandemic are based on quantitative statistics: dynamics of GDP and the output of goods and services, volumes of imports and exports, industry indicators, changes in global value chains (Jorda et al., 2020; Gollier and Straub, 2020; Fernandes, 2020; Bonadio et al., 2020; Guerrieri et al., 2020). Such statistics are usually published with a significant lag, although the need for flash estimates based on monitoring economic sentiments of businesses and consumers increases during periods of crisis.

The seminal papers on nowcasting economic growth (Angelini et al., 2008; Banbura & Runstler, 2007) 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 & Maurin, 2008; Drechsel & Maurin, 2011; Girardi, 2014; Girardi et al., 2015).

Various econometric methods are applied to produce early estimates of economic growth using BCS indicators. 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 the nowcasting of Argentinian GDP growth by using bridge equations and the dynamic factor model (DFM) with consumer surveys data. DFM models, which include survey information, are also used to forecast GDP for the euro area (Banbura & Runstler, 2007; Basselier et al., 2017), along with France, Germany, Italy, Japan, the United Kingdom, and the United States of America (Ollivaud et al., 2016). Galli et al. (2019) apply the DFM and mixed frequency data sampling (MIDAS) regression models to monitor short-term economic developments in Switzerland. The nowcasting performance of the MIDAS regression model for the euro area GDP in a pseudo real-time setting is evaluated in (EC, 2018).

Vector autoregressive (VAR) models based on BCS data or combined hard and soft statistics are developed in Hansson et al. (2003), Mattos et al. (2016), and in articles by the EC (2014). The researchers conclude that VAR forecasting accuracy often outperforms the alternatives procedures including DFM.

Among the publications of Russian experts of business cycle, as far as we know, there are still no detailed studies directly related to the analysis of the long-term dynamics of business activity of economic agents, based on large-scale Rosstat surveys, and its compliance with quantitative statistics over a period of more than 20 years. However, it is precisely in the dynamics of entrepreneurial sentiments in various cyclical phases that important short-term impulses are observed associated with further economic growth, which, in our opinion, should be used when analysing statistical information. In this regard, it is worth noting the scientific and analytical publications of experts from the Center for Business Tendency Studies at the Higher School of Economics, which widely use the long-term and large-scale dynamics of the results of Rosstat business surveys.

In particular, the predictive value of ESI due to its high cyclical sensitivity to short-term GDP dynamics was proved in (Kitrar et al., 2020, 2014; Kitrar, Lipkind, 2020), with the following empirical observations for specific time intervals:

- In periods of economic overheating, the ESI grows faster than GDP and can act as a leading indicator that anticipates cyclical reversals towards a phase of growth slowdown;
- The rate of growth of negative sentiments of economic agents synchronously exceeds the intensity of the slowdown in GDP growth. In such periods, the TESI is defined as a coincident indicator, which confirms the transition of economic growth to a phase of contraction;
- After crisis period, there is a significant gap and lag between an intense GDP growth and a less pronounced ESI improvement. The four-year period since the 2015–2016 recession should be defined as the 'new normal' in the dynamics of entrepreneurial opinions and expectations in Russia.

To simulate the relationship between the analysed indicators – GDP growth and the ESI, we chose relatively simple model specifications. Typically, such specifications consist of a minimum number of equations that reflect a single theoretical macroeconomic relationship, and they only operate with significant determinants of the modelled process. Therefore, we used an approach to modelling the cyclical relationship of indicators based on empirical facts about business cycles and vector autoregressions, initially allowing no more than seven to eight parameters of the standard VAR model (e.g. Bernanke et al., 2005; Kitrar et al., 2020).

Such model representations can differ significantly. For example, they can reflect the a priori assumed theoretical macroeconomic ratio (Korhonen & Mehrotra, 2010; Mehrotra & Ponomarenko, 2010). Korhonen and Mehrotra (2009) identify economic shocks based on a theory-driven identification scheme. In articles by Granville and Mallick (2010) and Mallick and Sousa (2013), sign restrictions are imposed on the response impulse functions. Rautava (2013) considers them as the most important determinants of the modelled process. A class of Bayesian VAR (BVAR) models is aimed at overcoming the 'curse of dimensionality.' Reducing the number of estimated parameters is conducted based on the researcher's a priori ideas about the possible distribution of their covariance error matrix; e.g. the introduction of the Minnesota prior, first highlighted by Litterman (1986). The BVAR models are very effective when incorporating many various time series with a 'jagged edge,' frequent adjustments, and revisions. They include information matrices of large dimensions, e.g. for the formulation of monetary policy, which is a common practice of many central banks (Banbura et al., 2010, 2014; De Mol et al., 2008).

In our case, the selected time series were primarily aggregated into a composite ESI indicator. Then, the statistical relationship between the dynamics of this indicator and quantitative reference series (GDP growth) were confirmed through VAR-modelling, when the behaviour of any variable depended both on its past values and on the values of other series included in the model (Mayr & Ulbricht, 2007; Lütkepohl, 2011).

Based on literature review, we see the *scientific novelty* of our study in the substantiation of the possibility of using accumulated ESI values in the short term forecasting of GDP growth in the context of the ongoing COVID-19 crisis. The proposed method is available to most researchers and experts; it is flexible and applicable for solving more complex problems with the introduction of additional indicators and complication of the model specification.

Including dummy variables – which fix the periods of deep economic recessions (including those associated with the coronavirus crisis) – in the VAR model specification enhance the forecasting performance. Using this specification, we simulated three scenario forecasts depending on the expected impact of various new coronavirus shocks; all of them indicate a slow recovery of economic growth, reaching the level from the end of 2019 in the second half of 2021 only.

Data source and research methodology

This study is based on the results of business and consumer surveys conducted by Rosstat in 85 regions of Russia, six basic sectors of the economy and among households. They are conducted regularly (monthly and quarterly) and cover more than 29,000 economic agents: 3100 manufacturing firms, 500 mining firms, 6000 construction organisations, 4000 retail firms, 4000 wholesale firms, 6000 services organisations, and 5100 households.[8] The surveys contain qualitative assessments and expectations: all respondents are asked about the current level, along with 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, i.e. 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. The balances, as aggregates of balances statistics, are used to build various composite indicators through their ‘vertical quantification’ in statics or dynamics (Kitrar et al., 2018), harmonised as much as possible with the recommendations of the European Commission and OECD (EC 2020) for cross-country comparative analysis.

For the ESI calculation, we aggregate 18 indicators, from regular BCS by Rosstat, which promptly reflect the short-term fluctuations in entrepreneurial estimates of business tendencies in the Russian economy in 1998–2020. These indicators (Table 1) cover economic activities with a total contribution to GDP of over 70%. At present, it is the only quantitative aggregate of all

[8] Survey results (time series, not seasonal adjusted) and metadata are presented on the Rosstat website (only in Russian), https://rosstat.gov.ru/leading_indicators. Survey questionnaires are presented in the album of statistical observation forms (also in Russian), https://rosstat.gov.ru/monitoring.

categorical statistics - in terms of coverage of sample populations and sectors as well as the duration of dynamics - which reflects economic sentiment in Russia.

Table 1. List of ESI components: the BCS results

№	Indicator	Attribute
Mining		
1	Output	expectations
2	Demand	level
3	Stocks of finished goods	changes
Manufacturing		
4	Output	expectations
5	Demand	level
6	Stocks of finished goods	changes
Construction		
7	Orders book	changes
8	Employment	expectations
Retail trade		
9	Economic situation	changes
10	Economic situation	expectations
11	Stocks	level (inverted sign)
Wholesale trade		
12	Economic situation	changes
13	Economic situation	expectations
14	Stocks	level (inverted sign)
Services		
15	Economic situation	changes
16	Demand	changes
17	Demand	expectations
Households		
18	Confidence indicator	-

The ESI calculation algorithm includes seasonal adjustment and the standardisation of components, their weighting according to their shares in GDP[9], summing up of the components and normalising the result with an average value of 100 and a standard deviation of 10.

The time series of the ESI and the GDP growth for the period from Q1-1998 to Q3-2020 were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The null hypothesis was the presence of a unit root; if it was rejected, the series were considered stationary. The obtained p-values of less than 0.01 for both variables for the entire observation period allowed for the rejection of the null hypothesis, and the analysed dynamics were considered stationary at the 1% significance level.

In the studies (Kitrar et al., 2020, 2014; Kitrar, Lipkind 2020; Kitrar, Ostapkovich, 2013), the ESI series were iteratively tested for sensitivity to a short-term cyclical profile in the dynamics of GDP growth. The proximity of the peaks and troughs of the observed growth cycles in the indicators' co-movement and the significant synchronous correlation of the series was the

[9] In 2020, the following weights were used: mining - 0.16, manufacturing - 0.21, construction - 0.7, retail trade - 0.7, wholesale trade - 0.9, services - 0, 30; the household sector is assigned an estimated weight of 0,10.

main criterion for assessing the ESI cyclical sensitivity and for examining its impact on GDP growth prospects.

Thus, changes in time of both economic indicators (ESI and GDP growth) are stationary series; the same order of their integrability and the presence of cyclical sensitivity make possible to apply VAR modeling.

The proposed model specification includes two endogenous variables: $\mathrm{X_t}$ (seasonally adjusted ESI) and $\mathrm{Y_t}$ (GDP growth as a percentage to the corresponding quarter of the previous year) in which t is quarters for the period from Q1-1998 to Q3-2020. The selected extreme points of the time series sufficiently affected the simulation results; the used sample length was currently available.

Also, we proved that two lags (quarters) were the optimal lag number for this specification, based on the minimum values of generally accepted information criteria, which were determined for the model with two lags (Table 1).

Table 1. Selecting the number of lags for the model

Lags	Likelihood logarithm	Akaike information criteria (AIC)	Schwartz information criteria (BIC)	Hennan-Quinn information criteria (HQC)
1	-374.11335	9.746496	9.927781	9.819068
2	-358.05864	9.437401*	9.739543*	9.558354*
3	-355.20766	9.466863	9.889862	9.636197
4	-353.29068	9.520274	10.06413	9.737989
5	-348.52688	9.500689	10.165402	9.766786
6	-346.78149	9.5585	10.344069	9.872978
7	-345.84565	9.637068	10.543494	9.999927

Note: * marks the lowest values of each criterion.
Source: Authors' calculation conducted in Eviews.

We used a second-order VAR model of two equations, each of which (separately for $\mathrm{X_t}$ and $\mathrm{Y_t}$) included autoregressive components of the second order: $\mathrm{X_{t-1}}$, $\mathrm{X_{t-2}}$, $\mathrm{Y_{t-1}}$, $\mathrm{Y_{t-2}}$:

$$X_t = c_1 + a_{1,1}X_{t-1} + a_{1,2}X_{t-2} + a_{1,3}Y_{t-1} + a_{1,4}Y_{t-2} + a_{1,5}D_1 + a_{1,6}D_2 + a_{1,7}L_1 + a_{1,8}L_2 + a_{1,9}L_3 + \varepsilon_{1,t} \quad (1)$$

$$Y_t = c_2 + a_{2,1}X_{t-1} + a_{2,2}X_{t-2} + a_{2,3}Y_{t-1} + a_{2,4}Y_{t-2} + a_{2,5}D_1 + a_{2,6}D_2 + a_{2,7}L_1 + a_{2,8}L_2 + a_{2,9}L_3 + \varepsilon_{2,t} \quad (2)$$

in which:

X_t – ESI seasonal adjusted series

Y_t – GDP growth, y-o-y, %

D_1 – dummy variable for the external crisis, active (=1) for Q3-1998, Q4-2008, Q1-2009, Q2-2020, Q4-2020

D_2 – dummy variable for recovering from a severe crisis, active (=1) for Q1-1999, Q1-2009, Q3-2020, Q1-2021

L_1 – dummy variable for a very weak TESI fall compared to the strong GDP fall in Q3-1998

L_2 – dummy variable for strong GDP growth without TESI growth in Q3-1999

L_3 – dummy variable for a strong TESI fall without a GDP fall in Q1-2002, Q1-2015

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

$$E(\varepsilon_{1t}) = 0, Var(\varepsilon_{1t}) = \sigma^2 \quad (3)$$

$$E(\varepsilon_{2t}) = 0, Var(\varepsilon_{2t}) = \sigma^2 \quad (4)$$

The presence of delayed relationships for two quarters allowed us to classify this model as dynamic. The universality and simplicity of the proposed model were among the main advantages that guided us. The model specification was clearly limited according to the goal of the study. We introduced dummy variables into the model specification to account for unexpected crises (including those related to the coronavirus pandemic in Russia in 2020) in the trajectory of the analysed indicators. These dummy variables reflect not only the crisis event, but also the fact that the 'bottom' of this episode has already been reached and a recovery has started. In this case, any variable 'crisis' had a value of 1, and for the rest of the dynamics, 0. To fix the recovery period the variable 'recovery' was activated (with a value of 1). This allowed us to take into account the specifics of this period in the short- and medium-term forecasting of GDP growth without over-complicating the model.

Note that before the inclusion of dummy variables in the model, autocorrelation was observed in the random residuals of the equations and they did not follow the normal distribution law. Analysis of the graphs of random errors for each of the equations confirmed the presence of strong outliers.

The proposed model specification with dummy variables (formulas 1-4) was evaluated as consistent. According to the Doornik-Hansen test, for the first four lags, the null hypothesis of the normal distribution of residuals was not rejected at the 5% significance level (p-value 0.177). The hypothesis of no autocorrelation according to the Broysch-Godfrey test was not rejected at the 5% significance level (p-values for each lag are higher than 0.05). The VAR-simulation results are presented in Table 2.

Table 3. Results of the VAR simulation

Lags	Coeffi-cients	Standard error	t-statistics	p-values	Coeffi-cients	Standard error	t-statistics	p-values
	Equation: GDP				Equation: ESI			
const	16.97	3.85	4.41	0.00	7.90	7.92	0.99	0.32
X_1	0.08	0.04	2.13	0.04	0.86	0.08	10.62	0.00
X_2	−0.09	0.04	−2.45	0.02	−0.17	0.08	−2.15	0.03
Y_1	1.07	0.08	13.36	0.00	0.38	0.16	2.28	0.03
Y_2	−0.23	0.08	−2.91	0.01	−0.15	0.16	−0.93	0.36
D_1	−8.79	0.68	−12.86	0.00	−22.78	1.41	−16.19	0.00
D_2	5.20	0.96	5.41	0.00	16.70	1.98	8.45	0.00
L_1	0.59	1.51	0.39	0.69	13.09	3.11	4.20	0.00
L_2	6.49	1.33	4.87	0.00	−1.12	2.74	−0.41	0.68
L_3	−2.86	1.30	−2.20	0.03	−10.89	2.67	−4.08	0.00

Source: Authors' calculation conducted in Eviews.

In the next step, we used the impulse response function (IRF) to clarify the relationship between two series in the model and to estimate the strength and direction of the shock, and the duration of adjusting the estimated series (GDP growth) to the shock in TESI equal to one standard deviation. First of all, the residuals that are obtained when evaluating the VAR model should be presented as a linear combination of uncorrelated shocks, and preferably with the possibility of economic justification of such a transformation. In our study, the Cholesky decomposition of the estimated covariance matrix of the model residuals was used to identify shocks; the order of the variables was set by variance decomposition. This is one of the methods of identification; it is also possible to impose a priori restrictions based on economic theory about the short-term or long-term reaction of some indicators to others. The optimal ordering provided the greater impact of the ESI on the GDP growth. This result of variance decomposition of GDP series was achieved with the following ordering of the variables: the ESI → the GDP growth.

We also tested causal relationships between the ESI and GDP growth (Table 3).

Table 3. Granger causality test results

Hypothesis	Chi-square	p-value	Result
TESI does not affect GDP growth	3.2364	0.0446	Rejected
GDP growth does not affect TESI	3.1243	0.0494	Rejected

Source: Authors' calculation conducted in Eviews.

The results of the Granger causality test showed that there are dependencies of the ESI in the GDP growth and the GDP growth in the ESI. However, in our ordering, shocks in economic sentiment affected both the ESI and the GDP growth, while shocks in the GDP growth had an immediate impact only on economic growth. Therefore, for further forecasting of economic development, we were considering a situation when GDP growth does not have a leading effect on economic sentiment.

Next, the impulse response function (IRF) is constructed; it reflects the percentage change in the endogenous variable (GDP growth) in response to a sudden change in the random error of another endogenous variable (ESI) by one standard deviation. Based in IRFs, we calculated scenario forecasts of GDP growth until the end of 2021, taking into account possible gaps in the ESI at the end of 2020 relative to the long-term average level of its dynamics.

We also compared the forecast values of GDP growth with their real retrospective on the in-sample interval, both with and without dummy variables, to confirm the quality of forecasts using the proposed model specification. On the in-sample interval (from the Q1-1998 to Q1-2020), the model acceptability for the quarterly forecast was confirmed based on parameters of the forecast quality (Table 4).

Table 4. Parameters of the forecast quality

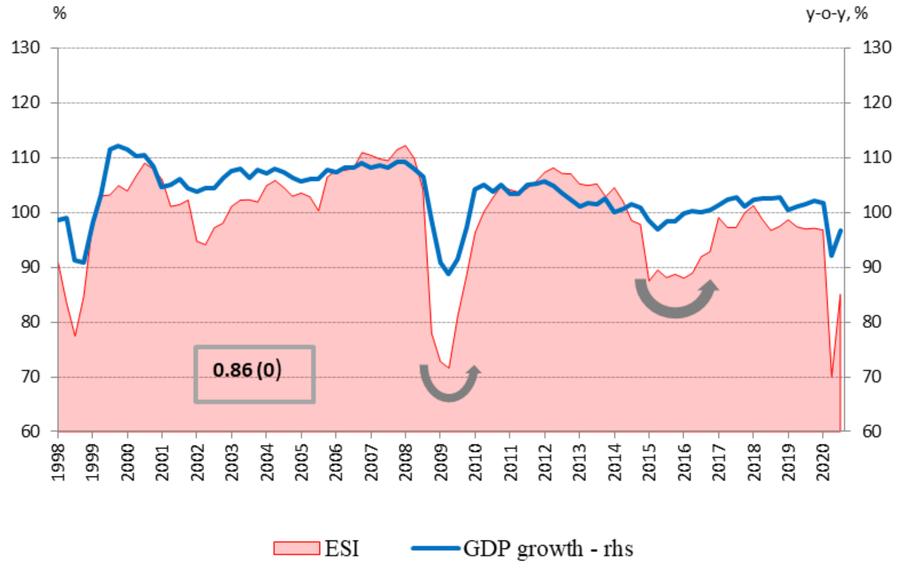
Forecast without dummies		Forecast with dummies		Forecast without pandemic shock	
R-squared	0.78	R-squared	0.93	R-squared	0.93
Sum sq. resids	542.54	Sum sq. resids	130,29	Sum sq. resids	116.88
S.E. equation	2.32	S.E. equation	1.29	S.E. equation	1.24
MSE	5.08	MSE	1.46	MSE	1.34
RMSE	2.26	RMSE	1.21	RMSE	1.16
ME	4.38	ME	4,15	ME	-4.48
MAE	1.41	MAE	0.94	MAE	0.87
MAPE	0.01	MAPE	0.01	MAPE	0.01

Source: Authors' calculation conducted in Eviews.

Thus, the analysis of the relationship of indicators based on the VAR-modeling with dummy variables – which fix the periods of strong fluctuations – increases the statistical efficiency of the forecast in the on the in-sample interval. The behavior of the reference macroeconomic indicator is estimated based on the response of its time series to the impulse in the ESI series. The result is statistically effective forecasts of the GDP growth both on the in-sample and out-of-sample intervals, based on possible simulations of further development.

Research results

Figure 1 presents the time series of the ESI and the GDP growth (1998–2020).

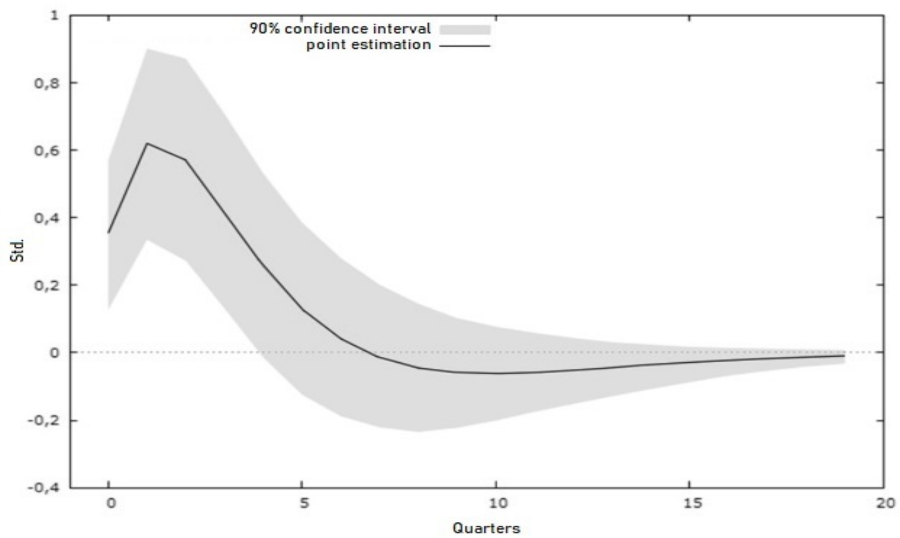


Note: The marker indicates the coefficient of synchronous correlation between the ESI and GDP growth series.
Source: Authors' elaborations based on Rosstat data.

Figure 1. ESI and GDP growth dynamics in 1998–2020

In Q2-2020, we observed the sharpest and almost vertical collapse of the aggregate sentiment of Russian entrepreneurs and households. The sudden and unprecedented TESI drop was obviously associated with strict measures to contain the pandemic, which had an extremely adverse effect on business and the population both on the demand (reduced household consumption, investment activity, export earnings) and supply side (a decline in production and services, disruptions in production and supply chains). According to the estimates of GDP growth in Q2-2020, this period can be defined as the immersion of the economy in a new crisis, the onset of which was caused mainly by non-economic factors (Kitrar et al., 2020). The subsequent slowdown in the GDP decline in Q3-2020 occurred against the backdrop of a clear "rebound" in the ESI downward trend. During this period, we observed a clear and rapid adaptation of economic agents to the new economic reality, a positive response to timely measures to support businesses and households.

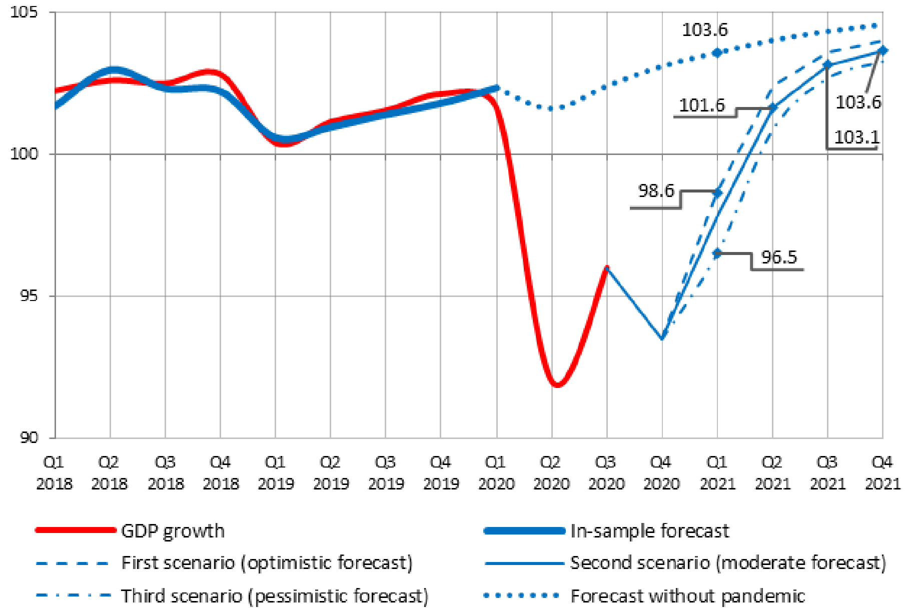
The results of the VAR simulation through the IRF (see Figure 2) allows us to estimate the strength and direction of the impact of an artificial shock in the TESI series on the GDP growth and the duration of the GDP growth adjustment to the shock. On this basis, the initial hypothesis about a significant unidirectional relationship of two indicators is confirmed: each clear surge (equal to one standard deviation) in the ESI dynamics contributes to the expansion of economic growth by 0.6 standard deviations, which continues in the next quarter, but with a lower intensity. The response of the GDP growth to an impulse in the ESI fades for at least six quarters, and then the reference indicator stabilises, reaching its initial level.



Source: own calculation conducted in Eviews.

Figure 2. The response of the GDP growth to the impulse in ESI: the degree and direction of impact (Cholesky decomposition)

We calculated scenario forecasts for GDP growth until the end of 2021 driven by the GDP response to actual and expected impulses in the dynamics of the aggregate economic sentiment from Q1-1998 to Q3-2020. Consequently, the calculations were based on the indicator values for the entire period, including a sharp decline in its dynamics due to the Covid-19 crisis. Moreover, we introduced an expertly set interval of ESI values that are possible in Q4-2020 if expectations were to remain uncertain; in particular, due to large-scale vulnerability and slow recovery of the most affected activities, new local lockdowns, the pressure of external and internal challenges, delays in the vaccination of the population and other preventive antiviral measures. The simulation of ESI values was conducted by the input of conditional impulses as deviations from the long-term average value (100), depending on the potential of new crisis shocks at the end of 2020. Figure 3 also presents expected estimates of GDP growth if the coronavirus shock had not occurred in Q2-2020.



Note: For the period from Q1-2018 to Q1-2020, the blue line denotes in-sample forecast.
Source: Authors' calculations based on Rosstat data.

Figure 3. Scenario forecasts of GDP growth

The first scenario forecast of the GDP growth is associated with a more optimistic version of the ESI decline in Q4-2020 (by 0.5 standard deviations). The moderate scenario forecast was calculated based on the possible ESI falling by 1.5 and the most pessimistic scenario assumes a new strong contraction of aggregate economic sentiment by 2.5.

Conclusions

In this study, we propose a method of statistical analysis of the relationship between the results of business tendency surveys by Rosstat, combined into a composite indicator of economic sentiment, and GDP growth. This method is available to most researchers and experts; it is flexible, convenient and acceptable as a basis for solving more complex problems with the introduction of additional indicators and complication of the model specification.

The analysed time series clearly indicate the replacement of the sluggish growth of Russian GDP, observed over the past two years, with a lower trajectory. The values of the ESI, which aggregates the results of the largest entrepreneurial surveys in Russia, allow us to record an increase in the post-crisis (2015-2016) cognitive 'downward shift' in the long-term average level of sectoral assessments of economic agents' confidence in 2020.

Statistically significant results of the VAR-modeling with dummy variables – which fix the periods of deep economic recessions (including those associated with the coronavirus crisis) – enable the performance of short-term forecasting of the GDP growth.

The forecast results reflect the non-linear relationship of two series with the response of the estimated variable (GDP growth) to the reaction of the business environment and to the simulation of the variations we set in the ESI dynamics, which reflect possible economic sentiments under crisis events at the end of 2020.

According to the calculations, the expected estimates of the economic growth in the first half of 2021 – caused by the previous values (actual and target) in the ESI dynamics – may differ between the extreme forecasts of the GDP growth by two percentage points, on average. Nevertheless, under all scenarios for the development of business trends in Q4-2020 – if we do not take into account the possible further aggravation of risks for business and consumers – the economic growth can exceed the level of the end of 2019 from Q3-2021. In particular, according to the moderate scenario, the GDP growth will amount to 103.6% in Q4-2021. National economic growth could return to a phase of sustainable recovery in 2022 only if the COVID-19 crisis is limited, local, and short-term – when only some sectors of the economy are affected – and assuming the introduction of rapid vaccinations in early 2021, full control over the viral situation, and the strengthening of business confidence.

For short-term forecasts of the GDP growth we use only a composite indicator that summarises the survey results. Despite the consistency of the proposed model specification, we assume that forecasting performance can improve if quantitative economic variables are included in the model. Another area for the further development of survey-based methods of analysis and forecasting is the improvement of the TESI leading properties by updating its composition and selecting the optimal set of components.

Acknowledgements

The article was prepared within the framework of the Basic Research Program at the National Research University Higher School of Economics.

References

Angelini, E., Camba-Méndez, G. Giannone, D., Rünstler, G., & Reichlin L. (2008). Short-term forecast of euro area GDP growth. ECB Working Paper, 949. https://ssrn.com/abstract=1275821.

Banbura, M., & Runstler, G. (2007). A look into the factor model black box – publication lags and the role of hard and soft data in forecasting GDP. ECB Working Paper, 751. https://ssrn.com/abstract=984265.

Banbura, M., Giannone, D., & Reichlin, L. (2010). Large Bayesian VARs. J. of Applied Econometrics, 25 (1), 71–92.

Banbura, M., Giannone, D., & Lenza, M. (2014). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. ECARES working paper, 15.

Basselier ,R., de Antonio Liedo, D., & Langenus, G. (2017). Nowcasting real economic activity in the euro area: Assessing the impact of qualitative surveys. National Bank of Belgium Working Paper, 331. Available at: https://www.nbb.be/doc/ts/publications/wp/wp331en.pdf.

Bernanke, B., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. The Quarterly Journal of Economics, 12, 387-422.

Bonadio, B., Huo, Zh., Levchenko, A., & Pandalai-Nayar, N. (2020). Global Supply Chains in the Pandemic. CEPR Discussion Paper, DP14766. https://ssrn.com/abstract=3603998.

Cesaroni, T. (2011). The Cyclical Behavior of the Italian Business Survey Data. Empirical Economics, 41(3), 747–768. https://doi.org/10.1007/s00181-010-0390-7.

Cesaroni, T., & Iezzi, S. (2017). The Predictive Content of Business Survey Indicators: Evidence from SIGE. Journal of Business Cycle Research, 13(1), 75-104. https://doi.org/10.1007/s41549-017-0015-8.

D´Amato, L., Garegnani, L., & Blanco, E. (2015). GDP Nowcasting: Assessing business cycle conditions in Argentina. BCRA Working Paper Series, 2015/69. Available at: https://www.bcra.gob.ar/Pdfs/Investigaciones/WP_69_2015%20i.pdf.

Darracq Paries, M., & Maurin, L. (2008). The role of country-specific trade and survey data in forecasting euro area manufacturing production: perspective from large panel factor models. European Central Bank Working Paper, 894. https://ssrn.com/abstract=1120700.

De Mol, C., Giannone, D., & Reichlin, L. (2008). Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components? J. of Econometrics, 146(2), 318–328.

Drechsel, K., & Maurin, L. (2011). Flow of Conjuntural Information and Forecast of Euro Area Economic Activity. Journal of Forecasting, 30(3), 336-354. https://doi.org/10.1002/for.1177.

European Commission (2020). The Joint Harmonised EU Programme of Business and Consumer Surveys. User Guide. Available at: https://ec.europa.eu/info/sites/info/files/bcs_user_guide_en_0.pdf.

European Commission (2018). Nowcasting euro area GDP growth with Mixed Frequency Models (European Business Cycle Indicators – 1st Quarter 2018, Publications Office of the European Union). https://doi.org/10.2765/17446.

European Commission (2014). What do survey data tell us about future price developments? (European Business Cycle Indicators – 2nd Quarter 2014, Publications Office of the European Union). Available at: https://ec.europa.eu/economy_finance/publications/cycle_indicators/2014/pdf/ebci_2_en.pdf.

Fernandes, N. (2020). Economic Effects of Coronavirus Outbreak (COVID-19) on the World Economy. IESE Business School Working Paper, WP-1240-E. http://dx.doi.org/10.2139/ssrn.3557504.

Galli A., Hepenstrick C., Scheufele R. (2019). Mixed-Frequency Models for Tracking Short-Term Economic Developments in Switzerland // International Journal of Central Banking. Vol. 58, P. 151-178. Available at: https://www.ijcb.org/journal/ijcb19q2a5.htm.

Girardi, A. (2014). Expectations and macroeconomic fluctuations in the euro area. Economics Letters, 125 (2), 315-318. https://doi.org/10.1016/j.econlet.2014.09.031.

Girardi, A., Gayer, C., & Reuter, A. (2015). The Role of Survey Data in Nowcasting Euro Area GDP Growth. Journal of Forecasting, 35(5), 400-418.

Gollier, C., & Straub, S. (2020). The Economics of Coronavirus: Some Insights. Toulouse School of Economics: Public Policy. Retrieved from: https://www.tse-fr.eu/economics-coronavirus-some-insights on November 20, 2020.

Granville, B., & Mallick, S. (2010). Monetary Policy in Russia: Identifying exchange rate shocks. Economic Modelling, 27(1), 432–444. https://doi.org/10.1016/j.econmod.2009.10.010.

Guerrieri, V., Lorenzoni, G., Straub, L., & Werning, I. (2020). Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages? NBER Working Paper, 26918. http://dx.doi.org/10.3386/w26918.

Hansson, J., Jansson, P., & Löf, M. (2003). Business survey data: Do they help forecasting the macro economy (4th Eurostat and DG ECFIN colloquium on modern tools for business cycle analysis). Available at: https://ec.europa.eu/eurostat/documents/3888793/5828897/KS-AN-03-051-EN.PDF/aed6487a-4816-4846-9abb-f6cbfd98afd5.

Jorda, O., Singh, S.R., & Taylor, A.M. (2020). Longer-Run Economic Consequences of Pandemics. NBER Working Paper, w26934. https://doi.org/10.3386/w26934.

Kitrar L., Lipkind T. (2020). Analiz vzaimosvyazi indikatora ekonomicheskih nastroenij i rosta VVP [Analysis of the Relationship Between the Economic Sentiment Indicator and GDP Growth]. Ekonomicheskaya Politika, vol. 15, no. 6, pp. 8-41 (in Russ.).

Kitrar L., Lipkind T., Ostapkovich G. (2020). Ekonomicheskoe razvitie i tsiklicheskie nastroeniya rossiyskikh predprinimateley posle retsessii 2014-2016 godov [Economic Development and Cyclical Sentiment of Russian Entrepreneurs After the Recession in 2014-2016]. Voprosy statistiki, vol. 27, no. 1, pp. 53-70 (in Russ.).

Kitrar L., Lipkind T., Ostapkovich G. (2018). Kvantifikatsiya kachestvennykh priznakov v kon'yunkturnykh obsledovaniyakh [Quantification of Qualitative Variables in Business Surveys]. Voprosy statistiki, vol. 25, no. 4, pp. 49-63 (in Russ.).

Kitrar L., Lipkind T. Ostapkovich G. (2014). Dekompozitsiya i sovmestnyy analiz tsiklov rosta v dinamike indikatora ekonomicheskogo nastroeniya i indeksa fizicheskogo ob'ema valovogo vnutrennego produkta [Decomposition and Joint Analysis of Growth Cycles in the Dynamics of the Economic Sentiment Indicator and the Index of Physical Volume of Gross Domestic Product]. Voprosy statistiki, no. 9, pp. 41-47 (in Russ.).

Kitrar L., Ostapkovich G. (2013). Integrirovannyj podhod k postroeniyu kompozitnyh indikatorov so vstroennym algoritmom ocenki ciklichnosti v dinamike rezul'tatov kon'yunkturnogo monitoring [An Integrated Approach to the Construction of Composite Indicators with a Built-in Algorithm for Assessing Cyclicality in the Dynamics of Market Monitoring Results]. Voprosy statistiki, no. 9, pp. 23-34 (in Russ.).

Korhonen, I., & Mehrotra. A. (2009). Real exchange rate, output and oil: Case of four large energy producers (BOFIT Discussion Paper, 6). http://dx.doi.org/10.2139/ssrn.1428238.

Korhonen, I., & Mehrotra, A. (2010). Money demand in post-crisis Russia: de-dollarisation and remonetisation. Emerging Markets Finance and Trade, 46(2), 5–19. http://dx.doi.org/10.2753/ree1540-496x460201.

Lehmann, R., & Wohlrabe, K. (2013). Forecasting GDP at the Regional Level with Many Predictors. CESifo Working Paper Series, 3956.

Lipkind, T., Kitrar L., & Ostapkovich, G. (2019). Russian Business Tendency Surveys by HSE and Rosstat in: Business Cycles in BRICS / Ed. by Smirnov S., A. Ozyildirim, P. Picchetti, Springer. Ch. 13. pp. 233–251.

Litterman, R. (1986). Forecasting with Bayesian vector autoregressive model – five years of experience. Journal of Business & Economic Statistics, 4(1), 21-36.

Lütkepohl, H. (2011). Vector Autoregressive Models. In: Lovric M. (eds) International Encyclopedia of Statistical Science. Springer, Berlin, Heidelberg.

Mallick, S.K., & Sousa R.M. (2013). Commodity Prices, Inflationary Pressures, and Monetary Policy: Evidence from BRICS Economies. Open Economies Review, 24(4), 677–694.

Mattos, D., Sequeira, A.N., & Lobão, W., & Costa Ferreira, P. (2016). Forecasting Brazilian industrial production with the VAR model and SARIMA with smart dummy (Presentation at the CIRET conference, Copenhagen).

Mayr, J., & Ulbricht, D. (2007). VAR Model Averaging for Multi-Step Forecasting. Ifo Working Paper, 48. Available at: https://www.ifo.de/DocDL/IfoWorkingPaper-48.pdf.

Mehrotra, A., & Ponomarenko, A. (2010). Wealth effects and Russian money demand. BOFIT Discussion Paper Series, 13. http://dx.doi.org/10.2139/ssrn.1665039.

Ollivaud, P., Pionnier, P-A, Rusticelli, E. Schwellnus, C., & Seung-Hee Koh (2016). Forecasting GDP during and after the Great Recession: A contest between small-scale bridge and large-scale dynamic factor model. OECD Economics Department Working paper 1313. Available at: https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=ECO/WKP(2016)37&docLanguage=En.

Rautava, J. (2013). Oil prices, Excess Uncertainty and Trend Growth: a Forecasting Model for Russia's Economy (Austrian Central Bank, Focus on European Economic Integration, 4, 77-87). Available at: https://www.oenb.at/dam/jcr:aeee8d5b-ff32-4db7-919c-7e37e5d1fcb9/feei_2013_q4_studies_rautava.pdf.

UNECE (2019). Guidelines on Producing Leading, Composite and Sentiment Indicators. United Nations, Geneva.

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