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Defining the Determinants of Corporate Financial Performance: A Machine Learning Approach

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Abstract

This study investigates the determinants of corporate financial performance (CFP) among Russian enterprises (2012–2023) through the lens of geopolitical disruptions, employing ensemble machine learning (ML) to address methodological gaps in modeling non-linear institutional interactions. Using data from 25 large non-financial firms, we analyze sectoral, organizational, and strategic drivers, integrating train-test splits (75%/25%) and 10-fold cross-validation to mitigate overfitting. Results reveal that industry affiliation, initially dominant (28% explanatory power pre-2022), declined sharply post-sanctions (15%), reflecting vulnerabilities in globally integrated sectors like manufacturing and extractives. Organizational size exhibited a nonlinear relationship with CFP, favoring comparatively smaller firms' agility over larger enterprises' rigidity, consistent with transaction cost economics. Strategic investments in corporate social responsibility (CSR) and research and development (R&D) diminished post-2022 as firms prioritized liquidity and operational stability, aligning with resource-based view principles. Methodologically, Shapley Additive Explanations (SHAP) clarified threshold effects in CSR returns and innovation's reduced role under sanctions. The study innovates by applying ensemble machine learning to sanction-affected emerging markets, challenging linear econometric assumptions and advancing institutional theory through a crisis-contextualized framework of resource dependence and stakeholder salience. Findings underscore the fragility of intangible assets under systemic shocks and advocate adaptive resource allocation frameworks to balance short-term survival with long-term resilience. This work provides policymakers and managers actionable insights for fostering operational agility and strategic foresight in volatile institutional environments.

Keywords:

Corporate Financial Effectiveness;
Ensemble Machine Learning;
Geopolitical Risk;
Sanctions; Resource Dependence Theory;
Resource-Based View (RBV);
Shapley Additive Explanations (SHAP);
Russian Enterprises;
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1- Introduction

Corporate Financial Performance (CFP) remains a pivotal indicator of organizational resilience, synthesizing operational efficiency, governance quality, and macroeconomic adaptability [1, 2]. Grounded in foundational principles of financial analysis [3] and capital structure theory [4], CFP evaluation has evolved to incorporate dynamic capabilities [5] and institutional transitions [6]. While existing studies have mapped key CFP determinants using traditional econometric methods [7, 8], including capital structure dynamics [9], the application of advanced computational techniques – particularly ensemble machine learning (ML) – to dissect complex, non-linear relationships in crisis contexts remains nascent [10, 11]. Recent sector-specific applications, such as Yıldırım et al. (2024) [11], demonstrate ML's efficacy in ranking financial performance determinants within energy sectors, highlighting the method's potential for domain-specific insights. Theoretical frameworks such as agency theory [12] and stakeholder theory [13, 14] underscore the multifaceted nature of CFP determinants, with evolutionary perspectives highlighting adaptive processes [15].

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Prior work relies heavily on linear regression, which struggles to capture non-linear interactions and threshold effects – critical in sanction-driven economies where variables like research and development (R&D) spending may exhibit discontinuous impacts [16, 17]. For example, the resource-based view (RBV) [18] highlights R&D's role in competitive advantage, but liquidity constraints under sanctions may distort this relationship [19], complicating the curvilinear association between social investments and financial outcomes [20]. Emerging methodologies, such as deep learning architectures integrating environmental, social, and governance (ESG) data [21], offer novel pathways to quantify these interactions, particularly in forecasting performance under volatility. Frequently traditional frameworks inadequately model how internal factors (e.g., liquidity) and external shocks (e.g., sanctions) interactively amplify or mitigate risks. For instance, corporate social responsibility's (CSR) role may shift from profit-enhancing to survival-critical under sanctions [22, 23], a transition stakeholder theory attributes to shifting salience among competing claims [14] as firms prioritize short-term legitimacy over long-term ethics [24] – a dynamic linear models fail to disentangle. Aksoy and Yilmaz (2024) [23] further emphasize the moderating role of sustainability performance in crisis resilience, revealing that firms with robust ESG practices mitigated pandemic-induced financial losses more effectively.

While sector-specific vulnerabilities are acknowledged [25], predictive analytics under systemic shocks are rare. Institutional theory [6, 26] suggests firms in crisis adopt isomorphic survival strategies during institutional transitions, yet such adaptations remain poorly quantified. Russia's post-2022 environment, marked by abrupt supply chain disruptions and ownership restructuring [27, 28], demands tools that handle high-dimensional, noisy data [29]. Despite ML's rise in finance, few studies employ ensemble techniques to improve robustness in CFP prediction, particularly in sanction-affected contexts where evolutionary adaptations occur. Hsu et al. (2025) [21] advance this discourse by integrating ESG metrics into deep learning frameworks, demonstrating enhanced predictive accuracy for firms operating in regulated industries. Stewardship theory [30] posits that managerial autonomy enhances resilience, but existing models lack the granularity to test this in high-stakes environments. Ensemble models, which aggregate multiple algorithms (e.g., Random Forests, Gradient Boosting), remain untapped for isolating key drivers of financial resilience.

The aim of this paper is twofold: First, to empirically identify the non-linear, crisis-driven interactions between CFP determinants – including R&D, CSR, leverage, and industry dynamics – in Russia's post-2022 sanction context, using ensemble ML to overcome limitations of traditional econometrics. Second, to theorize how institutional upheavals reshape the relevance of foundational frameworks (agency, stakeholder, RBV) in emerging markets, particularly through the lens of dynamic capabilities [5]. By bridging the post-2022 empirical void, this study advances CFP theory by contextualizing universal determinants within institutional upheavals [1, 2]. Recent empirical work highlights the duality of firm-specific factors: larger firms benefit from economies of scale [31] but face innovation inertia as they age [32], while liquidity management balances growth opportunities against debt risks [19]. Industry dynamics further modulate outcomes – emerging sectors thrive on disruption through dynamic capabilities [5], whereas regulated industries face structural constraints [33].

Theoretical synthesis reveals competing priorities: agency theory advocates governance controls to curb managerial excess [34], while stewardship theory emphasizes trust-based autonomy [35]. Stakeholder theory bridges profit motives with ESG considerations [14, 36], yet CSR's financial returns remain contested [10, 37, 38]. These tensions are magnified in crises, where survival imperatives reshape strategic investments [31].

The remainder of this paper proceeds as follows: Section 2 outlines the data and methodology, Section 3 presents the empirical results and discussion, and Section 4 concludes with theoretical and policy implications.

2- Data and Methodology

To conduct the empirical analysis, data spanning 2012–2023 were collected from official corporate reports and websites of 25 large Russian non-financial companies, yielding 300 firm-year observations (see Table 1). The restricted sample size reflects the voluntary disclosure practices governing CSR and innovation metrics in Russia, where dominant market actors disproportionately publish such data. While this limitation introduces potential selection bias, the dataset was retained to align with the study's focus on CSR and innovation as critical determinants of firm performance. Despite the modest sample, ensemble machine learning (ML) methods remain methodologically appropriate due to their inherent compatibility with bootstrap resampling techniques, which mitigate overfitting risks in small-n contexts.

The market-to-book (MTB) ratio was selected as the dependent variable, operationalizing firm value as the ratio of market capitalization to book equity. This metric was prioritized over profitability-based indicators (e.g., ROA, ROE) due to its relative stability during macroeconomic volatility, as it captures investor expectations of future growth rather than transient accounting performance [3, 39].

Explanatory variables encompass both financial and non-financial dimensions: EBITDA margin, company size, age, industry affiliation, financial leverage, innovation activity, CSR expenditures, and observation year (2012–2023).

Control variables such as industry and year were included to isolate firm-specific effects from sectoral trends and temporal shocks. Financial leverage and EBITDA margin account for capital structure and operational efficiency, while innovation and CSR expenditures test hypotheses derived from resource-based and stakeholder theories.

Table 1. Descriptive statistics of data for 25 large Russian enterprises from 2012 to 2023

Indicators	Description	Designation on the graph	Mean	std	Min	Median	Max
Company	Company affiliation	Company	13.039	7.187	1.000	13.000	25.000
Year	Number of the year	Year	2017.4	3.470	2012.0	2017.0	2023.0
Innovations	R&D expenses / Revenue	Innov	0.002	0.005	0.000	0.001	0.043
EBITDA margin	EBITDA / Revenue	Ebitda Margin	0.268	0.136	0.000	0.262	0.647
Size	Natural logarithm of revenue	Size	12.098	3.106	0.000	12.609	16.273
CSR	CSR expenses / Revenue	Csr	0.015	0.159	0.000	0.002	2.667
CSR (staff)	Education Expenditures / Wage Fund	Csrstaff	0.005	0.017	0.000	0.002	0.196
M/B	Capitalization / Book value	m/b	1.109	0.908	0.000	0.915	3.980
Age	Number of years since the company's registration	Age	13.227	9.993	0.000	16.000	28.000
Leverage	Ratio of the sum of short-term and long-term loans to the sum of equity and borrowed funds	Lev	0.383	0.235	0.000	0.367	0.928
Industry characteristic	Belonging to the sector: 1: Extractive; 2: Manufacturing; 3: Transport and telecommunications	Field	1.461	0.827	0.000	1.000	3.000

Note: Compiled by the authors based on calculations obtained using the Python programming language.

The present investigation focused on two key variables within the framework of CSR. The first variable analyzed was the proportion of CSR expenditures relative to enterprise revenue, a metric that provides foundational insight into the organization's commitment to social responsibility initiatives. The second variable examined the relationship between employee training costs and the labor remuneration fund, grounded in the premise that investments in workforce development represent a critical dimension of CSR with the potential to enhance organizational efficiency. Additionally, innovation was operationalized through the ratio of R&D expenditures to revenue, a widely recognized indicator for assessing technological advancement and its contribution to economic growth. These metrics collectively aimed to evaluate the interplay between CSR practices, human capital investment, and innovation in driving organizational and economic outcomes.

The statistical analysis reveals that the innovation, CSR, and CSRstaff variables exhibit mean values exceeding their respective medians, consistent with a positively skewed distribution characterized by a concentration of outliers in the upper range. This asymmetry underscores the presence of firms with disproportionately high innovation and social responsibility investments within the sample.

To address overfitting risks inherent in machine learning applications, two methodological strategies were employed: First, a train-test split partitioned the dataset into a training subset (n = 225 observations, 75% of the data) and an independent test subset (n = 75 observations, 25%), ensuring that model performance could be rigorously assessed against unseen data to evaluate generalizability. Second, 10-fold cross-validation was applied to the training data, iteratively dividing it into 10 mutually exclusive folds. For each iteration, one-fold served as a validation subset while the remaining nine were used for model training. This protocol facilitated hyperparameter optimization while providing a systematic evaluation of model stability across heterogeneous data partitions.

Figure 1 provides a schematic overview of the ensemble methodology.

Data → Train-Test Split → CV on Train → Ensemble Training → Test Evaluation

Figure 1. Flowchart of the ensemble methods process

The empirical analysis employed a multi-model framework to evaluate the hypotheses, with Table 2 summarizing performance metrics – including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), R-squared (R^2), root mean squared logarithmic error (RMSLE), and mean absolute percentage error (MAPE) – for all algorithms. Models were ranked by adjusted R^2 to prioritize explanatory power while penalizing overfitting, a critical consideration given the study's limited sample size.

Table 2. Models and their quality metrics for the period of 2012-2023

	Model	MAE	MSE	RMSE	R^2	RMSLE	MAPE
Ensemble Methods	**Extra Trees Regressor**	**0.3970**	**0.3910**	**0.5932**	**0.4395**	**0.2438**	**0.3760**
	Random Forest Regressor	0.4424	0.4418	0.6397	0.3934	0.2662	0.4566
	Light Gradient Boosting Machine	0.4425	0.4355	0.6311	0.3815	0.2621	0.4702
	Extreme Gradient Boosting	0.4417	0.4462	0.6356	0.3561	0.2626	0.4342
	Gradient Boosting Regressor	0.4518	0.4712	0.6511	0.2992	0.2698	0.5077
	AdaBoost Regressor	0.5452	0.5254	0.7017	0.2457	0.3141	0.7427
Traditional Methods	K Neighbors Regressor	0.6055	0.6499	0.7883	0.1643	0.3446	0.7781
	Ridge Regression	0.6315	0.6806	0.8068	0.1602	0.3612	0.8778
	Decision Tree Regressor	0.4942	0.5865	0.7437	0.1419	0.3111	0.4986
	Elastic Net	0.7167	0.8394	0.8851	0.0302	0.3951	0.9837
	Lasso Regression	0.7226	0.8597	0.8970	0.0051	0.4010	1.0157
	Lasso Least Angle Regression	0.7226	0.8597	0.8970	0.0051	0.4010	1.0157
	Linear Regression	0.7257	2.4714	1.1785	-4.2882	0.3937	1.0056

Note: Calculated by the authors using the Python programming language

The top-performing cohort comprised six **ensemble machine learning models**, categorized into two methodological groups:

1. **Bagging algorithms**: Extra Trees Regressor and Random Forest Regressor.
2. **Boosting algorithms**: Light Gradient Boosting Machine (LGBM), Extreme Gradient Boosting (XGBoost), Gradient Boosting Regressor, and AdaBoost Regressor, which iteratively minimize bias via error-correcting ensembles.

Boosting methods train homogeneous models sequentially, with each iteration addressing residuals from prior models. In contrast, Random Forest – a bagging technique – aggregates predictions from an ensemble of decision trees, averaging outputs to stabilize results. The Extra Trees Regressor diverges from Random Forest by selecting splits randomly rather than algorithmically, accelerating model training without significant performance degradation. This feature renders it advantageous for large-scale datasets, though it typically omits bootstrapping.

Classical machine learning models were evaluated for benchmarking, including:

1. **Linear regression variants**: Ordinary Least Squares (OLS), Lasso, Least Angle Regression (LARS), Elastic Net, and Ridge Regression.
2. **Non-parametric methods**: Decision Tree Regressor and K-Nearest Neighbors (KNN) Regressor.

Ensemble methods consistently outperformed classical approaches across metrics (Table 2), though all models exhibited modest predictive accuracy in the post-2022 sanction context. This contrasts with pre-2022 data (2012–2021), where ensemble models achieved robust performance (Random Forest: adjusted $R^2 = 0.73$; Extra Trees: adjusted $R^2 = 0.72$; Table 3). The decline in post-2022 explanatory power likely reflects exogenous geopolitical shocks, which introduced unobserved determinants of financial efficiency.

Table 3. Models and their quality metrics for the period of 2012-2021

	Model	MAE	MSE	RMSE	R^2	RMSLE	MAPE
Ensemble Methods	Random Forest Regressor	0.3337	0.2277	0.4595	**0.7275**	0.1735	0.3478
	Extra Trees Regressor	0.3314	0.2369	0.4680	0.7236	**0.1700**	**0.3241**
	Extreme Gradient Boosting	**0.3192**	**0.2257**	**0.4534**	0.7209	0.1745	0.3300
	Light Gradient Boosting Machine	0.3530	0.2285	0.4673	0.7047	0.1822	0.3420
	Gradient Boosting Regressor	0.3476	0.2532	0.4831	0.6888	0.1831	0.3415
	AdaBoost Regressor	0.4149	0.2699	0.5107	0.6573	0.2222	0.6432
Traditional Methods	Linear Regression	0.5088	0.4211	0.6409	0.4436	0.2756	0.6610
	Decision Tree Regressor	0.4481	0.4906	0.6664	0.3834	0.2409	0.4428
	Ridge Regression	0.5779	0.5172	0.7065	0.3461	0.3024	0.7571
	K Neighbors Regressor	0.5482	0.5097	0.7020	0.2900	0.2801	0.7051
	Elastic Net	0.7471	0.8559	0.9092	-0.0635	0.3719	1.0715
	Lasso Regression	0.7516	0.8844	0.9220	-0.0831	0.3758	1.1304
	Lasso Least Angle Regression	0.7516	0.8844	0.9220	-0.0831	0.3758	1.1304

Note: Calculated by the authors using the Python programming language

Validation results revealed critical insights:

- **2012–2023**: Cross-validation $R^2 = 0.44$ (Figure 2, right) versus test set $R^2 = 0.72$ (training $R^2 = 1.00$), indicating pronounced overfitting (Figure 3, right).
- **2012–2021**: Cross-validation $R^2 = 0.73$ (Figure 2, left) versus test $R^2 = 0.81$, (training $R^2 = 0.97$), suggesting mild overfitting (Figure 3, left).

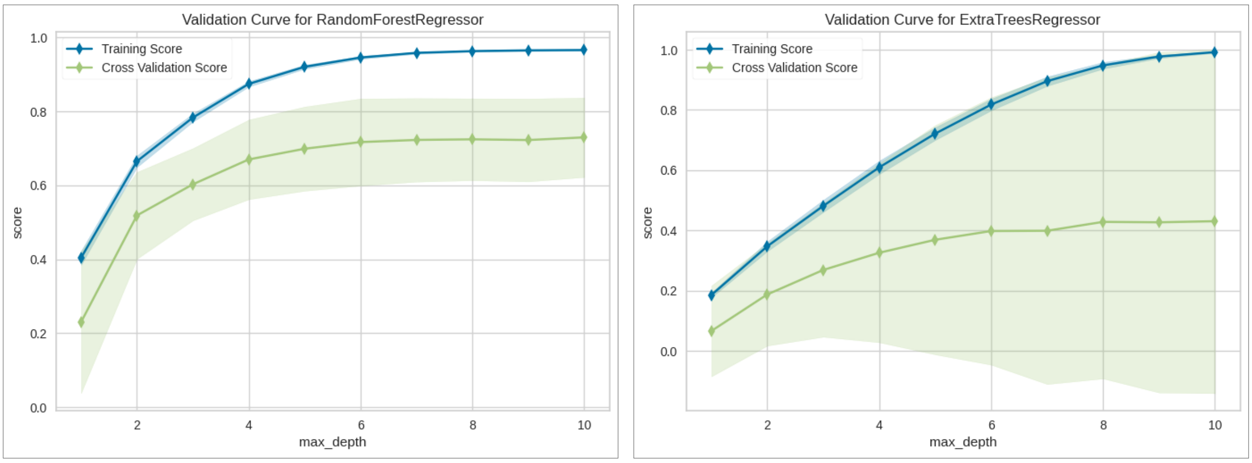

Figure 2. Validation Curves for Random Forest Regressor (2012-2021) and Extra Trees Regressor (2012-2023)

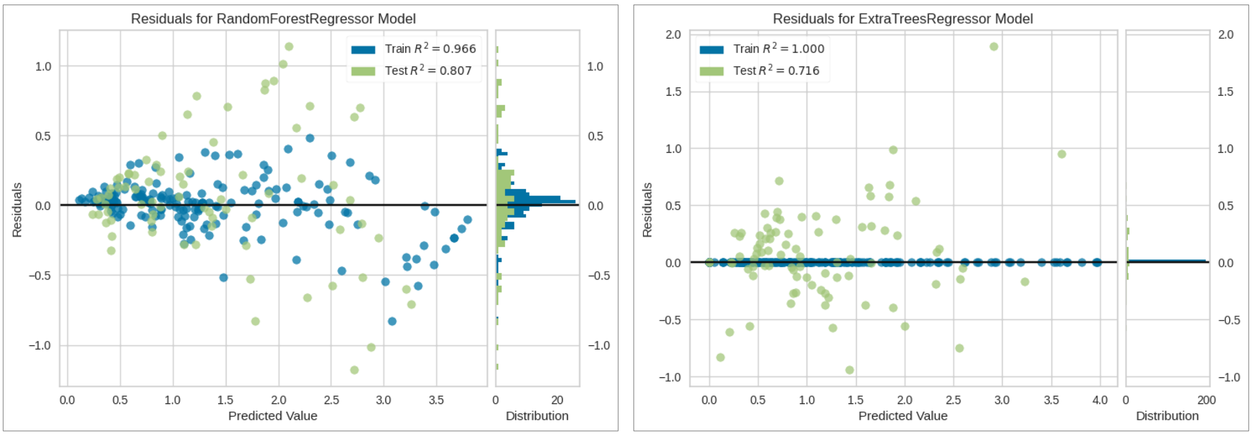

Figure 3. Residuals' graphs for Random Forest Regressor (2012-2021) and Extra Trees Regressor (2012-2023)

These disparities underscore the necessity of cross-validation to mitigate overfitting and balance model complexity with generalizability.

The comparative analysis of pre- and post-2022 periods highlights the methodological necessity of contextualizing model performance within institutional upheavals.

3- Results and Discussion

A previously noted limitation of the model is its interpretational complexity. To contextualize this challenge, the Scikit-Learn library's feature importance methodology can be examined (Figure 4). Feature importance values are computed as the mean and standard deviation of accumulated impurity reduction across all decision trees within the ensemble, reflecting each variable's contribution to predictive accuracy.

Industry affiliation emerged as a substantively weighted factor in modeling financial efficiency, accounting for 15% of explanatory power in the 2012–2023 period and 28% in 2012–2021. Comparative analysis between the extended (2012–2023) and initial (2012–2021) periods reveals shifts in determinant significance: firm size increased from 14% to 21%, EBITDA margin from 6% to 11%, and the individual firm effect (captured by company-specific fixed factors) rose from 4% to 11%. Conversely, CSR metrics exhibited minimal variation, with general CSR expenditures contributing 5%–6% and employee-focused CSR 7.5%–9% across both intervals. Age (5% to 8%) and financial leverage (4% to 8%) also gained marginal relevance.

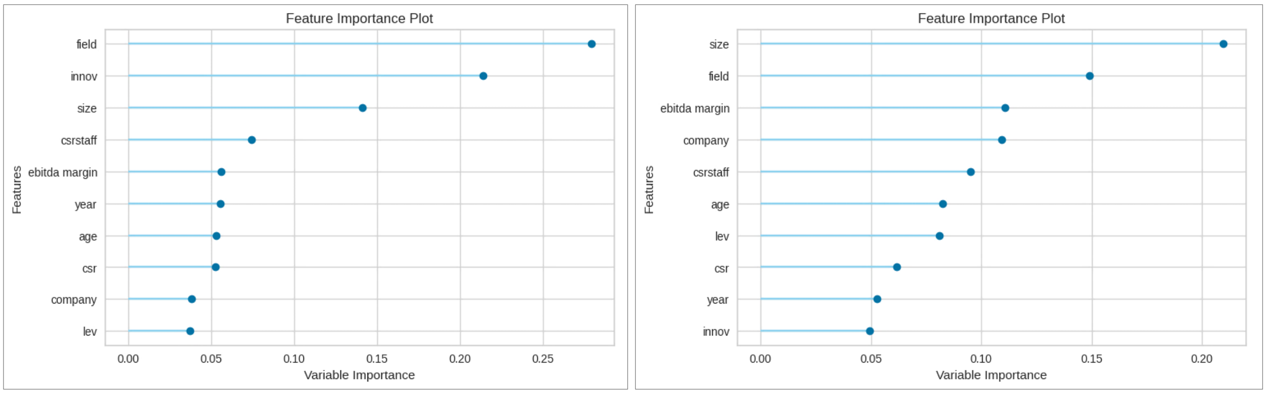

Figure 4. Feature importance plot for the periods of 2012-2021 and 2012-2023

The most pronounced shift occurred in innovation's explanatory role, which declined from 22% (2012–2021) to 5% (2012–2023). This suggests firms under geopolitical strain – particularly post-2022 – may reallocate resources from innovation (a capital-intensive endeavor) toward operational stabilization.

To enhance interpretability, the Shapley Additive Explanations (SHAP) method offers a theoretically grounded alternative. Rooted in cooperative game theory, SHAP quantifies feature contributions by decomposing predictions into Shapley values, which assign marginal impact scores to each variable based on its synergistic role across all possible feature combinations.

The SHAP summary plot (Figure 5) ranks features by their absolute impact on the target variable for both periods, with vertical positioning indicating effect magnitude. Features higher on the y-axis exert greater influence, while horizontal dispersion reflects the directionality (positive/negative) and consistency of their effects across observations.

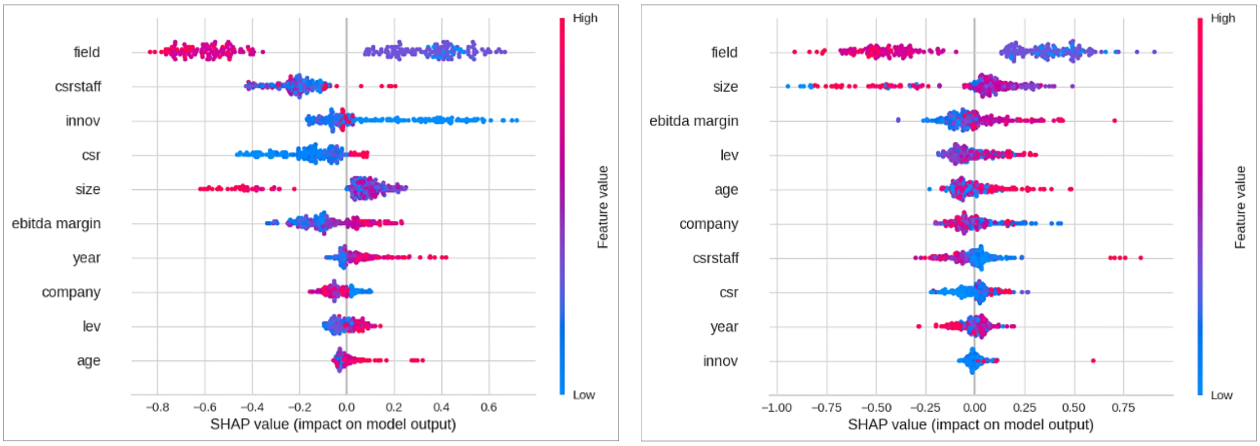

Figure 5. Importance of factors influencing CFO for the periods of 2012-2021 and 2012-2023

The prominence of the extractive and manufacturing sectors in driving financial performance – compared to transport and telecommunications – reflects structural differences in capital intensity, global market integration, and regulatory exposure. Extractive industries, such as oil and mining, often benefit from commodity price cycles and export-driven revenue models, while manufacturing sectors leverage economies of scale and supply chain control, as Chandler (1990) [40] observed in his analysis of industrial evolution. The 28% to 15% decline in sectoral factor importance post-2022 (Figure 3) suggests disruptions tied to geopolitical events, notably sanctions on Russian exports. For instance, manufacturing sectors reliant on imported technologies faced supply chain bottlenecks, while extractive industries contended with redirected trade flows and price volatility. These dynamics align with resource dependence theory, which emphasizes how external shocks disproportionately affect industries with high dependency on global markets or foreign inputs.

The increased significance of organizational size during the 2012–2023 period underscores its nonlinear relationship with financial outcomes, a phenomenon consistent with transaction cost economics, first theorized by Williamson (1981) [41]. Large enterprises – though not the largest – demonstrated stable positive impacts, likely due to economies of scale, financing access, and risk diversification. However, the largest firms exhibited variable effects, potentially due to bureaucratic inertia or overextension in turbulent markets. Sanctions may have amplified this dichotomy: smaller firms within the "large" category adapted nimbly to regulatory changes, while mega-corporations faced operational rigidity or geopolitical targeting, such as asset freezes. This mirrors the threshold effect described by Coase (1937) [42], wherein organizational size optimizes efficiency until coordination costs dominate.

Economic performance, financial leverage, and firm age influenced financial efficiency in ways resembling direct relationships. Economic performance, measured by EBITDA margins, enhanced financial efficiency by freeing capital for reinvestment and debt servicing, a principle foundational to Modigliani & Miller's (1958) [4] propositions on capital structure. Financial leverage exhibited a dual role: moderate debt amplified returns through tax shields and low-cost capital, but excessive leverage increased vulnerability to interest rate hikes or revenue shocks – a trend exacerbated by post-2022 macroeconomic instability, as Baker & Wurgler (2002) [9] theorized. Firm age correlated positively with efficiency, reflecting accumulated expertise and stakeholder trust, a pattern Nelson & Winter (1982) [15] attributed to evolutionary organizational learning. However, older firms risked path dependency, hindering innovation during crises – a tension central to dynamic capability theory, as articulated by Teece et al. (1997) [5].

The reduced importance of CSR and R&D expenditures post-2022 signals a strategic pivot toward survival amid sanctions. Companies deprioritized CSR initiatives, such as employee welfare and environmental programs, to conserve liquidity – a decision aligned with the RBV principles outlined by Barney (1991) [18]. Similarly, R&D's diminished role highlights a shift from long-term innovation to short-term operational stability. Notably, the study's observation that R&D quality – not expenditure – drove pre-2022 success aligns with Cohen & Levinthal's (1990) [43] absorptive capacity theory, which emphasizes the role of prior knowledge in leveraging R&D investments.

Figure 5 reveals that low CSR expenditures correlated with negative returns, while high CSR yielded positive – albeit infrequent – outcomes. This suggests a threshold effect: minimal CSR may harm reputation and employee morale, but beyond a baseline, marginal returns diminish, a phenomenon Barnett & Salomon (2012) [20] documented in their analysis of CSR-performance relationships. Post-2022, the rarity of high CSR investments reflects firms' triage of stakeholder commitments. For example, companies maintained essential employee welfare programs to retain talent but curtailed community initiatives. This selective retention mirrors stakeholder salience theory, wherein firms prioritize stakeholders critical to immediate survival, such as employees and regulators, as Mitchell et al. (1997) [14] proposed.

The post-2022 resurgence of traditional factors (e.g., size, profitability) and decline in strategic investments (e.g., R&D, CSR) underscore the RBV's applicability in emerging markets under stress, a framework Peng (2003) [6] advanced in his work on transitional economies. Sanctions forced firms to rely on tangible resources, such as physical assets and liquidity, rather than intangible capabilities. These findings also resonate with institutional theory, as abrupt regulatory changes disrupted norms, compelling firms to adopt conservative, compliance-driven strategies, a process DiMaggio & Powell (1983) [26] termed "coercive isomorphism."

The methodological rigor of the study is reinforced by its use of SHAP values, a technique used to enhance the interpretability of machine learning models. While SHAP's ability to quantify each factor's marginal contribution strengthens causal inference, its sensitivity to temporal data shifts – such as the 2022 sanctions – necessitates cautious interpretation, as abrupt changes may reflect outlier events rather than systemic trends. Extending the analysis to 2023 captures acute crisis responses but risks overlooking long-term adaptations, a limitation that future studies could address by incorporating longitudinal data.

These findings also highlight critical avenues for further inquiry. First, longitudinal research could assess whether short-term reductions in CSR and R&D undermine organizational resilience in subsequent crises, testing the enduring implications of resource reallocation. Second, cross-country comparisons may reveal whether sanctions uniformly erode strategic investments or if institutional contexts mediate firm responses. Third, sectoral analyses could explore how extractive and manufacturing firms navigated sanctions differently, particularly examining whether vertical integration or domestic supplier networks mitigated risks. Such investigations would deepen understanding of how geopolitical shocks interact with industry-specific dynamics to reshape financial efficiency.

4- Conclusion

This analysis identifies sectoral, organizational, and strategic determinants of corporate financial performance (CFP) across Russian enterprises from 2012 to 2023, contextualized within geopolitical disruptions. Industry affiliation emerged as the most consequential predictor, with extractive and manufacturing sectors demonstrating outsized influence relative to transport and telecommunications due to capital intensity and global market integration. However, the explanatory weight of this factor declined sharply post-2022 (28% to 15%), reflecting sector-specific vulnerabilities to sanctions, including supply chain bottlenecks and commodity price volatility – a pattern aligned with resource dependence theory. Organizational size exhibited a nonlinear relationship with CFP: mid-sized firms capitalized on economies of scale and adaptability, while the largest enterprises grappled with bureaucratic inertia, echoing transaction cost economics' emphasis on coordination thresholds. Traditional drivers, such as economic performance (EBITDA margins) and firm age, retained stable impacts, though excessive financial leverage amplified post-2022 risks. Notably, strategic investments in CSR and R&D – critical for long-term competitiveness – were deprioritized during sanctions as firms reallocated resources toward short-term survival, a strategic shift consistent with the RBV. These results illustrate how geopolitical shocks reconfigure corporate priorities, eroding the value of intangible assets like innovation pipelines while amplifying reliance on tangible resources and operational efficiency.

The findings highlight the RBV's applicability in emerging markets under systemic stress, where institutional turbulence compels firms to prioritize static, defensive strategies over dynamic capabilities. However, the observed retrenchment from innovation and stakeholder engagement raises concerns about long-term resilience, as these investments are pivotal for post-crisis recovery. Policymakers must address this tension by incentivizing sustained R&D and CSR continuity through mechanisms such as tax relief or targeted subsidies. Corporate leaders, conversely, should balance operational agility with strategic foresight, fostering absorptive capacity to mitigate external shocks. Future research should investigate cross-country variations in sanction responses, sector-specific adaptation pathways (e.g., vertical integration in manufacturing), and the longitudinal consequences of CSR/R&D divestment. Ultimately, the analysis reveals the fragility of competitive advantages in volatile markets and underscores the imperative of adaptive resource allocation frameworks to sustain growth amid geopolitical uncertainty. By situating universal determinants like size and profitability within institutional upheavals, this work advances CFP theory while offering pragmatic insights for firms and regulators navigating contested economic landscapes.

5- Declarations

5-1- Author Contributions

Conceptualization, I.B. and A.D.; methodology, I.B.; software, I.B.; validation, I.B. and A.D.; formal analysis, I.B. and A.D.; investigation, I.B. and A.D.; resources, I.B. and A.D.; data curation, I.B. and A.D.; writing—original draft preparation, I.B.; writing—review and editing, A.D.; visualization, I.B. and A.D.; supervision, I.B.; project administration, I.B. and A.D.; funding acquisition, I.B. and A.D. All authors have read and agreed to the published version of the manuscript.

5-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5-4- Institutional Review Board Statement

Not applicable.

5-5- Informed Consent Statement

Not applicable.

5-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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