UNITED NATIONS
INDUSTRIAL DEVELOPMENT ORGANIZATION

Inclusive and Sustainable Industrial Development Working Paper Series
WP 2 | 2022

Short-term forecasting of economic growth in Russia amid uncertainty based on the opinions of entrepreneurs and consumers

DEPARTMENT OF POLICY, RESEARCH AND STATISTICS

WORKING PAPER 2/2022

Short-term forecasting of economic growth in Russia amid uncertainty based on the opinions of entrepreneurs and consumers

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Vienna, 2022

Acknowledgements

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

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Abstract

This paper analyses the short-term effects of aggregate economic sentiment on expected GDP growth in Russia based on the results of regular large-scale business and consumer surveys for 1998–2021. The main purpose of our study is to investigate the predictive value of the opinions and expectations of economic agents, especially in the context of crises and uncertainty. A composite economic sentiment indicator (ESI) combines 18 quarterly time series – the results of surveys of around 24,000 organizations engaged in economic activities and 5,000 consumers in all regions of Russia.

A vector autoregression (VAR) model with dummy variables is applied to measure the relationship between quarterly gross domestic product (GDP) growth and ESI time series as well as short-term GDP growth forecasting. Scenario forecasts until the end of 2022 are determined by GDP growth response to impulses in the ESI. Additionally, we set interval of ESI values in Q4-2021 according to possible changes in the estimates and expectations of economic agents is introduced into the calculation of the forecast for Q1-2022. Under all forecast scenarios, economic growth in Russia will move into a phase of sustainable recovery which will become more pronounced in the second half of 2022.

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

JEL: C53, E32, E37, O47

Introduction

The challenge of measuring short-term economic growth has become considerably more complicated in the face of new uncertainties and shocks that have emerged in the context of the COVID-19 crisis. Due to the increased vulnerability of many activities, the recovery of economic growth and the effectiveness of public policies have become grown more dependent on the adaptation of entrepreneurs and households.

Large-scale, short-term data based on the opinions and expectations of economic agents and obtained from business and consumer surveys (BCS) are essential for reliably measuring national progress and the effectiveness of new growth models.

BCS are well-established tools for assessing and analysing economic development (UN, 2015). They provide valuable information in addition to the available quantitative statistics. Entrepreneurs and consumers are asked about past developments, assessments of the current situation and expectations for the near future. The biggest advantage of BCS is their timeliness: due to simple questionnaires, the data processing time is very short. Moreover, BCS provide unique information on events and phenomena that are not covered in official statistical observations, such as agents' expectations. Since survey results are generally not subject to revisions, they are particularly useful for business cycle analysis.

Composite survey-based indicators can increase the efficiency of statistical monitoring in the new economic situation and have 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 involving managers and consumers, i.e. the economic sentiment indicator (ESI), for the period 1998–2021. ESI's advantages include its significant correlation with quarterly GDP growth (as a year-on-year percentage) and harmonization with the composite index used by the European Commission to aggregate BCS results in European countries.

The key question our study addresses is whether the quantified opinions of economic agents, combined in composite indicators, are relevant for measuring short-term prospects of GDP growth in the context of economic uncertainty and shocks arising from crises. As a special case for flash quarterly estimates of GDP growth, we examine the strong negative impact on the ESI dynamics caused by the coronavirus pandemic in 2020–2021.

We use a universal model specification for two economic indicators—GDP growth and ESI—to determine the empirical and predictive value of aggregated BCS results for contributing to short-term insights on economic growth in Russia. Such information is useful for decision-makers and other relevant stakeholders, especially during periods of crises and post-crisis recovery.

Our main research objective is to conduct a statistical analysis of two time series including an assessment of their integrability with testing for stationarity and causality. The functional relationship of the series is identified using the dynamic specification of the universal vector autoregression (VAR) model with dummy variables that capture episodes of strong fluctuations, including those caused by the coronavirus pandemic in 2020–2021. This study moreover evaluates the statistical efficiency of the predicted values using the proposed modification of the VAR model and the response function of the reference macroeconomic indicator to impulses on the ESI dynamics.

The main theory of our research is that the compatibility of cyclical dynamics of aggregate economic sentiment with GDP growth allows for the use of ESI to provide early estimates of economic growth, in particular taking their timely publication into account.

The scientific hypothesis is based on a quantitative assessment of the response of GDP growth to impulses on the ESI dynamics: each clear short-term surge in the aggregate economic sentiment synchronously contributes to the expansion of economic growth; the expansion then 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 analyses. We then describe the data and methodology used. Next, we calculate scenario forecasts for GDP growth until the end of 2022 by using a VAR model with dummy variables. The concluding section discusses the main results and possible areas for future research.

1. Literature review

All issues considered in this study are discussed in the scientific and expert literature. This includes methodological and empirical problems of using the results of surveys involving economic agents and survey-based composite indicators in macroeconomic analyses and forecasting. Publications on econometric forecasting methods are also of significant relevance.

In the international practice of studying the opinions and expectations of businesses and consumers, the ESI belongs to a group of coincident composite indicators of business activity, as it changes synchronously with the dynamics of the reference statistic: GDP growth. The ESI uses simple questionnaires and short data processing, and 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 ESI's key 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 to forecast economic activity reflects a broad consensus on their predictive capabilities. Specifically, Cesaroni (2011) provides evidence of the high predictive ability of business tendencies and the possibility of using these in high-frequency forecasting of the development of economic growth. Cesaroni and Iezzi (2017) note the effectiveness of 'soft' statistics in predicting short-term macroeconomic dynamics.

Most studies that focus on the economic consequences of the COVID-19 pandemic are based on quantitative statistics: the dynamics of GDP and the output of goods and services, the volume of imports and exports, industry indicators, and 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 of 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 nowcasting and forecasting 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 to forecast GDP in German regions. D'Amato et al. (2015) nowcast Argentina's GDP growth by using bridge equations and the dynamic factor model (DFM) with consumer survey data. DFM models, which include survey information, are also used to forecast GDP for the euro area (Banbura & Runstler, 2007; Basselier et al., 2017), as well as for France, Germany, Italy, Japan, the United Kingdom and the United States (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 GDP in the euro area in a pseudo real-time setting has also been evaluated (EC, 2018).

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 alternative procedures, including DFM.

To our knowledge, there are no comprehensive studies on the long-term dynamics of business activity of economic agents in Russia based on large-scale surveys conducted by the Federal State Statistics Service of the Russian Federation (Rosstat) 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 divulge important short-term impulses associated with further economic growth, which, in our opinion, should be used when analysing statistical information. In this respect, the scientific and analytical publications of the Center for Business Tendency Studies at the Higher School of Economics are notable; the long-term and large-scale dynamics of the results of Rosstat business surveys are extensively used.

The predictive value of ESI due to its high cyclical sensitivity to short-term GDP dynamics was confirmed 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 slowdown;
- The growth rate of negative sentiments among economic agents synchronously exceeds the intensity of the slowdown in GDP growth. During such periods, the TESI is defined as a coincident indicator, which confirms the transition of economic growth to a phase of contraction;
- After a crisis period, there is a significant gap and lag between 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 model the cyclical relationship of indicators based on empirical facts about business cycles and vector autoregressions, initially allowing no more than seven to eight parameters for 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 to be the most important determinants of the modelled process. A class of Bayesian VAR (BVAR) models aims to overcome the 'curse of dimensionality.' Reducing the number of estimated parameters is 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 different time series with a 'jagged edge', frequent adjustments and revisions. They include information matrices of large dimensions, e.g. on 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 are primarily aggregated into a composite ESI indicator. The statistical relationship between the dynamics of this indicator and the quantitative reference series (GDP growth) are then confirmed based on VAR-modelling, when the behaviour of any variable depends both on its past values and on the values of other series included in the model (Mayr & Ulbricht, 2007; Lütkepohl, 2011). The proposed forecasting method is available to most researchers and experts; it is flexible and can be used to solve more complex problems with the introduction of additional indicators and by expanding the model specifications. Introducing dummy variables that capture periods of deep economic recession (including those associated with the coronavirus crisis) in the VAR model specification enhance the forecasting performance.

2. 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, involving six basic sectors of the economy and households. They are conducted regularly (monthly and quarterly) and include over 29,000 economic agents: 3,100 manufacturing firms, 500 mining firms, 6,000 construction organizations, 4,000 retail firms, 4,000 wholesale firms, 6,000 services organizations and 5,100 households.[1] The surveys contain qualitative assessments and expectations: all respondents are asked about their current situation, and about 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,

[1] Survey results (time series, not seasonally 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.

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 are used to build various composite indicators through their ‘vertical quantification’ in statics or dynamics (Kitrar et al., 2018), harmonized as much as possible with the recommendations of the European Commission and OECD (EC, 2020) for cross-country comparative analyses.

For the ESI calculation, we aggregate 18 indicators that reflect the short-term fluctuations in the entrepreneurial estimates of business tendencies in the Russian economy in 1998–2021. These indicators (Table 1) cover economic activities with a total contribution to GDP of over 70 per cent. At present, it is the only quantitative aggregate of all categorical statistics—in terms of the coverage of sample populations and sectors as well as the duration of dynamics—reflecting economic sentiment in Russia.

The ESI calculation algorithm includes seasonal adjustment and the standardization of components, their weighting according to their shares in GDP[2], summing up the components and normalizing the result with an average value of 100 and a standard deviation of 10.

The time series of the ESI and GDP growth for the period Q1-1998 to Q3-2021 are tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The null hypothesis is the presence of a unit root; the series is considered stationary if it is rejected. The obtained p-values of less than 0.01 for both variables over the entire observation period allows for the rejection of the null hypothesis; the analysed dynamics are considered stationary at the 1 per cent significance level.

In previous studies (Kitrar et al., 2020, 2014; Kitrar, Lipkind 2020; Kitrar, Ostapkovich, 2013), the ESI series were 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 main criterion for assessing ESI cyclical sensitivity and for examining its impact on GDP growth prospects.

[2] In 2021, 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.

Table 1: List of ESI components: BCS results

No.	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	-

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

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* denotes the quarters for the period Q1-1998 to Q3-2021. For this model specification, the optimal lag number of two quarters is determined based on the minimum values of generally accepted information criteria (Table 2).

Table 2: 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

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

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

$$X_t = c_{2,0} + \sum_{i=1}^{2} a_{2,1}^{i} Y_{t-i} + \sum_{i=1}^{2} a_{2,2}^{i} X_{t-i} + \sum_{j=1}^{2} a_{2,j}^{3} D_j + \sum_{j=1}^{6} a_{2,j}^{4} L_j + \varepsilon_{2,t} \tag{1}$$

$$Y_t = c_{1,0} + \sum_{i=1}^{2} a_{1,1}^{i} Y_{t-i} + \sum_{i=1}^{2} a_{1,2}^{i} X_{t-i} + \sum_{j=1}^{2} a_{1,j}^{3} D_j + \sum_{j=1}^{6} a_{1,j}^{4} L_j + \varepsilon_{1,t} \tag{2}$$

where:

X_t – GDP growth, y-o-y, %;

Y_t – ESI seasonally adjusted series;

D_j *u* L_j – dummy variables.

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

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

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

We use a universal dynamic model with a well-defined specification corresponding to the study's objective. Introducing dummy variables *D* into the model specification allows us to fix not only severe crisis events, but also when the 'bottom' of such episodes has been reached, the GDP growth rate's minimum value and the onset of recovery. Dummy variables *L* are relevant for periods of increased economic uncertainty. The advantage of introducing dummy variables lies in their ability to capture episodes of severe crisis, moments of 'low' cyclical reversals with minimum values in the intensity of GDP growth, and the onset of the recovery phase over the entire observation period. the lowest ESI values in Russia in 2020 were primarily triggered by the 'unforeseen shocks' triggered by the coronavirus pandemic. To determine the recovery period, in particular in Q3-2020 and Q1-2021, the 'recovery' variable was activated (with a value of 1). Thus, the introduction of dummy variables aims to keep the model specification simple and to predict the expected GDP growth rate based on the impulse response function, taking the specifics of the recessionary events in the country into account.

The proposed model specification with dummy variables is evaluated as being consistent. According to the Doornik-Hansen test, for the first four lags, the null hypothesis of the normal distribution of residuals is not rejected at the 5 per cent significance level (p-value 0.177). The hypothesis of no autocorrelation according to the Broysch-Godfrey test is not rejected at the 5 per cent significance level (p-values for each lag are higher than 0.05). The VAR-simulation results are presented in Table 3.

Table 3: Results of the VAR simulation

Lags	Coefficients	Standard error	t-statistics	p-values	Coefficients	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 use the impulse response function (IRF) to explore the relationship between the two series in the model, to estimate the strength and direction of the shock as well as the duration of adjusting the estimated series (GDP growth) to the shock in ESI equal to one standard deviation. First, the residuals obtained when evaluating the VAR model should be presented as a linear combination of uncorrelated shocks, 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 is used to identify shocks; the order of the variables is 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 for the short-term or long-term reaction of some indicators to others. Optimal ordering provides greater impact of the ESI on GDP growth. This result of variance decomposition of GDP series is achieved using the following order of variables: ESI → GDP growth.

We also test causal relationships between the ESI and GDP growth (Table 4).

Table 4: 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 reveal dependencies between the ESI and GDP growth and between GDP growth and the ESI. In our ordering, however, shocks in economic sentiment affect both the ESI and GDP growth, while shocks in GDP growth only have an immediate impact on economic growth. Therefore, to further forecast economic development, we consider a situation in which GDP growth does not have a major effect on economic sentiment.

Next, we construct the IRF; 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 on IRFs, we calculate scenario forecasts of GDP growth until the end of 2022, taking possible gaps in the ESI at the end of 2021 into account, relative to the long-term average level of its dynamics.

We also compare 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. For the in-sample interval (from Q1-1998 to Q1-2021), the model acceptability of the quarterly forecast is confirmed based on the parameters of forecast quality (Table 5).

The introduction of dummy variables in the model specification increases the forecast performance of the in-sample interval. The behaviour of the reference macroeconomic indicator is estimated based on the response of its time series to the impulse in the ESI series. The result are statistically efficient forecasts of GDP growth, both in the in-sample and out-of-sample intervals, based on possible simulations of further developments.

Table 5: Parameters of forecast quality

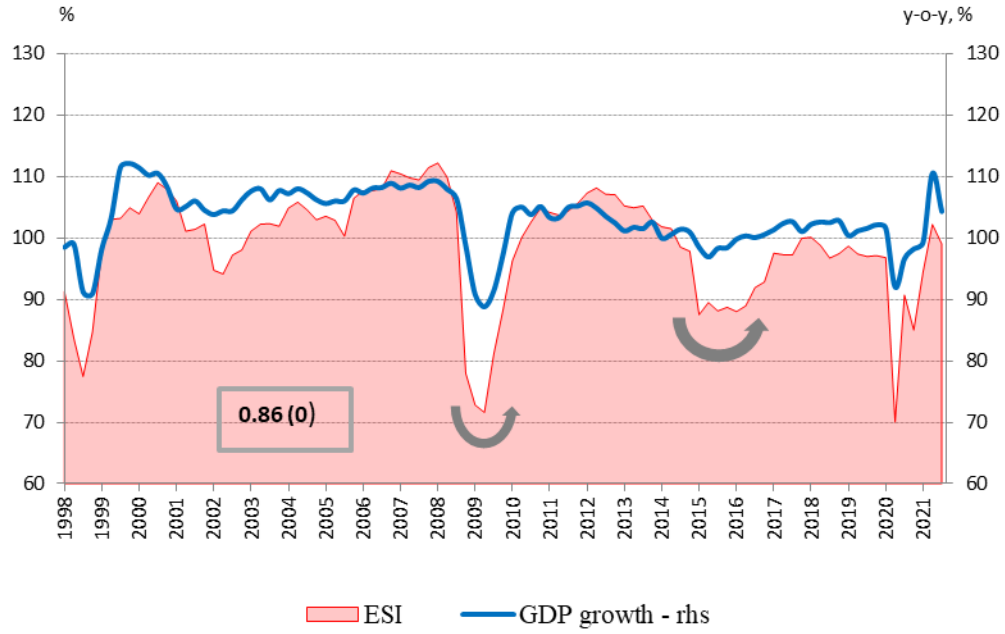
Forecast without dummies		Forecast with dummies		Forecast without pandemic shock	
R-squared	0.78	R-squared	0.93	R-squared	0.93
Sum sq. resids	542.54	Sum sq. resids	130,29	Sum sq. resids	116.88
S.E. equation	2.32	S.E. equation	1.29	S.E. equation	1.24
MSE	5.08	MSE	1.46	MSE	1.34
RMSE	2.26	RMSE	1.21	RMSE	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.

3. Research results

Figure 1 presents the time series of ESI and GDP growth (1998–2021).

Figure 1: ESI and GDP growth dynamics in 1998–2021



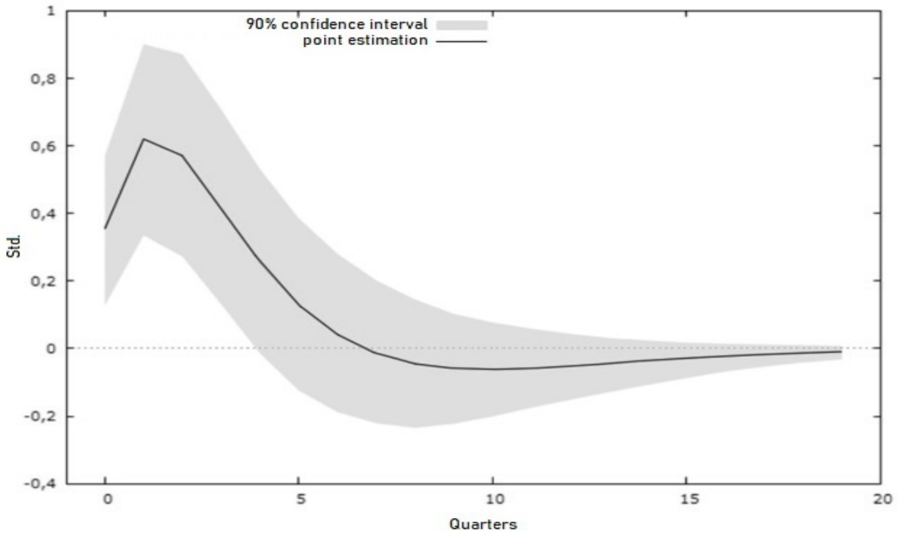
Source: Authors' elaborations based on Rosstat data.

Note: The marker indicates the coefficient of synchronous correlation between the ESI and GDP growth series.

We observe the most severe, an almost vertical collapse of aggregate sentiment among Russian entrepreneurs and households in Q2-2020. The sudden and unprecedented drop in the ESI was obviously associated with the strict measures to contain the pandemic, which had an extremely adverse effect on businesses and the population, both in terms of demand (reduced household consumption, investment activity, export earnings) and supply (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 during a new crisis, the onset of which was caused mainly by non-economic factors (Kitrar et al., 2020). The subsequent slowdown in the decline of GDP in Q3-2020 occurred against the backdrop of a clear 'rebound' in the ESI downward trend. We observe a clear and rapid adaptation of economic agents to the new economic reality during this period, a positive response to timely measures to support businesses and households. The further ESI dynamics reflect a gradual recovery in the aggregate economic sentiment of entrepreneurs and consumers, with the short-term deterioration mainly associated with new waves of the pandemic.

The results of the VAR simulation based on the IRF (see Figure 2) allow us to estimate the strength and direction of the impact of an artificial shock in the ESI series on GDP growth and the duration of the GDP growth's adjustment to the shock. On this basis, the initial hypothesis about a significant unidirectional relationship between the 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 GDP growth to an impulse in the ESI fades for at least six quarters, and then the reference indicator stabilizes, reaching its initial level.

Figure 2: Response of GDP growth to impulses in ESI: the degree and direction of impact (Cholesky decomposition)



Source: Authors' calculation conducted in Eviews.

We calculate scenario forecasts for quarterly GDP growth until the end of 2022, driven by GDP response to actual and expected impulses in the ESI dynamics from Q1-1998 to Q3-2021. The calculations were based on the indicator values for the entire period, taking all cyclical phases in their dynamics into account, including a sharp decline, further fluctuations due to the coronavirus crisis in Q2-2020 and the subsequent protracted pressure of uncertainty on economic activity.

The predictive capabilities of the proposed approach are presented by an example where we set the range of ESI values in Q4-2021 in accordance with possible changes in the assessments and expectations of economic agents (both positive and negative).

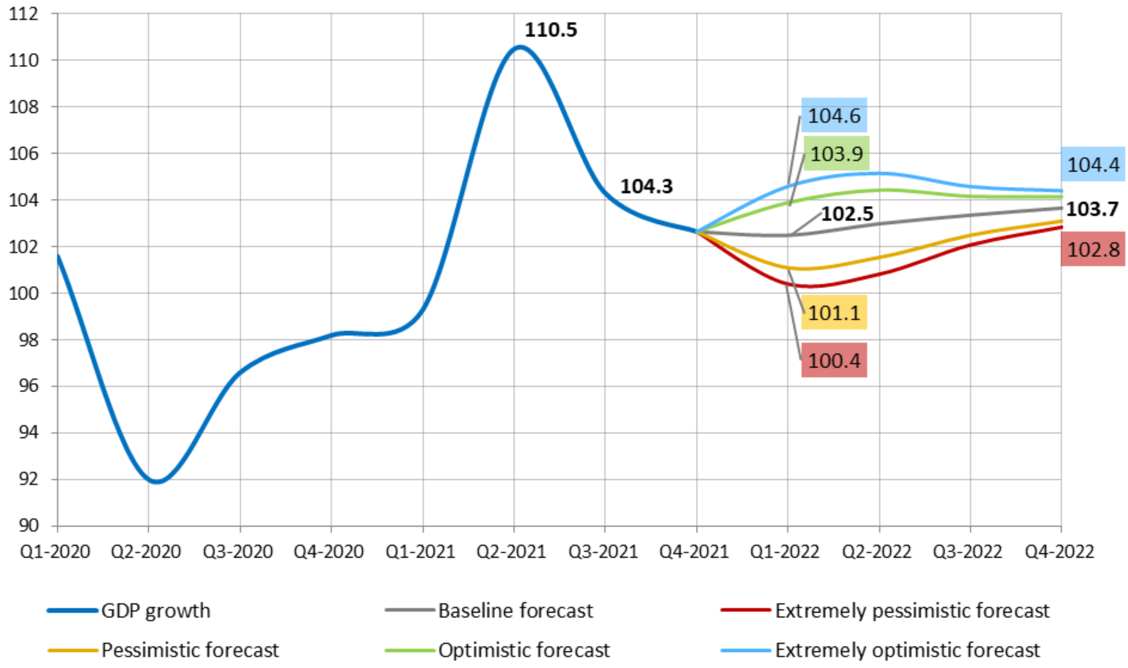
The pessimistic forecasts are based on a simulation of predominantly negative sentiments associated with a possible upcoming decline in economic activity. In this case, the key risks are a slowdown in the pace of recovery; coronavirus-related 'damage' to the transport and logistics chain; inflationary effects of a ‘price rally’ in commodity markets; maintaining restrictive anti-pandemic measures; ‘stalled’ vaccination campaign; growing price pressure; increase in the main interest rate; irreducible geopolitical tensions; and the continuing uncertainty of new waves of the pandemic.

The baseline forecast is based on moderate economic expectations at the end of 2021. The entrepreneurial sentiments consider containing the spread of the virus, strengthening global economic growth, rising commodity prices and expanding exports, increasing demand under a soft monetary policy, returning to pre-pandemic production levels, and the absence of new industry events that exacerbate ‘economic anxiety’ and uncertainty.

The optimistic forecasts are primarily based on more favourable expectations of businesses and households. They reflect the rapid and successful elimination of the ‘traces and damage’ of the coronavirus crisis; accelerated immunization rates and overcoming the regional vaccination gap; lifting all restrictive measures; expanding economic stimulus measures; faster and more sustainable growth of the world economy, oil demand and domestic consumption; reducing economic uncertainty and vulnerability.

The simulation of ESI values is based on the introduction of conditional impulses as deviations from the long-term average of its dynamics (100 points) – plus/minus 10 and 15 points – depending on the new crisis shocks at the end of 2021. Figure 3 presents all scenario forecasts of GDP growth until the end of 2022.

Figure 3: Scenario forecasts of GDP growth



Source: Authors' calculations based on Rosstat data.

4. Conclusions

In this study, we present a method of statistical analysis to evaluate the relationship of the results of business and consumer surveys conducted by Rosstat, by combining them into one composite indicator of economic sentiment and GDP growth. This method is available to most researchers and experts; it is flexible and convenient for solving more complex problems by introducing additional indicators and expanding the model specifications.

The statistically significant results of VAR-modelling using dummy variables to capture periods of severe economic recession (including those associated with the coronavirus crisis) allow for short-term forecasting of GDP growth. Under all forecast scenarios, economic growth in Russia will move into a phase of sustainable recovery, which will become more pronounced in the second half of 2022.

For short-term forecasts of GDP growth, we use a composite indicator that summarizes the survey results only. Despite the consistency of the proposed model specification, we believe that the forecasting performance can be improved if quantitative economic variables are included in the model. Another area of survey-based methods of analysis and forecasting that could be further developed is an improvement of ESI's leading properties by updating its composition and selecting an optimal set of components.

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