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Efficiency of Public Social Security Expenditure: A Cross-Country Study Using Factor Analysis and Advanced Machine Learning

M.L. Dorofeev
Financial University under the Government of the Russian Federation, Moscow, Russian Federation

ABSTRACT

Research objectives. Contemporary global challenges, such as demographic shifts, the climate crisis, and rapid technological transformation, necessitate innovative approaches to managing social security systems. This study addresses the urgent need for tools to enhance the efficiency of Financial-Investment Models of Social Security (FIMSS), particularly under constrained fiscal resources and heightened uncertainty. The aim is to develop and validate a comprehensive approach for assessing FIMSS efficiency, incorporating modern challenges and public finance management specifics. **Methods.** By integrating ratio analysis, factor analysis, and advanced machine learning techniques, including gradient boosting (XGBoost), this study establishes a robust, multi-level framework for efficiency evaluation. The dataset covers 38 Organisation for Economic Co-operation and Development (OECD) countries, Russia, and China over the period 2005–2022, enabling cross-country comparisons, with regression analysis limited to a subsample of 26 countries due to data availability. **The scientific novelty** lies in introducing the EffCoverSP indicator, which accounts for social protection coverage and employing partial dependence plots (PDP) to uncover nonlinear relationships among socioeconomic factors, extending macroeconomic theories of social system sustainability and social justice frameworks. **Results** reveal that FIMSS efficiency is driven by moderate budgetary expenditures, public debt below 50% of gross domestic product, a Gini index of 0.37–0.43, urbanization of 63–74%, and fertility rates of 1.55–1.7. **The practical significance** lies in the potential application of this approach to reform FIMSS, enhancing their sustainability and adaptability to global challenges, thereby informing evidence-based policy decisions.

Keywords: FIMSS; social security; social expenditure; economic inequality; XGBoost; budgetary expenditure efficiency; poverty; effective social protection coverage; social policy

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Эффективность государственных расходов на социальное обеспечение: кросс-страновое исследование с использованием факторного анализа и продвинутого машинного обучения

М.Л. Дорофеев
Финансовый университет при Правительстве Российской Федерации, Москва, Российская Федерация

АННОТАЦИЯ

Цели исследования. Современные глобальные вызовы, такие как демографические сдвиги, климатический кризис и быстрые технологические трансформации, требуют инновационных подходов к управлению системами социального обеспечения. Настоящее исследование отвечает на острую необходи-

мость в инструментах для повышения эффективности финансово-инвестиционных моделей социального обеспечения (ФИМСО), особенно в условиях ограниченных фискальных ресурсов и повышенной неопределенности. Цель состоит в разработке и валидации комплексного подхода к оценке эффективности ФИМСО, учитывающего современные вызовы и специфику управления общественными финансами. **Методы**. Комбинация коэффициентного, факторного анализа и методов машинного обучения создает комплексный и многоуровневый методический подход к оценке эффективности ФИМСО. Набор данных охватывает 38 стран Организации экономического сотрудничества и развития (ОЭСР), Россию и Китай за период 2005–2022 гг., что позволяет проводить межстрановые сравнения, при этом регрессионный анализ ограничен подвыборкой из 26 стран из-за доступности данных. **Научная новизна** заключается во введении показателя эффективного покрытия населения программами социальной защиты (EffCoverSP) и использовании графиков частичной зависимости (PDP) для выявления нелинейных связей между социально-экономическими факторами, расширяя макроэкономические теории устойчивости социальных систем и рамки социальной справедливости систем социального обеспечения. **Результаты** показывают, что эффективность ФИМСО определяется умеренными бюджетными расходами, государственным долгом ниже 50% ВВП, индексом Джини 0,37–0,43, урбанизацией 63–74% и уровнем рождаемости 1,55–1,7. **Практическая значимость** заключается в потенциальном применении этого подхода для реформирования ФИМСО, повышая их устойчивость и адаптивность к глобальным вызовам, тем самым способствуя принятию обоснованных политических решений на основе доказательств.
Ключевые слова: ФИМСО; социальное обеспечение; социальные расходы; экономическое неравенство; XGBoost; эффективность бюджетных расходов; бедность; эффективное покрытие программами социального обеспечения; социальная политика

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1. Introduction

The long-term transformation cycle of social security systems aligns with demographic, technological, and economic cycles. The evolution of social security (SS) prior to the emergence of the Bismarckian model can be characterized as a prolonged period dominated by the concept of decentralized social security, during which the state played a less significant role in the economy compared to contemporary conditions.

In modern contexts, the potential of decentralized social security models proves insufficient to support sustainable socioeconomic development, particularly in advanced economies with high levels of urbanization. In the 21st century, the state's role as the primary actor in social security has become indisputable and vital for any highly developed post-industrial economy with elevated social standards. However, slowing population growth and increasing demographic pressures have begun to undermine the efficiency of social security systems, posing risks to their long-term financial sustainability. This has led to a global rise in public debt and necessitated unpopular reforms in the social spheres of many countries. Further increases in budgetary expenditures allocated to the operation of financial and investment models of social security (hereafter FIMSS[1]) have become exceedingly challenging for high-income countries. The current demographic situation compels governments to either seek additional sources of funding for social expenditures or gradually reduce them as a percentage of gross domestic product (GDP).

A recent report of the International Labour Organization[2] (ILO) highlights a narrative deserving particular attention. The report focuses on the so-called triple planetary climate crisis, encompassing climate change (global warming), environmental pollution, and biodiversity loss. The structural transformation of economies resulting from climate-focused financial policies may lead to increased poverty, unemployment, inequality, and slower economic growth in many countries [1].

Addressing future existential crises in social security financing requires coordinated efforts across countries and the application of tailored

[1] The Financial-Investment Model of Social Security (FIMSS) is defined as a framework for organizing financial relations associated with managing social risks and addressing other objectives in the field of public social security.

[2] ILO. World Social Protection Report 2024–26 Universal social protection for climate action and a just transition. URL: https://www.social-protection.org/gimi/Media.action?id=10982 (accessed on 10.01.2025).

methods of public administrative, financial, and monetary regulation. The constraints of limited financial resources, high levels of uncertainty, and adverse demographic trends underscore the need to develop and substantiate strategies for enhancing the efficiency of FIMSS. In this context, the development of a comprehensive approach for analyzing FIMSS efficiency, aimed at enabling objective and multifaceted monitoring of efficiency-enhancing processes, remains highly relevant.

The objective of this study is to develop and test a novel, comprehensive approach for analyzing the efficiency of FIMSS, aligned with contemporary challenges in the management of social security finances.

2. Literature review

The relevance and practical significance of evaluating the efficiency of public expenditure in the context of global challenges are indisputable, as evidenced by a substantial body of scientific research and thematic publications by global organizations [2].

The issue of efficiency evaluation is addressed in the scientific literature through various approaches. These include simple methods based on ratio analysis [3–5], graphical data representation [6], and methods involving data ranking and clustering based on indices, composite indicators, or individual coefficients [7–9].

Foreign empirical studies predominantly focus on cross-country comparisons, examining the efficiency of public expenditure by analyzing specific indicators across a broad sample of countries or territorial units within a single country[3] [2] or within a limited sample based on specific criteria [10–12].

The most common approaches to analyzing the comparative efficiency of public expenditure involve constructing efficiency frontiers using methods such as Free Disposal Hull (FDH) and Data Envelopment Analysis (DEA) [2, 3, 13, 14]. However, as FDH and DEA efficiency metrics often provide limited insight into the causality of high or low efficiency, they are frequently combined with other research methods in empirical studies.

Another common approach in the literature involves efficiency assessments based on Agent-Based Stock-Flow Consistent (AB-SFC) modeling [15, 16]. Limitations of this method at its current stage of development include the inherent constraints of macroeconomic models and challenges in aligning them with the real dynamics of socio-economic processes due to the large number of parameters and uncertainty factors [17].

Machine learning methods, particularly gradient boosting techniques, are less commonly applied in the context of public expenditure efficiency evaluation. Nevertheless, their successful application in healthcare and insurance suggests significant potential for tasks such as forecasting public expenditure, evaluating the efficiency of social programs, and analyzing risks. For instance, XGBoost has been utilized for data classification [18, 19] and forecasting macroeconomic, budgetary, and other indicators [20–23]. Numerous studies highlight XGBoost's high accuracy, performance, reliability, and computational speed compared to traditional regression analysis methods, which is particularly relevant given the well-known limitations of classical regression analysis, such as heteroskedasticity, autocorrelation of residuals, and data stationarity issues [24–27].

Based on the literature review, the following research hypothesis (H1) is formulated: The efficiency of FIMSS is determined by the ability of public social security systems to minimize poverty and ensure adequate coverage of social protection programs while maintaining moderate levels of budgetary expenditure and public debt, under the influence of nonlinear contextual factors (inequality, urbanization, and fertility rates).

3. Materials and methods

3.1. Overview of the research methodology

Afonso et al. (2010) define the efficiency of public expenditure as the minimization of costs while achieving specified social outcomes, such as poverty reduction [2]. Drawing on the findings of prior studies [17, 24], a comprehensive approach for evaluating the efficiency of FIMSS is proposed. This approach enables the analysis of budgetary efficiency at the level of subnational entities within a single country, as well as cross-country comparisons (*Fig. 1*).

In this study, the efficiency of FIMSS is defined as the system's ability to ensure a high standard of living through adequate coverage of social risks and broad access to social security programs with

[3] Most commonly, the research methodology design follows this exact approach.

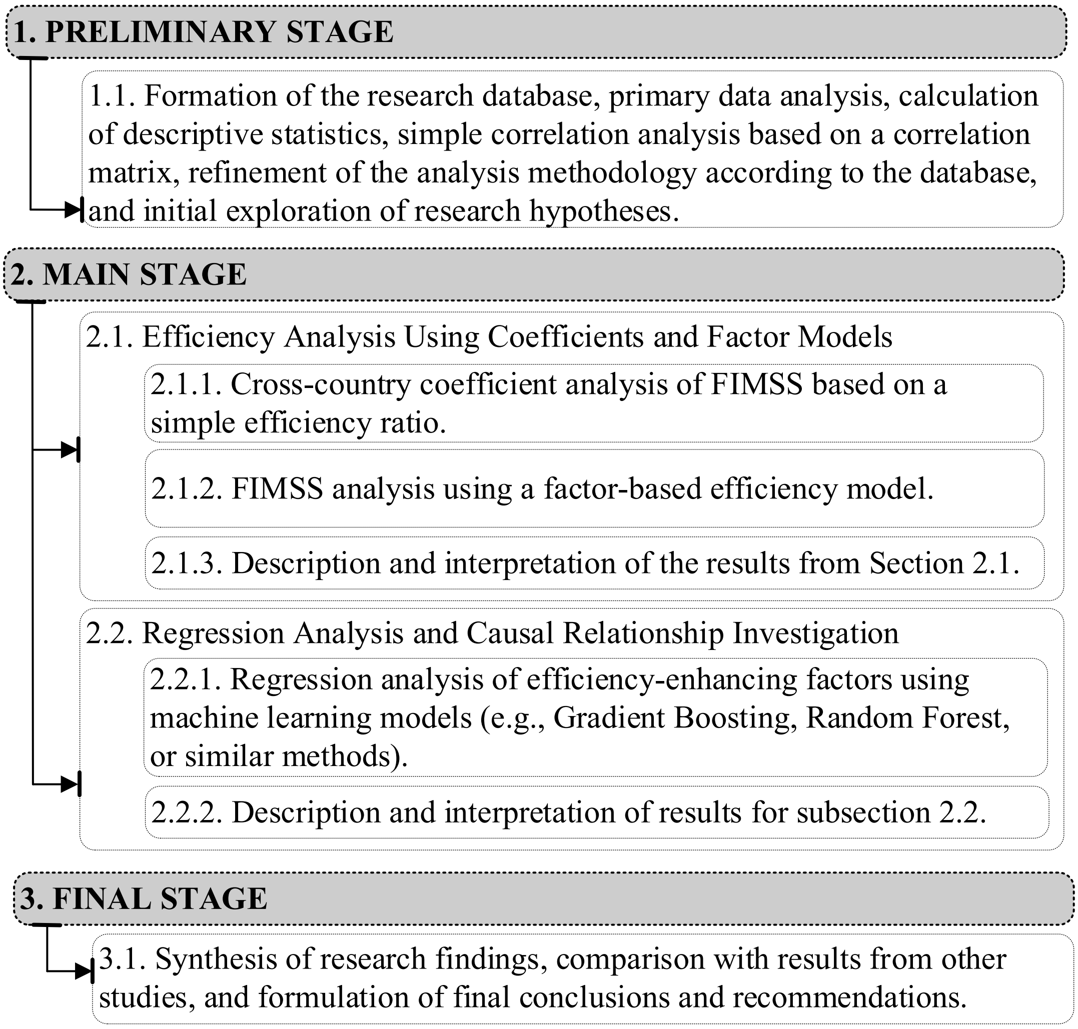

Fig. 1. **Overview of the approach for conducting a cross-country analysis of FIMSS efficiency**

Source: Compiled based on the research materials.

minimal budgetary expenditures, aligning with the principles of economy and effectiveness outlined in the Budget Code of the Russian Federation (BCRF).

Ratio and factor analysis are based on a combination of four interrelated coefficients. Public expenditure on social security within state-managed FIMSS (as a percentage of GDP) per 1% of the poor population, as a relative efficiency coefficient, is presented in formula (1) [17, 24].

$$K1 = \frac{TotGovSSS2GDP}{PPovLM50}, \qquad (1)$$

where: *TotGovSSS 2GDP* — public expenditure on social security (GovSoex2GDP) and healthcare; *PBPovLM50* — the share of the population with incomes below 50% of the median per capita income.

The coefficient K1 serves as a relative measure of FIMSS efficiency, reflecting the volume of budgetary expenditure on social security and healthcare (as a percentage of GDP) per 1% of the "poor" population (those with incomes below 50% of the median per capita income). Its economic significance lies in evaluating the intensity of budgetary resources allocated to supporting the most vulnerable population groups.

A high K1 value may indicate either excessive expenditure or insufficient effectiveness of public social protection programs if they fail to reduce the share of the poor population.

Healthcare expenditure is included in the FIMSS efficiency assessment approach because it provides social guarantees for free medical care, reducing poverty risks associated with medical expenses. This aligns with Organisation for Economic Co-operation and Development (OECD) standards, where healthcare constitutes a significant portion of budgetary social expenditure for most countries. While *K*1 can be used to analyze FIMSS efficiency, for accurate interpretation, it is recommended to transform the denominator of Formula 1 by replacing *PBPovLM50* with (*1 — PB-PovLM50)*, i.e., the share of the "non-poor" population (those with per capita incomes above the subsistence minimum or 50% of the median per capita income).

Denoting the share of the population with incomes above 50% of the median per capita income as *PBPovLM50*, formula (1) is reformulated as shown in formula (2).

$$K2 = \frac{TotGovSSS2GDP}{1 - PBPovLM50} = \frac{TotGovSSS2GDP}{PUPovLM50} \rightarrow min, \qquad (2)$$

where: *PUPovLM*50 — the share of the population with incomes above 50% of the median per capita income.

The coefficient *K*2, defined as the ratio of budgetary expenditure on social security and healthcare (as a percentage of GDP) to the share of the "non-poor" population, serves as a key criterion for FIMSS efficiency. Its economic significance lies in assessing how effectively budgetary resources contribute to maintaining a high standard of living for the majority of the population (those with incomes above the poverty threshold). A lower *K*2 value indicates a more economical and effective public social security system, as a smaller share of expenditure (as a percentage of GDP) supports the well-being of a larger proportion of the population.

As noted earlier, ratio analysis is frequently employed in studies of social expenditure efficiency, as it provides straightforward and interpretable assessments of the relationship between socioeconomic outcomes and the financial resources allocated to achieve them. For the state, an efficient system (economical in expenditure and effective in increasing the share of the "non-poor" population) is characterized by the lowest possible *K*2 value.

Formulas for *K*1 and *K*2 are based on ratio analysis approach of Timofeev and Tumanyants [3], where efficiency is evaluated as the ratio of costs to social outcomes. The introduction of *K*3 extends this approach by incorporating the factor EffCoverSP, enhancing the objectivity of the assessment and contributing to the methodological novelty of this study, formula (3).

$$\begin{cases} K3 = \dfrac{K2}{EffCoverSP} = \dfrac{TotGovSSS2GDP}{PUPovLM50 * EffCoverSP} = \\ = \dfrac{TotGovSSS}{TotGovBSp} * \dfrac{TotGovBSp}{GDP} * \dfrac{Pop}{PUPovLM50} * \dfrac{1}{EffCoverSP}; \\ K3 \rightarrow min \end{cases} \qquad (3)$$

where: *GDP* — Gross Domestic Product, in monetary units; *TotGovSSS* — Public expenditure on social security, in monetary units; *TotGovBSp* — total public expenditure, in monetary units; *Pop* — total population, in persons; *EffCoverSP* — effective coverage of the population by social protection programs, measured on a scale from 0 to 1 (as per ILO standards).[4]

The proposed factor model enables the decomposition of the *K*3 coefficient into several interrelated components, providing significantly more informative insights for comparative cross-country analysis of FIMSS efficiency. Each factor in this model carries distinct economic significance, facilitating a transition from simple ratio analysis to comprehensive factor analysis based on widely used and interpretable coefficients (*Appendix 1*).

The *K*3 coefficient reflects how effectively budgetary resources allocated to social security achieve socioeconomic outcomes — namely, a high standard of living for the majority of the population (the share of the "non-poor" population) while accounting for the coverage of social protection programs.

[4] The EffCoverSP indicator, developed by the International Labour Organization (ILO) and measured in relative units on a scale from 0 to 1, represents the proportion of the population covered by at least one social protection program (e.g., pensions, unemployment benefits, health insurance, maternity payments, etc.). A value of 0 indicates no coverage whatsoever, while 1 signifies universal coverage of the entire population by at least one program.

A lower $K3$ value indicates a more efficient FIMSS, as the state achieves substantial social outcomes (a high share of the "non-poor" population and broad program coverage) with moderate budgetary expenditures on social security.

Conversely, a high $K3$ value may indicate FIMSS inefficiency, such as excessive expenditures, low program coverage, or insufficient poverty reduction.

It should be emphasized that expenditure minimization is considered in the context of optimization, not complete replacement with private financing.

Thus, $K3$ integrates the results of ratio analysis (coefficients $K1$ and $K2$) and supplements them with a control factor — the effective coverage indicator (EffCoverSP). This makes $K3$ more objective, as it accounts not only for monetary poverty indicators but also for the accessibility of social programs, aligning with ILO standards and the UN Sustainable Development Goals (SDGs). The decomposition of $K3$ into interrelated factors (expenditures, GDP, population, and program coverage) enables cross-country analysis and identification of key drivers of FIMSS efficiency.

In this study, $K3$ is used for ranking countries and analyzing the dynamics of FIMSS efficiency, as well as a dependent variable in regression analysis employing gradient boosting to identify nonlinear relationships with exogenous factors (e.g., public debt, urbanization, and fertility rates).

The XGBoost algorithm was selected due to its ability to handle nonlinear relationships and missing data, which is particularly relevant for analyzing OECD countries [20, 21]. The XGBoost model, in its basic form, can be described as shown in Formula (4).

$$F(x) = F_0(x) + \sum_{m=1}^{M} \gamma_m h_m(x), \qquad (4)$$

where: $F(x)$ — the predictive model, minimizing the error between predicted values $F(x_i)$ and actual values (from the test data subset), constructed through $m = 1,2,\ldots,$ M iterations of parameter calculations, where decision trees are added, and residuals (gradients of the loss function based on model predictions) are computed to guide improvements in the model's predictive power in subsequent gradient descent iterations; x_i — the vector of features, exogenous independent variables used to further explain the causality of the calculated FIMSS efficiency indicators; γ_m — the step size for minimizing the loss function; $h_m(x)$ — the decision tree.

The advantage of this method lies in its additional capability for graphical data representation and the construction of Partial Dependence Plots (PDP-plots). These plots facilitate factor analysis of efficiency based on a set of independent variables and demonstrate the nonlinearity of the relationship between the dependent variable and explanatory variables.

3.2. Research database

The study utilizes data from open sources, including the OECD,[5] the World Bank,[6] IMF,[7] the World Inequality Database (WID),[8] the ILO,[9] Rosstat, and the Ministry of Finance of Russia.[10]

The indicator of effective coverage by social security programs, sourced from the ILO database, serves as a control variable in the proposed approach for assessing FIMSS efficiency. For the purposes of this study, it is assumed that the value of this indicator remains constant across all years, based on the data available from the ILO for 2021, as this is the only publicly accessible information at the time of the research.

The study covers data from 38 OECD countries, Russia, and China over the period 2005–2022. The ratio and factor analyses of efficiency include data from Russia and China, whereas the regression analysis is limited to a smaller sample of 26 countries (excluding Russia and China) due to data scarcity and a high number of missing values, even within the OECD database.

OECD countries provide standardized and reliable data on public expenditure, social security, demographic indicators, and other variables (through OECD, ILO, and World Bank (WB) databases), ensuring high-quality and comparable information for cross-country analysis. The inclu-

[5] OECD database. URL: https://stats.oecd.org/Index.aspx?datasetcode=SOCX_REF# (accessed on 30.12.2024).

[6] WorldBank database. URL: https://data.worldbank.org/indicator (accessed on 30–12–2024).

[7] IMF database. URL: https://data.imf.org/?sk=a0867067-d23c-4ebc-ad23-d3b015045405 (accessed on 30.12.2024).

[8] WID database. URL: https://wid.world/data/ (accessed on 30.12.2024).

[9] ILOSTAT. URL: https://www.ilo.org/data-and-statistics (accessed on 30.12.2024).

[10] Ministry of Finance. URL: https://minfin.gov.ru/ru/perfomance/budget/policy/osnov (accessed on 30.12.2024).

sion of Russia and China accounts for the diversity of economic structures and expands the sample, potentially making the results more generalizable.

Challenges in forming the research database for gradient boosting modeling necessitated the use of the *K*3 coefficient as the dependent variable, calculated not for a specific year but as a five-year moving average over the period 2005–2022. This approach reduced the number of missing values and smoothed the results.

In the regression analysis using gradient boosting, additional exogenous factors were incorporated. Income inequality, urbanization, and fertility rates are considered external challenges to which FIMSS must respond. The efficiency of FIMSS is measured by the system's ability to minimize poverty and ensure program coverage under the influence of these factors.

Descriptive statistics of the research database are presented in *Appendix 2*.

4. Results and discussion

4.1. Ratio and factor analysis

The calculation of efficiency coefficients and their dynamic assessment were conducted considering the limitations of the research database. The most comprehensive data from recent reporting periods in the compiled database were available starting from 2019 and earlier. Consequently, the primary efficiency indicators were calculated for 2019 rather than later periods. To analyze efficiency dynamics, the average values of factors for each country over the last five years were also calculated (see *Table*). The right-hand side of *Table* presents the assessment of efficiency dynamics. Descriptive statistics for each factor across the full sample of countries for the period 2005–2021 are provided in rows 41–46.

Indicators in columns 2–11, consistent with the logic of the efficiency assessment model, should be minimized. The values of the control coefficients for effective coverage in columns 6 and 11 are identical, as only 2021 data are available in open sources, leading to the assumption that these indicators are conditionally constant. In future studies, these indicators should be applied dynamically if the ILO provides such data.

Columns 12–15 show changes in factors that should be minimized, comparing the current year to the five-year moving average. A decrease in the indicator reflects an increase in FIMSS efficiency. Descriptive statistics, calculated for the period 2005–2022, also allow for assessing efficiency relative to global averages (Russia is highly efficient). Instead of ranking, a heatmap construction method is applied. In the heatmap, the highest coefficient value is highlighted in red, and the lowest in green, as the *K*3 efficiency coefficient, per the proposed approach, should be minimized.

Significant progress in reducing poverty has been observed in Ireland and Portugal, leading to increased FIMSS efficiency in these countries. In contrast, Russia's share of the poor population, according to the applied approach, has increased. Nevertheless, the efficiency indicator decreased due to a reduction in the share of public social security expenditure within the budget structure, coupled with an increase[11] in total budgetary expenditure as a percentage of GDP. As the indexation rate of social policy expenditures slightly lags behind the growth rate of total public expenditure, Russia's FIMSS remains relatively efficient in the context of cross-country comparisons.

In Russia, the control factor for effective population coverage by social programs (1/coverage coefficient) stays at low levels. This indicates that, during the study period, Russia's social security system performs relatively well (relative to budgetary expenditures and the socioeconomic outcomes of other countries).

Low *K*3 value suggests a potentially more efficient FIMSS in Russia, as a smaller share of social expenditure (as a percentage of GDP) supports a high proportion of the "non-poor" population (PUPovLM50). However, a reduction in *K*3 driven by an increase in non-social budgetary items, such as defense spending in 2022–2025, without improvements in social outcomes (e.g., increases in PUPovLM50 or program coverage, EffCoverSP) should be considered a negative factor affecting FIMSS efficiency.

The unprecedented reduction in poverty in Russia, alongside a decline in the share of social expenditure in GDP, should be interpreted cau-

[11] According to Rosstat data, the primary poverty level indicator based on the subsistence minimum is significantly lower and shows a declining trend by the end of the study period. We utilized Rosstat's median income statistics to ensure the comparability of our analysis. Even under these conservative parameters, Russia demonstrates remarkable competitiveness in the K3 indicator, performing comparably to EU nations that have long served as benchmarks for our socio-economic policy.

Table
Ratio and factor analysis of FIMSS efficiency

№	Country	2019 Data					5-Year Average (2015–2019)					Efficiency Dynamics			
		K3	F1	F2	F3	F4	K3	F1	F2	F3	F4	K3	F1	F2	F3
	1	2	3	4	5	6	7	8	9	10	11	12=3/8–1	13=4/9–1	14=5/10–1	15=6/11–1
1	Australia	–	0.459	0.360	–	1.000	–	0.466	0.362	–	1.000	–	–1.65%	–0.41%	–
2	Austria	–	0.586	0.486	–	1.014	0.333	0.582	0.495	1.140	1.014	–	0.53%	–1.82%	–
3	Belgium	0.298	0.517	0.519	1.111	1.000	0.298	0.513	0.526	1.105	1.000	0.02%	0.85%	–1.42%	0.60%
4	Canada	0.211	0.516	0.375	1.088	1.002	0.210	0.525	0.368	1.089	1.002	0.32%	–1.55%	1.83%	–0.05%
5	Chile	–	–	–	1.130	1.425	–	–	0.254	1.141	1.425	–	–	–	–0.98%
6	Colombia	–	–	–		1.905	–	–	–	1.195	1.905	–	–	–	–
7	Costa Rica	–	–	0.320	1.248	1.724	–	–	0.303	1.259	1.724	–	–	5.49%	–0.80%
8	Czech Republic	0.239	0.489	0.410	1.059	1.126	0.240	0.496	0.404	1.062	1.126	–0.14%	–1.33%	1.45%	–0.28%
9	Denmark	0.359	0.605	0.497	1.070	1.117	0.367	0.598	0.516	1.065	1.117	–2.03%	1.17%	–3.66%	0.47%
10	Estonia	0.222	0.476	0.391	1.175	1.016	0.220	0.463	0.393	1.187	1.016	1.23%	2.73%	–0.46%	–1.01%
11	Finland	0.333	0.585	0.533	1.068	1.000	0.340	0.585	0.545	1.067	1.000	–1.92%	0.03%	–2.11%	0.15%
12	France	–	0.574	0.553	–	1.000	–	0.573	0.562	–	1.000	–	0.21%	–1.50%	–
13	Germany	0.303	0.598	0.450	1.122	1.005	0.298	0.599	0.443	1.115	1.005	1.78%	–0.27%	1.40%	0.65%
14	Greece	0.451	0.535	0.477	1.130	1.563	0.460	0.515	0.497	1.151	1.563	–1.87%	3.83%	–3.91%	–1.83%
15	Hungary	0.220	0.374	0.460	1.101	1.160	0.233	0.390	0.472	1.092	1.160	–5.72%	–4.12%	–2.50%	0.86%
16	Iceland	–	0.430	0.437	–	1.235	0.236	0.408	0.445	1.057	1.235	–	5.32%	–1.61%	–
17	Ireland	0.163	0.555	0.243	1.088	1.110	0.175	0.542	0.266	1.095	1.110	–7.02%	2.31%	–8.59%	–0.64%
18	Israel	0.356	0.418	0.387	1.209	1.821	0.352	0.414	0.383	1.218	1.821	1.12%	1.01%	0.80%	–0.69%
19	Italy	0.393	0.575	0.485	1.157	1.220	0.394	0.567	0.490	1.162	1.220	–0.16%	1.36%	–1.10%	–0.42%
20	Japan	–	0.618	0.385	–	1.020	0.283	0.616	0.382	1.186	1.020	–	0.37%	0.76%	–
21	Korea	–	–	–	1.195	1.294	–	–	0.311	1.206	1.294	–	–	–	–0.94%
22	Latvia	0.200	0.425	0.381	1.193	1.036	0.194	0.406	0.384	1.200	1.036	3.31%	4.67%	–0.81%	–0.53%
23	Lithuania	0.235	0.532	0.347	1.182	1.079	0.225	0.509	0.343	1.195	1.079	4.73%	4.45%	1.31%	–1.07%
24	Luxembourg	0.273	0.546	0.430	1.117	1.042	0.266	0.547	0.413	1.126	1.042	2.90%	–0.24%	3.98%	–0.81%

Table (continued)

№	Country	2019 Data					5-Year Average (2015–2019)					Efficiency Dynamics			
		K3	F1	F2	F3	F4	K3	F1	F2	F3	F4	K3	F1	F2	F3
	1	2	3	4	5	6	7	8	9	10	11	12=3/8–1	13=4/9–1	14=5/10–1	15=6/11–1
25	Mexico	–	–	–	–	1.603	–	–	–	1.194	1.603	–	–	–	–
26	Netherlands	0.259	0.551	0.421	1.087	1.026	0.264	0.551	0.431	1.086	1.026	–2.12%	–0.04%	–2.20%	0.11%
27	New Zealand	0.193	0.479	0.350	1.148	1.000	0.197	0.481	0.353	1.160	1.000	–2.34%	–0.46%	–0.84%	–1.04%
28	Norway	0.321	0.551	0.511	1.092	1.044	0.318	0.560	0.500	1.091	1.044	0.80%	–1.49%	2.20%	0.11%
29	Poland	0.281	0.516	0.419	1.104	1.178	0.276	0.508	0.416	1.112	1.178	1.67%	1.62%	0.75%	–0.71%
30	Portugal	0.290	0.550	0.424	1.119	1.109	0.298	0.532	0.448	1.128	1.109	–2.71%	3.48%	–5.27%	–0.84%
31	Slovakia	0.236	0.494	0.405	1.085	1.086	0.245	0.500	0.416	1.087	1.086	–3.95%	–1.39%	–2.47%	–0.18%
32	Slovenia	0.249	0.534	0.431	1.080	1.000	0.260	0.528	0.451	1.090	1.000	–4.15%	1.12%	–4.38%	–0.91%
33	Spain	0.339	0.561	0.416	1.172	1.236	0.334	0.551	0.417	1.175	1.236	1.51%	1.99%	–0.24%	–0.26%
34	Sweden	0.286	0.529	0.491	1.100	1.000	0.294	0.541	0.495	1.098	1.000	–2.88%	–2.38%	–0.66%	0.15%
35	Switzerland	0.176	0.461	0.320	1.110	1.079	0.178	0.461	0.322	1.109	1.079	–0.64%	0.04%	–0.77%	0.08%
36	Turkey	0.238	0.464	0.348	1.176	1.253	0.224	0.454	0.336	1.180	1.253	6.26%	2.35%	3.45%	–0.31%
37	United Kingdom	0.273	0.549	0.408	1.142	1.070	0.275	0.551	0.413	1.131	1.070	–0.62%	–0.37%	–1.15%	0.91%
38	United States	0.273	0.446	0.382	1.220	1.314	0.271	0.446	0.381	1.215	1.314	0.70%	0.06%	0.28%	0.36%
39	Russia	0.207	0.404	0.378	1.222	1.110	0.210	0.417	0.372	1.222	1.110	–1.55%	–3.19%	1.52%	0.00%
40	China	–	0.351	0.315	–	1.412	–	0.335	0.310	–	1.412	–	4.86%	1.90%	–
Descriptive Statistics for 2005–2022 Period															
41	Minimum	0.146	0.108	0.189	1.047	1.000	0.146	0.184	0.210	1.052	1.000	–7.02%	–4.12%	–8.59%	–1.83%
42	1st Quartile	0.227	0.452	0.369	1.092	1.015	0.232	0.453	0.372	1.092	1.015	–2.12%	–0.42%	–1.89%	–0.82%
43	Median	0.274	0.506	0.426	1.125	1.086	0.275	0.503	0.421	1.132	1.086	–0.16%	0.37%	–0.71%	–0.29%
44	Mean	0.279	0.493	0.423	1.135	1.186	0.279	0.491	0.422	1.141	1.186	–0.47%	0.74%	–0.58%	–0.31%
45	3rd Quartile	0.313	0.547	0.488	1.171	1.236	0.312	0.546	0.490	1.186	1.236	1.23%	2.15%	1.33%	0.12%
46	Maximum	0.525	0.619	0.649	1.404	1.905	0.479	0.616	0.578	1.404	1.905	6.26%	5.32%	5.49%	0.91%

Source: Compiled based on the research materials.

Notes: Hyphen symbol (–) in a cell without numbers signifies that the data are not available. Descriptive statistics were calculated for the period 2005–2022. However, the moving average values of *K*3 are presented only for the period 2015–2022, as this five-year period has the most complete data availability in the research database.

tiously as a factor of improved FIMSS efficiency. This reduction is driven by the lagging indexation of the absolute poverty threshold amidst faster growth in prices and labor incomes, rather than the quality and accessibility of social security programs.

4.2. Regression analysis of efficiency coefficients using gradient boosting

For the construction of gradient boosting models, the research database was randomly split into two subsets: 85% of the data were used for model training, and the remaining 15% for testing. The modeling results and the model with the best performance characteristics are presented in *Appendix 3*.

Partial dependence plots (PDP) for FIMSS efficiency are presented in *Fig. 2*, ordered by the decreasing significance of explanatory factors.

The results indicate that higher budgetary expenditures, including defense spending, are associated with lower FIMSS efficiency. Similar findings are reported in studies by Astapov et al. [28] and Smykova et al. [29], which note that certain budgetary expenditures have low fiscal multipliers and act as a burden on the economy. Thus, excessively high social policy expenditures should be avoided, and principles of efficiency, targeting, and means-testing should be adhered to. A significant negative impact on efficiency occurs in the range of 35–42% of GDP, corresponding to a 0.04 percentage point increase in the efficiency coefficient. A further 0.02 percentage point reduction in efficiency occurs in the range of 46–48% of GDP.

Although the construction of *K*3 implies a negative relationship between FIMSS efficiency and budgetary expenditures for its financing, XGBoost identified threshold values of budgetary expenditures (35–42% of GDP) where FIMSS efficiency declines sharply, confirming earlier empirical findings by Afonso et al. (2010) [2].

The impact of defense spending is considerably lower than that of total expenditures, yet its increase negatively affects FIMSS efficiency. Similar results are shown in studies by Arzhenovsky [30] and Kudrin and Knobel [31], which explain that the growth of the "non-productive economy" can accelerate inflation and slow economic growth, creating challenges for effective management of social security finances. A 0.003 percentage point increase in the FIMSS efficiency coefficient occurs in the range of 1.3–1.6% of GDP, after which additional increases in defense spending have minimal impact on FIMSS efficiency per the *K*3 coefficient.

Among the factors, public debt has the most significant negative impact on FIMSS efficiency. Interestingly, in the range of 0–50% of GDP, rising public debt enhances FIMSS efficiency, but beyond this threshold, each additional percentage point of public debt reduces efficiency. A sharp decline in FIMSS efficiency (by 0.075 percentage points) occurs in the range of 130–140% of GDP. Rising borrowing costs and the crowding-out effect create challenges for economic growth, threatening social stability and FIMSS efficiency in the long term, particularly during periods of high inflation and rising interest rates [32].

Pre-tax income inequality exhibits a nonlinear relationship with FIMSS efficiency. The most efficient FIMSS systems are associated with a Gini index range of 0.37–0.43. An increase in the Gini index beyond this range to 0.48 is associated with a 0.006 percentage point reduction in FIMSS efficiency. However, further increases in income inequality do not significantly affect FIMSS efficiency.

The impact of wealth inequality differs from that of income inequality. An increase in this indicator leads to a reduction (increase) in the FIMSS efficiency coefficient. Changes in the wealth Gini index within the range of 0.66–0.76 do not significantly affect FIMSS efficiency.

A decline in the birth rate to 9 newborns per 1,000 population reduces FIMSS efficiency by approximately 0.006 percentage points. Similarly, a total fertility rate below 1.55 leads to a gradual reduction in FIMSS efficiency. The most efficient FIMSS systems are observed in countries with a total fertility rate of 1.55–1.7. A decline in the share of the young population below 14.5% and the exacerbation of population aging reduce FIMSS efficiency by 0.025 percentage points.

Optimal FIMSS efficiency with respect to urbanization is achieved by targeting an urban population share of 63–74% of the total population. An increase in urbanization reduces FIMSS efficiency more significantly than a decrease below this range. Urbanization within this range ensures the optimal concentration of economic activity, enabling cities to provide high-quality social

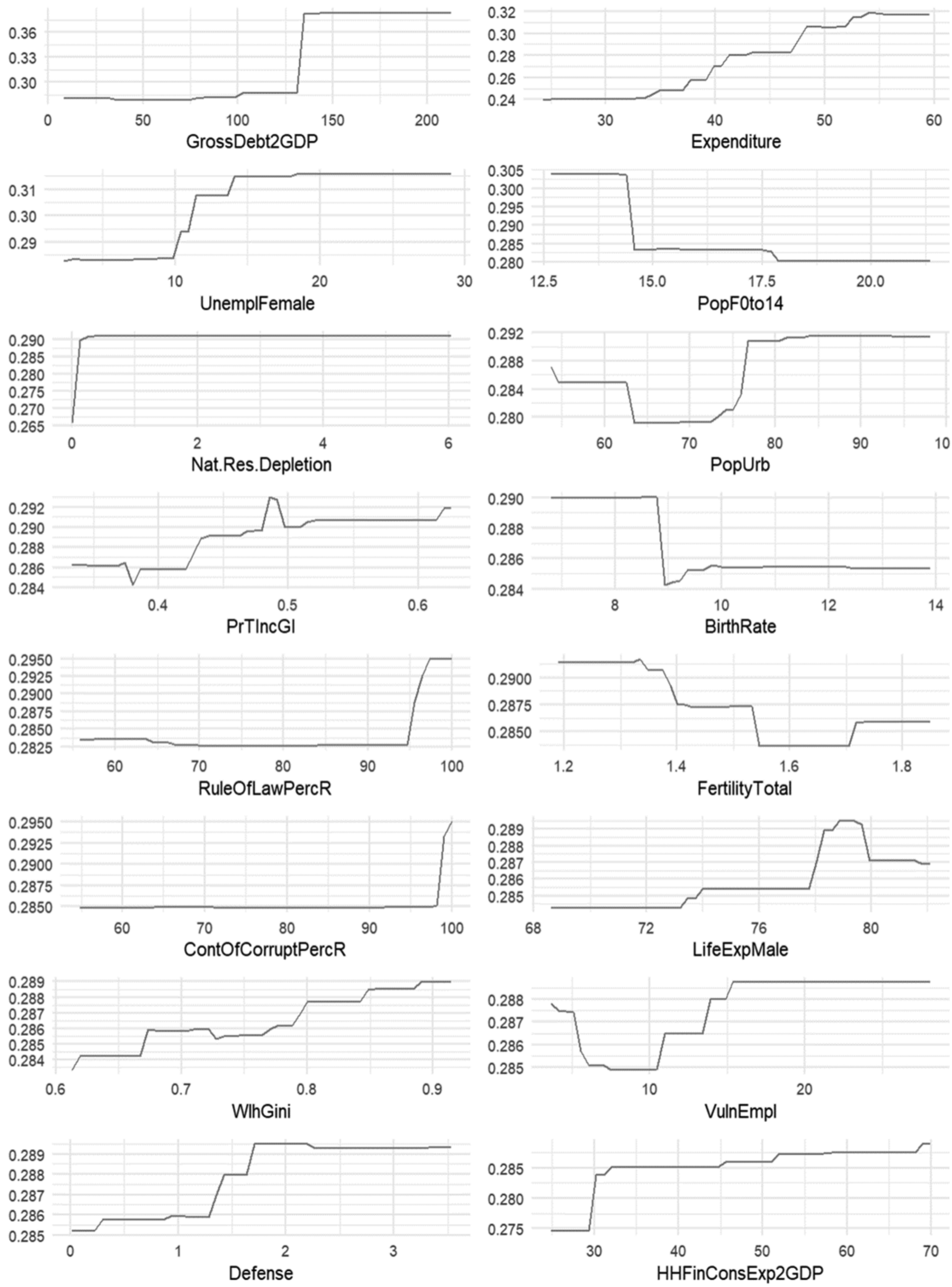

Fig. 2. **Partial dependence plots for FIMSS efficiency**

Source: Compiled by the author based on the research materials.

services (healthcare, education) and economic opportunities due to scale and density.

5. Research limitations and directions for future research

The limitations of the approach in this study stem from challenges in forming the research database and the fact that the factor model does not account for the impact of non-state FIMSS on the *K*3 efficiency coefficient.

Limitations of the data, such as the use of a five-year moving average for the *K*3 coefficient and the reduction of the sample to 26 countries for regression analysis due to data unavailability, constrain the scope of the study. These limitations can be addressed in future research by expanding the sample or integrating additional data sources.

It should also be noted that the study does not include private-sector healthcare or pension systems, which are well-developed in certain countries, such as the United States. This exclusion is due to limitations in the research database and may be addressed in future studies.

6. Conclusion

Contemporary challenges facing social security systems underscore the importance of developing a comprehensive approach for analyzing the efficiency of Financial and Investment Models of Social Security. Within the framework of this study, a novel comprehensive approach for assessing FIMSS efficiency was developed and tested, integrating ratio analysis, factor analysis, and the gradient boosting method.

The study successfully confirmed hypothesis H1, which posits that FIMSS efficiency is determined by the ability of public social protection systems to minimize poverty and ensure coverage by social security programs while maintaining moderate levels of budgetary expenditure and public debt. The ratio and factor analyses demonstrated that countries with low *K*3 values achieve high economy and effectiveness through optimized expenditure and an increased share of the “non-poor” population. The XGBoost model confirmed the nonlinear influence of contextual factors: optimal levels of income inequality (Gini index of 0.37–0.43), urbanization (63–74%), and fertility rates (1.55–1.7) are associated with minimal *K*3 values, consistent with the hypothesis. Public debt contributes to FIMSS efficiency when it remains below 50% of GDP, but its increase beyond 130% significantly reduces efficiency indicators.

The findings can be applied to reform FIMSS to enhance their resilience amid global challenges, such as demographic decline, the climate crisis, and technological transformation. Future research prospects include further development of the proposed approach for analyzing other areas of public policy and its integration with big data to improve the accuracy of forecasts and the granularity of analysis.

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ABOUT THE AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

Mikhail L. Dorofeev — Cand. Sci. (Econ.), Associate Professor, Department of Public Finance, Financial University under the Government of the Russian Federation, Moscow, Russian Federation
Михаил Львович Дорофеев — кандидат экономических наук, доцент кафедры общественных финансов, Финансовый университет при Правительстве Российской Федерации, Москва, Российская Федерация
http://orcid.org/0000-0002-2829-9900
dorofeevml@yandex.ru

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APPENDICES

Appendix

Characteristics of the general economic meaning of components in the factor model described in formula (3)

Factor	*K*3	*F*1	*F*2	*F*3	*F*4
	$\frac{TotGovSSS2GDP}{PUPovLM50} =$	$\frac{TotGovSSS}{TotGovBSp}$ *	$\frac{TotGovBSp}{GDP}$ *	$\frac{Pop}{PUPovLM50}$ *	$\frac{1}{EffCoverSP}$
Title	State-type FIMSS efficiency ratio	Social security and healthcare expenditures as a share of budget spending	Government expenditures as a percentage of GDP	Ratio of total population to population above poverty line	Adjustment coefficient for population coverage by social protection programs

Appendix 1 (continued)

Factor	***K*3**	***F*1**	***F*2**	***F*3**	***F*4**
	$\frac{TotGovSSS2GDP}{PUPovLM50} =$	$\frac{TotGovSSS}{TotGovBSp}$ *	$\frac{TotGovBSp}{GDP}$ *	$\frac{Pop}{PUPovLM50}$ *	$\frac{1}{EffCoverSP}$
Economic Meaning	The specific level of budget expenditures on social security and healthcare as a percentage of GDP spent per 1% of population above the poverty line. Rationale for Indicator Selection Social security and healthcare expenditures primarily target low-income citizens while being funded by middle- and high-income citizens. When evaluating expenditure efficiency — which according to the Russian Budget Code represents both effectiveness (poverty reduction or growth of non-poor population) and economy (means-tested targeted assistance ensuring expenditure minimization) — we can compare "resources spent" (input) with "outcomes achieved" (one of socioeconomic development indicators). Here, we could use either the poor population share or non-poor population share in the denominator. However, using the poor population share would distort the efficiency indicator's meaning, as it would require reducing the numerator to obtain a lower denominator value, creating interpretation challenges. Therefore, I propose using specifically the "non-poor population" share in the denominator. This allows unambiguous coefficient interpretation: lower values indicate better performance, achieved either through reduced funding for the same non-poor population or through faster growth of non-poor population relative to funding increases	The share of social security and healthcare expenditures in total budget system spending. Reflects the budget's social orientation level	Budget system expenditures as percentage of GDP. Reflects: The budget system's economic scale; Current fiscal pressure level; Government involvement in public goods provision	Values closer to 1 indicate smaller poor population share (defined based on income below 50% of median per capita income). Can also be expressed as [1/(1-poor population share)]	Adjusts state-type FIMSO efficiency for population coverage by at least one social protection program. Enables monitoring justification for reducing government expenditures in this area. The inverse value is used because efficiency is evaluated from the perspective of minimization

Appendix 1 (continued)

Factor	***K*3**	***F*1**	***F*2**	***F*3**	***F*4**
	$\frac{TotGovSSS2GDP}{PUPovLM50} =$	$\frac{TotGovSSS}{TotGovBSp}$ *	$\frac{TotGovBSp}{GDP}$ *	$\frac{Pop}{PUPovLM50}$ *	$\frac{1}{EffCoverSP}$
Areas for Optimization to Enhance Efficiency	The coefficient is optimized toward lower values. Given the inverse relationship between social security expenditures and economic growth, it is advisable to reduce the numerator while maintaining or increasing the denominator. This indicator can be interpreted as the "cost of decent living" for the population, primarily linked to social security and secondarily to healthcare. Since the analysis employs a poverty metric based on median income (rather than the conventional Russian poverty line), an important consideration arises: This poverty assessment framework does not imply the elimination of poverty, as a segment of the population will always have incomes below a defined threshold (e.g., 40%, 50%, or 60% of the median). Thus, poverty is approached here as a regulated process — focused on control and minimization rather than eradication. This differs fundamentally from the subsistence minimum (ПМ), which can be administratively set (e.g., yielding 4–5% poverty in Moscow but 10%+ in other Russian regions). In this context, the indicator represents the economic cost — in terms of budget expenditures — required to ensure that a given share of the population maintains incomes above the poverty threshold	Reducing this indicator could free up fiscal resources for redirecting budget allocations toward infrastructure and economic investments	A reduction in the government's economic footprint may lead to lower tax burdens and create greater opportunities for accelerating technological progress and economic growth. Moreover, when economic growth outpaces the expansion of public spending, this dynamic serves as a fundamental driver for enhancing FIMSO efficiency	This coefficient will exceed 1, but the government should implement measures to gradually reduce it toward 1 and maintain it at modest levels, which would indicate effective poverty control.	The adjustment coefficient increases the K3 coefficient to account for underdeveloped social protection programs and low population coverage. Within this approach, higher values of the indicator correspond to lower FIMSO efficiency

Source: Compiled by the author from research materials.

Appendix 2

Descriptive statistics of the research dataset

Indicator Name		Min	Median	Average	Max	Max/ min
Full Name	**Abbrev.**					
Year	**Year**	**2015**	**2018**	**2018**	**2021**	**–**
Social expenditure efficiency indicator for social security and healthcare, 5-year moving average	K3_5YAv	0.17	0.28	0.29	0.48	2.80
Social security and healthcare expenditures as share of budget spending, 5-year moving average	F1_5YAv	0.37	0.52	0.51	0.60	1.64
Government expenditures as percentage of GDP, 5-year moving average	F2_5YAv	0.25	0.45	0.45	0.56	2.21
Ratio of total population to population above poverty line, 5-year moving average	F3_5YAv	1.05	1.11	1.12	1.22	1.16
Adjustment coefficient, 5-year moving average (ILO basis)	F4_5YAv	1.00	1.08	1.11	1.56	1.56
Pre-tax Gini index (WID basis)	PrTIncGI	0.33	0.45	0.45	0.63	1.88
Post-tax Gini index (WID basis)	PostTIncGI	0.24	0.35	0.36	0.63	2.62
Wealth Gini index (WID basis)	WlhGini	0.61	0.74	0.75	0.91	1.49
Total budget system expenditures as% of GDP (IMF basis)	Expenditure	24.28	44.94	44.89	59.62	2.46
Defense expenditures as % of GDP (IMF basis)	Defense	0.02	1.12	1.25	3.53	213.38
Healthcare expenditures as % of GDP (IMF basis)	Health	2.10	6.98	6.70	10.44	4.97
Education expenditures as % of GDP (IMF basis)	Expenditure_on_ education	2.93	5.04	5.16	8.12	2.77
Social security expenditures as% of GDP (IMF basis)	Social_protection	7.49	16.88	16.68	25.50	3.40
Household final consumption expenditures as % of GDP (IMF basis)	HHFinConsExp2GDP	23.65	52.06	52.44	69.88	2.95
Population aged 0–14 (% of total) (WB basis)	PopF0to14	12.65	15.62	15.96	21.36	1.69
Population aged 15–64 (% of total) (WB basis)	PopF15to64	61.68	65.14	65.28	70.45	1.14
Population aged 65+ (% of total) (WB basis)	PopF65	13.12	19.05	18.75	23.68	1.81
Urban population (% of total) (WB basis)	PopUrb	53.73	75.71	75.73	98.12	1.83
Agricultural land (% of land area) (WB basis)	AgricultLandShare	2.69	44.36	40.56	72.42	26.88
Total fertility rate (children per woman) (WB basis)	FertilityTotal	1.19	1.57	1.56	1.85	1.55
Life expectancy at birth, total (years) (WB basis)	LifeExpTotal	73.28	81.31	80.36	83.90	1.14
Life expectancy at birth, female (years) (WB basis)	LifeExpFemale	78.00	83.70	83.15	86.70	1.11

Appendix 2 (continued)

Indicator Name		Min	Median	Average	Max	Max/min
Full Name	**Abbrev.**					
Year	**Year**	**2015**	**2018**	**2018**	**2021**	**–**
Life expectancy at birth, male (years) (WB basis)	LifeExpMale	68.60	78.90	77.70	82.10	1.20
Birth rate (per 1,000 people) (WB basis)	BirthRate	6.80	10.10	10.05	13.90	2.04
Total dependency ratio (% of working-age population) (WB basis)	AgeDependRatTol	41.94	53.50	53.28	62.13	1.48
Old-age dependency ratio (% of working-age population) (WB basis)	AgeDependRatOld	20.02	29.25	28.81	37.19	1.86
Youth dependency ratio (% of working-age population) (WB basis)	AgeDependRatYoung	19.87	23.59	24.47	32.60	1.64
Unemployment rate, total (% of labor force) (WB basis)	UnemplTotal	2.02	5.97	6.93	24.98	12.37
Unemployment rate, female (% of female labor force) (WB basis)	UnemplFemale	2.39	5.71	7.16	29.03	12.16
Unemployment rate, male (% of male labor force) (WB basis)	UnemplMale	1.73	5.79	6.75	21.74	12.60
Vulnerable employment (% of total employment) (WB basis)	VulnEmpl	3.64	9.70	10.12	28.08	7.71
CO_2 emissions (metric tons per capita) (WB basis)	CO2Emis	3.24	6.19	6.86	16.03	4.94
Renewable energy consumption (% of total) (WB basis)	RenewEnergCons	5.62	18.69	26.31	82.79	14.73
Natural resource depletion (% of GDP) (WB basis)	Nat.Res.Depletion	0.00	0.08	0.28	6.05	–
Forest area (% of land area) (WB basis)	ForestArea	0.48	33.65	34.68	73.74	153.49
Government debt (% of GDP) (WB, OECD basis)	GrossDebt2GDP	8.20	64.64	70.97	212.39	25.89
Control of Corruption Index (score 0–100)	ContOfCorruptPercR	54.81	89.90	83.74	100.00	1.82
Government Effectiveness Index (score 0–100)	GovEffPercR	59.62	87.74	86.01	99.52	1.67
Political Stability Index (score 0–100)	PolStabilPercR	38.57	74.76	74.32	99.53	2.58
Regulatory Quality Index (score 0–100)	RegQualPercR	60.58	90.14	86.79	99.52	1.64
Rule of Law Index (score 0–100)	RuleOfLawPercR	55.77	88.94	86.08	100.00	1.79
Voice and Accountability Index (score 0–100)	VoicePercR	57.97	89.86	86.86	100.00	1.72
Log of land area per capita (for land resource availability analysis)	LogLandArPerCap	0.28	0.97	1.08	2.48	8.76

Source: Compiled by the author from research data.

Appendix 3

Description of XGBoost model variations and optimal model parameters (best-performing model highlighted in gray shading, R^2 = 0.99135)

eta	max_depth	nrounds	RMSE	Rsquared	MAE	RMSESD	RsquaredSD	MAESD
0.1	2	50	0.022484	0.900105	0.015949	0.001700	0.019115	0.000689
0.3	2	50	0.020780	0.906189	0.014195	0.001215	0.029219	0.001640
0.1	4	50	0.020536	0.907934	0.013685	0.002696	0.033642	0.001895
0.3	4	50	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	100	0.020857	0.909325	0.014433	0.001958	0.019927	0.000817
0.3	2	100	0.020427	0.908986	0.013820	0.001163	0.028252	0.001392
0.1	4	100	0.019856	0.913201	0.013020	0.002481	0.029539	0.001229
0.3	4	100	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	200	0.020487	0.911290	0.013936	0.001942	0.022071	0.000833
0.3	2	200	0.020382	0.909402	0.013777	0.001135	0.028151	0.001352
0.1	4	200	0.019821	0.913510	0.012991	0.002481	0.029762	0.001237
0.3	4	200	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	300	0.020331	0.912339	0.013710	0.001897	0.022301	0.000797
0.3	2	300	0.020382	0.909402	0.013777	0.001135	0.028151	0.001352
0.1	4	300	0.019821	0.913510	0.012991	0.002481	0.029762	0.001237
0.3	4	300	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	400	0.020287	0.912666	0.013685	0.001859	0.022487	0.000765
0.3	2	400	0.020382	0.909402	0.013777	0.001135	0.028151	0.001352
0.1	4	400	0.019821	0.913510	0.012991	0.002481	0.029762	0.001237
0.3	4	400	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	500	0.020287	0.912666	0.013685	0.001859	0.022486	0.000765
0.3	2	500	0.020382	0.909402	0.013777	0.001135	0.028151	0.001352
0.1	4	500	0.019821	0.913510	0.012991	0.002481	0.029762	0.001237
0.3	4	500	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	600	0.020287	0.912666	0.013685	0.001859	0.022486	0.000765
0.3	2	600	0.020382	0.909402	0.013777	0.001135	0.028151	0.001352
0.1	4	600	0.019821	0.913510	0.012991	0.002481	0.029762	0.001237
0.3	4	600	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756
0.1	2	1000	0.020287	0.912666	0.013685	0.001859	0.022486	0.000765
0.3	2	1000	0.020382	0.909402	0.013777	0.001135	0.028151	0.001352
0.1	4	1000	0.019821	0.913510	0.012991	0.002481	0.029762	0.001237
0.3	4	1000	0.021034	0.903364	0.013904	0.001771	0.004682	0.000756

Source: Compiled from research data.

Notes: eta — Learning rate controlling each decision tree's contribution; nrounds — Number of decision trees; RMSE (Root Mean Squared Error) — Square root of the average squared errors; R^2 (Rsquared) — Coefficient of determination; MAE (Mean Absolute Error) — Average absolute difference between predicted and actual values; RMSESD (RMSE Standard Deviation) — Model stability metric showing variation across cross-validation folds; RsquaredSD — Standard deviation of R^2 across cross-validation folds; MAESD (MAE Standard Deviation) — Standard deviation of mean absolute errors.