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Factor-based modeling and forecasting of innovation activity in manufacturing

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Abstract. This study aims to develop a fit-for-purpose model of the manufacturing innovation activity index for quantitatively assessing changes in sectoral innovation development over time. The analysis focuses on manufacturing, one of the core sectors of the Russian economy. The study integrates scenario matrices with tools for quantifying the fiscal effects associated with the integration of government information systems. A multiple linear regression model is estimated for the manufacturing innovation activity index. The model can be used by federal economic agencies, executive authorities in the constituent entities of the Russian Federation, development institutions, corporations, and expert communities when developing and adjusting tax policy, drafting regulations, and supporting investment projects in manufacturing industries.

Keywords: manufacturing, econometric modeling, multiple linear regression, innovation activity index, innovation performance index, innovation development, macroeconomic indicators

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Факторное моделирование и прогнозная оценка инновационной активности обрабатывающей промышленности

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Аннотация. Цель исследования заключается в разработке релевантной модели индекса инновационной активности обрабатывающей промышленности для количественной оценки отраслевого уровня инновационного развития в динамике. Авторами выбрана одна из базовых отраслей экономики России – обрабатывающая промышленность. В исследовании произведен синтез сценарных матриц и инструментов количественной оценки фискальных эффектов при интеграции государственных информационных систем. В ходе исследования построена модель многофакторной линейной регрессии отраслевого индекса инновационной активности обрабатывающей промышленности, которая может применяться федеральными экономическими ведомствами, органами исполнительной власти субъектов РФ, институтами развития, корпоративными структурами и экспертными сообществами при разработке и корректировке налоговой политики, подготовке нормативных актов и сопровождении инвестиционных проектов в обрабатывающих отраслях промышленности.

Ключевые слова: обрабатывающая промышленность, эконометрическое моделирование, многофакторная линейная регрессия, индекс инновационной активности, индекс инновационной результативности, инновационное развитие, макроэкономические показатели

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制造业创新活跃度的因子建模与预测评估

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摘要: 本研究的目的是开发制造业的创新活跃度指数模型, 用于动态地量化评估行业的创新发展水平。作者选取了俄罗斯经济的基础性行业之一——制造业作为研究对象。研究中综合运用了情景矩阵和整合国家信息系统时的财政效应定量评估工具, 建立了制造业创新活跃度行业指数的多元线性回归模型。该模型可供俄罗斯联邦经济部门, 联邦主体的行政机关, 发展机构, 企业和专家团体在制定和调整税收政策, 编制法规性文件以及支持制造业投资项目时使用。

关键词: 制造业, 计量经济学建模, 多元线性回归, 创新活跃度指数, 创新绩效指数, 创新发展, 宏观经济指标

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Introduction

The Russian economy faces numerous challenges with implications for key areas of economic policy and, ultimately, national security. Sanctions are accelerating import substitution and the development of high-technology sectors through the adoption of advanced solutions. Innovation ensures the resilience of the Russian economy as a means of countering external aggression and overcoming structural economic imbalances [1]. Conversely, a failure to achieve scientific and technological transformation may lead to socioeconomic decline and increasing isolation from global economic and technological processes [2].

Government support for core sectors is currently a policy priority because these sectors underpin the economy by creating value added, fostering innovation-driven development, attracting investment, supporting employment, and contributing to economic security. Scenario-based forecasts are needed to identify the principal drivers of and barriers to innovation in these

sectors, as well as the factors affecting the development of critical infrastructure. Such forecasts can also inform the modernization of strategic planning tools and the design of targeted government programs that combine sector-specific support measures, promote inter-industry cooperation, and strengthen technological security.

A cluster-based approach plays an important role in innovation-driven development and economic modernization [3]. By bringing together businesses and educational institutions within regional and sectoral networks, clusters bridge the gap between research and its practical application. Cooperation among cluster participants generates synergies. In this regard, clusters become drivers of regional growth by creating jobs, supporting the development of modern and needed infrastructure, and improving living standards in the region.

The cluster-based approach has been widely used to examine innovation-driven economic development [4; 5] and collaboration between educational institutions and businesses [6].

It has also informed assessments of the effectiveness of tax incentives [7], including their role as fiscal instruments for supporting R&D and innovation [8] and as components of contemporary business diversification strategies [9]. Previous studies emphasize the need to adapt tax incentive mechanisms to current socioeconomic conditions [10; 11] and to realize the innovation potential of manufacturing enterprises [12]. Researchers have also examined and classified different forms of interregional economic integration [13; 14] and developed models of innovation activity at both the regional [15] and sectoral levels [16].

This study employs multiple linear regression within a cluster-based analytical framework. The method was selected for its relative simplicity, reliability in applied settings, flexibility, and suitability for scenario forecasting. It also makes it possible to account for several factors and assess their joint effect on sector-level innovation performance – an issue of particular relevance in the current economic environment.

The study contributes to the literature by integrating a cluster-based approach with regression analysis of innovation activity, identifying cluster-specific factors associated with innovation activity in manufacturing, and developing a multiple linear regression model for the manufacturing innovation activity index. It also proposes a framework for monitoring the effectiveness of inter-industry and cluster development programs.

Theoretical analysis

The assessment of innovation activity and the role of clusters in fostering innovation at the regional and sectoral levels have received considerable attention in the literature.

L.S. Shakhovskaya and E.V. Goncharova examine university-industry collaboration in the context of economic digitalization, taking into account the operating characteristics of the clusters formed through such collaboration. They view these clusters as a key mechanism for connecting research and business and identify the conditions required for successful regional cluster formation and the generation of synergies [6].

N.E. Buletova and A.M. Gubin analyze integration processes as the foundation of the cluster-based approach. Using data from the Federal State Statistics Service (Rosstat), they classify Russia's regions into three groups according to the structure of their regional economies: agricultural, industrial, and service-oriented. They also classify models of interregional integration in the Russian economy [13].

L.S. Valinurova and V.V. Oreshnikov review definitions of key concepts in innovation activity and approaches to regional innovation forecasting and modeling, concluding that the approaches considered are not suitable for the purposes of their study. Building on a model of innovation activity, they develop a broader model of regional socioeconomic development: a structural and logical model of regional innovation activity [14].

N.P. Ketova and V.N. Ovchinnikov investigate ways to improve the performance of regional innovation clusters in Russia and strengthen their role in the development of innovation systems. They examine the current state of leading Russian clusters in core sectors and the prospects for implementing innovation ecosystem strategies in these clusters [15].

M.V. Raiskaya and A.V. Aksyanova review existing methods for assessing innovation performance and propose a method based on relative measures of innovation efficiency and cluster analysis. They identify three clusters that are homogeneous in terms of innovation process performance and industry characteristics and argue that their method is broadly applicable to manufacturing [16].

The literature on innovation-driven development in Russia and on the formation and operation of regional and sectoral clusters points to a broad consensus that clusters can generate multiplier effects across industries and regions by unlocking the innovation potential of individual regions and the country as a whole [17]. Mathematical and econometric models are widely used in cluster analysis, regional development forecasting, and the classification of regions according to various criteria.

Promoting innovation and business activity is a priority for long-term economic develop-

ment [16]. Despite Russia's leading position in terms of formal indicators of innovation activity, its comparatively low level of R&D expenditure is a destabilizing factor that may eventually erode the benefits of structural incentives and lead to a contraction in innovation activity [18]. This makes it necessary to test the underlying theoretical propositions and determine the magnitude and direction of the relationships between key drivers and macro-level innovation outcomes. A shift from qualitative analysis to economic modeling is therefore warranted. Such modeling should account for economy-wide and more narrowly defined factors characterizing the national economy's innovation potential, the level of state-supported technological development, and the competitiveness of knowledge-intensive industries, using the Global Competitiveness Index as a point of reference [19].

This study develops a multiple linear regression model relating the manufacturing innovation activity index to macroeconomic indicators and to development factors in core sectors that underpin the wider economy [20].

A comparison of the manufacturing innovation activity index (MIAI) with international innovation indicators, such as the Global Innovation Index (GII), European Innovation Scoreboard (EIS), and Bloomberg Innovation Index (BII), reveals several fundamental differences:

1) the MIAI focuses exclusively on manufacturing as a core sector, whereas the international indices assess innovation performance across a country's economy as a whole;

2) the GII, EIS, and similar indices are designed for cross-country comparisons and country-level assessments of innovation performance. The MIAI is better suited to analyzing the dynamics, resilience, and innovation trajectory of a specific Russian industry;

3) specifying the relationship between the set of explanatory factors and the MIAI makes it possible to model alternative forecast scenarios for innovation activity;

4) the MIAI can be used to assess the resilience of a sectoral innovation system to external challenges. Assessments of innovation activity need to account for industry-specific

characteristics in order to identify competitive advantages that can help firms realize their innovation potential.

Four levels of implementation can be distinguished depending on how the expected effects of innovation activity are used:

Level 1. Generation: identifying demand for innovation and developing a market-ready product for subsequent commercialization.

Level 2. Implementation: producing and deploying innovations for widespread use as a driver of economic growth.

Level 3. Integration: modernizing operational processes through innovation while retaining the underlying technological model.

Level 4. Service: applying innovations through consumer-facing applications or management functions that help maintain a safe and stable operating environment.

Manufacturing was selected as the object of the study because it corresponds to the second and third levels, since the practical implementation of innovation development measures is based primarily on industrial production.

The principal factors stimulating innovation activity in manufacturing are as follows:

– adapting innovations to the needs of the real economy;

– modernizing the economy by creating new production capacity or upgrading the existing production base;

– industry-specific customization to meet customer and consumer needs;

– improving operational efficiency through innovative solutions that optimize the operations of individual enterprises.

Model specification

In the multiple linear regression model, the manufacturing innovation activity index (MIAI) is the dependent variable Y (the outcome), while $X_1, X_2, \dots, X_{23}$ are the independent variables (factors).

The following factors were considered in specifying the model:

Y – manufacturing innovation activity index (MIAI);

X_1 – gross domestic product (GDP), RUB million;

X_2 – inflation, %;
 X_3 – USD/RUB exchange rate, RUB per USD;
 X_4 – Urals crude oil price (global market price), USD per barrel;
 X_5 – exports, USD;
 X_6 – imports, USD;
 X_7 – trade balance, USD;
 X_8 – profit of profitable organizations for accounting purposes, RUB billion;
 X_9 – profit from all activities, RUB million;
 X_{10} – retail trade turnover, RUB million;
 X_{11} – volume of paid services to households, RUB million;
 X_{12} – value of goods shipped (work performed and services rendered), RUB million;
 X_{13} – labor force, million persons;
 X_{14} – employment, million persons;
 X_{15} – average annual subsistence minimum per capita, RUB per month;
 X_{16} – average annual subsistence minimum for the working-age population, RUB per month;
 X_{17} – average annual subsistence minimum for pensioners, RUB per month;
 X_{18} – average annual subsistence minimum for children, RUB per month;

X_{19} – payroll of employees of organizations, RUB million;

X_{20} – average monthly nominal accrued wages of employees of organizations, RUB per month;

X_{21} – average annual value of depreciable assets, RUB million;

X_{22} – depreciation of fixed assets charged by commercial organizations for the reporting year, RUB million;

X_{23} – fixed capital investment in the Russian Federation, RUB million.

These factors are reflected not only in the structure of budget revenues and expenditures but also in the country's economic and social development indicators [21].

The multiple regression equation can be used to generate MIAI forecasts for future periods. The sample comprises actual values of the variables for 2005–2024 and forecast values for 2025–2028 (**Fig. 1**). The relevant factors were selected using backward elimination: the procedure begins with the full set of variables and then removes them sequentially until a prespecified mathematical criterion is met.

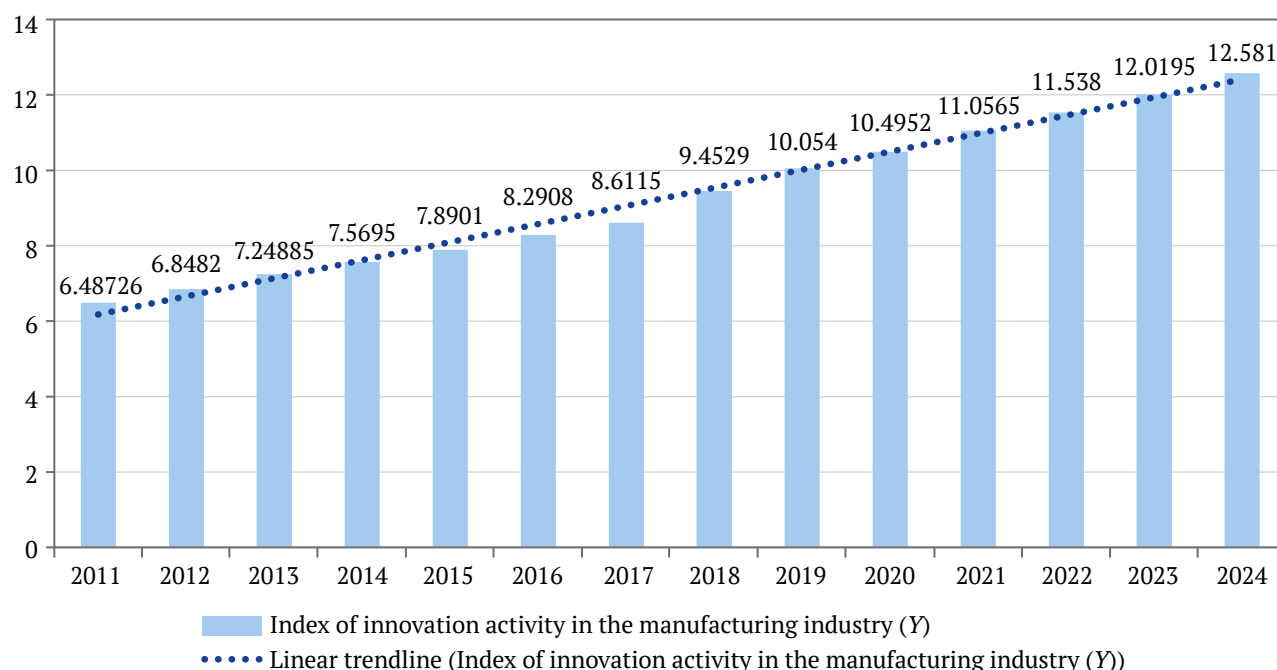


Fig. 1. Manufacturing innovation activity index (2011–2024)

Source: Compiled by the authors using data from the Federal State Statistics Service (Rosstat)

Available at: <https://www.rosstat.gov.ru/folder/10705> (accessed on 10.01.2026) and the Federal Tax Service of Russia.

Available at: <https://analytic.nalog.gov.ru/> (accessed on 14.01.2026).

A regression model can accommodate any number of factors, but including all available variables is rarely necessary in practice. Factors are initially selected through qualitative theoretical and economic analysis. Such analysis, however, cannot always provide an unambiguous answer regarding the strength of the relationships among the variables considered for inclusion or the value of adding a particular factor. Factor selection therefore proceeds in two stages. First, variables are selected on the basis of the economic substance of the problem; second, the statistics for the regression parameters are estimated using the correlation matrix.

To assess the relationship between macroeconomic variables and the MIAI and subsequently select variables for the multiple regression model, the independent variables are screened for multicollinearity using a correlation matrix containing the partial correlation coefficients for each pair of variables. A correlation coefficient greater than zero indicates a positive relationship between X and Y : as one variable increases, the other also increases.

The highest correlation coefficient is observed between X_{15} and X_{16} (0.9999), reflecting their direct economic relationship. Similar coefficients are obtained for all subsistence-minimum indicators (X_{15} – X_{18}); consequently, only one of these variables, with an appropriate level of statistical significance, is retained in the model. High correlations are also observed between X_{19} and X_{20} (0.9997) and between X_{21} and X_{22} (0.9991), indicating direct positive linear relationships within each pair. When factors are strongly correlated, their separate effects on the outcome (Y) cannot be identified.

Table 1

Pairwise correlation matrix for the factors selected for modeling				
X_4	X_7	X_{14}	X_{20}	
1.0000	0.5863	−0.5508	−0.3900	X_4
	1.0000	−0.2271	−0.0343	X_7
		1.0000	0.6680	X_{14}
			1.0000	X_{20}
R^2		0.969194		

Factor multicollinearity is assessed using the determinant of the matrix of pairwise factor correlation coefficients (Table 1). The two-tailed 5% critical value for a sample of 14 observations is 0.5324.

After excluding factors with overlapping effects on Y , the following variables were retained for the multiple regression model of the relationship between the MIAI and macroeconomic indicators: the global market price of Urals crude oil (X_4 , USD per barrel), the trade balance (X_7 , USD million), employment (X_{14} , million persons), and the average monthly nominal accrued wages of employees of organizations (X_{20} , RUB per month).

X_4 has a substantial inverse effect (−0.4920, or 49.20%) on the economy and, in turn, on the MIAI. X_7 is an important factor: although its effect on Y is smaller (−0.0130, or 1.3%), it is characterized as direct and is not correlated with the other indicators (factors X). X_{14} is included in the MIAI analysis, with an estimated effect of 65.24% on Y , while X_{20} has the strongest effect on the MIAI (0.9674), corresponding to a direct effect of 96.74%. The remaining factors exhibited overlapping effects on the MIAI and were excluded from the regression model.

Construction of a multiple regression model and estimation of its parameters

The parameters of a regression model that is linear in its parameters are estimated using ordinary least squares (OLS) (Table 2).

The multiple regression equation is as follows:

$$Y = -0.0221469 \cdot X_4 + 5.60029 \cdot 10^{-6} \cdot X_7 - 0.0781147 \cdot X_{14} + 9.57950 \cdot 10^{-5} \cdot X_{20} + 11.1267. \tag{1}$$

The coefficient of determination (R^2) is 0.969194, indicating that the selected macroeconomic indicators explain 96.92% of the variation in the MIAI; the remaining 3.08% is attributable to other factors.

Regression model adequacy tests

The statistical significance of the estimated coefficients is assessed using Student's t -test. The null hypothesis H_0 states that a coefficient does not differ significantly from zero. Its significance is evaluated by comparing the estimated coefficient with its standard error.

Table 2

Ordinary least squares estimates of the linear regression model

Factor	Coefficient	Standard error	<i>t</i> -statistic	<i>p</i> -value
Constant	11.1267	6.91599	1.609	0.1421
X_4	-0.0221469	0.00716098	-3.093	0.0129
X_7	$5.60029 \cdot 10^{-6}$	$2.63739 \cdot 10^{-6}$	2.123	0.0627
X_{14}	-0.0781147	0.0968227	-0.8068	0.4406
X_{20}	$9.57950 \cdot 10^{-5}$	$8.43961 \cdot 10^{-6}$	11.35	<0.0001

Normality tests for Y:

Doornik-Hansen test = 1.793; *p*-value = 0.407994Shapiro-Wilk test (W) = 0.945393; *p*-value = 0.491711Lilliefors test = 0.132833; *p*-value ≈ 0.72Jarque-Bera test = 1.08131; *p*-value = 0.582367

Fig. 2. Normality tests for the dependent variable

Statistical software packages use *p*-values for hypothesis testing. The authors use Gretl, a software package for econometric modeling and model-specification testing. A *p*-value is the probability, under the null hypothesis, of obtaining a test statistic at least as extreme as the observed value. If the *p*-value is below the selected significance level α ($p < \alpha$), the null hypothesis H_0 is rejected. The *p*-value also indicates the lowest significance level at which the null hypothesis can be rejected.

Since the *p*-values are below 0.1 for most of the coefficients, the null hypothesis H_0 that the coefficients are statistically insignificant is rejected (Table 3), with the exception of X_{14} . The statistical insignificance of X_{14} does not imply that it has no effect, and excluding this variable may result in inconsistent estimates. Employment (X_{14}) is an essential factor that should be considered in the analysis of the MIAI, as its effect on *Y* is estimated at 65.24%. This factor was therefore included in the model.

Thus, the estimated regression equation contains predominantly statistically significant parameters.

Statistical tests of this type require the dependent variable *Y* to be normally distributed. This condition was supported by the normality tests performed in Gretl (Fig. 2).

The overall significance of the model is assessed using Fisher's *F*-test. The relevant test statistics were obtained in Gretl (Table 4).

Table 3

P-values for the regression coefficients

Factor	<i>p</i> -value
Constant	0.1421
X_4	0.0129
X_7	0.0627
X_{14}	0.4406
X_{20}	<0.0001

Table 4

Linear regression model fit statistics

<i>F</i> (4,9)	70.78849
<i>p</i> -value (<i>F</i>)	$8.47 \cdot 10^{-7}$

White's test for heteroskedasticity
OLS, using observations 1-14
Dependent variable: uhat^2

	coefficient	standard error	t-statistic	p-value	
Constant	-90.4391	54.6419	-1.655	0.1588	
X4	-0.0424817	0.0171144	-2.482	0.0557	*
X7	1.52019e-05	2.95078e-06	5.152	0.0036	***
X14	2.59121	1.56230	1.659	0.1581	
X20	-2.45452e-05	1.30240e-05	-1.885	0.1182	
sq_X4	0.000218600	0.000108499	2.015	0.1000	
sq_X7	-3.26212e-011	6.09657e-012	-5.351	0.0031	***
sq_X14	-0.0183738	0.0111496	-1.648	0.1603	
sq_X20	2.83530e-010	1.19121e-010	2.380	0.0632	*

Unadjusted R^2 = 0.929811

Test statistic: TR^2 = 13.017349

p-value = P(Chi-square(8) > 13.017349) = 0.111254

Fig. 3. White's test for heteroskedasticity

The model yields $F(4, 9) = 70.78849$ with a p -value of $8.47 \cdot 10^{-7}$. Since the p -value is below the chosen significance level, the null hypothesis H_0 is rejected in favor of the alternative hypothesis H_1 . The multiple regression model is therefore statistically significant overall, which, according to the authors, indicates the high quality of the estimated regression equation.

Testing for heteroskedasticity

Heteroskedasticity¹ in the random errors distorts OLS estimates, making statistical inference based on them unreliable. The presence of heteroskedasticity is tested using White's test (Fig. 3).

Because the p -value (0.111254) exceeds 0.1, the null hypothesis H_0 of no heteroskedasticity is not rejected, indicating that the model is suitable for practical application.

The authors constructed a multiple regression model relating the MIAI to the selected factors (X_4, X_7, X_{14} and X_{20}). The model accounts for external macroeconomic influences and thereby improves forecast accuracy.

¹ Heteroskedasticity refers to heterogeneity among observations, manifested in unequal variances of the random errors in an econometric model.

Retrospective MIAI forecast for 2011–2024

Data for the selected factors (X_4, X_7, X_{14}, X_{20}) for 2011–2024 were used to calculate retrospective MIAI forecasts using the multiple linear regression model. For example, the retrospective MIAI forecast for 2011 is:

$$Y_{2011} = -0.0221469 \cdot 10^9 + 5.60029 \cdot 10^{-6} \cdot 196853 - 0.0781147 \cdot 67.7 + 9.57950 \cdot 10^{-5} \cdot 23369 + 11.1267 = 6.76.$$

The trend in the retrospective MIAI forecasts generated by the multiple linear regression model for 2011–2024 is shown in Fig. 4. The average relative forecast error is 3.2%, indicating that the model is applicable in practice.

The accuracy of the model's forecasts depends on the forecasts of the explanatory variables, which introduces additional error into the calculation of forecast MIAI values. The model can be considered valid because its average relative forecast error is 3.2%, which is acceptable for the purposes of this forecast (within 5%). Moreover, if the data for 2015, when the deviation was 6.8%, are excluded, the average relative forecast error decreases to 2.9%.

Forecast through 2028

The forecast based on officially approved macroeconomic projections is limited to 2028. The regression model extrapolates historical relationships and trends in key macroeconomic indicators; beyond this period, its reliability declines substantially because of structural shifts, external challenges, and other exogenous factors.

Forecast values of the factors included in the regression equation are required to project the

MIAI for 2025–2028. The MIAI forecast for 2025 obtained using the multiple linear regression model is:

$$Y_{2025} = -0.0221469 \cdot 58.5 + 5.60029 \cdot 10^{-6} \cdot 86770.5 - 0.0781147 \cdot 74.3 + 9.57950 \cdot 10^{-5} \cdot 102728 + 11.1267 = 14.35.$$

The trend in the prospective MIAI forecasts generated by the multiple linear regression model for 2025–2028 is shown in Fig. 5.

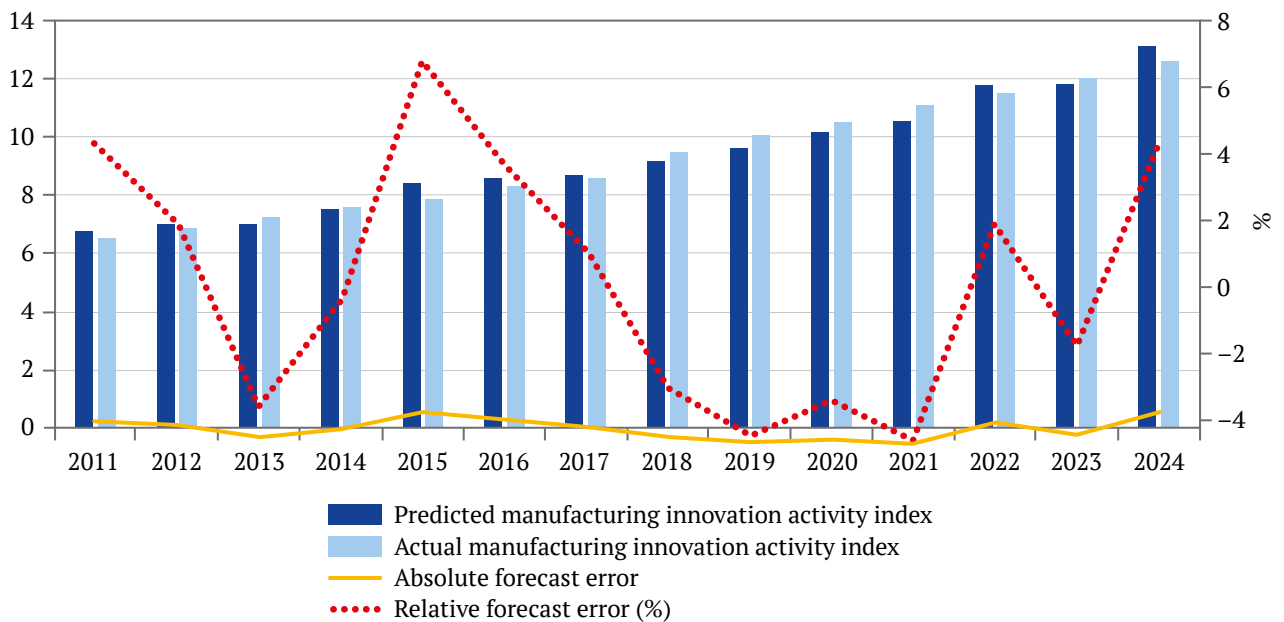


Fig. 4. Trend in the retrospective forecast of the manufacturing innovation activity index (2011–2024)

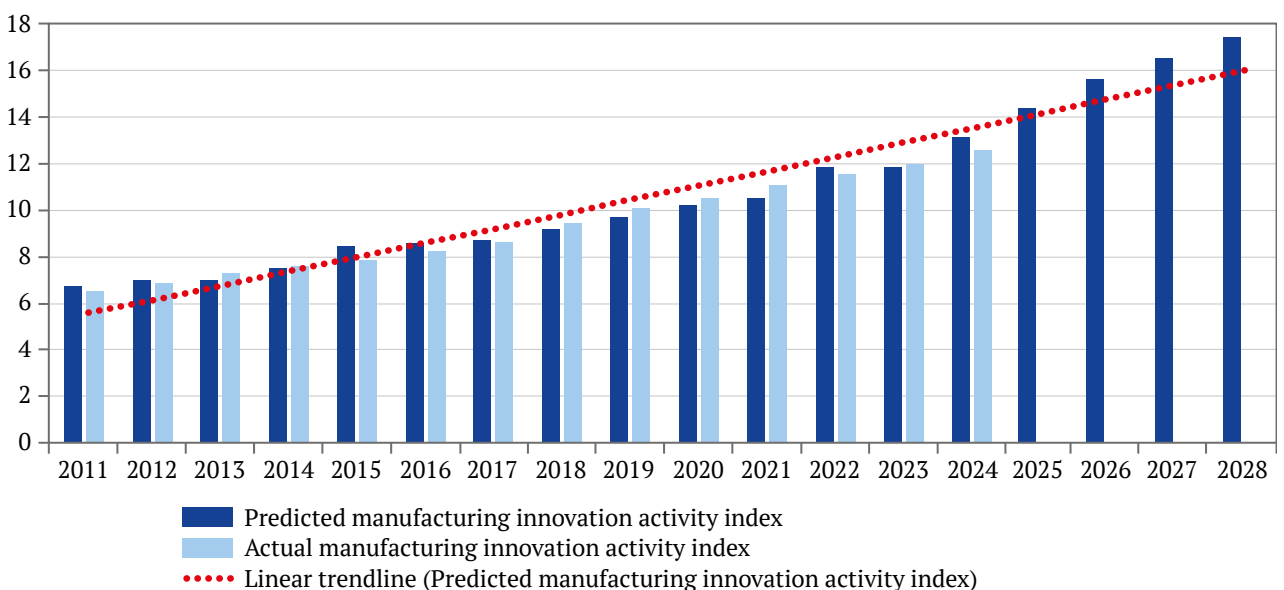


Fig. 5. Trend in the prospective forecast of the manufacturing innovation activity index (2025–2028)

The forecast MIAI values are positively related to the forecast values of the regression factors X_7 and X_{20} and negatively related to X_4 and X_{14} . High forecast values of the trade balance and the average monthly nominal accrued wages of employees of organizations will result in MIAI values above their retrospective levels, implying a positive scenario for the innovation-driven development of manufacturing as a core sector. At the same time, according to the estimated model, high forecast values of Urals crude oil prices and employment will reduce the MIAI relative to its retrospective values.

The retrospective analysis showed that the deviations between actual and forecast values were within acceptable limits. Therefore, given the specified values of Urals crude oil prices, the trade balance, employment, and the average monthly nominal accrued wages of employees of organizations, the MIAI values will be close to the forecast level.

Conclusion

The study developed an integrated model combining scenario-based and econometric approaches to modeling tax support instruments intended to promote innovation-driven development in Russia. The model provides tools for decision-making and for subsequently monitoring the effectiveness of cluster programs.

The model can be adapted to other core sectors and modified to accommodate specific parameters and objectives, including those of a comprehensive regional economic analysis. The comparability of the results will make it pos-

sible to compare growth drivers, key factors, and spatial effects across sectors.

The practical value of the model lies in its applicability to the formulation of key economic policy parameters and its ability to quantify the effects of the selected factors and identify the principal prerequisites for strategic decisions on fine-tuning Russia's economic policy to stimulate core sectors. The modeling results help identify priority areas of support for different types of regions, optimize the allocation of budgetary funds, and coordinate interregional innovation projects, including special territories and clusters.

The combination of scenario matrices, tools for quantifying fiscal effects, and mechanisms for integration with government information systems demonstrates the originality of the authors' approach and distinguishes it from existing alternatives. The model's suitability is supported by its capacity to accommodate prompt revisions to scenario assumptions and to the parameters of tax instruments and other macroeconomic factors. The proposed approach provides the greatest possible degree of control over tax policy while accounting for sectoral effects amid macroeconomic volatility and international tax reforms.

Thus, the multiple linear regression model is a comprehensive tool for analyzing and forecasting the innovation-driven development of core sectors. It accounts for a broad range of factors (macroeconomic indicators) that have divergent effects on the realization of the innovation potential of manufacturing enterprises.

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