NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

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EXPLORING THE POTENTIAL OF BUSINESS UNCERTAINTY INDICATORS IN FORECASTING ECONOMIC ACTIVITY: THE CASE OF RUSSIA

BASIC RESEARCH PROGRAM
WORKING PAPERS

SERIES: SCIENCE, TECHNOLOGY AND INNOVATION

WP BRP 128/STI/2024

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Exploring the potential of business uncertainty indicators in forecasting economic activity: The case of Russia[3]

This paper investigates the utility of business uncertainty indicators as predictive tools for forecasting economic activity in the context of Russia. In an era characterized by global economic volatility and geopolitical shifts, understanding the dynamics of economic uncertainty and its impact on overall economic performance is of paramount importance. The study utilizes a comprehensive dataset based on the results of business tendency surveys in Russia, spanning the period from 2009 to the first half of 2024. Given the importance of uncertainty in shaping economic outcomes, the central research question of this study is: “Can uncertainty indicators predict business activity in Russia or not?”. To address this question, we compared two alternative approaches to calculating business uncertainty: the ex-ante approach, which uses the business community's assessments of future business trends to measure uncertainty as a measure of the dispersion of opinions expressed, and the ex-post approach, which uses entrepreneurial assessments of both future and current trends to determine business uncertainty as the degree of deviation of entrepreneurial expectations from the real picture. National indicators and sectoral indicators were calculated for the mining and quarrying industry, manufacturing industry, construction, retail trade, wholesale trade and services. For most of the industries under consideration (except for the construction and service sector) and at the national level, the specifications of vector autoregression models that were effective for forecasting real indicators of economic activity, characterized by lower forecast errors compared to standard autoregressive models, were built. According to the results obtained, at the national level, when forecasting GDP, clear preference should be given to the ex-post indicator.

Keywords: uncertainty, business tendency survey, Russia, forecasting.

JEL Classification: C82, D81, E32.

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[3] The article was prepared within the framework of the Basic Research Program of the HSE University.

1. Introduction

Over the past decade, macroeconomists have begun to pay more attention to the concept of economic or business uncertainty. The very concept of "uncertainty" began to be widely used in the economic context after the publication of F. Knight's book "Risk, Uncertainty, and Profit" (Knight, 1921). Even though risk and uncertainty are often examined without clear distinctions, it can be important to recognize the conceptual differences (Cascaldi-Garcia et al., 2020). Risk, often interchangeably associated with volatility, is a statistical gauge of the variability in observed results. Uncertainty, on the other hand, is defined by both unknown outcomes and probability distributions.

Despite the difficulty of measuring uncertainty due to the lack of objective empirical measures, in modern macroeconomic literature one can increasingly find empirical studies of uncertainty using various proxy indicators. Popular methods for their construction at the moment include, but are not limited to:

- measures of the dispersion of economic actors' views on the economic situation and expected prospects – noticeable dispersion is associated with high uncertainty (Bachmann et al., 2013; Girardi and Reuter, 2017; Claveria, 2019);
- indicators based on forecast errors – the more erroneous economic forecasts, the greater the uncertainty at the time of the forecasts (Jurado et al., 2015; Girardi and Reuter, 2017);
- indicators that track uncertainty in news articles by counting keywords (Baker et al., 2016).

One of the most popular sources of data for calculating uncertainty indicators are business tendency surveys. The key features of the information obtained in the course of business tendency surveys include the fact that it describes the perception of company managers and consumers of observed economic trends, its non-quantitative nature, representativeness and relatively large size of samples used, as well as the relative promptness of obtaining compared with official quantitative statistics. For all questions concerning assessments of the dynamics (trends) of indicators, a three-category graduation is used: respondents choose between growth or improvement (+), no change (=) and decline or deterioration (-).

Indicators based on data on entrepreneurial expectations obtained as part of business tendency monitoring have advantages over alternative measures, since they are based on the knowledge of economic agents directly operating in the market and provide detailed information on many economic variables, many of which have no analogues in quantitative statistics. In addition, the international harmonization of business tendency monitoring makes it possible to compare survey results in different countries and use them in cross-country business cycle studies (Claveria, 2021a).

A technique for using business tendency survey data to indirectly measure uncertainty was first proposed by Bachmann et al. (2013); various modifications have subsequently been developed (see, e.g., Claveria, 2021b, 2021c; Girardi and Reuter, 2017). This approach has now become one of the leading ones in the empirical analysis of uncertainty (see, for example, Binding and Dibiasi, 2017; Girardi and Reuter 2017; Meinen and Röhe, 2017; Mokinski et al., 2015). The methodology proposed by Bachmann et al. (2013) consists in defining uncertainty as the dispersion of forecasts made by economic agents regarding future events. Accordingly, during periods of high uncertainty there will be greater dispersion of forecasts about the future, whereas during periods of low uncertainty respondents will be more likely to agree in their assessments. We call indicators constructed using this methodology ex-ante business uncertainty indices.

Subsequently, European Commission researchers developed alternative measures of uncertainty based on the same empirical basis (Girardi and Reuter, 2017). One is based on a measurement of respondents' forecast errors by adjusting expected trends recorded in the previous month, quarter or year, taking into account current trends recorded in the current month, quarter or year. Uncertainty in this case is understood as a measure of the unpredictability of future economic trends. We call such indicators ex-post business uncertainty indices. Their construction becomes possible only when we can assess the accuracy of reported expectations.

The purpose of this article is to test these approaches to measuring business uncertainty in the context of forecasting the dynamics of economic activity in Russia. For the Russian economy, business uncertainty is especially important due to the country's dependence on the export of raw materials and geopolitical turbulence. In this sense, it is the current period, accompanied by unprecedented industry deformations, that represents a suitable information environment for the development of new methodological tools to measuring and analyzing business uncertainty in Russian statistical practice.

The goal is achieved within the framework of the following tasks:

— development and testing of new business uncertainty indices, which will serve as measures of the current level of total uncertainty on the scale of the country and its key industries

— study of the potential of business uncertainty indices in forecasting economic activity using pseudo-out-of-sample analysis with different econometric models (vector autoregression, Bayesian vector autoregression and dynamic factor models).

Indicators based on data from business tendency surveys were tested by the authors in previous studies, where a leading relationship was demonstrated between time series of the survey-based indicators and quantitative time series (Authors, 2021; Authors, 2020; Authors, 2019). The methodology for constructing business uncertainty indices on Russian data has been already described in detail in the authors' previous study in this area of research (Authors, 2024).

2. Material and methods

The paper uses observational data from the Russian Federal State Statistics Service (Rosstat) to measure business activity in mining and quarrying, manufacturing, retail trade, wholesale trade, construction, and services. The time series cover the period from I quarter 2009 to II quarter 2024 (mining and quarrying, manufacturing, retail trade, wholesale trade, construction) and from I quarter 2012 – II quarter 2024 (services). The respondents are representatives of enterprises (executives or senior managers) who have the necessary level of competence on the questions asked in the questionnaire.

When filling out the questionnaires, respondents are asked, among other things, to assess trends in the development of such indicators of business activity as demand for manufactured products, volume of sales or services provided, sales prices of goods or services, the number of employees at the enterprise, economic situation, etc. Questions in the questionnaires may concern events over the past three months or year (current trends), as well as expectations for the next three months or years (expected trends). The main way to quantify such non-parametric data is the balance method (OECD, 2003). Balances are calculated as the share of respondents who gave a positive answer minus the share of those who answered negatively.

The paper describes the following indicators – ex-ante and ex-post business uncertainty indices: at the national level, in mining and quarrying, in manufacturing, in construction, in retail trade, in wholesale trade and in the service sector. The methods used are primarily based on the experience of the European Commission in the field of uncertainty measurement (Girardi and Reuter, 2017).

First, let us consider the methodology for calculating ex-ante indicators that operationalize uncertainty as a measure of the dispersion of respondents' expectations regarding the future business environment:

1. The calculation of the cross-sectional deviations of positive and negative responses for each survey question considered in each quarter using the following formula:

   $$\sigma = \sqrt{P + N - (P - N)^2} \quad (1)$$

   where P is the proportion of positive answers to survey questions, N is the proportion of negative answers to survey questions.

2. The standardization and normalization of the constructed time series in order to avoid the predominance of questions with particularly pronounced dispersion in answers and/or high absolute average values when constructing an overall index accumulating the results for individual questions.
3. The construction of time series aggregated at the industry level as the average value for series of indicators related to individual questions.
4. The calculation of the national ex-ante index based on a weighted aggregation of standardized values obtained within individual industries. When aggregating industry values, the percentage shares of industry subsamples in terms of the number of enterprises in the total population were used as weights.
5. To simplify interpretation, scaling indices so that the mean is 100 and the standard deviation is 10. Thus, values above 110 or below 90 should indicate an extremely high or low level of uncertainty respectively.

Let us move on to the method of calculating ex-post indices, based on measuring respondents' forecast errors by the comparison of assessments of the current situation for any parameter with previously recorded expectations. In the surveys, the same period is assessed twice: once in terms of expected changes and a second time in terms of current (i.e., already occurred) changes. For example, expected changes in the number of people employed in the first quarter are reported in the January survey, and current changes in this indicator for the first quarter are reported in the March survey. This makes it possible, using both types of answers, to estimate how much the range of current estimates deviated from the range of expectations. Since the dispersion of responses regarding current trends reflects only the heterogeneity of respondents without the effect of uncertainty, scaling the dispersion of expected trends recorded in the previous period using the dispersion of estimates of actual trends allows us to neutralize the effect of heterogeneity of respondents on the dispersion of expectations and retain only the effect of uncertainty. This is a theoretical advantage of the ex-post indicator compared to its ex-ante counterpart.

Accordingly, the methodology for constructing ex-post indices was as follows:

1. The calculation of the cross-sectional deviations of positive and negative responses for each survey question considered in each quarter using the following formula:
$$\sigma = \sqrt{P + N - (P - N)^2} \quad (1)$$
where P is the proportion of positive answers to survey questions, N is the proportion of negative answers to survey questions.
2. Scaling the dispersion of expected trends recorded in the previous period using the dispersion of estimates of actual trends recorded in the current period, which makes it possible to highlight the dispersion of expectations provoked by uncertainty. For each indicator within each industry, logic ratios of the standard deviations of positive and negative expected assessments of entrepreneurs in period t-1 to current assessments in period t were calculated. The following formula was used:
$$U_t = \ln(\sigma_{t-1}^{e} / \sigma_t^{c}) \quad (2)$$
where e and c indicate whether the estimate is an expected or current trend, and t indicates the point in time (quarter) in which the study was conducted.
3. The construction of time series based on indicators calculated using formula (2) related to individual questions in the questionnaire.
4. The standardization and normalization of the constructed time series in order to avoid the predominance of questions with particularly pronounced dispersion in answers and/or high absolute average values when constructing an overall index accumulating the results for individual questions.
5. The construction of time series aggregated at the industry level as the average value for series of indicators related to individual questions.

6. The calculation of the national ex-post index based on a weighted aggregation of standardized values obtained within individual industries. When aggregating industry values, the percentage shares of industry subsamples in terms of the number of enterprises in the total population were used as weights.
6. To simplify interpretation, scaling indices so that the mean is 100 and the standard deviation is 10. Thus, values above 110 or below 90 should indicate an extremely high or low level of uncertainty respectively.

To build the ex-ante and ex-post national indices, the following indicators were selected that correspond to survey questions relating to key aspects of business activity of enterprises: demand / number of concluded contracts / orders for the supply of goods; product output / physical volume of work / sales volume / volume of services provided; sales prices of goods/services; number of employees at the enterprise; economic situation.

When constructing ex-ante and ex-posts indices for the mining and quarrying industry and indices for the manufacturing industry, the following indicators were used: product output; finished product inventories; profit; general demand for products; demand for products in the foreign market; selling prices of goods; number of employees at the enterprise; economic situation.

In turn, the following indicators became the components of indices in construction: physical volume of work; number of concluded contracts; number of employees at the enterprise; own competitive position; prices for materials; prices for construction and installation work; profit; own financial resources; the access to credit resources; investment; economic situation.

The following indicators were the components of indices in retail trade: sales volume; trade turnover; orders for the supply of goods; number of employees at the enterprise; range of goods; economic situation; own financial resources; investments for expansion of activities, repairs and modernization; profit; selling prices of goods; competitiveness.

When constructing indices in wholesale trade, the following indicators were used: demand; turnover; volume of sales; number of employees at the enterprise; range of goods; stocks; own financial resources; the access to credit resources; profit; prices for purchasing goods; selling prices of goods; economic situation.

The following indicators were selected as components of indices in the service sector: own competitive position; the volume of provided services; profit; demand; prices for services; number of employees at the enterprise; economic situation.

Due to the fact that data on the service sector are available only from 2012, in the calculations of the national indices for 2009–2011, this industry was not taken into account. Table 1 presents the weights used (it should be noted that national indicators summarize the results of surveys by type of activity with a total contribution to GDP of more than 70%).

Table 1. Percentage shares of industry subsamples by number of enterprises

Industry	**Number of firms**	**Weight for calculation** (up to 2012) (%)	**Weight for calculation** (since 2012) (%)
Mining and quarrying	600	3%	2%
Manufacturing	3 800	18%	15%
Electricity, gas, steam and air conditioning supply[4]	300	1%	1%
Construction	6 000	29%	23%
Retail trade	4 000	19%	15%
Wholesale trade	6 300	30%	24%
Services	5 000	–	19%
TOTAL	26 000	100%	100%

[4] Only used when calculating the national indices.

3. Calculation

This section presents the main methodological principles used to build the models, as well as the results of intermediate tests. Calculations were carried out using the EViews statistical software package.

Below is the applied algorithm for modeling the relationship between the effects of uncertainty on economic activity:

1. Testing time series for stationarity (Augmented Dickey-Fuller test).
2. Determination of the optimal order of lags based on the Akaike information criterion (AIC).
3. Test for lack of cointegration (Johansen test).
4. Testing of indices for mutual cross-correlation with GDP and Granger causality analysis between these series.
5. Pseudo-out-of-sample analysis using three different econometric models (vector autogestion, Bayesian vector autoregression and dynamic factor models) for the ex-ante and ex-post business uncertainty indices.

The final stage of the study involved pseudo-out-of-sample analysis, which simulates out-of-sample analysis by artificially dividing the existing total sample into two subsamples (Inoue and Kilian, 2005). In this case, the first subsample is used to build a forecast, and the second is used to evaluate it by comparing the model results with real data.

As part of the pseudo-out-of-sample analysis, different models were built at the national level and within each industry under consideration – based on business uncertainty indices 1) ex-ante and 2) ex-post. Vector autoregression models (VAR) were used as an initial benchmark. In addition, Bayesian vector autoregression models (BVAR), which are especially useful when dealing with limited time series, were used to test the forecasting potential of the indices.

For each of these econometric frameworks, fourteen models were built examining the following relationships between the variables (see Table 2). The selection of reference statistical series for the indicators was carried out in accordance with the recommendations of the European Commission (European Commission, 2023, p. 14). All models were identified according to a standard recursive ordering procedure, where variables are ordered in an order consistent with standard practice in the literature (Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015; Girardi and Reuter, 2017; Baker et al., 2016; Sahinoz and Erdogan Cosar, 2020). The recursive order of variables in each model was as follows: the reference variable (e.g., GDP, sectoral GVA, etc.) – the index variable (e.g., the national ex-ante index, the ex-post index in manufacturing, etc.).

Table 2. Researched relationships between indicators of economic activity and the business uncertainty indices within the industries under consideration

Industry	Dependent variables	Independent variables
National level	GDP (log)	National ex-ante index
		National ex-post index
Mining and quarrying	GVA of mining and quarrying (log)	Ex-ante index in mining and quarrying
		Ex-post index in mining and quarrying
Manufacturing	GVA of manufacturing (log)	Ex-ante index in manufacturing
		Ex-post index in manufacturing
Retail trade	Turnover of retail trade (log)	Ex-ante index in retail trade
		Ex-post index in retail trade
Wholesale trade	Turnover of wholesale trade (log)	Ex-ante index in wholesale trade
		Ex-post index in wholesale trade
Construction	GVA of construction (log)	Ex-ante index in construction
		Ex-post index in construction
Services	GVA of services (log)	Ex-ante index in services
		Ex-post index in services

At the first stage, using the Augmented Dickey-Fuller test (ADF-test), the time series under study were tested for stationarity, which is an important condition for constructing adequate VAR models. The test results presented in Table 3 indicate that all the time series under study are stationary in first differences, so we can proceed to modeling.

Table 3. Stationarity check of the time series using the Augmented Dickey-Fuller test

Industry	**First differences of variables**	**t-statistic**	**Critical value** (10% significance level)	**p-value**
National level	National ex-ante index	-4,77	-2,60	0,00
	National ex-post index	-4,48	-2,60	0,00
	GDP (log)	-2,96	-2,60	0,10
Mining and quarrying	Ex-ante index in mining	-3,97	-2,60	0,02
	Ex-post index in mining	-6,24	-2,60	0,00
	GVA of mining and quarrying (log)	-3,43	-2,60	0,06
Manufacturing	Ex-ante index in manufacturing	-4,44	-2,60	0,00
	Ex-post index in manufacturing	-5,26	-2,60	0,00
	GVA of manufacturing (log)	-3,32	-2,60	0,08
Retail trade	Ex-ante index in retail trade	-5,06	-2,60	0,00
	Ex-post index in retail trade	-5,06	-2,60	0,00
	Turnover of retail trade (log)	-3,97	-2,60	0,02
Wholesale trade	Ex-ante index in wholesale trade	-4,29	-2,60	0,00
	Ex-post index in wholesale trade	-6,22	-2,60	0,00
	Turnover of wholesale trade (log)	-3,81	-2,60	0,03
Construction	Ex-ante index in construction	-3,74	-2,60	0,03
	Ex-post index in construction	-4,36	-2,60	0,00
	GVA of construction (log)	-3,34	-2,60	0,08
Services	Ex-ante index in services	-4,21	-2,61	0,01
	Ex-post index in services	-6,99	-2,61	0,00
	GVA of services (log)	-3,45	-2,61	0,06

The optimal numbers of model lags were selected based on the Akaike Information Criterion (AIC). Table 4 shows the AIC values depending on the number of lags in the models. The value “4” was taken as the maximum number of lags, in accordance with the standard practice of determining this parameter in existing empirical studies based on quarterly data. Models with the optimal number of lags are characterized by the lowest AIC value. Thus, in all the cases under consideration, models with 4 lags (p = 4) are optimal, with the exception of the mining industry – in this industry, model with 1 lag turned out to be optimal.

Table 4. Determination of the optimal number of models lags based on the Akaike information criterion (AIC)

Lag	**AIC**						
	National level	**Mining and quarrying**	**Manufactu-ring**	**Retail trade**	**Wholesale trade**	**Construction**	**Services**
1	-0,50	**-0,50***	0,02	-0,23	-0,16	2,19	-1,13
2	-0,69	-0,39	-0,15	-0,44	-0,57	1,93	-1,22
3	-1,12	-0,44	-1,18	-1,36	-1,03	-1,38	-2,15
4	**-2,03***	-0,40	**-1,42***	**-1,76***	**-1,15***	**-1,72***	**-3,18***

The time series under study were also successfully tested for the absence of cointegration using the Johansen test.

To confirm the hypotheses about the presence of predictive power of business uncertainty indices in the dynamics of economic activity indicators, Granger causality tests were carried out, the results of which are presented in Table 5. Almost in all cases, p-values were less than 0.1, therefore, hypotheses about the presence of Granger cause of economic indicators from the constructed business uncertainty indices are accepted at the 10% significance level.

Table 5. Granger causality tests

Hypothesis	Chi-square	p-value	Result
National ex-ante index Granger causes GDP (log)	3,87	0,06	Accepted
National ex-post index Granger causes GDP (log)	6,83	0,01	Accepted
Ex-ante index in mining and quarrying Granger causes GVA of the industry (log)	3,80	0,06	Accepted
Ex-post index in mining and quarrying Granger causes GVA of the industry (log)	0,85	0,4	Not accepted
Ex-ante index in manufacturing Granger causes GVA of the industry (log)	13,73	0,00	Accepted
Ex-post index in manufacturing Granger causes GVA of the industry (log)	4,38	0,04	Accepted
Ex-ante index in retail trade Granger causes turnover of the industry (log)	2,10	0,1	Accepted
Ex-post index in retail trade Granger causes turnover of the industry (log)	4,00	0,05	Accepted
Ex-ante index in wholesale trade Granger causes turnover of the industry (log)	13,89	0,00	Accepted
Ex-post index in wholesale trade Granger causes turnover of the industry (log)	8,28	0,00	Accepted
Ex-ante index in construction Granger causes GVA of the industry (log)	9,49	0,00	Accepted
Ex-post index in construction Granger causes GVA of the industry (log)	3,83	0,06	Accepted
Ex-ante index in services Granger causes GVA of the industry (log)	5,05	0,03	Accepted
Ex-post index in services Granger causes GVA of the industry (log)	5,23	0,03	Accepted

The following periods were specified for model evaluation (depending on the availability of quantitative data):

• from 1q2009 to 4q2022 (56 observations) at the national level and in retail and wholesale trade;

• from 1q2011 to 4q2022 (48 observations) in mining and quarrying, manufacturing and construction;

• from 1q2012 to 4q2022 (44 observations) in services.

Forecasts were calculated for the period from 1q2023 to 2q2024 (6 quarters).

In accordance with the most common practice, the selection of periods for pseudo-out-of-sample analysis was carried out in chronological order, simulating the real scenario in which future observations are projected, with the ratio of sample and out-of-sample periods being determined at approximately 80/20.

To assess the effectiveness of the constructed models, the root mean squared forecast errors (RMSFEs) were calculated as a loss function for forecasting economic activity indicators based on business uncertainty indices. We also calculated the RMSFE of reference autoregressive (AR) models based on quantitative referents, within which the forecast values of economic activity indicators are calculated based on their previous dynamics, without taking into account business uncertainty indices. Next, the RMSFE ratios between, on the one hand, VAR and BVAR models based on business uncertainty indices and, on the other hand, reference AR models (rRMSFE) were calculated:

$$rRMSFE = \frac{RMSFE^{VAR}}{RMSFE^{AR}}$$

Thus, in cases where these ratios take values less than one, models based on business uncertainty indices have higher predictive abilities of economic activity indicators than autoregressive models.

However, the calculated rRMSFE values do not fully clarify the presence of statistical differences in the forecast errors of models based on business uncertainty indices and autoregressive models. Because of this, an additional Diebold-Mariano (DM) test was also conducted (Diebold and Mariano, 1995), in which, under the null hypothesis, it is assumed that the expected difference in the mean square errors of the forecast is zero.

4. Results

Table 6 shows the calculated rRMSFE ratios between VAR and AR models at the national level and for the six industries considered, representing the results of the pseudo-out-of-sample analysis.

Table 6. RMSFE relationships between VAR models based on business uncertainty indices and reference AR models

Industry	**rRMSFE**	
	VAR model based on **ex-ante index**	VAR model based on **ex-post index**
National level	0,92	0,85
Mining and quarrying	0,64	0,71
Manufacturing	0,75	0,66
Retail trade	0,95	0,99
Wholesale trade	0,99	0,86
Construction	1,12	1,07
Services	1,59	0,49

The results obtained indicate differences in the effectiveness of forecasting based on the constructed specifications of VAR models among the industries under consideration, depending on the methodology used for calculating business uncertainty indices:

• at the national level, in terms of forecasting GDP, models based on both methods for calculating the indices were almost equally effective, but model with using of ex-post index had better accuracy (rRMSFE coefficient equals to 0.85 against 0.92 for model with using of ex-ante index);

• in turn, in mining and quarrying, a model based on the ex-ante index was more effective for forecasting the GVA of the industry (rRMSFE=0.64), and the current specification of the model based on the ex-post index had a little bit worse predicting opportunities (rRMSFE=0.71);

• at the same time, the opposite trend is observed in the manufacturing industry and wholesale trade – the rRMSFE of the models based on the ex-ante index were 0.75 and 0.99, and on the basis of the ex-post index – 0.66 and 0.86 respectively;

• in retail trade, similar to the mining industry, a model based on ex-ante index turned out to be more effective for forecasting industry turnover (rRMSFE=0.95), while the current specification of the model based on ex-post index was less effective (rRMSFE=0.99);

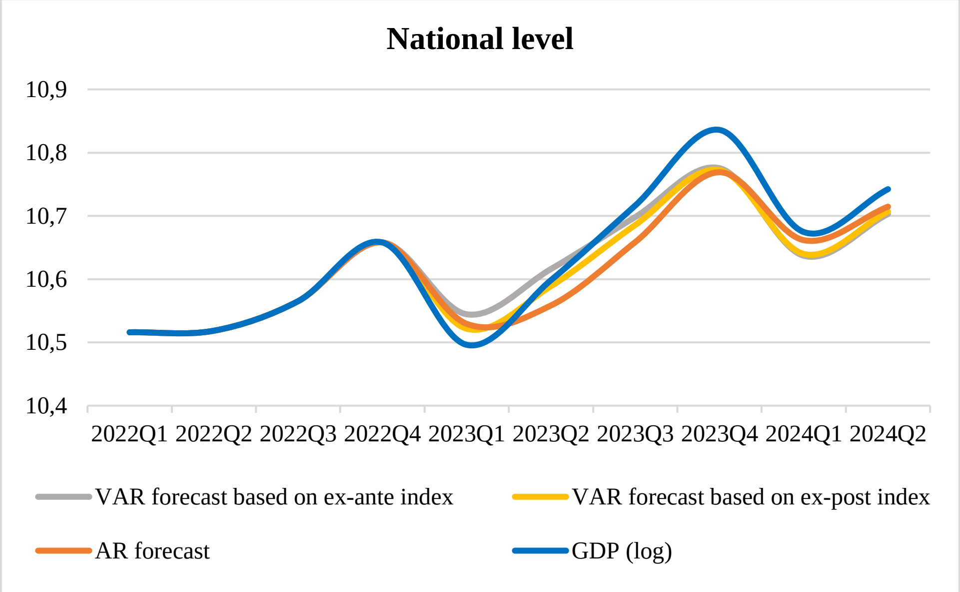
• at the same time, in construction, the prepared models' specifications did not show sufficient effectiveness for predicting the industry's GVA (in both cases, rRMSFE>1);

• finally, in the services, model based on the ex-post index was equally effective (rRMSFE equals to 0.49), while model based on ex-ante index worse than AR model predicts the dynamics of GVA of considered industry (rRMSFE = 1.59);

Thus, within the framework of most of the industries under consideration (except for construction), as well as at the national level, VAR model specifications that were effective for forecasting real indicators of economic activity were built, characterized by lower forecast errors compared to standard autoregressive models (rRMSFE<1). This interpretation was also confirmed by tests for the difference between forecast errors within each two separately compared models and is consistent with theoretical studies.

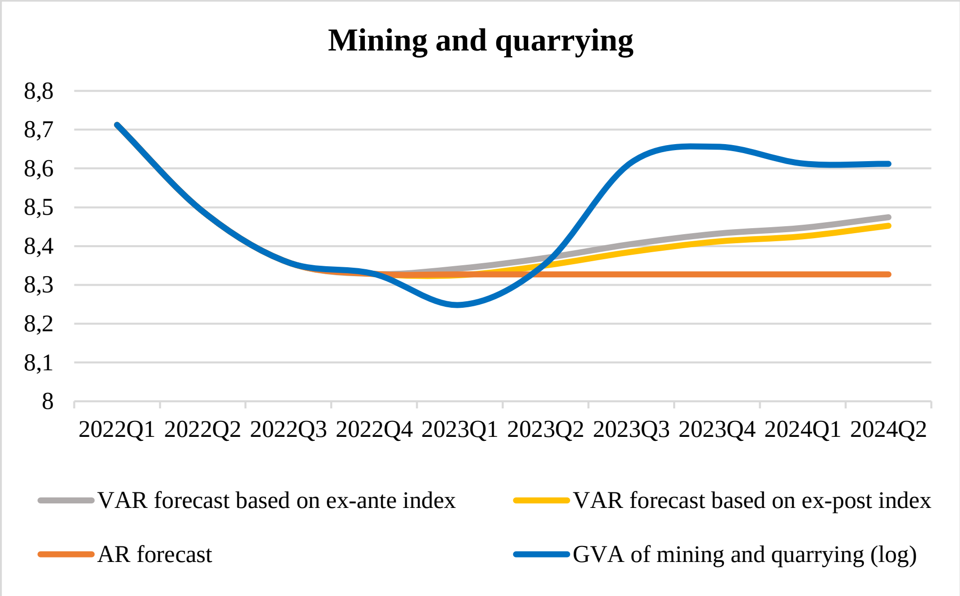
The following is a visualization of forecast estimates obtained on the basis of VAR and AR models constructed within the framework of pseudo-out-of-sample analysis.

Figure 1. The dynamics of Russia's actual GDP (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2009-4q2022; number of observations: 56)



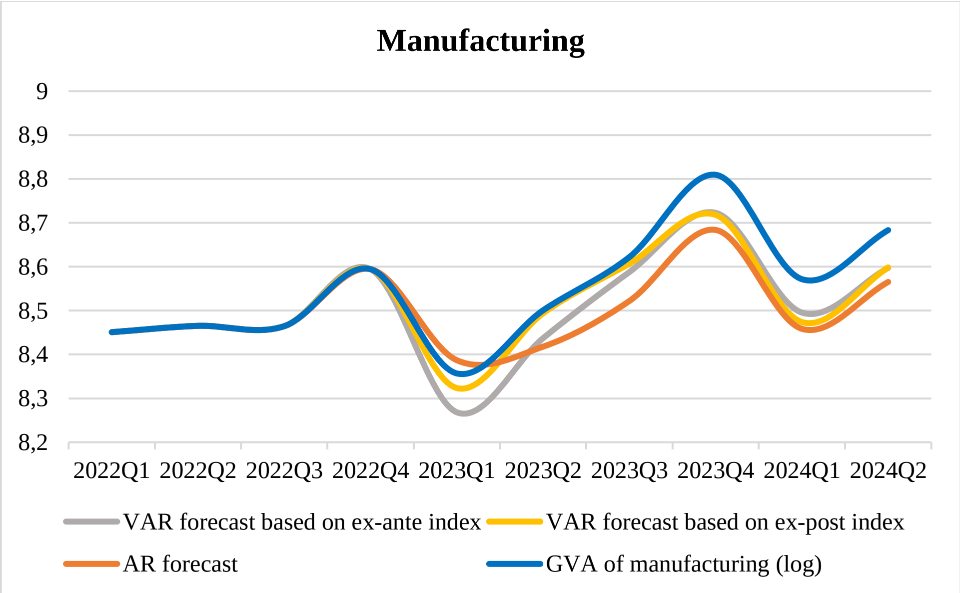
The graph of the dynamics of Russia's actual GDP (log) and its forecasts, obtained using the constructed VAR models based on the national ex-ante and ex-post indices, as well as an autoregressive model, demonstrates the maximum accuracy of forecasting the dynamics of GDP precisely on the basis of the national ex-post index, while forecasts constructed using the AR model and VAR model based on ex-ante index are less accurate and generally have similar dynamics.

Figure 2. The dynamics of mining and quarrying actual GVA (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2011-4q2022; number of observations: 48)



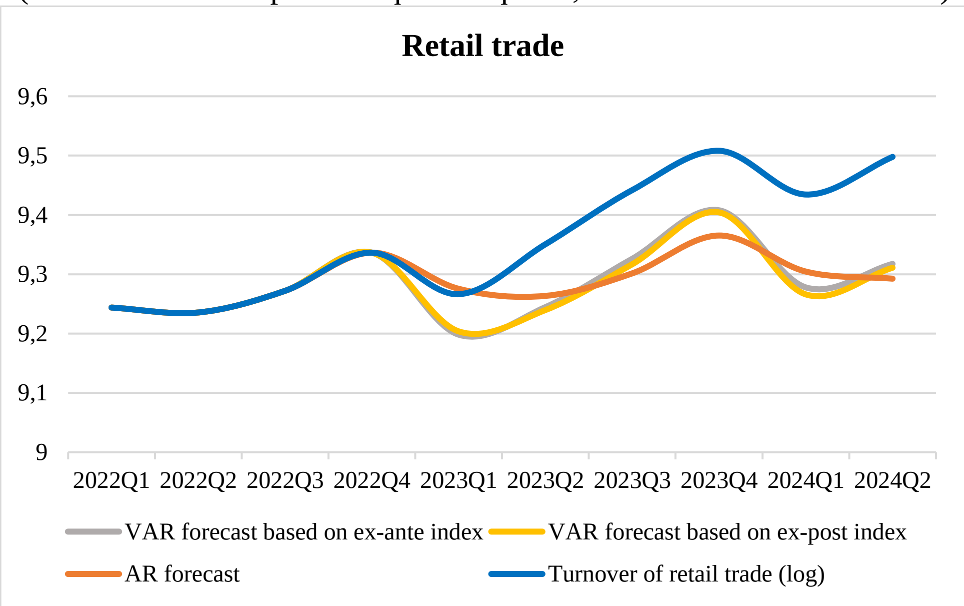
In mining and quarrying, there is a relative similarity of industry GVA forecasts based on three models, all of them do not have high accuracy. By a slight margin, the most accurate forecast is obtained using a VAR model based on the ex-ante index (formal mathematical confirmation of this is given above). AR model did not cope with the task of forecasting at all: it got the same predicted value for all 6 quarters.

Figure 3. The dynamics of manufacturing actual GVA (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2011-4q2022; number of observations: 48)



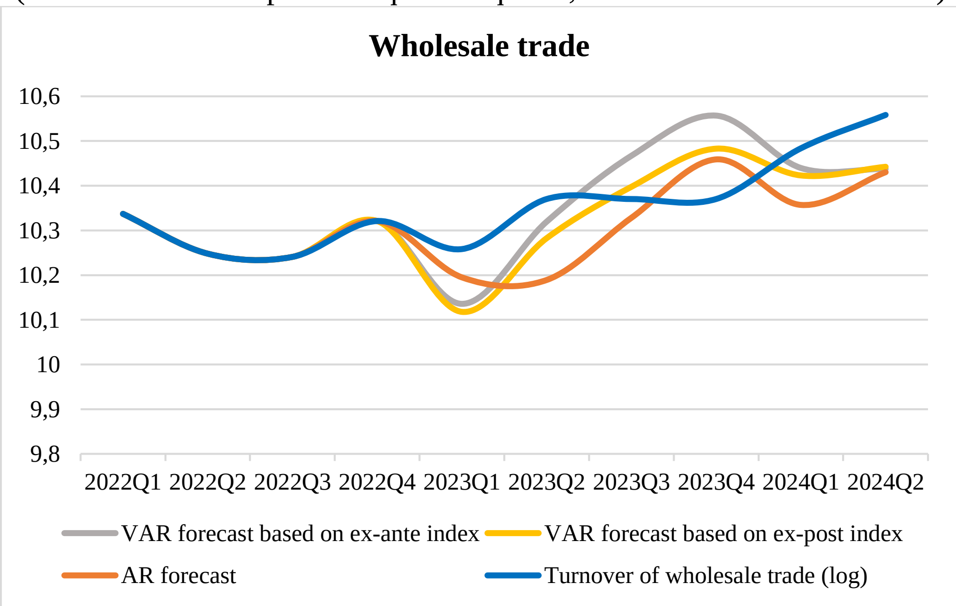
In turn, in manufacturing there is a similar picture with the dynamics at the national level – the most accurate forecast of the industry's GVA, built using a VAR model based on ex-post index, despite the fact that its advantage is not as pronounced as at the national level.

Figure 4. The dynamics of retail trade actual turnover (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2009-4q2022; number of observations: 56)



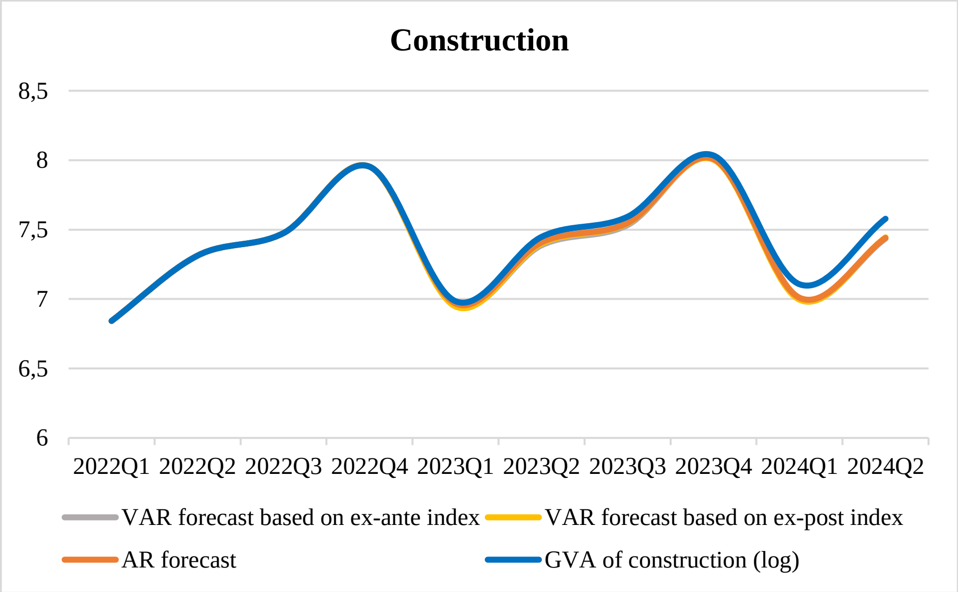
In retail trade, despite the initial visual impression of the relative accuracy of industry turnover forecasts built on the basis of three models, the forecast obtained using a VAR model based on ex-ante index should be considered the most accurate by a slight margin.

Figure 5. The dynamics of wholesale trade actual turnover (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2009-4q2022; number of observations: 56)



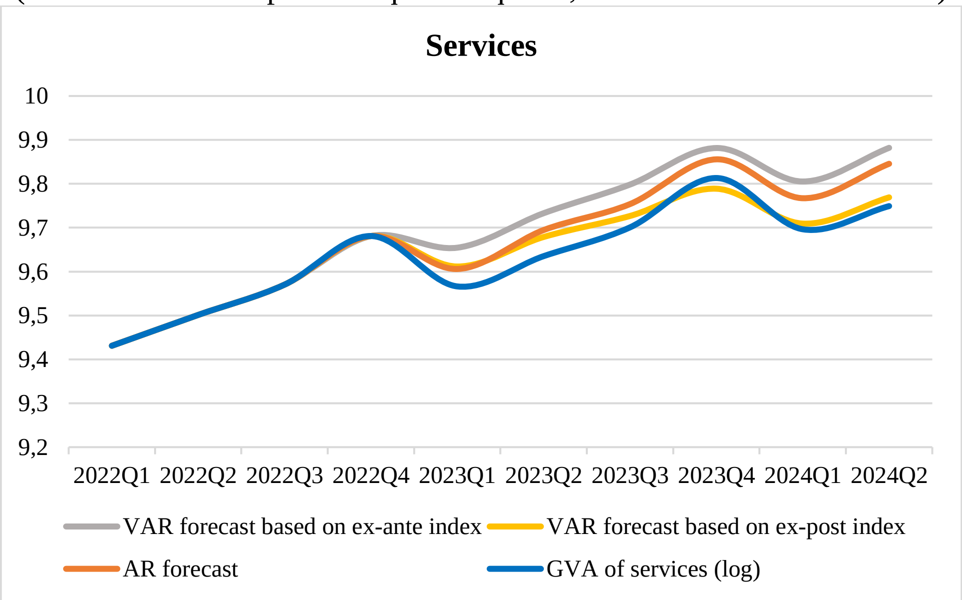
At the same time, in wholesale trade, all 3 models did not get extremely effective results but there is a higher efficiency of the forecast built on the basis of a VAR model based on ex-post index.

Figure 6. The dynamics of construction actual GVA (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2011-4q2022; number of observations: 48)



In the construction industry, we can note that there is an insufficient effectiveness of industry GVA forecasts built on the basis of VAR models based on ex-ante and ex-post indices – the forecast obtained using an autoregressive model is more accurate to the real dynamics of the quantitative referent.

Figure 7. The dynamics of services actual GVA (log) and forecasts based on the constructed VAR and AR models
(models evaluation period: 1q2012-4q2022; number of observations: 44)



Finally, in the service sector, we want to highlight the most accurate forecast values of the industry's GVA, built on the basis of a VAR model based on ex-post index. Also, it is worth mentioning that all 3 models repeat the dynamics of the quantitative referent very well.

In addition, Bayesian vector autoregression models (BVAR), were also calculated to test the forecasting potential of the indices. Table 7 presents the rRMSFE values for the BVAR and AR models based on business uncertainty indices ex-ante and ex-post.

Table 7. RMSFE relationships between BVAR models based on business uncertainty indices and reference AR models

Industry	**rRMSFE**	
	BVAR model based on **ex-ante index**	**BVAR** model based on **ex-post index**
National level	0,35	0,34
Mining and quarrying	0,64	0,65
Manufacturing	0,88	0,89
Retail trade	0,29	0,28
Wholesale trade	0,91	0,92
Construction	0,76	0,77
Services	1,10	1,12

Estimates obtained using BVAR models also confirm the effectiveness of forecasting real economic indicators based on business uncertainty indices in most industries, although slightly differ from the results of VAR modeling. In particular:

• at the national level, both models (based on ex-ante and ex-post indices) turned out to be more effective in forecasting GDP than AR processes (rRMSFE were 0.35 versus 0.34, respectively) – as well as within VAR modeling, estimates based on the ex-post index are more accurate;

• in mining and quarrying, models based on both indices also turned out to be more effective than AR processes, with a slight advantage in favor of estimates based on the ex-ante index (rRMSFE=0.64 versus 0.65 for the model based on the ex-post index);

• a similar trend is observed in manufacturing and construction (rRMSFE=0.88 and 0.76 for the model based on the ex-ante index and 0.89 and 0.77 for estimates based on the ex-post index respectively);

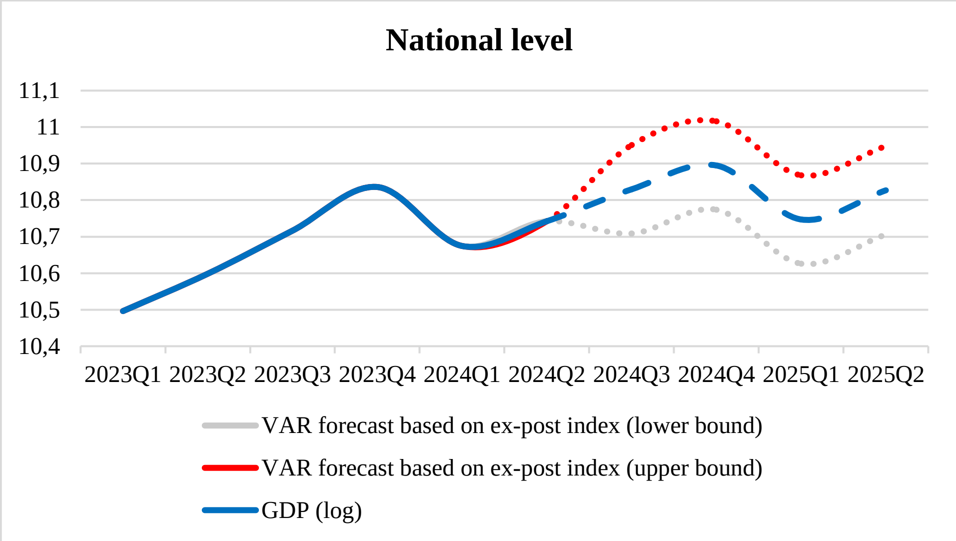
• in retail trade, slightly more noticeable predictive abilities were observed in model based on ex-post index (rRMSFE = 0.28 versus 0.29);

• in wholesale trade, both models turned out to be to an equally small extent more effective in predicting industry GVA than AR processes (rRMSFE was 0.91 and 0.92);

• in services, the considered specifications of BVAR models based on both indices turned out to be insufficiently effective in predicting the GVA of industries (the rRMSFE values in all cases turned out to be greater than 1).

In addition, on the basis of the VAR model, which is based on the business uncertainty index, which has the best predictive abilities (ex-post) in terms of forecasting the quantitative referent (GDP), forecasts for 3-4q2024 and 1-2q2025 were calculated at the national level. A graph with the obtained forecast values is presented in Fig. 8.

Figure 8. The dynamics of Russia's actual GDP (log) and the forecast till the first half of 2025, based on the optimal VAR model
(model evaluation period: 1q2009-2q2024; number of observations: 62)
(confidence interval: +– 2 s.e.)



5. Discussion

Assessing the predictive power of uncertainty indicators is important in determining their usefulness in informing economic policy decisions. Uncertainty can stem from various sources and affect the economy through various channels. For example, an increase in the uncertainty perceived by economic agents can change their decisions regarding consumption, investment, hiring, etc. (Lautenbacher, 2021). Businesses must consider uncertainty when making decisions to invest in new technologies, as external factors beyond their control can fundamentally affect future sales and profits (Avalos et al., 2022). To account for this uncertainty, entrepreneurs carefully evaluate scenarios in which results could be worse or better than expected before making final decisions and take into account the potential risks associated with these forecasts. In situations of high uncertainty, they may prefer to wait and see how the situation develops to avoid costly mistakes (Bernanke, 1983). However, such behavior can have negative consequences for the national economy in the form of reduced productivity, as waiting leads to delays and sometimes complete cancellation of projects. This issue is particularly relevant in developing countries, where insufficient investment and delays in technology adoption often hamper productivity growth.

In addition to the fact that the sentiments of real economic agents are recorded, there are several reasons to believe that business survey data in certain segments of the economy are best suited for measuring the level of business uncertainty. The so-called "wait-and-see" effect of uncertainty, resulting from adjustments to perceived risks in the use of capital or labor, operates primarily in the short term, making high-frequency data a better candidate for capturing these dynamics. At the same time, the use of an industry cross-section is based on the assumption that respondents themselves generate idiosyncratic shocks through their intentions and actions, so that aggregate fluctuations in opinion dispersion also include an element of fluctuation in perceived uncertainty, and not just objective compositional changes in the cross-section. Surveys with broader coverage allow for more precise testing of these compositional effects.

According to the results obtained, we can highlight that, firstly, indexes reflected the degree of uncertainty among economic agencies can be used to determine the dynamics of business activity in Russia successfully and, secondly, at the national level, when forecasting GDP, clear preference should be given to the ex-post business uncertainty indicator. It proved to be effective within the frameworks of VAR and BVAR, better improving forecasts compared to the national ex-ante business uncertainty indicator. It is worth noting that ex-ante indices also have a conceptual problem in that when relying only on the spread of expectations, we can deal with heterogeneous, but quite confident expectations due to objective differences in the economic situation among enterprises. In the case of expectations, variance can be influenced by both uncertainty and heterogeneity of respondents and the information available to them.

6. Conclusions

The paper examined ex-ante measures of business uncertainty, using estimates of the business community regarding future business trends to determine uncertainty as a measure of the spread between expressed opinions, and ex-post measures, using assessments of both future and current trends, defining business uncertainty as the degree of deviation of entrepreneurial expectations from the real picture. Returning to the research question, which was posed at the beginning of the work, it is safe to say that calculated business uncertainty indicators have great opportunities to describe the dynamics of economic activity in Russia. According to the empirical results obtained and due to the theoretical advantages of the approach, the ex-post approach should be considered preferable for modeling based on business survey data. In terms of forecasting at the industry level, business uncertainty indices were particularly effective in construction, manufacturing and services, while for other industries the results were negative or weakly robust.

First of all, the proposed measures seem suitable within the framework of nowcasting forecasting, understood as prediction of the present, near future and recent past (Banbura et al., 2013). Nowcasting methods are relevant for those key macroeconomic aggregates that are published with a relatively low frequency (usually on a quarterly basis) and with a significant lag. Early estimates of these key economic indicators use relevant information, collected more frequently and published more quickly.

Thus, with the help of the constructed indices, we have expanded the ability to interpret the assessments of more than 55 thousand respondents in Russia, opening up the opportunity to create regular monitoring of the uncertainty of the business environment, promptly providing information that can be used in the development of scenario-based socio-economic forecasts.

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