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Assessing the Investment Attractiveness of Metallurgical Enterprises to Improve the Efficiency of Their Sustainable Investment Activities

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Abstract

The objective of this study is to develop a methodological approach to the integral assessment of the investment attractiveness of metallurgical enterprises to improve the efficiency of investment activities and the implementation of projects and ensure sustainable development. The metallurgy industry faces the challenge of balancing efficiency goals and sustainable objectives (ESG) and risks. Our approach takes into account the relationship between investment potential, realized opportunities, and the level of risk. Based on a systematic analysis of theoretical approaches, an integral investment attractiveness index is proposed that aggregates investment potential (consisting of seven sub-potentials), an assessment of the results of project implementation, and an aggregated risk index. Assessing investment attractiveness is important for ensuring the sustainable implementation of effective projects and determining their priority. A panel dataset was constructed using data from two metallurgy companies. The relationship between investment attractiveness and classical indicators (ROIC, EVA, MVA, Tobin's Q, and P/BV) is examined through panel regression with fixed effects, cross-correlation analysis of the temporal structure of relationships, a CUSUM test for model stability, and decomposition of investment attractiveness changes. Decomposition of investment attractiveness changes makes it possible to quantify the contribution of potential, opportunities, and risk to the dynamics of investment attractiveness across various periods, including crisis and post-crisis ones describing the specifics of the metallurgic industry. The presented methodology is relevant for increasing the efficiency of project implementation within the framework of an integral company policy and contributes to the acceleration of industrial implementation of sustainable projects in the metallurgy sector.



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1. Introduction

In this research, we develop a methodological approach to assessing the investment potential of an enterprise, using the example of two companies in the field of metallurgy. Metallurgy has a significant impact on industry, construction, and the energy complex—which together account for a substantial share of gross domestic product. The metallurgical

sector is primarily represented by vertically integrated, full-cycle companies [1,2]. This structure enables a complete production cycle—from ore extraction to the output of finished metal products—within a single enterprise.

The level of a company's investment attractiveness is closely linked to its sustainable financial performance. Investment attractiveness research is mainly directed at the study of the energy sector [3–6]; our contribution is to study the relationship between investment potential and attractiveness in the metallurgy sector. The relevance of our study is based on the following considerations:

- Metallurgical enterprises face specific challenges: a changing macroenvironment, a reorientation toward new markets, an increasing tax burden, changes in environmental legislation, and the emergence of innovations in metallurgy [7].
- A number of methodologies address investment attractiveness at the enterprise level and at the country level, as well as investment potential and the investment climate [8–10]. However, they exclude the connections between these investment environment parameters.

The transformation of the current operating conditions for metallurgical enterprises under environmental, social, and governance (ESG) principles requires a deeper analysis in assessing investment attractiveness. This can be achieved by integrating the concepts of investment attractiveness and investment potential [11,12]. Research on investment attractiveness and investment potential only covers one side of the relation, highlighting the theoretical differences between them [3,4,7].

The task of constructing an investment attractiveness model, based on the investment attractiveness multipliers, has not previously been addressed in the literature. Decomposition of investment attractiveness into its components (potential, opportunities, and risk) makes it possible to identify model scenario forecasts through targeted variation of manageable factors.

To verify the theoretical propositions and substantiate the applicability of the developed methodological approach, the following hypotheses are put forward for validation within the framework of the study:

- The integral investment attractiveness index (IA) has a positive and statistically significant relationship with classical investment attractiveness indicators—return on invested capital (ROIC), economic value added (EVA), and market value added (MVA)—as well as market multipliers (Tobin's Q and P/BV).
- Changes in the investment attractiveness index act as a leading indicator with respect to the dynamics of ROIC, allowing investment attractiveness to be used for forecasting a company's future efficiency with a lag of 1–2 years.
- The decomposition of the investment attractiveness index into its components—investment potential, realized opportunities (projects), and risk level—makes it possible to quantify its components and forecast variations.

2. Literature Review

2.1. Assessing the Concept of the Investment Attractiveness of an Enterprise

This article establishes a distinction between “investments” and the terms “investment potential” and “investment attractiveness.” Investment potential is defined as the totality of a company's capabilities and resources used to achieve its own business goals and generate an increase in the company's market value and resulting performance indicators through conversion into investment demand.

Investment potential is linked to a specific economic entity. The resources that generate it at the company level are subject to external environmental influences. The category

that takes into account the totality of external environmental factors is the investment climate. We define the investment climate as the totality of various economic, financial, infrastructural, political, environmental, social, organizational, legal, and other conditions that determine the scale of investment in a company's fixed capital [13]. An assessment of the investment environment for companies in the metallurgical industry is carried out at the regional and national levels to take into account the scale of their operations.

Investment attractiveness is the main element of the formation of an investment decision. This is a concept generally explored at a macroeconomic level; however, we concentrate on studies in the literature at the enterprise level. Some authors analyze the concept as derived from the institutional framework, the financial capabilities of the enterprise and risk management of the firm [3,14]. Therefore, decision making analysis tools are often used as methodological instruments to study this component.

Investment potential is inextricably linked to investment attractiveness and has a significant impact on it [15]. While indicators are useful for various assessment purposes, the final value for assessing the feasibility of investing in a particular company from an investor's perspective is investment attractiveness. In addition to the internal aspects of the company's current functioning, it also takes into account its situation at the industry, regional, and national levels [4]. The investment potential at the company level is not identified as a separate category in most studies, and its calculations are performed as a component of investment attractiveness.

The Resource-Based View (RBV) and Sustainable Finance offer contrasting approaches for assessing investment attractiveness. RBV focuses internally, evaluating a firm's constituent resources—such as patents, brand equity, or metallurgy technology—as drivers of sustained competitive advantage and long-term profitability, often overlooking external environmental or social factors [16,17]. In contrast, Sustainable Finance adopts an external-oriented, risk–return framework that integrates environmental, social, and governance (ESG) criteria, considering how regulatory shifts, climate risks, or stakeholder pressures impact financial performance and resilience. Sustainable Finance systematically prices externalities and non-financial factors into valuation, making it more responsive to systemic risks but potentially less focused on a firm's unique strategic assets [18,19]. In our research, we aim to address the sustainability challenge from the RBV perspective. RBV explains why some firms outperform others based on internal strengths, and only after the analysis do we evaluate whether their actions conduce to a sustainable outcome. Sustainable Finance instruments are taken into account to present a risk analysis for the studied companies.

2.2. Investments in the Metallurgy Sector

The specific literature on the financial decisions of the metallurgy sector is limited. Interesting approaches, such as analysis of price determination in commodity markets, study cases of big players (companies in China, India, the USA, Russia and Brazil) and the managerial implications of vertically integrated companies, are present in this literature. The high costs of a project, the dynamics of the commodities market, and high risks in the industry are variables that characterize the metallurgy sector. Studies use the net present value of a project as the dependent variable in regression models to take into account metallurgy variables as a way of evaluating different investment alternatives, as in the case of Brazil [20]. Changing prices of commodities affect the stability of investments in the metallurgy sector. Based on the analysis of substitution elasticity, a more stable price framework for the inputs of this industry may improve energy efficiency in its processes by up to a fifth [21]. Mining projects in Argentina Australia, Canada, and the United States reflect consistent cost overruns due to varying risk metrics and variables being reported to investors [22].

The ferrous metallurgic sector is linked to complementary investments in energy and mining, for example, those in the expansion of iron ore mining and coking coal. Quality in iron extraction is key in metallurgy as long-term industrial exploitation leads to changes in chemical composition and thus quality [23]. Assessment of a company's required return and capitalization, as in the case of the PJSC Magnitogorsk Iron and Steel Works for the acquisition of a coalmine, increased the capitalization as it contributed to the growth of the company [24].

The economic evaluation of land plots determined for extraction, processing, and enrichment of solid minerals should be based on the overall profitability of a company [25]. Investments based on these valuations may also consider complementary measures, such as transport, terrain and climate conditions, to compare them at an economic level between the producing areas [26]. Essential infrastructure is often loosely linked with the mining sites and the transformation factory and services grids; this represents a sustainability cost that also affects the attractiveness of a natural resources company [27].

The managerial organization of the sector is a vertically integrated structure, which determines the type of investments made across the whole company. The recent literature explores the technical aspects of energy-saving technologies across individual processes like coking, sintering, and ironmaking—the very structure of the industry [24,28,29]. By owning and managing upstream suppliers such as iron ore mines and coking coal operations, as well as downstream rolling and finishing mills, a vertically integrated firm can implement system-wide optimizations that are impossible for a single-plant operator. For instance, integrated innovations in continuous casting and rolling processes are a way to reduce energy consumption in intensive reheating steps. Integrated energy-saving technologies demonstrate that efficiencies are achieved not in isolation but through coordinated management across the entire value chain.

The research gap for the investment dimension represents the integration of these approaches according to a specific financial analysis methodology. Investment analysis in the metallurgic sector has addressed the potential of companies from the production and project sides, while we aim to address their financial capabilities.

2.3. The Sustainability of the Economics of Metallurgical Enterprises

There is a limited literature exploring the investment and business activity of the ferrous metallurgy industry. Studying the sector at the company level offers a picture of the investment dynamics of the sector [30].

Investment in the development of a mineral resources industry addresses the natural resources paradox [31]. The owner of the subsoil receives a differential rent and the mining company a ratio of these earnings. But when the economy concentrates its effort to maximize this rent through investments in the mineral sector, it may displace the rate of innovation adoption, ultimately harming the sustainability of the sector itself.

The resources paradox left without balance, combined with the high entry costs of ferrous metallurgy, could generate concentrated markets. This lack of competition may lead to slower innovations in the sector and limited social rents, as in the case of Mexico [32].

The investment trends driven solely by the private sector are changing. A more active role of the state in regulating and driving the allocation of the resource flows in the mineral sector is defining the priorities of investors [33]. Social goals established in the rules of participation in the mineral sector can help spread the effects of this mining rent on resource-rich countries. Increasing the investment attractiveness of one region has a regional effects in the shared market of the industry for the natural resource sector [34].

Environmental, social, and governance (ESG) principles are directing investments in metallurgy industries worldwide. The ferrous metallurgic sector generates around 8%

of global emissions of CO₂ [35]. The steel sector intensively generates CO₂ emissions due to its use of carbon. Global steel demand is increasing and will continue to expand if projections take into account faster equipment turnover and higher electrification [36]. While the directions of industry transformation have been adopted in general there is little consensus on how to implement them in specific companies [37].

Sustainable practices of ferrous metallurgy enterprises can be tracked in the non-financial reports of ferrous metallurgy enterprises. These practices are aimed at attracting financing for adaptation and transformation to cleaner production. Among the instruments of climate finance for ferrous metallurgy, companies report carbon credit trading, green finance and bonds, green tariffs in energy, climate-sensitive pricing, and climate change risk hedging in financial markets [11]. These investment priorities to incorporate social governance are also linked to non-ferrous metallurgy [38], deposits of rare minerals [39], and the oil and gas sector [40,41].

Some studies address investments in metallurgy through the concept of green metallurgy. In the case of China, the demand for metallurgy products will continue to increase, and the industry must introduce investments regarding energy use as a carbon-intensive industry [42]. Resource efficiency in this sector can be assessed through the simulation of life cycles of production systems. This circular economy approach relates the energy output to the carbon footprint of a process [43].

Production-linked incentives are used to stimulate investment in a particular direction; the case of India's incentive for specialty steels illustrates the need for a design to attract investment in a capital-intensive industry. The use of this instrument for triggering a green transformation is constrained by industry dynamics. Investment attractiveness considers long-term and profitability estimations rather than responding to short-term incentives [44,45].

Self-investment in innovation and adaptation is a key indicator for investment attractiveness; the internal rate of return must be considered as an evaluation criterion of self-investment in transformation within the company [1]. Assessing investment potential is important for the implementation of innovative projects and the overall innovation policy of an enterprise.

ESG components can also be included in human capital formation for the ferrous metal sector [46,47]. Along with human capital, investment attractiveness in the minerals and metallurgy sector is related to the betterment of work safety, quality of steel materials and residues practices [48,49], as well as innovations in material manufacturing and sensors for detecting possible deformations in equipment [50,51] and new solutions in the framework of improving the fire resistance of materials in metallurgical enterprises [52].

Another research gap relates to a question that is absent in the literature: Does the pursuit of ESG goals makes a metallurgy company more attractive to investors? Authors have addressed components of this dilemma using specific projects. We also strive to answer this question on an empirical level for the case of two companies. Our contribution represents the construction of a model that links the two sides of this relation within the finances of the enterprise.

3. Materials and Methods

3.1. Integrating Investment Attractiveness Assessment in a Sustainable Investment Policy

A comprehensive assessment of investment attractiveness improves the effectiveness of an enterprise's investment activities and the implementation of sustainable projects. The proposed sequence for developing and selecting projects within the framework of a sustainable investment policy is shown in Figure 1 in the following order:

- Formation of methodological concepts of investment potential.

- Development of an investment policy in the metallurgical sector. Its main goal is to maximize returns while minimizing risks.
- Development of innovation strategies and generalization of practical experience in assessing investment attractiveness.
- Study of external and internal environmental factors.
- Identification and recognition of weak signals.
- Formulation of objectives for investment policies of metallurgical enterprises.
- Definition of problems and goals, project development.
- Formation of problem and project banks.
- Comprehensive assessment of investment attractiveness.
- Selection of innovative projects for implementation.
- Evaluation of results.
- Development of corrective actions.

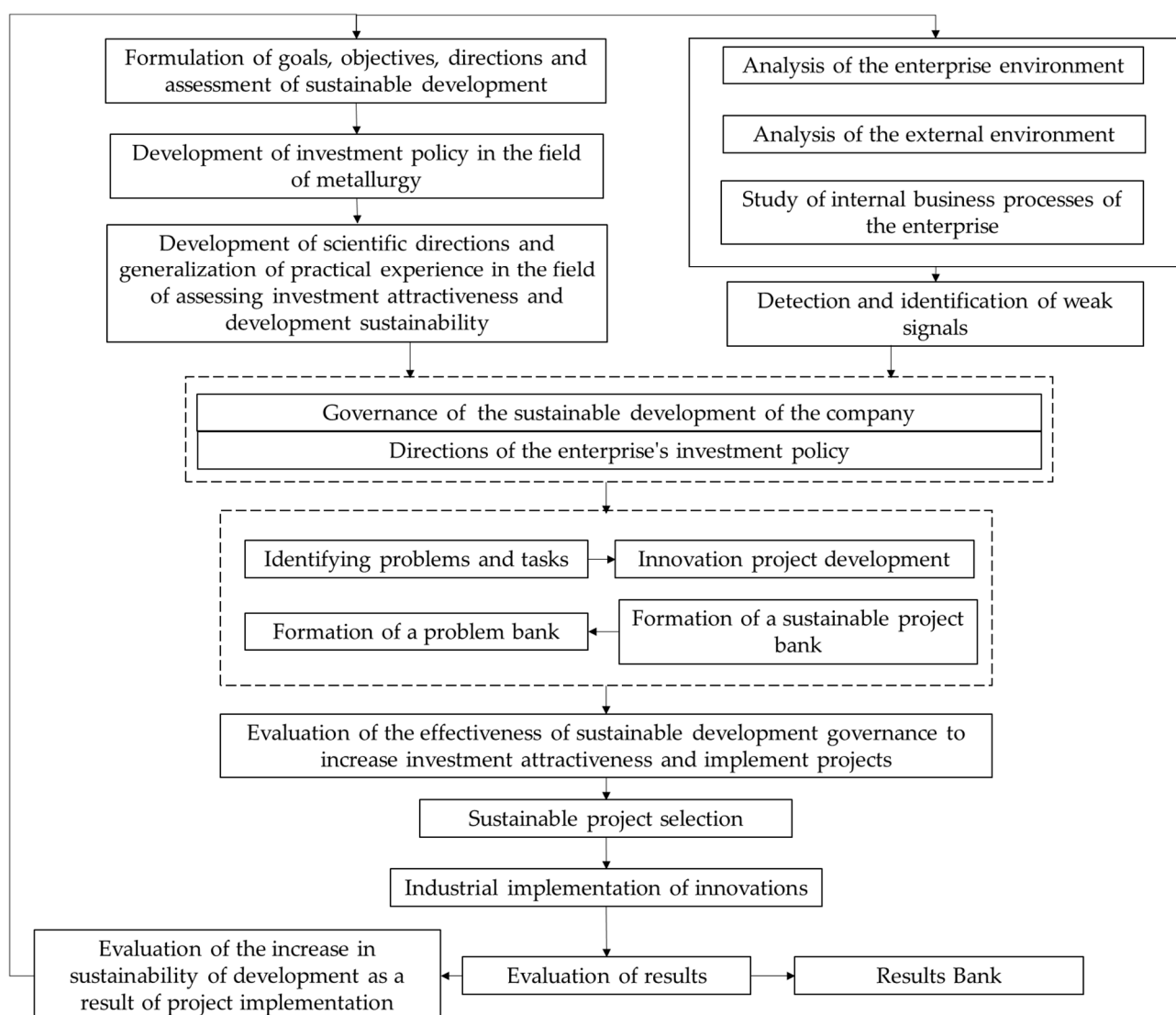


Figure 1. Sustainable development governance based on increasing investment attractiveness. Source: compiled by the authors.

An integrated assessment of investment attractiveness roadmap is presented in Figure 1. The main goal of the investment policy is to maximize returns while minimizing risks. This is achieved by identifying priority projects, assessing opportunities and threats, and

selecting projects based on the investment attractiveness and potential of the enterprise. Following a basic analysis of the enterprise's environment, it is advisable to analyze weak signals that characterize initial developing trends and may develop into threats or missed opportunities. Mandatory steps include creating a problem bank and a sustainable project bank.

Forming a problem bank involves three main stages: identifying a variety of enterprise problems; assessing the fundamental feasibility and feasibility of solving them using a project-based approach; and conducting a comprehensive assessment of the significance of each problem. Following this, a project bank is created. The fundamental difference between a project bank and a set of projects is that projects included in the project bank have a number of additional characteristics that highlight their place, role, and interaction. Project selection is based on an assessment of investment attractiveness and potential. During project implementation, corrective actions are implemented if any deviations from the intended goals occur.

The novelty of our methodological approach is presented as follows:

1. Investment attractiveness factors were systematized by constructing a two-dimension model, including an inner dimension (resources and capabilities).
2. The limitations of existing quantitative, qualitative, and comprehensive methods for assessing investment attractiveness were identified, and a conceptual model for assessing the investment attractiveness of a metallurgical enterprise was developed. This model is based on the synthesis of three measurable components: investment potential, realized capabilities, and an aggregated index of total risk.
3. A methodology for assessing investment potential through weighted aggregation of normalized partial indicators was proposed, allowing for a quantitative measurement of the enterprise's resource base over time.
4. A methodological approach to measuring realized capabilities was developed through the formation of a three-component model combining direct economic, ESG, and technological effects, as well as a method for constructing an aggregated risk index differentiated into external and internal components.

3.2. Methodological Approaches to Assess the Investment Potential of a Company

Assessing investment attractiveness is the subject of numerous studies in the literature. In Table 1, we present a schematization of the range of concepts and methodologies classified according to the categories of analytical tools used.

Cluster analysis for assessing investment attractiveness is a widespread analytical instrument [5,53,54]. The use of this method in the study of a metallurgical enterprise should include additional groups of indicators related to productivity as well environmental, innovative, and social factors.

The multiplicative method has been discussed in various geographies as an investment attractiveness assessment [55–57]. Among the advantages of using multipliers is their versatility, as they are suitable for assessing the economics of enterprises in any industry and have a known acceptable range of values, which in some cases are adjusted depending on the specifics of the industry. The most comprehensive multipliers, for example, EVA/EBITDA and debt/EBITDA values, are used as indicators of the dynamics of the investment attractiveness of enterprises in various industries [58–60].

The next methodology to consider is the dynamic method for assessing the effectiveness of projects as an aspect of influencing investment attractiveness. It is necessary to consider such methods as the assessment of the net present value of the project, taking into account the difference in the value of money over time and the calculation of related indicators—DPP, PI, and IRR [61]. As an alternative, when choosing from several scenarios

for the implementation of projects, methods of expert assessment and multi-criteria analysis are used, among which the following methods are to be highlighted:

- The multi-criteria decision-making method TOPSIS, which involves choosing an alternative that is closest to the ideal solution and the smallest distance from the worst solution, is one of the most widespread methods to assess investments attractiveness, especially in the energy sector [8,9,12,62,63].
- VIKOR, which includes a choice based on a compromise between several different solutions, is considered an alternative to the TOPSIS method [64].
- ELECTRE—a method of elimination based on the dominance of alternatives, which is used for fuzzy and partially fuzzy data [65,66].
- PROMETHEE, which includes a choice based on paired comparisons [67].
- SAW (Simple Additive Weighting)—a method of linear aggregation of weighted normalized values, where the alternative with the highest total score is considered the best, considered when working with fuzzy data [68].
- AHP (Analytic Hierarchy Process), which involves hierarchical decomposition of the problem and expert comparison of pairs of criteria and alternatives [69].
- MAUT and MAVT (Multi-Attribute Utility Theory and Multi-Attribute Value Theory) are approaches to decision-making based on the construction of utility functions and value functions that aggregate several criteria into a single overall assessment [70].
- UTADIS is a multi-criteria classification method based on the construction of additive utility functions for classifying alternatives into certain categories. It combines the ideas of MAUT (utility theory) and discriminant analysis to categorize objects [71].

Table 1. Classification of methods for assessing investment attractiveness.

Types of Assessment Methods	Assessment Methodologies	Characteristics of the Assessment Methodologies (for the Company Level)
Quantitative Groups of Assessment Methods	Cluster Analysis Method	Grouping companies into clusters based on similar financial indicators (profitability, liquidity, and debt burden) for comparative analysis of investment attractiveness
	Multiplicative Method	Valuation based on multiplier values based on key performance indicators, including aggregated ones
	Dynamic Methods for Assessing Project Implementation Effectiveness	Project evaluation based on project implementation performance indicators—NPV, DPP, PI, and IRR
Qualitative	Expert Assessment Method	Assessing the degree of influence of factors on investment decision-making indicators
	Correlation–Regression Analysis Method	Assessing the influence of factors on key company performance indicators
	GRA Analysis	Accounting for environmental uncertainties
Statistical	Fuzzy Set Analysis	Obtaining a comprehensive assessment of a company's investment attractiveness in an environment of uncertainty, transforming qualitative expert assessments into a mathematical model that takes into account both financial indicators and non-financial factors
Mixed	Integrated Indicator Calculation Method	Combining financial and qualitative indicators into a single index of a company's investment attractiveness

Source: compiled by the authors.

Using these methods, the optimal option for an enterprise is selected and the economic impact of implementing the chosen scenario is then calculated by calculating the net present value or using alternative economic assessment methods [72]. Benchmarking of the company's financial activities, such as operating costs, financial and investment trends, and the pace of business development, should be taken into account [7].

Correlation and regression analysis, gray relational analysis (GRA), and the fuzzy time data method are presented as statistical methods for assessing investment attractiveness. Correlation and regression analysis of investment attractiveness [6] is used to present a relation between the capital productivity indicator, which is the ratio of the volume of shipped products in the industry to the volume of investment in fixed capital, and investment attractiveness factors consisting of three groups: resource-production, financial-economic, and social. Environmental institutional framework variables can be added to this analysis [73]. Among the advantages of this type of analysis is the search for statistical interdependencies between value changes over time [74]. However, the time frame of our study is small for such a large number of factors—8 years for 16 factors—which may contribute to a distortion of the results. In order to narrow the object to the enterprise level, it is necessary to rely on the specific indicators of an individual enterprise to select factors that may be more suitable for predicting its investment activity and level of investment attractiveness.

GRA is the subject of a number of studies: it is used to increase market competitiveness by improving production capabilities through grey relational analysis for multiple-criteria decision-making problems [75], for solving optimization problems [76], for determining the weight of criteria when selecting parameters [10,77], and for evaluating underground space [78]. Thus, GRA analysis can be used as a tool for working with data uncertainties, for example, for selecting parameters in order to find options for increasing the investment attractiveness of enterprises and for determining the weights of criteria instead of using expert assessments when forming aggregated indicators of investment attractiveness [79]. It is worth noting the presence of an expert element within the GRA analysis, where the authors used expert weights for fuzzy data parameters. Despite this, GRA is a tool with a wide range of options for solving specific problems in research on determining investment attractiveness.

Fuzzy sets, as used in GRA, are an effective tool for working with data, particularly for calculating data on potential indicators, such as investment potential [80]. The current method can be used to generate an assessment based on a block of indicators with uncertainties and to identify both a qualitative assessment based on membership in a certain subset, the characteristics of which will be specified in advance, and its translation into a numerical value for the purposes of generating an aggregate indicator or solving other problems.

We examine the entropy method for determining weights as an objective criterion-based approach. This method is widely used in multi-criteria decision-making (MCDM) to determine the relative weights of evaluation indicators [81,82]. Also, it is combined with TOPSIS to provide a more objective assessment of preference order [83]. Rooted in information theory, the method quantifies the amount of decisional information emitted from a dataset by measuring the dispersion or contrast intensity among alternatives for each criterion. Entropy quantifies the degree of uncertainty inherent in a system. The determined value is based on the inverse relationship between the amount of information conveyed and the level of uncertainty: a lower informational content corresponds to greater uncertainty, which is subsequently reflected in a lower entropy value [83].

The formation of an integrated indicator is a result of research on assessing investment attractiveness [84]. The advantages of this method include its complexity and flexibility—it

allows for the consideration of multiple parameters or groups of indicators at the discretion of the authors and depending on the specifics of the industry. However, the method requires data standardization to allow for the possibility of their subsequent aggregation, and also, as a rule, includes a section with expert assessment, which is associated with the weights of the parameters, when a particular parameter or group of parameters is prioritized depending on the specifics of the industry. To obtain the most objective assessment result, it is necessary to maximize the number of indicators and the width of the studied range.

The selection of factors for assessing investment attractiveness, for example, may be based on the organization's strategic planning. Considering the company's development prospects, which requires working with a large number of factors, contributes to a higher assessment accuracy; however, it makes the methodology less universal due to its emphasis on the specifics of the enterprise's activities and the external environmental factors affecting it at various levels, including regional and national ones.

3.3. Characteristics of the Relationship Between Investment Environment Indicators

In the context of the current study, investment attractiveness will be understood as the interrelated characteristics of economic potential, the profitability of asset transactions, and the investment risk of an economic entity that has a certain capacity for sustainable development in a competitive environment.

The relationship between the categories of investment potential, investment climate, and investment attractiveness is presented in Figure 2.

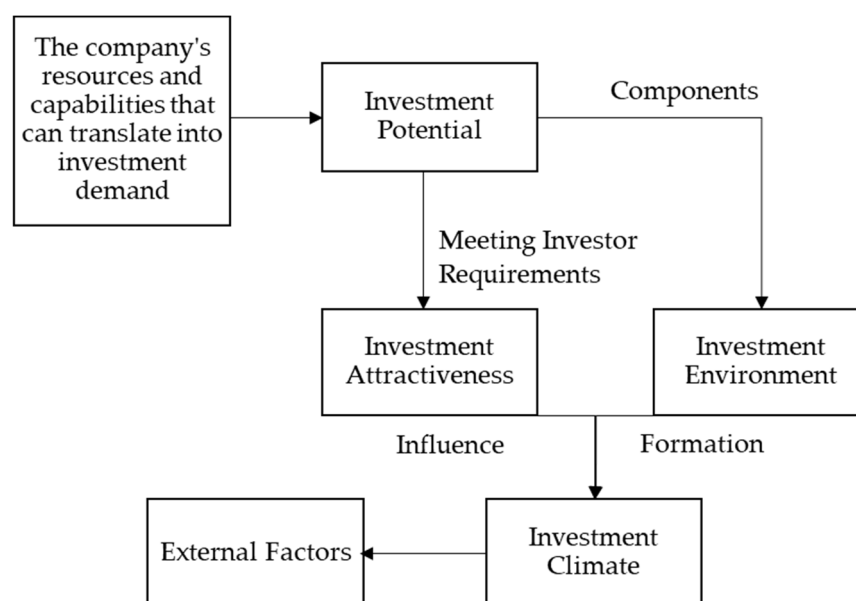


Figure 2. Interrelationship of key concepts of the investment environment from a market participant's perspective. Source: compiled by the authors.

Investment attractiveness is determined by a company's investment potential, which encompasses its core resources and capabilities, and the investment climate, which aggregates external environmental factors representing the totality of exogenous risks from the company's perspective.

Differences in the scale of definitions of investment potential and investment attractiveness are related to the scope of factors aggregated by the indicators. This aspect creates differences between the end users of the indicators, as reflected in Figure 3.

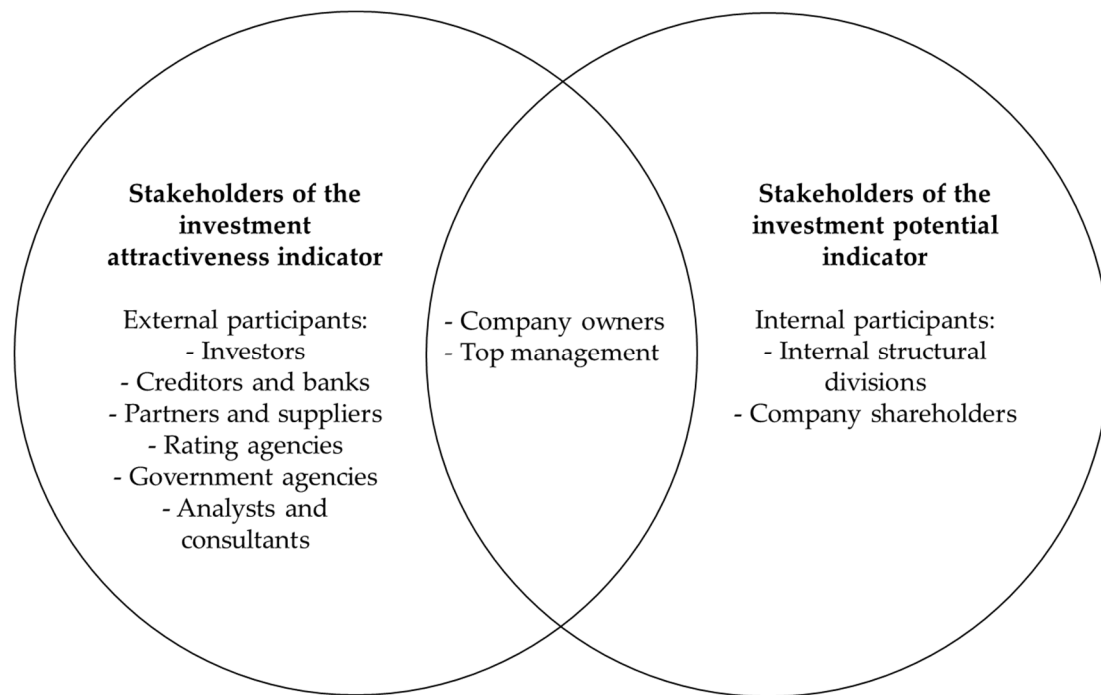


Figure 3. Stakeholders in investment potential and investment attractiveness. Source: compiled by the authors.

Investment potential is assessed internally as an indicator of a company's achievement of investment policy goals. Investment attractiveness is a more informative indicator for exogenous stakeholders, as it takes into account the specifics of the industry, region, and country.

Within the framework of the considered stakeholder classification, the decisive driver for increasing a company's investment potential, contributing to the growth of resources and capabilities through the investment of equity or borrowed funds, is the investor.

3.4. Assessment of Investment Potential

In this study, investment potential is considered as a category that involves assessing the impact of a company's internal resources on generating investment income or other positive effects, depending on individual stakeholder goals. These methods are consistent with the idea of compiling and assessing a company's internal resources.

The investment potential of a metallurgical company will be assessed dynamically over several years. Given the calculation methods in the proposed methodologies, this study will assess investment potential using the following calculation formula, which involves calculating the sum of partial potentials for groups of indicators (1):

$$I_{invp} = v_1 \times I_{pp1} + v_2 \times I_{pp2} + \dots + v_m \times I_{ppm}, \quad (1)$$

where I_{invp} is the investment potential indicator, I_{pp} is the private potential indicator, and v is the weight of private potentials within the investment potential indicator.

To calculate private potential, use the following Formula (2):

$$I_{pp} = w_1 \times a_1 + w_2 \times a_2 + \dots + w_n \times a_n, \quad (2)$$

where a is the normalized assessment of individual potential, w is the weight of the indicator within the group of individual potential indicators, and n is the number of indicators within the individual potential.

To assess investment potential, it is necessary to determine the indicators that will comprise the aggregated investment potential indicator. Taking into account the previously discussed set of internal resources and capabilities of the company that shape the investment potential of enterprises in the metallurgical industry, each group of the company's resources and capabilities should be assessed, focusing on the key groups of performance indicators for these resource and capability groups, as presented in Table 2.

Table 2. Groups of evaluation indicators for the resources and capabilities of a metallurgical company.

Resources and Capabilities Group	Group of Indicators
Material and Technical Resources	Indicators of production potential, indicators of environmental potential
Financial Resources	Indicators of liquidity, financial stability, profitability
Intangible Assets	Indicators of innovation potential
Human Resources	Indicators of social potential
Organizational Resources	Indicators of business activity
Innovative Potential	Indicators of innovation potential

Source: compiled by the authors.

For each of the previously considered groups of resources and capabilities, the indicators most suitable for reflecting aspects of the enterprise's operations were examined, taking into account the industry specifics of metallurgical enterprises. Stricter environmental regulations, growing public attention to environmental issues, and the implementation of sustainable development principles (ESG) have a significant impact on the financial performance, reputation, and growth opportunities of companies. An analysis of the dynamics of environmental indicators in the metallurgical sector is relevant due to the negative impact of their production processes. In evaluating intangible assets, indicators of innovative potential were identified as a group of indicators. The majority of patents and licenses on a company's balance sheet are related to the company's innovative activities, and therefore indicators for innovative intangible assets were calculated and assigned to the appropriate group. Thus, it is possible to assess investment potential by creating an aggregated indicator that takes into account the impact of each group of enterprise resources and capabilities. The weights of the indicators within the limits of the partial potentials will be calculated using the entropy method.

The specifics of calculating the indicators included in the private potentials are reflected in Table 3.

Table 3. Indicators of private investment potential.

Private Potential	Indicator	Code	Optimal Range/Target	Formula
Liquidity	Absolute liquidity ratio	x1	0.2–0.5	(Cash + short-term financial investments)/Current liabilities
	Current ratio	x2	≥ 2	Current assets/Current liabilities
	Quick ratio (intermediate coverage)	x3	≥ 1	(Current assets – Inventories)/Current liabilities

Table 3. Cont.

Private Potential	Indicator	Code	Optimal Range/Target	Formula
Liquidity	Operating solvency	x4	>1	Operating cash flow/Current liabilities
	Working capital liquidity	x5	≥ 1	Current assets/Total liabilities
Financial stability	Equity to working capital ratio	x6	≥ 0.1	(Equity – Non-current assets)/Current assets
	Equity ratio (autonomy)	x7	≥ 0.5	Equity/Total assets
	Long-term sources structure ratio	x8	≥ 0.6	(Equity + Long-term liabilities)/Non-current assets
	Interest coverage ratio	x9	≥ 1	EBITDA/Interest payable
Profitability	Return on operating expenses	x10	Increase	Sales profit/Operating expenses
	Return on equity (ROE), net	x11	$\geq 15\%$	Net profit/Equity
	Return on assets (ROA)	x12	$\geq 5\%$	Net profit/Assets
	Net profit margin	x13	$\geq 10\%$	Net profit/Revenue
	Economic profitability (ROA, EBIT)	x14	$\geq 10\%$	EBIT/Assets
Innovation potential	R&D expenses as % of revenue	x15	$\geq 1\%$	R&D expenses/Revenue
	Share of patents and licenses in revenue	x16	Increase	Change in intangible assets/Revenue
	Share of premium products	x17	Increase	Premium product revenue/Total revenue
Production potential	Capacity utilization	x18	$\geq 80\%$	Actual output/Potential output
	Labor productivity (conventional t/person/year)	x19	Increase	Output/Average headcount
	Energy intensity of production (GJ/t steel)	x20	Decrease	Energy consumption/Production volume
	Cost of fixed assets (thousand of millions of rub.)	x21	–	Book value of fixed assets
Environmental potential	Specific CO ₂ emissions (t)	x22	Decrease	Tons CO ₂ /ton of product
	Share of recycled materials	x23	Increase	Recycled material volume/Raw material volume
	Environmental program costs	x24	$\geq 0.5\%$	Environmental costs/Revenue
Social potential	Wage to subsistence minimum ratio	x25	≥ 2	Average salary/Subsistence minimum
	Staff training costs (millions rub.)	x26	Increase	Training expenses

Table 3. Cont.

Private Potential	Indicator	Code	Optimal Range/Target	Formula
Social potential	Lost Time Injury Frequency Rate	x27	Decrease	Number of incidents $\times$ 1,000,000/Hours worked
	Inventory turnover	x28	Increase	Revenue/Average inventory
Business activity	Receivables turnover	x29	Increase	Revenue/Average accounts receivable
	Cash conversion cycle (days)	x30	Decrease	Inventory turnover period + Receivables turnover period–Payables turnover period

Source: compiled by the authors.

3.5. Assessment of Company's Opportunities

The proposed approach to assessing the economic results of implementing corporate projects and initiatives—the variable opportunities in Formula (3)—is based on a three-component analysis that aggregates heterogeneous effects into a single measurable indicator. The key principle of this methodology is a strict distinction between the concepts of “costs” and “benefits”: only actual economic gains obtained by the company during the reporting period are taken into account, not the volume of invested funds. This avoids a common methodological error whereby capital expenditures are mistakenly treated as value created.

The first component of the model covers the direct economic effect, which stems from internal operational efficiency improvement programs. It includes the results of implemented organizational and technical measures aimed at reducing production costs by optimizing the consumption of raw materials, supplies, and energy resources. This also includes the economic effect of implementing low-budget, high-efficiency investment projects, as well as rationalization and inventive activities, provided that the latter are not double-counted under other savings items. This component is typically reflected directly in company reports as declared cost savings.

The second, more complex component—the ESG effect—represents the results of the company's activities in the environmental, social, and governance spheres, converted into monetary equivalent. The environmental dimension is calculated through avoided payments for negative environmental impact: savings arise when the volume of pollutant emissions into the air, discharges into water bodies, and waste disposal is reduced, leading to lower corresponding payments. The social effect is assessed through savings on personnel-related costs. For example, reducing occupational injuries lowers direct payments for sick leave and compensation, as well as indirect losses from downtime. Lower staff turnover, in turn, saves on hiring and training new employees. The governance dimension primarily manifests itself in an improvement in the company's credit ratings. A rating upgrade leads to lower interest rates on borrowed capital, and the resulting savings on interest payments can be quantified.

The third component—the innovation effect—is intended to reflect the results of research and development work as well as the implementation of new technologies. It includes the actual economic effect of completed R&D, confirmed by the company's reporting, and the additional profit from the sale of new types of products introduced during the reporting period. When calculating this component, special attention is paid to avoiding double counting: the effect of rationalization proposals, if already included in the direct effect of cost reduction, must not be included again.

Thus, the assessment of a metallurgical enterprise's opportunities (capabilities) is carried out using the following formula:

$$\text{Opportunities} = \frac{\text{Direct economic effect} + \text{ESG effect} + \text{Innovation effect}}{\text{Revenue}}, \quad (3)$$

The final step of the methodology is the normalization of the aggregated indicator. The total effect of all three components is compared to the company's consolidated revenue for the same reporting period. The resulting percentage value allows for an objective assessment of the scale of additional value created during the year relative to the overall size of the business, as well as a comparative analysis of project implementation efficiency over several years. This approach ensures the comprehensiveness of the assessment and makes it possible to identify structural shifts in the sources of the company's value creation.

3.6. Assessment of the Company's Risk Level

To quantitatively assess the risk level associated with the operation of a metallurgical enterprise in an investment environment, an aggregated risk index is proposed. The need to develop this index is driven by the requirement for a single adjustment coefficient that can be integrated into the investment attractiveness model. The structure of the aggregated risk index will include external risks—macroeconomic, country, and regulatory conditions—which are uniform for all industry players in a given period, arising from its production structure, resource availability, condition of fixed assets, and human resources potential.

The final risk index is a weighted average:

$$R_{\text{total}} = w_{\text{ext}} \cdot R_{\text{ext}} + w_{\text{int}} \cdot R_{\text{int}}, \quad (4)$$

where w_{ext} and w_{int} are the weights of the components, satisfying $w_{\text{ext}} + w_{\text{int}} = 1$.

In this study, weights based on the entropy method are determined based on the information embedded in the indicators.

The external risk index is constructed based on open statistical data. For each year t in the period under review, a set of scores for seven factors is formed. Each factor is rated on a scale from 0 to 1, where 0 represents the minimum risk value and 1 the maximum. The final index value for year t is calculated as the arithmetic mean of the scores across all factors:

$$R_{\text{ext}}^{(t)} = \frac{1}{n} \sum_{i=1}^n S_i^{(t)}, \quad (5)$$

where $S_i^{(t)}$ is the score of the i -th risk factor in year t and n is the number of factors.

The external risk factors in the current model are: price volatility, currency risk, interest rate risk, demand decline risk, tax risk, tariff risk, and the risk of sanctions restrictions.

Risk of steel price decline is driven by the cyclical nature of commodity markets. The indicator used is the average annual price of hot-rolled coil (P_t), expressed in thousand RUB per tonne. The risk value is calculated as the deviation of the current price from the long-term average price ($\bar{P}$), normalized to unity. If the price is above the average, the risk is taken as zero.

$$S_1 = \max\left(0, \frac{\bar{P} - P_t}{\bar{P}}\right), \quad (6)$$

Currency risk in the current model is one of the key risks for exporting enterprises and is associated with a depreciation of the rouble. In 2025, Russian enterprises exported 12.1 million tonnes of steel, ranking sixth among global leaders in steel exports, confirming

the necessity of accounting for this risk. The assessment is as follows: the lower the exchange rate and the stronger the rouble, the higher the risk.

$$S_2 = 1 - \frac{K_t}{K_{\max}}, \quad (7)$$

where K_t is the average annual nominal USD/RUB exchange rate and $K_{\max}$ is the maximum exchange rate over the entire study period 2010–2025.

Interest rate risk in the current model is related to the possibility of more expensive debt financing. The benchmark is the average annual key rate of the Central Bank of the Russian Federation, and the calculation is performed by estimating the ratio of the average annual key rate to the average annual key rate over the analyzed period.

$$S_3 = \frac{r_t}{r_{\max}}, \quad (8)$$

where r_t is the average annual key rate of the CBRF in year t and $r_{\max}$ is the maximum key rate over the period.

Demand decline risk in this methodology is calculated through the dynamics of apparent steel consumption indices over the analyzed period. Apparent steel consumption is an economic indicator reflecting the total volume of steel used domestically, calculated as domestic production plus imports minus exports. This indicator reflects the demand of key domestic consuming industries—construction, automotive, and fuel and energy. It allows tracking of the current situation of major steel consumers. The formula for calculating demand decline risk is as follows:

$$S_4 = \max\left(0, 1 - \frac{I_t}{100}\right), \quad (9)$$

where I_t is the apparent steel consumption index for year t , representing the ratio of apparent steel consumption in year t to that in year $t - 1$. If the production index exceeds 1, implying positive dynamics, the risk is taken as zero.

Tax risk in the current model is associated with changes in the taxation system of the mining and metallurgical complex. The 2010 MET (Mineral Extraction Tax) rate is taken as the reference point. The coefficient will change in the event of tax policy tightening or easing based on an expert assessment of the scale of changes. The risk will increase by a factor of 0.25 if potential tax payments change by less than a factor of two after adjustments and by a factor of 0.5 if tax adjustments imply an increase in tax payments by more than a factor of two. The effect of adjustments will be cumulative—an increase in risk in year t with no adjustments in year $t + 1$ will maintain the risk coefficient value in year t as a result of adjustments. The formula for calculating tax risk is

$$S_5 = \frac{r_t}{r_{\max}}, \quad (10)$$

where r_t is the tax risk coefficient value in year t and $r_{\max}$ is the maximum tax risk coefficient over the analyzed period.

Tariff risk represents the risk of faster growth in prices for natural monopoly products—electricity, natural gas, and railway transportation. It is calculated as the sum of excesses of the tariff growth index over the inflation index for each of the presented cost items relative to the sum of tariff price changes in the current year. Tariff indices and prices are adjusted by weights depending on the share of these cost types for metallurgical enterprises in total costs. For electricity costs, a value of 4% of total costs of a metallurgical enterprise was

determined; for natural gas costs, -3% ; for railway transportation costs, -7% . The formula for calculating tariff risk is as follows:

$$S_6 = \frac{(Tel_t - Inf_t) \times w_{Tel} + (Tg_t - Inf_t) \times w_{Tg} + (Tr_t - Inf_t) \times w_{Tr}}{(Tel_t - Tel_{t-1}) \times w_{Tel} + (Tg_t - Tg_{t-1}) \times w_{Tg} + (Tr_t - Tr_{t-1}) \times w_{Tr}}, \quad (11)$$

where:

Tel_t —electricity price index in year t ;

w_{Tel} —weight of electricity costs in the total of electricity, railway, and gas costs based on their share in total metallurgical enterprise costs;

Tg_t —gas price index in year t ;

w_{Tg} —weight of natural gas costs in the same total;

w_{Tr} —weight of railway transportation costs in the same total;

Tr_t —railway tariff index in year t ;

Inf_t —inflation index in year t .

Sanctions risk in the current model accounts for geopolitical tensions and the imposition of restrictive measures against the Russian economy. A ternary scale is introduced: 0—no sanctions; 0.5—sectoral sanctions; 1—large-scale blocking sanctions.

The internal risk index is calculated individually for each enterprise based on its financial and non-financial reporting according to the following formula:

$$R_{int}^{(t)} = \frac{1}{m} \sum_{j=1}^m U_j^{(t)}, \quad (12)$$

where $U_j^{(t)}$ is the score of the j -th internal risk factor in year t and m is the number of factors.

The internal risk factors are: raw material security, environmental risk, human resources risk, equipment wear risk, and debt burden risk.

Raw material security risk is related to an enterprise's ability to self-supply with resources necessary for production. It is assessed through the share of own raw materials—iron ore and scrap—in production cost ($Share_{own}$). The higher the dependence on external suppliers, the higher the risk.

$$U_1 = \begin{cases} 0, & Share_{own} \geq 0.7 \\ 1, & Share_{own} \leq 0.3 \\ \frac{0.7 - Share_{own}}{0.4}, & 0.3 < Share_{own} < 0.7 \end{cases}, \quad (13)$$

where $Share_{own}$ is the share of own raw materials in production cost.

The environmental risk of a metallurgical enterprise is associated with generating a high carbon footprint and resulting financial obligations in the form of fines and reputational risks when producing products that do not meet global environmental standards. The key indicator in the assessment is the production technology type. Enterprises with a full metallurgical cycle have a higher carbon footprint and, consequently, a higher risk of future fines and carbon regulation. To differentiate in this methodology, CO₂ emission intensity per tonne of steel is used. The calculation is performed using the following formula, oriented toward reducing the carbon footprint:

$$U_2 = \max\left(0, \frac{E_t}{E_{t-1}} - 1\right), \quad (14)$$

where E_t (t CO₂/t) is the CO₂ emission intensity per tons of steel in year t .

Human resources risk is an integral indicator that considers the age structure, revealing potential problems of workforce aging, and the social burden of the enterprise. The social burden of the enterprise is the risk of being a city-forming enterprise, which represents a dependence on social and administrative pressure if the enterprise accounts for more

than 25% of the city's working-age population. Human resources risk in this methodology is calculated as the average of two sub-indices—the personnel age sub-index and the city-forming sub-index.

The personnel age sub-index is calculated as

$$\text{AgeIndex} = \frac{\text{Age}_{\text{avg}} - 35}{50 - 35}, \quad (15)$$

where Age_{avg} is the average age of employees.

The city-forming sub-index is determined as

$$\text{CityIndex} = \frac{N_{\text{empl}}}{N_{\text{city}}}, \quad (16)$$

where N_{empl} is the number of employees of the enterprise and N_{city} is the population of the city of location.

The final value of human resources risk is determined considering the values of the presented indicators:

$$U_3 = 0.5 \cdot \text{AgeIndex} + 0.5 \cdot \text{CityIndex}, \quad (17)$$

Equipment wear risk represents the potential danger of fixed assets obsolescence. This risk characterizes technological hazards and the need for capital expenditure. The fixed assets wear ratio (Wear_t , %) from the accounting statements is used for calculation.

$$U_4 = \frac{\text{Wear}_t}{100}, \quad (18)$$

where Wear_t , %, is the fixed assets wear ratio of the enterprise.

Debt burden risk reflects an enterprise's sensitivity to rising interest rates and falling income. Within this methodology, the debt-to-EBITDA ratio is used. The risk value is determined based on the following ranges:

$$U_5 = \begin{cases} 0, & L_t \leq 1 \\ 1, & L_t \geq 5 \\ \frac{L_t - 1}{4}, & 1 < L_t < 5 \end{cases}, \quad (19)$$

where L_t is the debt/EBITDA ratio value for year t .

The resulting final index R is a number in the interval $[0, 1]$ and is used in the investment attractiveness formula as an adjustment coefficient that reduces the potential effect of using the enterprise's resources and realizing opportunities in the form of projects. The closer the index value is to 1, the higher the overall risk level of the investment environment for the given enterprise in a given year.

Given the selection of maximum values for a number of indicators over a limited time range, comparisons of the risk indicator values for a single enterprise are possible only if the year for which the assessment is required is included in the assessed time range.

3.7. Aggregate Indicator of Investment Attractiveness

The proposed methodology is grounded in a multiplicative model that integrates resource, performance, and risk components. The resulting integral indicator of a company's investment attractiveness (IA) is computed using the following formula:

$$\text{IA} = (\text{IP} + \text{Opportunities}) \times (1 - R_{\text{total}}) \quad (20)$$

where:

IA—the integral indicator of investment attractiveness for the reporting year;

IP—investment potential, reflecting the aggregate of internal corporate resources assessed via a specialized system of indicators;

Opportunities—realized opportunities, i.e., the aggregated economic effect of corporate projects, normalized by the company's revenue;

R_{total} —the aggregated risk index, ranging from 0 (no risk) to 1 (maximum risk).

A detailed examination of each component is provided below.

Investment Potential (IP). For a metallurgical enterprise, investment potential is conceptualized as a multidimensional characteristic of its resource base, encompassing six functional groups: tangible fixed assets, financial resources, intangible assets, human capital, organizational resources, and innovative capacity. In contrast to conventional accounting-based models that primarily assess financial stability, the authors' approach involves calculating partial potentials for each group, followed by weighted aggregation into a single integral IP indicator.

Realized Opportunities (RO). The inclusion of the opportunities component is justified by the premise that the mere availability of resources (potential) does not guarantee value creation for investors. An increase in investment attractiveness is achieved only when resources are effectively deployed in specific projects and yield measurable economic benefits. Within this framework, opportunities are assessed through three types of effects:

Direct economic effect—cost savings from operational efficiency improvement programs, the implementation of low-budget investment projects (Baby Capex), and rationalization initiatives.

ESG effect—savings on environmental payments due to reduced emissions and discharges, decreased costs associated with occupational injuries and staff turnover, and lower interest expenses resulting from improved credit ratings.

Technological effect—additional profits from the commercialization of new products and completed research and development (R&D) activities.

All components are expressed in monetary terms, enabling their summation and subsequent normalization by consolidated annual revenue. Thus, the realized opportunities indicator reflects not merely stated intentions but actually created added value, thereby imparting a dynamic character to the assessment.

Aggregated Risk Index. The risk component is introduced not additively but multiplicatively through a discounting coefficient ($1 - R_{total}$). This approach is consistent with contemporary theoretical views, whereby risk does not simply “reduce” potential but rather discounts (devalues) the future benefits derived from its utilization. The index is constructed as a weighted average of external and internal risks:

$$R_{total} = w_{ext} \times R_{ext} + w_{int} \times R_{int} \quad (21)$$

where R_{ext} aggregates systematic (macroeconomic and sectoral) factors common to all industry players and R_{int} captures company-specific risks. The composition of external risk factors (price volatility, currency and interest rate risks, demand contraction risk, tax, tariff, and sanctions risks) is determined on the basis of critical factors derived from the industry-specific context of the object under analysis (i.e., the metallurgical enterprise). Internal risks encompass raw material security, environmental risk, human capital risk, equipment depreciation, and debt burden.

Formula (21) is structured such that even substantial potential and high realized opportunities can be significantly eroded under elevated aggregate risk. This premise is fully aligned with the industry specifics of metallurgy: in the face of sanctions shocks, commodity price volatility, or the threat of the Cross-Border Carbon Adjustment Mechanism (CBAM), even a financially stable and technologically advanced enterprise may lose its

appeal to investors. Conversely, a low-risk environment enables the full manifestation of existing potential.

Unlike ratio-based analysis, the proposed model evaluates not only the current state but also the realized effects of projects. In contrast to Discounted Cash Flow (DCF) and economic value added (EVA) methodologies, it does not rely on subjective long-term cash flow projections or discount rate assumptions. It further distinguishes itself from expert-rating systems through a formalized mechanism for translating qualitative parameters (ESG factors, sanctions exposure, and raw material independence) into quantitative scores and subsequent aggregation.

3.8. Assessment of Investment Attractiveness Multipliers

In order to compare the results of assessing the dynamics of investment attractiveness according to the proposed methodological approach with existing approaches for assessing investment attractiveness, for the purpose of comparing trends and determining correlation between indicators, investment attractiveness multipliers will be calculated.

Within the multiplicative methodology, the following indicators adopted in global business practice for comparing the financial position of companies in the same industry are used as investment attractiveness indicators: EVA, ROIC, MVA, P/BV, EVA/EBITDA, Debt/EBITDA, and Tobin's Q [85].

In this study, EVA was calculated using a combined methodology that accounts for regional and industry specifics. Determining EVA reveals three main elements of input data required for its calculation: the return on capital earned on investments; the cost of capital raised for those investments; and the capital invested in those investments. The usefulness of the EVA concept as a tool is determined by the extent to which, in management's view, it helps better align corporate strategy and investments with shareholder value.

To calculate EVA, it is necessary to determine the NOPAT value. NOPAT is an indicator of a company's operating efficiency that reflects profit from core operations after taxes but without considering financing costs (interest on debt) and non-operating income/expenses. For the data used in this work, it was calculated as profit before tax plus interest payable, tax rate—corporate profit tax rate, which is 20% within the studied time range.

Invested capital was calculated using an asset-based approach. To calculate WACC as the most comprehensive component, we use the following formula:

$$WACC = \frac{E}{D + E} \times \text{Cost of Equity} + \frac{D}{D + E} \times \text{Cost of Debt} \times (1 - \text{tax rate}), \quad (22)$$

where:

Equity (E)—shareholders' equity (RUB);

Debt (D)—interest-bearing debt (RUB);

Cost of Equity—cost of equity (%);

Cost of Debt—cost of debt (%);

tax rate—tax rate.

The company's cost of equity was calculated according to the CAPM methodology as the sum of the product of the country equity risk premium and levered β plus the risk-free rate for Russian securities:

$$\text{Cost of Equity} = \text{ERP} \times \beta + R_f, \quad (23)$$

where:

ERP—equity risk premium relative to risk-free assets;

β —measure of the asset's market risk relative to the market;

R_f —risk-free rate for companies operating in the Russian market.

The ERP indicator represents the risk premium for investing in equity instruments compared to risk-free assets, i.e., the additional return that investors require for investing in the stock market. To determine the equity risk premium for Russia, statistical materials from Aswath Damodaran were used [86].

The R_f indicator is the risk-free rate for companies operating in the Russian market, calculated as the average yield of Russian government bonds. The 10-year federal loan bonds—the RUGBITR10Y government bond index (5–10 years)—were used as the indicator.

The company's cost of debt was calculated using the following formula:

$$\text{Cost of Debt} = \text{Country risk premium} + R_f + \text{Spread}, \quad (24)$$

where:

Country risk premium—country-specific risk premium;

R_f —risk-free rate for companies operating in the Russian market;

Spread—metric reflecting the default risk premium of a specific company over the risk-free rate.

The country risk premium indicator is an additional risk premium that investors demand for investing in assets of a specific country compared to risk-free instruments, taken as US government bonds, according to Damodaran's methodology, and reflects the following key aspects: country credit risk; political instability; macroeconomic volatility; legal risks. To calculate WACC, the value of this indicator was taken from Damodaran's annual statistical reports.

The spread indicator is a metric reflecting the default risk premium of a specific company over the risk-free rate. The spread value was calculated using the tools proposed by Damodaran. According to Damodaran's methodology, the spread is determined by generating a default risk premium depending on the company's credit rating based on mapping ratings (Moody's/S&P) and spreads. The type of credit rating is determined by the interest coverage ratio.

We use the classical formulas for calculating the following indicators. The current approach to assessing the investment attractiveness of industrial enterprises based on EVA takes into account the regional specifics of different economic systems and industry structures—i.e., the assessment depends on the country of study, the industry of the object, the market value of the company's debt and equity, and the specifics of the state's fiscal policy—which allows for more accurate assessment and development of specific measures when implementing investment policy.

EVA is a numerical indicator that allows investors to understand the persistence of the gap between profit and expenses, as a positive value implies a firm's ability to create value. EVA provides a more realistic view of a company's costs by including both operating and capital expenditures.

The MVA multiplier, being one of the investment attractiveness multipliers, is a financial indicator that demonstrates how successfully a company has increased the wealth of its investors since its founding, assessing whether the company has created or destroyed value for shareholders and creditors. Positive MVA means that management has not only preserved but also increased invested capital. Negative MVA indicates that the company's market value turned out to be lower than the funds invested.

While EVA shows the effectiveness of management in a given year, MVA reflects the result of the company's entire activities, taking into account long-term investor expectations. High MVA makes a company attractive to investors, as it indicates its ability to generate wealth. MVA is highly dependent on stock market fluctuations and is not suitable for assessing effectiveness at lower management levels or for motivating personnel, as the market price of shares is influenced by many external factors.

The P/BV (Price-to-Book Value) multiplier is a financial ratio that shows the relationship between a company's market valuation and its book value of equity, allowing investors to assess whether the market overvalues or undervalues the company's assets relative to their accounting value. A value above 1 indicates that investors are willing to pay more for net assets in expectation of future growth, the presence of intangible assets, or a sustainable reputation; a value below 1 may indicate undervaluation or financial difficulties.

The EVA/EBITDA indicator is derived from economic value added and allows assessment of the share of operating profit (before interest, taxes, and amortization) the company is able to convert into net value that exceeds the required return of investors. A positive value indicates that management not only generates operating profit but also creates value above the cost of capital; a negative value signals value destruction even if EBITDA remains high.

The Debt/EBITDA multiplier is a key indicator of debt burden showing how many years it would take a company to repay its accumulated debt using the current level of operating profit before interest, taxes, and amortization. A value below 3–4 is generally considered comfortable for most industries and indicates high financial stability; an increase above 5 indicates elevated debt service risks and possible constraints on obtaining new financing.

Tobin's Q is an investment attractiveness indicator that compares the market value of a company's assets with their replacement cost, allowing inferences about investment incentives in the industry [87]. A Q value greater than 1 indicates that the market values the company above the replacement cost of its assets, creating an incentive for new investment; a value less than 1 may indicate undervaluation or that it is cheaper to acquire existing assets than to create new ones. Unlike most multipliers, Tobin's Q takes into account both equity and debt, reflecting long-term market expectations regarding the efficiency of using all assets.

4. Results

4.1. Assessment of the Investment Attractiveness of the MMK Enterprise

The selection of indicator value ranges is tied to the parameters adopted in practice for metallurgical enterprises [30]. The evaluation of our methodology will be carried out using the example of the PJSC Magnitogorsk Iron and Steel Works (MMK) and PJSC Severstal. Appendix A presents the dynamics of these indicators for MMK from 2010 to 2023. The data sources for the calculations are the company's annual reports [88,89].

For further calculations, it is necessary to create an aggregated indicator, presented in the previously discussed Formulas (1) and (2).

To create an aggregated indicator, normalization is necessary, which requires taking into account various indicator polarity parameters depending on the direction of their optimal value: striving for the maximum (stimulator) and the minimum (disstimulator).

In this study, the minimax normalization method will be used. This method allows for data to be normalized to a single range for different types of indicators, regardless of their initial scale, from 0 to 1. Given the solution to the problem of determining the degree of influence of individual investment potentials within a given range, minimum and maximum values will be assigned to indicators within a given time series.

The final element in calculating individual potential indicators is the weight of the indicators within the individual potential aggregate and the individual potentials themselves within the investment potential indicator. The weights are calculated using the entropy method.

The entropy method offers a clearer interpretation over subjective weighting techniques for assessing investment attractiveness, primarily due to its capacity to eliminate

external bias and capture the intrinsic information structure of the financial data. Investment attractiveness is inherently a multi-dimensional construct, requiring the synthesis of diverse quantitative indicators, including profitability ratios, liquidity metrics, and market volatility. The entropy method leverages the principle that the relative importance of a criterion should be a function of the contrast intensity among the alternatives being evaluated [82,83]. A financial indicator that shows high variance across a set of potential investments provides greater discriminatory power and, therefore, carries more decisional information. This data-driven objectivity ensures that the resulting composite attractiveness score is a direct reflection of empirical market dispersion rather than the preconceived notions of the analyst, making it a more robust and replicable tool for portfolio selection and comparative financial analysis.

The entropy weight assignment method possesses several theoretical advantages that justify its use in multi-criteria assessment tasks related to the following features:

- **Objectivity**—Unlike expert methods, the entropy approach relies solely on the initial data and does not require subjective judgments. Weights are determined based on the information embedded in the indicators.
- **Accounting for value differentiation**—The greater the dispersion of an indicator's values across objects (years, enterprises), the more informative it is and the greater the weight it receives. Indicators that change little are considered less significant.
- **Statistical justification**—The method is based on information theory: the weight is proportional to the amount of information contained in the indicator. The higher the entropy, the less predictable the indicator, and the more valuable it is for analysis.
- **Adaptability**—Weights are automatically recalculated when the sample changes, allowing new data to be incorporated without repeated expert surveys.

The calculation of weights using the entropy method begins with normalization of indicators. In the current case, since the private potential indicators of the investment potential are already normalized, the share of each indicator value in the sum of all values across all indicators for all years is calculated:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}, i = 1, \dots, m, j = 1, \dots, n, \quad (25)$$

where m is the number of years of observation, n is the number of indicators, and x_{ij} is the value of the j -th indicator for the i -th object.

The entropy of indicators is computed using the following formula:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln(p_{ij}), j = 1, \dots, n, \quad (26)$$

where E_j is the entropy of indicator j . The coefficient $1/\ln m$ ensures normalization of entropy to the interval $[0, 1]$. If all p_{ij} are equal—a situation of maximum chaos—then $E_j = 1$; if one $p_{ij} = 1$ and the rest are 0—a situation of complete certainty—then $E_j = 0$.

The smaller the entropy, the more information the indicator carries. The weight of an indicator should be greater, the smaller its entropy; therefore, the degree of differentiation (d_j) is calculated as

$$d_j = 1 - E_j, j = 1, \dots, n, \quad (27)$$

This indicator reflects the degree of difference between objects for the given indicator. The calculation of indicator weights is carried out by normalizing the degree of differentiation:

$$w_j = \frac{d_j}{\sum_{k=1}^n d_k}, j = 1, \dots, n, \quad (28)$$

The dynamics of the private potentials without weights from 2010 to 2025 is presented in Table 4.

Table 4. Dynamics of private potentials of PJSC MMK from 2010 to 2025.

Year	Liquidity Aggregate	Financial Stability Aggregate	Profitability Aggregate	Innovation Potential	Production Potential	Environmental Potential	Social Potential	Business Activity
2010	0.73	0.54	0.65	0.49	0.31	0.13	0.45	0.67
2011	0.62	0.34	0.34	0.20	0.37	0.36	0.58	0.39
2012	0.31	0.42	0.41	0.45	0.37	0.26	0.65	0.47
2013	0.08	0.36	0.00	0.67	0.40	0.20	0.63	0.48
2014	0.28	0.03	0.35	0.44	0.32	0.22	0.66	0.41
2015	0.33	0.14	0.55	0.47	0.34	0.36	0.63	0.46
2016	0.52	0.61	0.73	0.45	0.42	0.42	0.06	0.47
2017	0.45	0.61	0.69	0.55	0.55	0.52	0.11	0.48
2018	0.55	0.60	0.68	0.45	0.68	0.52	0.33	0.55
2019	0.56	0.50	0.59	0.89	0.58	0.46	0.36	0.53
2020	0.34	0.40	0.58	0.55	0.54	0.36	0.65	0.64
2021	0.48	0.66	1.00	0.40	0.73	0.56	0.68	0.33
2022	0.65	0.59	0.49	0.46	0.43	0.49	0.61	0.53
2023	0.52	0.62	0.64	0.70	0.82	0.62	0.77	0.50
2024	0.63	0.74	0.57	0.66	0.65	0.33	0.91	0.60
2025	0.46	0.79	0.41	0.72	0.47	0.56	0.81	0.67

Source: compiled by the authors.

To assess the robustness of the developed methodology, a sensitivity analysis of the integral investment attractiveness indicator (Y) with respect to changes in the weights of each of the seven private potentials was conducted. For each year of the study period (2010–2025), the weight of one indicator was successively varied by $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$ relative to the baseline value, while the remaining weights were adjusted proportionally to maintain the normalization condition. For each variation level, 14 scenarios were calculated—a decrease and an increase in each weight by the specified value. Based on these scenarios, the mean value of the integral indicator for that year was determined, as well as the confidence interval reflecting the spread of estimates due to weight uncertainty. The 95% confidence interval was calculated using the following formula:

$$CI = \bar{a} \pm t \times \sigma, \quad (29)$$

where $\bar{a}$ is the mean value of the scenarios for a given year, t is the Student's t -coefficient, and σ is the standard deviation of the scenarios from the baseline investment potential value.

Constructing a 95% confidence interval for 14 observations requires using a Student's t -coefficient of 2.16 according to tabulated data.

Figure 4 presents the dynamics of the baseline scenario Y_{base} and the confidence intervals for weight variations of $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$, characterizing the statistical uncertainty of the estimate for each year.

Throughout the entire study period, the mean values of the integral indicator for all weight variation levels maintain the same direction and structure of changes as the baseline scenario. Growth peaks in 2019 and 2023–2024 and declines in 2014 and 2020 fall in the same years regardless of which indicator's weight is changed and in which direction.

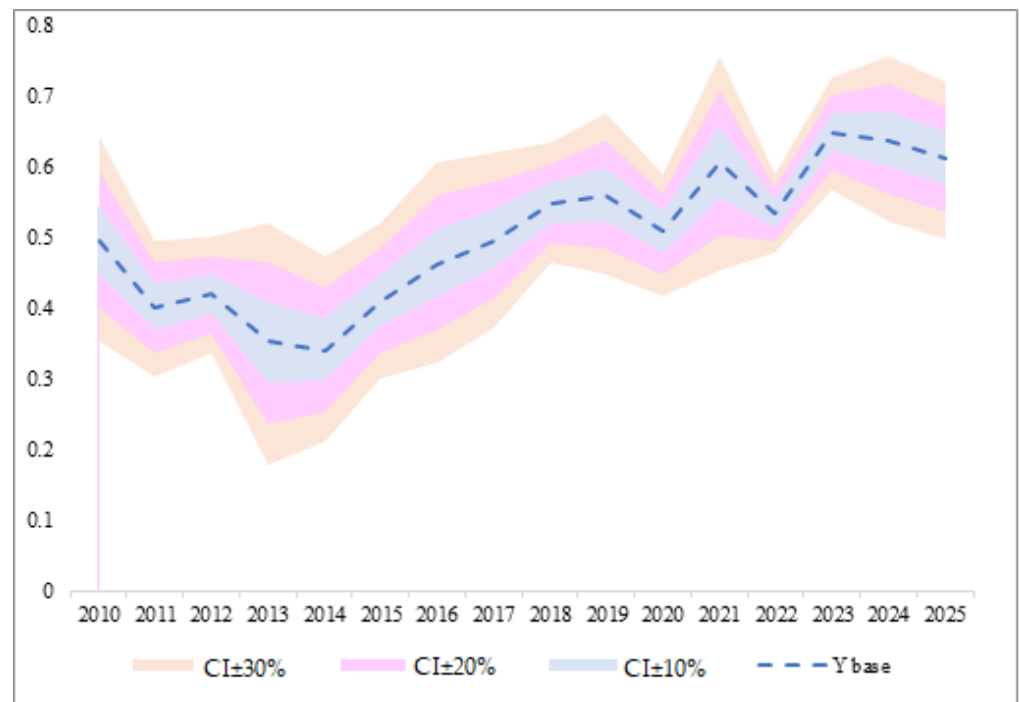


Figure 4. Dynamics of MMK's investment potential and confidence intervals for different weight variation scenarios, calculated based on the inverse of the number of indicators. Source: compiled by the authors.

The confidence intervals calculated for each year based on 14 scenarios remain narrow throughout the period. For a weight variation of $\pm 10\%$, the interval width does not exceed 0.05 in absolute terms, with an average spread of 7% from the baseline value; for $\pm 20\%$, it does not exceed 0.11, with an average spread of 13%; for $\pm 30\%$, it does not exceed 0.15, with an average spread of 20%.

The narrowest confidence intervals are observed in 2020–2022, indicating the low sensitivity of the model to weight choice during periods of low or stable integral indicator values. Conversely, the maximum spread of estimates occurs in 2013 for all variation levels due to the negative financial result that year and the consequent decline in profitability and liquidity potentials, as well as in 2016–2019 for $\pm 20\%$ and $\pm 30\%$ variations. The conducted sensitivity analysis confirms the high robustness of the current model under the chosen weights.

The dynamics of the private potentials, taking into account the weights of private potentials for the period from 2010 to 2025, are presented in Table 5. The values of the weights were obtained by the entropy method.

To interpret these results, the specificity of this calculation method should be noted. Given the limited range for data normalization and the use of the indicator values from the current time range as minimum and maximum values, the characterization of private potentials without reference to this time range is insignificant.

In this case, to assess the influence of the investment potential's private factors on investment attractiveness, the dynamics of changes in the private potential values over a limited time range for a single company were examined. This allowed the creation of a higher-quality regression model due to a sufficient number of observations and data comparability—something unattainable when comparing static values across different companies due to the potential for biased data arising from individual enterprise characteristics, including those tied to different time points.

At this stage, the research results should be defined as an assessment of MMK's investment potential from 2010 to 2025, identifying the points in time at which the greatest effect

of generating investment demand was achieved through the mobilization of the company's internal resources and opportunities that reached peak values within the period under review.

Table 5. Dynamics of MMK's weighted private and investment potentials from 2010 to 2025.

Year	Liquidity Aggregate	Financial Stability Aggregate	Profitability Aggregate	Innovation Potential	Production Potential	Environmental Potential	Social Potential	Business Activity	Aggregate Investment Potential
	0.125	0.123	0.123	0.125	0.13	0.122	0.124	0.127	
2010	0.73	0.54	0.65	0.49	0.31	0.13	0.45	0.67	0.50
2011	0.62	0.34	0.34	0.20	0.38	0.36	0.58	0.39	0.40
2012	0.31	0.42	0.41	0.45	0.38	0.26	0.65	0.47	0.42
2013	0.08	0.36	0.00	0.67	0.40	0.20	0.63	0.48	0.35
2014	0.28	0.03	0.35	0.44	0.32	0.22	0.66	0.41	0.34
2015	0.33	0.14	0.55	0.47	0.34	0.36	0.63	0.46	0.41
2016	0.52	0.61	0.73	0.45	0.42	0.42	0.06	0.47	0.46
2017	0.45	0.61	0.69	0.55	0.55	0.52	0.11	0.48	0.50
2018	0.55	0.60	0.68	0.45	0.69	0.52	0.33	0.55	0.55
2019	0.56	0.50	0.59	0.89	0.59	0.46	0.36	0.53	0.56
2020	0.34	0.40	0.58	0.55	0.55	0.36	0.65	0.64	0.51
2021	0.48	0.66	1.00	0.40	0.74	0.56	0.68	0.33	0.61
2022	0.65	0.59	0.49	0.46	0.45	0.49	0.61	0.53	0.53
2023	0.52	0.62	0.64	0.70	0.85	0.62	0.77	0.50	0.65
2024	0.63	0.74	0.57	0.66	0.65	0.33	0.91	0.60	0.64
2025	0.46	0.79	0.41	0.72	0.47	0.56	0.81	0.67	0.61

Source: compiled by the authors.

To assess the company's opportunities, projects planned for commissioning in the reporting year were analyzed, structuring the economic effects into direct effects from project implementation, ESG effects related to avoiding potential environmental fines, improving working conditions and the management system, and innovation effects related to obtaining economic benefits from the implementation of technological projects.

To assess the company's risks, consider the structure of internal and external risk indicators for MMK presented in Appendix B. As a result of calculating the indicator values, the values of external risks and internal risks of MMK for the period from 2010 to 2025 were obtained.

The investment attractiveness indicator, whose components are investment potential, assessment of company opportunities, and risk assessment, calculated dynamically for the period from 2010 to 2025 for MMK, is presented in Table 6.

The first period relates to the post-crisis recovery of the enterprise from 2010 to 2014. The dynamics of the investment potential indicator are associated with a deterioration in the company's financial performance—primarily, an increase in debt burden and a decline in profitability indicators; for example, in 2013 the company suffered significant losses.

The second period—from 2015 to 2019—reflects growth in the investment attractiveness indicator. Investment potential grows due to the restoration of financial stability potential, expansion of production potential, and improvement in key financial and economic indicators of the enterprise. The opportunity indicator during this period showed a decrease due to a lower economic effect generated by projects.

The third period—from 2020 to 2023—is marked by the peak value of investment attractiveness over the analyzed period. During this period, the enterprise managed to achieve high production volumes and maximum revenue. At the same time, the environmental component of the enterprise's operations noticeably improved due to the implementation of new environmental projects like the MMK "Clean Air" project.

The fourth period reflects the enterprise's activity in 2024 and 2025. After the peak value in 2023, a noticeable decline was observed in 2025. Investment potential showed a decrease due to a fall in production potential—indicators related to labor productivity and production volume declined during this period. Enterprise opportunities increased significantly due to the implementation of digital projects and a large-scale slag processing project.

Table 6. Dynamics of the aggregated opportunity indicator for MMK from 2010 to 2025 and its structure.

Year/Indicator, Billion RUB	Direct Economic Effect	ESG Effect	Innovation Effect	Aggregated Effect	Aggregated Opportunity Indicator	Investment Potential	Opportunities	Risk	Investment Attractive- ness
2010	2.00	0.18	0.00	2.18	0.0159	0.50	0.02	0.31	0.35
2011	5.20	0.59	0.00	5.79	0.0234	0.40	0.02	0.38	0.26
2012	3.33	0.04	3.50	6.87	0.0283	0.42	0.03	0.40	0.27
2013	3.40	0.01	2.73	6.15	0.0274	0.35	0.03	0.30	0.26
2014	6.03	0.02	0.05	6.10	0.0229	0.34	0.02	0.41	0.22
2015	6.73	0.71	0.05	7.49	0.0238	0.41	0.02	0.31	0.30
2016	4.03	0.02	0.05	4.10	0.0121	0.46	0.01	0.28	0.34
2017	4.34	0.00	0.05	4.40	0.0112	0.50	0.01	0.31	0.35
2018	4.93	0.17	0.10	5.20	0.0113	0.55	0.01	0.26	0.41
2019	4.42	0.72	0.15	5.29	0.0122	0.56	0.01	0.27	0.41
2020	0.52	2.60	0.39	3.51	0.0088	0.51	0.01	0.25	0.39
2021	0.48	9.46	0.20	10.14	0.0129	0.61	0.01	0.28	0.44
2022	0.69	8.93	0.30	9.92	0.0172	0.53	0.02	0.36	0.35
2023	3.73	17.54	0.57	21.84	0.0329	0.65	0.03	0.34	0.45
2024	5.00	28.25	2.20	35.45	0.0541	0.64	0.05	0.36	0.44
2025	4.00	19.00	1.00	24.00	0.0078	0.61	0.01	0.43	0.35

Source: compiled by the authors.

To compare the methodology with the value-based assessment of investment attractiveness, it is necessary to calculate the investment attractiveness multipliers in Table 7.

To analyze the dynamics of the EVA indicator, the sensitivity of the indicator to changes in NOPAT, IC, and WACC was assessed. Figure 5 presents a sensitivity graph of the EVA dynamics to changes in NOPAT.

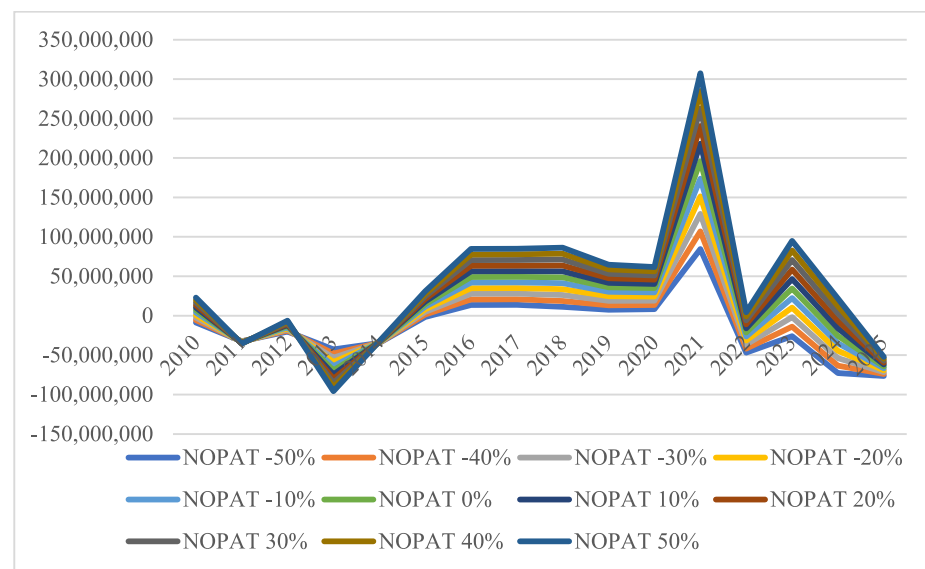


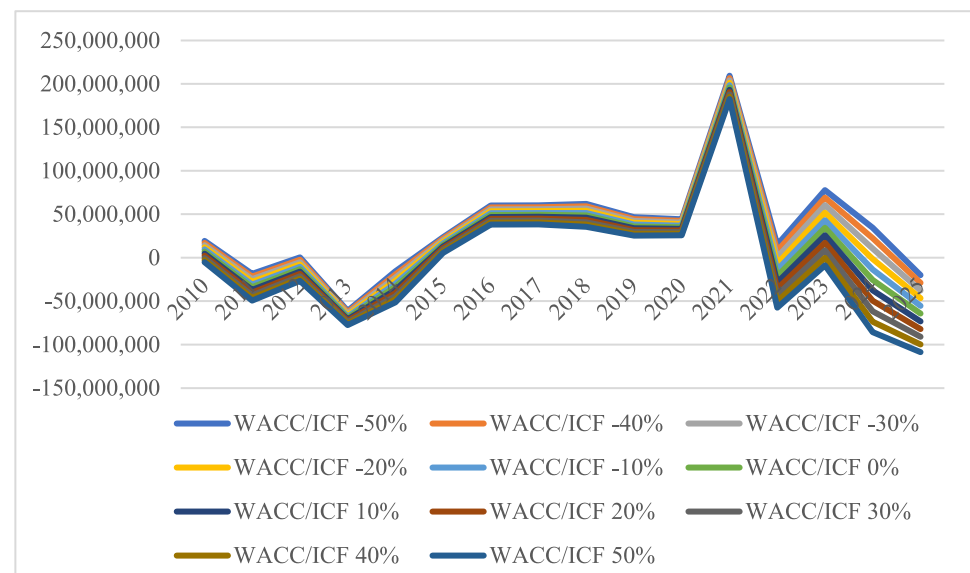
Figure 5. Sensitivity analysis of EVA dynamics to changes in NOPAT for MMK. Source: compiled by the authors.

Table 7. Dynamics of investment attractiveness multipliers of MMK from 2010 to 2025.

Year	EVA, Thousand RUB	ROIC	MVA	EVA/EBITDA	P/BV	Debt/EBITDA	Tobin's Q
	* >0— investment- attractive company *	ROIC > WACC	>0—company creates shareholder value	>10%—high value creation efficiency 0–10%— moderate value creation <0%— shareholder value destruction	<2.0—low debt burden, low risks 2.0–4.0— moderate debt burden, requires monitoring >4.0—high debt burden, elevated risks	>1.5—trades at premium, high ROE 0.8–1.5—fair valuation, near book value <0.8—discount to book value, possible undervaluation	>1.0—market value above replacement cost, value creation 0.7–1.0—moderate discount, growth potential <0.7—significant discount, possible structural problems
2010	7,058,404	0.16	122,395,793,172	0.24	1.63	2.69	1.16
2011	−33,999,971	−0.02	65,676,476,070	−9.95	1.35	32.39	0.94
2012	−13,253,112	0.07	−66,239,395,108	−0.93	0.66	6.81	0.55
2013	−69,266,863	−0.34	−35,607,072,319	1.36	0.72	−1.98	0.85
2014	−33,627,169	0.01	−34,609,889,825	−1.65	0.71	6.00	0.62
2015	14,587,884	0.22	49,583,217,229	0.23	1.34	1.68	0.88
2016	49,042,416	0.46	95,652,149,366	0.47	1.48	0.41	1.04
2017	49,255,807	0.43	194,653,641,498	0.50	1.84	0.28	1.26
2018	48,646,578	0.39	270,462,047,767	0.43	2.10	0.21	1.42
2019	35,958,895	0.30	227,645,299,941	0.42	1.93	0.16	1.26
2020	34,922,783	0.27	210,344,246,478	0.42	1.86	0.39	1.21
2021	196,015,469	0.80	345,997,894,363	0.68	1.95	0.16	1.35
2022	−21,272,506	0.14	−39,128,790,600	−0.23	0.91	−0.10	0.62
2023	34,395,120	0.28	−58,649,357,733	0.19	0.90	−0.06	0.60
2024	−25,593,036	0.21	−55,624,327,396	−0.16	0.91	−0.01	0.68
2025	−64,342,196	0.05	−254,745,749,279	−0.88	0.59	0.61	0.51

* The ideal values from the difference between ROIC and WACC should be positive. Source: compiled by the authors.

Changes in WACC and IC have the same effect on EVA; as presented in Figure 6.

**Figure 6.** Sensitivity analysis of EVA dynamics to changes in WACC for MMK. Source: compiled by the authors.

Within the current analysis, we perform an analysis of the elasticity of EVA to changes in NOPAT and WACC. The analysis of EVA elasticity to changes in NOPAT is presented in Table 8.

Table 8. Dynamics of EVA elasticity to changes in NOPAT and to changes in WACC for MMK.

Year	Range NOPAT Changes	Symmetry of Elasticity for +10% and −10% NOPAT Changes	Range WACC Changes	Symmetry of Elasticity for +10% and −10% WACC Changes
2010	5.97	0.90	4.63	−0.70
2011	0.13	0.02	1.21	0.18
2012	1.39	−0.21	2.73	0.41
2013	1.02	0.15	0.32	0.05
2014	0.08	−0.01	1.42	0.21
2015	2.99	0.45	1.65	−0.25
2016	1.93	0.29	0.60	−0.09
2017	1.93	0.29	0.59	−0.09
2018	2.05	0.31	0.72	−0.11
2019	2.12	0.32	0.78	−0.12
2020	2.04	0.31	0.71	−0.11
2021	1.52	0.23	0.18	−0.03
2022	3.21	−0.49	4.54	0.69
2023	4.68	0.71	3.35	−0.51
2024	4.93	−0.75	6.26	0.95
2025	0.50	−0.08	1.83	0.28

Source: compiled by the authors.

The conducted analysis of the range and symmetry of EVA elasticity with respect to NOPAT allows the identification of several qualitatively distinct stages in the company's development. In 2010, during the post-crisis recovery period, an anomalously high range (5.97) was observed, indicating extreme sensitivity of created value to fluctuations in operating profit, with NOPAT growth providing a significantly greater effect than a decline (asymmetry of 0.90). The subsequent period of 2011–2014 was characterized by minimal range values and near-zero symmetry, indicating low sensitivity of EVA to profit changes. The most qualitative and predictable stage occurred during 2015–2021, when the range stabilized at 1.5–2.1 and symmetry consistently maintained positive values in the range of 0.23–0.45. This means that the company responded stably to changes in operating profit. The crisis period of 2022–2024 was marked by a sharp increase in range to extreme values and extreme instability in the sign of symmetry. In 2024, the maximum negative asymmetry (−0.75) was recorded, where a fall in NOPAT destroyed EVA much more strongly than growth could create it. In 2025, a sharp reduction in range to 0.5 and a return of symmetry to near-zero values (−0.08) can be observed.

Within the current analysis, we perform an analysis of EVA elasticity to changes in NOPAT and WACC. The conducted analysis of EVA elasticity to changes in the weighted average cost of capital allows the identification of several qualitatively distinct stages in the evolution of the company's financial sensitivity.

During the period 2015–2021, the elasticity indicator was at minimal levels—0.18–0.78—and symmetry consistently maintained negative values—from −0.09 to −0.25. This means that the company was practically insensitive to fluctuations in the cost of capital, and in those rare cases where sensitivity manifested, a reduction in rates had a greater effect than their increase. Starting from 2022, a transformation of financial sensitivity occurred. The elasticity range sharply increased to 3.35–6.26, reaching an absolute maximum in 2024.

The crisis period of 2022–2024 led to a transformation of this model. Sensitivity to financial factors sharply increased, reaching the level of operational factors and even exceeding it—the range for WACC in 2024 was 6.26 versus 4.93 for NOPAT. Simultaneously,

an inversion of the sign of influence of both factors occurred: in 2022 and 2024, a decline in operating profit had a smaller impact on EVA than growth—that is, the EVA indicator decreased by a larger amount than it increased under analogous positive and negative changes. Similarly, an increase in WACC had a smaller impact on EVA than a decrease.

Comparing the elasticity of EVA with respect to WACC and with respect to NOPAT allows an important conclusion to be drawn about the shift in the dominant factor. If during 2015–2021 operational sensitivity (range: 1.5–2.1) dominated over financial sensitivity (0.2–0.8), then during the crisis years 2022–2024 financial sensitivity not only caught up but also surpassed operational sensitivity (6.26 versus 4.93 in 2024). The company transformed from operationally oriented to financially vulnerable, which radically changes the assessment of the EVA indicator.

Thus, the evolution of EVA elasticity in relation to WACC clearly reflects the transition from financial stability to crisis sensitivity and then to post-crisis anomaly. For an investor, this means that traditional assumptions about the low significance of financial leverage are no longer relevant, and forecasting should account for the possibility of inversion of the fundamental relationships between the cost of capital and the company's created value.

4.2. Assessment of Investment Attractiveness of PJSC Severstal

Within the framework of the developed approach, we begin the assessment of the investment attractiveness of PJSC Severstal with the calculation of its investment potential. Appendix C presents the dynamics of these indicators for Severstal from 2010 to 2025. The company's annual reports served as the data sources for the calculations [90].

The dynamics of private potentials for Severstal after the performed calculations are presented in Table 9.

Table 9. Dynamics of Severstal's private potentials from 2010 to 2025.

Year	Liquidity Aggregate	Financial Stability Aggregate	Profitability Aggregate	Innovation Potential	Production Potential	Environmental Potential	Social Potential	Business Activity
2010	0.84	0.49	0.31	0.29	0.40	0.37	0.37	0.39
2011	0.82	0.32	0.00	0.25	0.44	0.40	0.32	0.43
2012	0.32	0.40	0.11	0.47	0.43	0.33	0.38	0.56
2013	0.08	0.36	0.06	0.71	0.42	0.34	0.33	0.57
2014	0.29	0.02	0.18	0.68	0.45	0.35	0.33	0.60
2015	0.33	0.11	0.33	0.59	0.65	0.40	0.16	0.63
2016	0.48	0.61	0.63	0.61	0.67	0.40	0.33	0.59
2017	0.44	0.69	0.81	0.50	0.71	0.46	0.38	0.57
2018	0.52	0.67	0.67	0.59	0.77	0.40	0.39	0.62
2019	0.54	0.43	0.54	0.76	0.79	0.30	0.47	0.43
2020	0.38	0.35	0.57	0.56	0.59	0.58	0.45	0.55
2021	0.51	0.48	1.00	0.46	0.61	0.31	0.49	0.33
2022	0.66	0.57	0.52	0.28	0.36	0.33	0.50	0.55
2023	0.55	0.58	0.49	0.54	0.72	0.80	0.70	0.53
2024	0.64	0.68	0.31	0.67	0.67	0.43	0.90	0.55
2025	0.40	0.77	0.30	0.65	0.52	0.76	0.96	0.56

Source: compiled by the authors.

To assess the robustness of the developed methodology, a sensitivity analysis of the integral investment attractiveness indicator (Y) with respect to changes in the weights of each of the seven private potentials was conducted. The analysis was performed analogously to that for MMK.

Figure 7 presents the dynamics of the baseline scenario Y_{base} and the confidence intervals for weight variations of $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$, characterizing the statistical uncertainty of the estimate for each year.

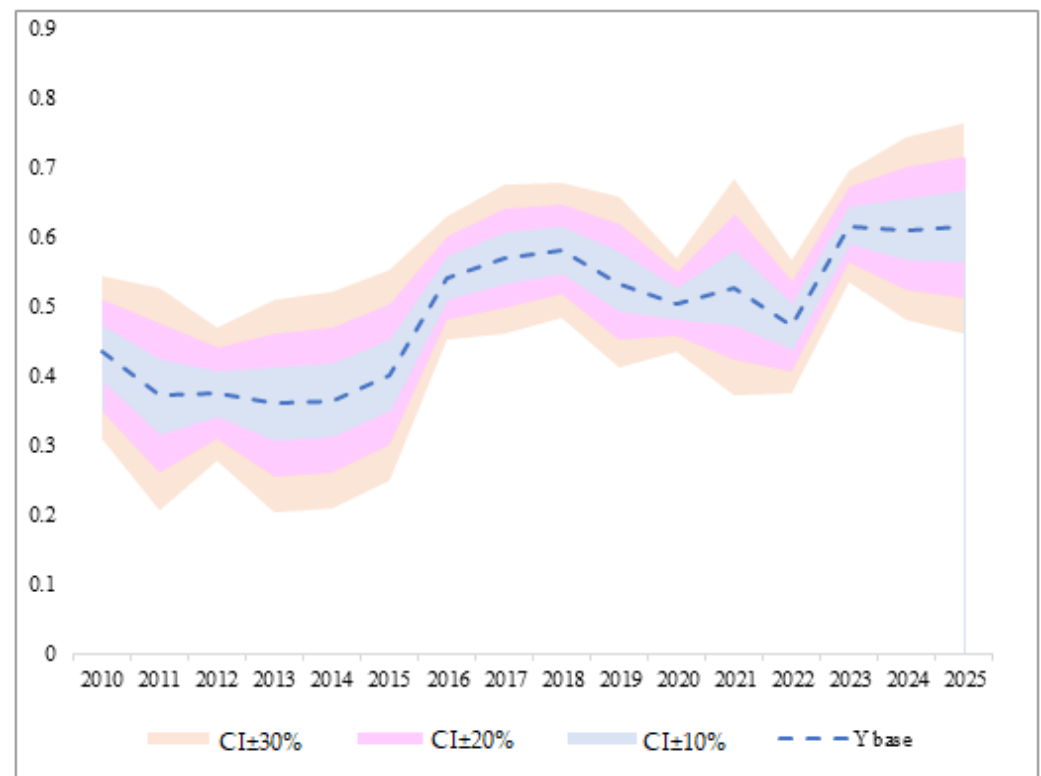


Figure 7. Dynamics of Severstal's investment potential and confidence intervals for different weight variation scenarios, calculated based on the inverse of the number of indicators. Source: compiled by the authors.

Throughout the entire study period, the mean values of the integral indicator for all weight variation levels maintain the same direction and structure of changes as the baseline scenario. The periods of decline in the early decade (2010–2015) and subsequent steady growth, reaching peak values in 2023–2025, are reproduced at any level of weight variation, regardless of which indicator's weight is changed and in which direction.

The confidence intervals calculated for each year based on the scenarios remain moderate for a weight variation of $\pm 10\%$: the average relative spread is 9% of the baseline value, with a maximum absolute interval width of 0.106. When the variation increases to $\pm 20\%$, the average spread rises to 15% with a maximum width of 0.21, and at $\pm 30\%$ it reaches 22% with a maximum width of 0.31.

The narrowest confidence intervals can be observed in 2020—widths of 0.045 at $\pm 10\%$, 0.09 at $\pm 20\%$, and 0.13 at $\pm 30\%$ —as well as in 2016 and 2023, indicating low sensitivity of the model to weight choice during periods of stable or average integral indicator values. Conversely, the maximum spread of estimates was recorded in 2025—a width of 0.30 at $\pm 30\%$ —as well as in 2011, 2021, and 2024. This objectively reflects greater uncertainty when assessing investment attractiveness during periods of structural changes and increased volatility, as well as on the forecasting horizon. The year 2020 stands as an expected outlier. For all years and variation levels, the deviations of minimum and maximum values from the baseline show symmetry, confirming the robustness of the methodology in accounting for weight variation.

The dynamics of the private potentials, taking into account the weights of private potentials for the period from 2010 to 2025, are presented in Table 10. The values of the weights were obtained by the entropy method.

Table 10. Dynamics of private potentials and investment potential of Severstal from 2010 to 2025.

Year	Liquidity Aggregate	Financial Stability Aggregate	Profitability Aggregate	Innovation Potential	Production Potential	Environmental Potential	Social Potential	Business Activity	Aggregate Investment Potential
	0.127	0.129	0.122	0.12	0.128	0.126	0.122	0.125	
2010	0.84	0.49	0.31	0.29	0.40	0.37	0.37	0.39	0.43
2011	0.82	0.32	0.00	0.25	0.44	0.40	0.32	0.43	0.37
2012	0.32	0.40	0.11	0.47	0.43	0.33	0.38	0.56	0.37
2013	0.08	0.36	0.06	0.71	0.42	0.34	0.33	0.57	0.36
2014	0.29	0.02	0.18	0.68	0.45	0.35	0.33	0.60	0.36
2015	0.33	0.11	0.33	0.59	0.65	0.40	0.16	0.63	0.40
2016	0.48	0.61	0.63	0.61	0.67	0.40	0.33	0.59	0.54
2017	0.44	0.69	0.81	0.50	0.71	0.46	0.38	0.57	0.57
2018	0.52	0.67	0.67	0.59	0.77	0.40	0.39	0.62	0.58
2019	0.54	0.43	0.54	0.76	0.79	0.30	0.47	0.43	0.53
2020	0.38	0.35	0.57	0.56	0.59	0.58	0.45	0.55	0.50
2021	0.51	0.48	1.00	0.46	0.61	0.31	0.49	0.33	0.52
2022	0.66	0.57	0.52	0.28	0.36	0.33	0.50	0.55	0.47
2023	0.55	0.58	0.49	0.54	0.72	0.80	0.70	0.53	0.62
2024	0.64	0.68	0.31	0.67	0.67	0.43	0.90	0.55	0.61
2025	0.40	0.77	0.30	0.65	0.52	0.76	0.96	0.56	0.62

Source: compiled by the authors.

At this stage, the research results should be defined as an assessment of Severstal's investment potential from 2010 to 2025, identifying the points in time at which the greatest effect of generating investment demand was achieved through the mobilization of the company's internal resources and opportunities that reached peak values within the period under review.

To assess the company's opportunities, projects planned for commissioning in the reporting year were analyzed, structuring the economic effects into direct effects from project implementation, ESG effects related to avoiding potential environmental fines, improving working conditions and the management system, and innovation effects related to obtaining economic benefits from the implementation of technological projects. The annual reports of metallurgical companies served as the source data. The results for Severstal from 2010 to 2025 are presented in Table 11.

To assess the company's risks, consider the structure of internal and external risk indicators for Severstal presented in Appendix B. As a result of calculating the indicator values, the values of external risks and internal risks of Severstal for the period from 2010 to 2025 were obtained.

The first period (2010–2014) is characterized by instability and relatively low values of the integral indicator, ranging from 0.27 to 0.40. The investment potential during this period is at the lowest levels ever observed, from 0.36 to 0.43. In this period, the company experiences a high debt burden from long-term liabilities. As a consequence of these factors, key financial performance indicators are low.

The second period (2015–2019) represents a phase of steady growth and qualitative improvement. From 2015 onwards, there is a steady increase in investment attractiveness, reaching a maximum value of 0.49 in 2016 and 2018. The opportunity indicator, by contrast, declines compared to the 2013 peak and stabilizes at a low level.

The third period (2020–2023) is marked by extreme values of the indicators. This stage is characterized by high volatility and a recurrence of the peak investment attractiveness value -0.49 in 2023. Investment potential continues to grow, reaching 0.62 due to favorable price conditions and the effect of currency revaluation. Opportunities remain at a low level; however, in 2023 a significant effect was achieved from the implementation of environmental projects.

The fourth period (2024–2025) is associated with adaptation to new conditions and a decline in investment attractiveness from 0.49 in 2023 to 0.42 in 2025. Investment potential, remaining at a high level of 0.61 – 0.62 , stops growing, which is linked to a slowdown in production growth due to falling demand. The company's opportunities are activated through the implementation of digital technologies and large-scale waste processing projects, but this effect is offset by a sharp increase in risk.

Table 11. Dynamics of the aggregated opportunity indicator for Severstal from 2010 to 2025 and its structure.

Year/Indicator, Billion RUB	Direct Economic Effect	ESG Effect	Innovation Effect	Aggregated Effect	Aggregated Opportunity Indicator	Investment Potential	Opportunities	Risk	Investment Attractive- ness
2010	1.56	0.65	0.01	2.22	0.011	0.43	0.01	0.24	0.34
2011	6.36	2.79	0.07	9.22	0.036	0.37	0.04	0.30	0.28
2012	12.42	0.00	0.00	12.42	0.056	0.37	0.06	0.31	0.30
2013	12.47	14.18	3.06	29.71	0.140	0.36	0.14	0.21	0.40
2014	6.50	0.00	0.08	6.58	0.028	0.36	0.03	0.31	0.27
2015	10.00	0.00	0.00	10.00	0.036	0.40	0.04	0.21	0.34
2016	23.45	0.00	0.00	23.45	0.077	0.54	0.08	0.20	0.49
2017	1.30	0.00	0.00	1.30	0.004	0.57	0.00	0.21	0.45
2018	1.30	0.00	0.00	1.30	0.003	0.58	0.00	0.17	0.49
2019	14.56	0.00	3.59	18.15	0.040	0.53	0.04	0.18	0.47
2020	11.00	0.00	0.00	11.00	0.024	0.50	0.02	0.15	0.45
2021	12.00	0.00	2.07	14.07	0.018	0.52	0.02	0.18	0.44
2022	13.00	0.00	0.00	13.00	0.022	0.47	0.02	0.26	0.36
2023	0.00	7.80	7.14	14.94	0.022	0.62	0.02	0.24	0.49
2024	1.70	0.57	8.20	10.47	0.014	0.61	0.01	0.26	0.46
2025	3.00	0.19	0.10	3.29	0.005	0.62	0.01	0.33	0.42

Source: compiled by the authors.

To compare the methodology with the value-based assessment of investment attractiveness, it is necessary to calculate the investment attractiveness multipliers, as presented in Table 12.

To analyze the dynamics of the EVA indicator, the sensitivity of the indicator to changes in NOPAT, IC, and WACC was assessed. Figures 8 and 9 present a sensitivity graph of the EVA dynamics to changes in NOPAT.

Changes in WACC and IC have the same effect on EVA; therefore, the impact on EVA was assessed when the WACC indicator was changed.

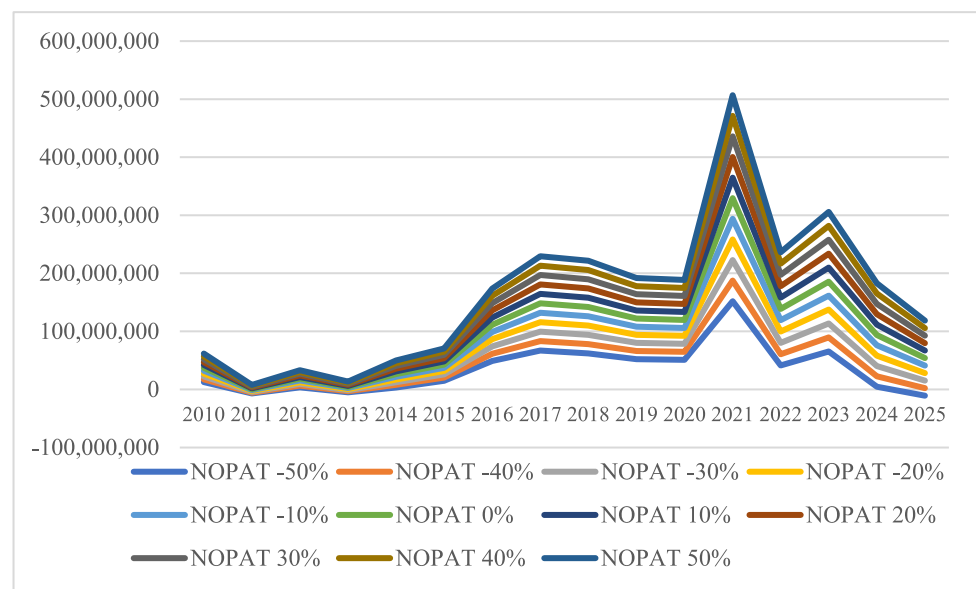
Within the current analysis, we perform an analysis of the elasticity of EVA to changes in NOPAT and WACC. The analysis of EVA elasticity to changes in NOPAT and to changes in WACC is presented in Table 13.

The conducted analysis of the range and symmetry of EVA elasticity with respect to NOPAT allows the identification of several qualitatively distinct stages in the company's development.

Table 12. Dynamics of investment attractiveness multipliers of Severstal from 2010 to 2025.

Year	EVA, Thousand RUB	ROIC	MVA	EVA/EBITDA	P/BV	Debt/EBITDA	Tobin's Q
	* >0— investment- attractive company *	ROIC > WACC	>0—company creates shareholder value	>10%—high value creation efficiency 0–10%— moderate value creation <0%— shareholder value destruction	<2.0—low debt burden, low risks 2.0–4.0— moderate debt burden, requires monitoring >4.0—high debt burden, elevated risks	>1.5—trades at premium, high ROE 0.8–1.5—fair valuation, near book value <0.8—discount to book value, possible undervaluation	>1.0—market value above replacement cost, value creation 0.7–1.0—moderate discount, growth potential <0.7—significant discount, possible structural problems
2010	37,049,316	0.57	133,190,760,614	0.68	2.07	1.69	1.19
2011	393,715	0.14	208,410,543,791	0.03	8.80	2.11	1.37
2012	18,276,933	0.31	133,947,965,633	0.66	6.00	1.69	1.16
2013	4,126,507	0.18	113,639,692,449	0.24	8.98	1.88	1.43
2014	26,443,719	0.42	167,706,808,719	0.66	4.89	2.40	1.33
2015	42,644,024	0.49	405,333,582,046	0.62	3.07	3.81	2.03
2016	111,297,901	1.13	434,195,867,585	0.93	1.66	3.16	2.19
2017	148,172,708	1.30	482,114,058,253	0.91	0.94	3.08	2.07
2018	141,862,182	1.10	576,013,518,945	0.88	0.99	3.34	2.20
2019	121,954,539	0.79	581,044,924,027	0.86	1.40	3.38	2.16
2020	119,692,435	0.63	560,872,472,658	0.81	1.43	3.29	2.03
2021	329,453,314	1.35	959,686,260,596	0.98	0.66	3.63	2.42
2022	138,708,076	0.72	334,287,239,726	0.66	0.14	1.73	1.19
2023	185,586,135	0.87	413,443,210,475	0.80	−0.53	1.73	1.18
2024	93,713,480	0.58	644,712,707,638	0.49	0.43	2.07	1.55
2025	53,830,796	0.34	283,743,462,649	0.32	0.71	1.45	1.19

* The ideal values from the difference between ROIC and WACC should be positive. Source: compiled by the authors.

**Figure 8.** Sensitivity analysis of EVA dynamics to changes in NOPAT for Severstal. Source: compiled by the authors.

In 2010, moderate values can be observed in NOPAT ranges. The company demonstrates a balanced and fairly linear response of EVA to changes in operating profit over a wide range, with a slight asymmetry in favor of NOPAT growth. In 2011, an extreme outlier is generated: range: 49.96, symmetry: 7.57. Such high values indicate a very strong non-linearity: the elasticity of EVA changed sharply depending on the magnitude of the

NOPAT deviation, and the advantage of profit growth over its decline was multiple. The period from 2015 to 2021 represents the most stable period. This is a sign of a mature operating model: the response of EVA to NOPAT changes is linear over a wide corridor ($\pm 50\%$), and the weak positive asymmetry indicates controlled operating leverage. The minimum values of range and symmetry occur in 2016–2021, indicating high business predictability. In 2024 and 2025, a marked increase in range and symmetry should be noted. Since 2022, a gradual increase in range and symmetry has been observed, indicating an increase in the sensitivity of EVA to operating profit and a strengthening of positive asymmetry.

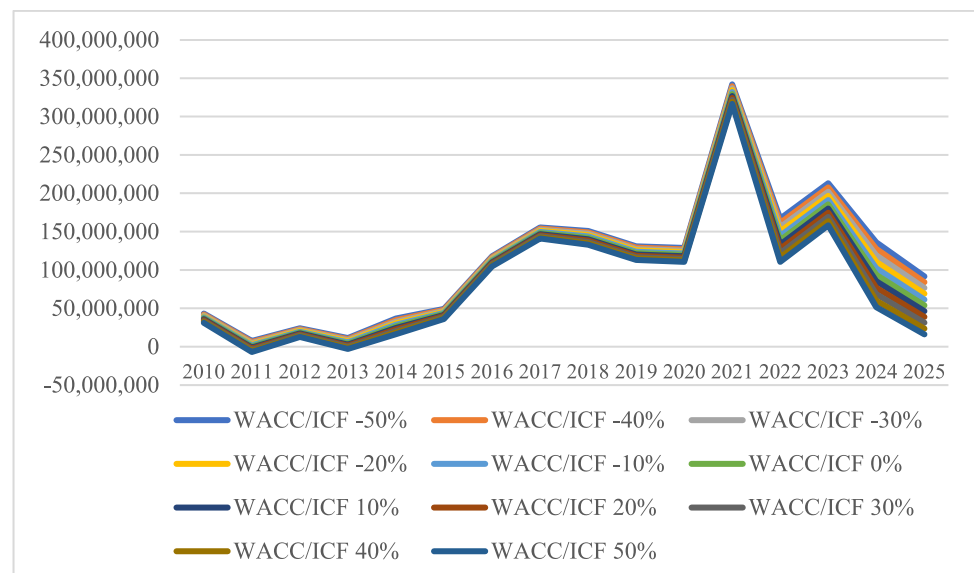


Figure 9. Sensitivity analysis of EVA dynamics to changes in WACC for Severstal. Source: compiled by the authors.

Table 13. Dynamics of elasticity to changes in NOPAT and to changes in WACC for Severstal.

Year	Range NOPAT Changes	Symmetry of Elasticity for +10% and −10% NOPAT Changes	Range WACC Changes	Symmetry of Elasticity for +10% and −10% WACC Changes
2010	1.77	0.27	0.44	−0.07
2011	49.96	7.57	48.63	−7.37
2012	2.15	0.33	0.82	−0.12
2013	5.93	0.90	4.60	−0.70
2014	2.36	0.36	1.02	−0.15
2015	1.74	0.26	0.41	−0.06
2016	1.49	0.23	0.16	−0.02
2017	1.46	0.22	0.13	−0.02
2018	1.50	0.23	0.17	−0.03
2019	1.53	0.23	0.19	−0.03
2020	1.53	0.23	0.20	−0.03
2021	1.44	0.22	0.10	−0.02
2022	1.88	0.28	0.54	−0.08
2023	1.73	0.26	0.39	−0.06
2024	2.54	0.38	1.20	−0.18
2025	3.20	0.49	1.87	−0.28

Source: compiled by the authors.

The conducted analysis of EVA elasticity to changes in the weighted average cost of capital allows the identification of several qualitatively distinct stages in the evolution of the company's financial sensitivity.

In 2010, moderately low sensitivity can be observed in WACC ranges. The company demonstrates a low and weakly asymmetric response of EVA to changes in WACC: a decrease in the cost of capital gives a slightly greater effect than an increase. In 2014, the values remain above the long-term trend but show movement towards stabilization. The period from 2015 to 2023 records sustainably low sensitivity: the range fluctuates in a narrow band of 0.10–0.54, symmetry from -0.02 to -0.08 . This is the most stable stage: the response of EVA to changes in WACC is linear (low range) and weakly asymmetric, with a consistent advantage from a decrease in the rate. Minimum values are reached in 2016–2021 (range: 0.10–0.20), indicating the high predictability of the financial model and an absence of sensitivity to the cost of capital as a significant factor. In 2024–2025, sensitivity increases. This signals a return of non-linearity and an increase in asymmetry: EVA begins to react more strongly to changes in WACC, and the advantage from a rate decrease becomes more pronounced.

Comparing the dynamics of EVA elasticity with respect to WACC and with respect to NOPAT allows the following conclusions to be drawn. The company gains more from NOPAT growth than it loses from its decline and simultaneously gains more from a decrease in WACC than it loses from its increase. Such a configuration is a sign of a balanced financial–operational profile, where both factors work in favor of shareholder value under favorable changes. To maintain the predictability of EVA, controlling the non-linearity of the operating model—NOPAT—remains key, as it is the main contributor to volatility. The financial component—WACC—was a neutral factor for a long time, but its growing sensitivity since 2024 requires monitoring of the capital structure and debt policy.

5. Discussion

5.1. General Characteristics of the Investment Attractiveness Indicator

In this article we propose a novel methodological approach, which addresses the following issues:

(1) Given the current operating conditions of Russian ferrous metallurgy enterprises, development trends in the global metallurgy industry, and the limitations of existing methods for assessing investment attractiveness, it is necessary to develop a conceptual model for an integrated assessment of investment attractiveness, taking into account the various potentials of an enterprise, macroeconomic, industry-specific, and internal factors, as well as economic, ESG, and technological effects.

(2) To determine the investment attractiveness of a metallurgical enterprise, it is necessary to synthesize investment potential, assessed by measuring the enterprise's resource base over time, realized opportunities, and an aggregated risk index differentiated into external and internal components. This allows for the development of a comprehensive toolkit adapted to industry specifics and taking into account its key risks.

Within the framework of further research, to substantiate the applicability of the investment attractiveness indicator and to identify its substantive relationship with traditional metrics of company performance, a comprehensive econometric analysis was conducted. The main objective of this stage of the research was to test the hypothesis that the proposed integral indicator not only reflects the internal characteristics of an enterprise's investment attractiveness but also correlates statistically significantly with widely recognized indicators.

Prior to performing the econometric analysis, the following hypotheses were formulated:

- There exists a statistically significant positive relationship between the authors' investment attractiveness indicator (IA) and classical indicators of investment attractiveness (ROIC, EVA, and MVA), as well as market multipliers (Tobin's Q and P/BV).
- Changes in investment attractiveness lead the dynamics of ROIC.
- The identified relationship is stable over time.
- Decomposition of investment attractiveness into its components (investment potential, opportunities, and risk) makes it possible to identify the contribution of each factor to changes in the indicator, thereby providing a basis for scenario forecasting.

To substantiate the applicability of the investment attractiveness indicator and to identify its relationship to traditional efficiency metrics, a set of econometric methods based on panel data structure was implemented. The panel was formed by combining time series of the two largest metallurgical companies—MMK and Severstal—for the period from 2010 to 2025. The initial data contained annual values of the authors' indicator, its components (potential, opportunities, and risk), as well as a number of performance indicators—ROIC, EVA, MVA, Tobin's Q, and P/BV. Prior to the econometric analysis, all variables were Z-normalized for the purposes of the cross-correlation analysis. However, the panel regressions were estimated using the original (non-normalized) data to preserve the interpretability of the coefficients. Accordingly, the reported coefficients in Table 14 are presented in their original units (e.g., thousands of RUB for EVA and MVA). The initial data for calculating panel regression is presented in Appendix D. The use of panel data made it possible to control for unobservable heterogeneity between companies through fixed effects, as well as to account for common time shocks affecting both organizations. This approach provided a more accurate estimation of the influence of investment attractiveness on the dependent variables, eliminating bias caused by persistent company differences and macroeconomic conditions.

Table 14. Results of fixed-effects panel regressions with financial indicators as dependent variables and IA as the explanatory variable.

Dependent Variable	Coefficient (β)	R ²	F-Statistic (Model)	p-Value (Model)	SE	t Statistics
EVA	5.97×10^8	0.36	16.12	0.00038	1.49×10^8	4.02
ROIC	2.88×10^0	0.44	22.87	0.00005	6.02×10^{-1}	4.78
MVA	1.44×10^{12}	0.30	12.17	0.00157	4.13×10^{11}	3.49
Q_Tobin	2.49×10^0	0.22	8.12	0.00797	8.72×10^{-1}	2.85
EVA_EBITDA	8.02×10^0	0.10	3.37	0.07687	4.3×10^0	1.83
P_BV	-2.24×10^1	0.08	2.65	0.11469	1.38×10^1	-1.63

Source: compiled by the authors.

The econometric specification takes the following form:

$$Y_{it} = \alpha + \beta \times IA_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \quad (30)$$

where Y_{it} represents the financial indicator (ROIC, EVA, MVA, Tobin's Q, P/BV, or EVA/EBITDA) for firm i in year t , IA_{it} is the integral investment attractiveness index, γ_i denotes firm-specific fixed effects, δ_t denotes year-specific fixed effects, and ε_{it} is the error term. Thus, IA serves as the explanatory (independent) variable, while each financial indicator is the dependent variable. This specification allows us to assess the extent to which variation in the composite IA explains changes in traditional financial metrics.

The results of the fixed-effects panel regressions are presented in Table 14. For each financial indicator, we estimated a separate regression with IA as the explanatory variable, controlling for firm and year fixed effects.

The results of fixed-effects panel regressions allow the following conclusions to be drawn regarding the nature and strength of the relationship between the authors' investment attractiveness index (IA) and traditional financial and market metrics.

Value-creation indicators (ROIC, EVA, and MVA) exhibit the most robust positive relationship with the IA. The coefficients for ROIC ($\beta = 2.88, p < 0.0001$), EVA ($\beta = 5.97 \times 10^8, p = 0.0004$), and MVA ($\beta = 1.44 \times 10^{12}, p = 0.0016$) are statistically significant. While the linear specification reveals a statistically significant positive relationship for EVA and MVA, the diagnostic tests indicate that non-linear specifications (e.g., quadratic or logarithmic forms) may provide a better fit. This suggests that the relationship between IA and these value-based metrics is not strictly linear, which is consistent with the theoretical expectation that value creation exhibits diminishing or increasing returns to improvements in investment attractiveness. This implies that, after controlling for persistent firm-specific differences and common macroeconomic shocks, changes in the IA explain between 30% and 44% of the variation in these indicators. This suggests that the proposed integral indicator adequately captures a firm's ability to generate returns in excess of the cost of capital, as well as to create added value in both accounting and market terms. Consequently, the "investment potential" component of the authors' methodology—which includes profitability and efficiency ratios—validly captures precisely this aspect of attractiveness.

Tobin's Q is also significantly related to the IA, confirming that the authors' measure incorporates long-term investor expectations. The coefficient is positive ($\beta = 2.49, p = 0.008$), and the model explains 22% of the within-firm variation. Since Tobin's Q reflects the ratio of market value of assets to their replacement cost, its significance indicates that the IA integrates forward-looking market assessments of future growth and intangible factors (technology and reputation). Thus, the IA is able to capture the strategic, "option-like" component of investment attractiveness that goes beyond current operating efficiency.

The EVA/EBITDA ratio, which characterizes the efficiency of converting operating profit into added value, is related to the IA only at the 10% significance level ($p = 0.077$), with relatively low explanatory power ($R^2 = 0.10$). The weakness of this relationship may be explained by the fact that EVA/EBITDA, as a normalized metric, partly duplicates information already contained in ROIC and EVA, and its variability is driven more by fluctuations in EBITDA than by dynamics in fundamental attractiveness. Nevertheless, the positive sign of the coefficient is consistent with theoretical expectations: an increase in IA is associated with greater efficiency in value creation from current operating cash flows, although this effect is weaker than for the "absolute" value measures.

The P/BV multiplier did not reveal a statistically significant linear relationship with the IA ($\beta = -22.41, p = 0.115, R^2 = 0.08$). The lack of significance indicates that the ratio of market value to book value of equity is not a reliable indicator of investment attractiveness for the metallurgical companies under analysis during the studied period. Possible reasons include the strong influence of accounting policies and accumulated depreciation on book value, as well as the high volatility of market prices driven by sanctions and geopolitical shocks, which obscures the link with the fundamental characteristics captured by the authors' index. This result further underscores the advantage of a multi-criteria approach that does not rely exclusively on book-value multipliers.

Overall, the analysis confirms that the authors' investment attractiveness index (IA) is statistically significant and positively related to key indicators reflecting value-creation efficiency (ROIC, EVA, and MVA) and long-term market expectations (Tobin's Q). This supports the validity of the proposed methodology as an integral metric that covers both

operational and strategic dimensions of attractiveness. The absence of a significant relationship with P/BV and the weak relationship with EVA/EBITDA do not contradict the theoretical framework; rather, they demonstrate that the authors' index does not duplicate book-value multipliers and provides additional information relevant for assessing the investment attractiveness of metallurgical enterprises in the current environment.

It should be noted that the investment potential component, which constitutes one of the three pillars of the integral index, includes profitability and efficiency ratios. This creates a certain degree of overlap with the traditional financial multipliers (ROIC, EVA, and MVA) used for validation. Such overlap is not a methodological flaw but a conceptually justified consequence of the fact that profitability is an objective and inherent characteristic of a company's resource efficiency and, consequently, its investment attractiveness. Validation through ROIC, EVA, MVA, and Tobin's Q serves as a test of convergent validity [91,92]: we examine the extent to which the proposed integral indicator—which accounts not only for profitability but also for realized ESG effects and aggregated risk—aligns with established metrics widely recognized in both academic and practical contexts. The high correlation with these indicators confirms that the new index is consistent with traditional approaches, while at the same time it provides additional information related to sustainable development and risk management that is not captured by classical multipliers. Thus, the partial overlap of indicators is expected and does not diminish the value of the proposed methodology; on the contrary, it strengthens confidence in it as a comprehensive tool for assessing investment attractiveness.

To identify the temporal structure of the relationship, cross-correlation analysis with lags was used, which made it possible to determine whether investment attractiveness is a leading indicator relative to other indicators—ROIC and Tobin's Q. Decomposition of investment attractiveness changes by components (potential, opportunities, and risk) allowed us to identify the contribution of each factor to the dynamics of the indicator. For both companies, the maximum cross-correlation between investment attractiveness and ROIC is achieved at zero lag (0.664 for MMK and 0.690 for Severstal), indicating a synchronous relationship between the two indicators. Notably, for Severstal, correlations remain relatively high at positive lags +1 and +2 (0.54 and 0.59), and for MMK at lag +2 (0.50). These findings provide preliminary indications that investment attractiveness may exhibit some leading tendency relative to ROIC with an interval of one to two years, which is consistent with the duration of the investment cycle in the metallurgical industry. However, these results should be interpreted with caution, as cross-correlation analysis alone does not establish causality or predictive power. Further research using more rigorous methods (e.g., Granger causality tests or Vector Autoregression models) is required to confirm the predictive potential of the indicator. The cross-correlation analysis of investment attractiveness with Tobin's Q showed that for MMK the maximum is achieved at lag +3 (0.445), while for Severstal a similar pattern can be observed. As with the ROIC analysis, these results should be considered preliminary and require confirmation through more robust econometric methods.

Next, a CUSUM test was performed to examine the stability of the relationship between investment attractiveness and ROIC over time. This test allows for the detection of structural breaks in the regression model, which is particularly relevant under conditions of high volatility in the metallurgical sector. The CUSUM test did not reveal structural breaks throughout the entire study period: *p*-values were 0.4822 for MMK and 0.6989 for Severstal. However, these results should be interpreted with caution, as the test has limited power with only 16 annual observations per firm. The absence of detected breaks does not constitute definitive evidence of stability; rather, it indicates that no significant structural changes were identified within the studied period. Claims of stability “despite external

shocks” or extrapolation to the future would require longer time series or more powerful testing procedures.

Finally, a decomposition of the change in investment attractiveness by components (potential, opportunities, and risk) was performed based on the total differential formula. This allowed us to quantitatively assess the contribution of each factor to the annual dynamics of investment attractiveness and to identify periods when one or another component had a dominant influence. The decomposition is shown in Figures 10 and 11.

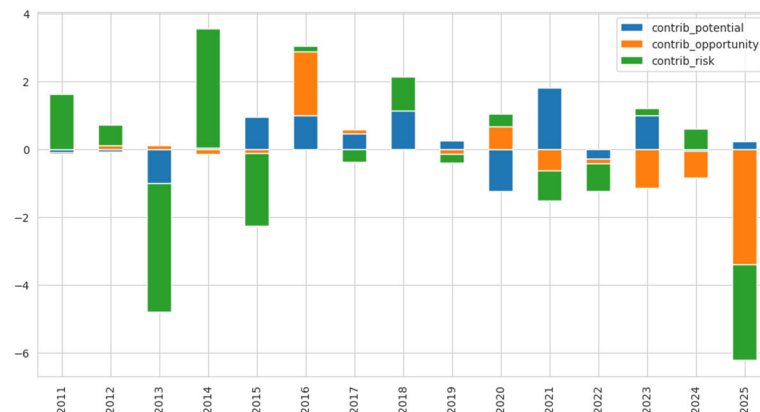


Figure 10. Decomposition of MMK investment attractiveness changes. Source: compiled by the authors.

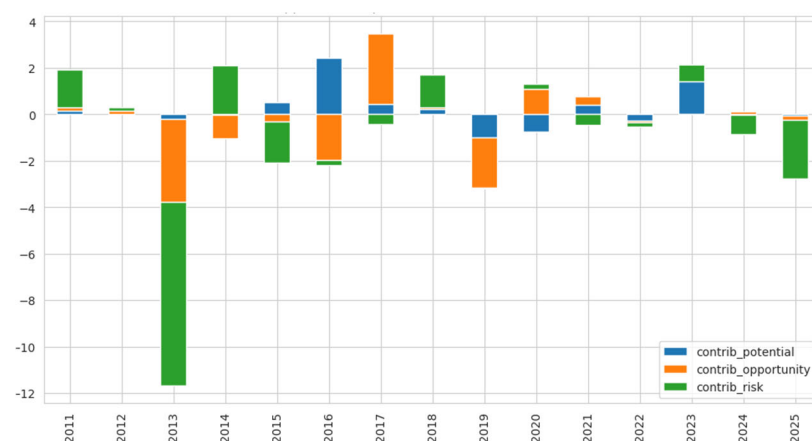


Figure 11. Decomposition of Severstal investment attractiveness changes. Source: compiled by the authors.

The results of applying the above methods allowed us to confirm Hypothesis 1 for ROIC and Tobin’s Q (significant positive coefficients in panel regressions), while the relationship with P/BV was not statistically significant. For EVA and MVA, the need for a non-linear specification was identified. Cross-correlation showed the presence of maximum values at positive lags for both companies, thereby confirming Hypothesis 2.

The CUSUM test did not reveal structural breaks, confirming Hypothesis 3. Decomposition of investment attractiveness made it possible to meaningfully interpret the role of each component in different periods, creating a basis for the development of predictive models.

Within the studied sample, the results suggest that the indicator of investment attractiveness, constructed on the basis of decomposition into investment potential, opportunities, and risk, is a statistically significant and substantively interpretable predictor of ROIC and Tobin’s Q. The relationship with P/BV was not statistically significant in the current specification. Its dynamics are synchronous with the return on invested capital and, with

respect to Tobin's Q, exhibit some leading tendency, opening up possibilities for further investigation into predictive models focused on managing the structural components of the indicator. The temporal stability of the relationships within the studied period and sample suggests the reliability of the methodology, while the identified limitations with respect to EVA and MVA define directions for further research, including the application of non-linear specifications and the expansion of the set of control variables.

5.2. Conceptual Approach to Evaluate the Sustainability of the Investment Potential

To make an assessment of the sustainability of these two companies in the metallurgy sector, it is necessary to identify the environmental impact resulting from industrial operations. These activities diminish the potential to continue operations efficiently in a region. The adoption of a comprehensive and systematic framework can only be realized through a unified concept of socioeconomic development and state regulation [93].

In this regard, H. Bossel argued for the use of parameters to determine the developmental levels of system components and their respective contributions to the effective operation of the broader socioeconomic system [94]. To sustain requisite levels of functionality and stability, a system must possess the capacity to respond to threats, adapt accordingly, and implement damage prevention measures. The proposed approach is further employed to assess the level of economic development within a given territory, including the specific dimension of national "sustainability."

System stability is contingent upon adherence to six fundamental principles: existence, effectiveness, freedom of action, security, adaptability, and co-development [94]. The system's developmental efficacy and trajectory are constrained by its minimum satisfaction threshold.

The system must exhibit adaptive properties. In the studied cases, sustainable components represent a small part of the overall index, which is a sign to initiate a transformation of priorities in these metallurgy enterprises. Given the dynamic nature of socioeconomic systems, their evolution is particularly influenced by the volatility of commodities markets in the last six years. Vertically integrated companies deal with the macro-level environment, but to translate sustainable goals into a company strategy of investment requires the examination of the whole value chain to the ultimate consumer. The literature has identified the need to reach the end of the value chain [95,96]. When systemic approaches are not taken into account, isolated policies for innovation and sustainability can produce limited effects [44]. Other metallurgy industries as well are taking steps in decarbonization aligning company priorities with de Development Sustainable Goals [97].

The PJSC Magnitogorsk Iron and Steel Works and PJSC Severstal, as two of the largest metallurgical companies in Russia, were selected for pilot testing of the methodology. Further studies may extend this analysis to companies in other leading metallurgical countries, such as China and India, to assess sectoral implications. The literature analysis revealed that the number of studies linking financial activity and sustainability in the sector is limited. This study contributes to addressing this gap by proposing a methodological framework that links financial analysis with sustainability capabilities and risks, using two Russian metallurgical companies as a study case.

5.3. Practical Implications and Implementation Guidelines

The proposed integrated assessment methodology for investment attractiveness is designed for practical applications in metallurgical enterprises, as well as investment funds and banks specializing in industrial project financing. Its practical value is determined by several key aspects.

Firstly, the methodology enables a quantitative linkage between strategic sustainable development (ESG) objectives and operational and investment decisions. Unlike traditional approaches that rely predominantly on financial multipliers, the proposed index incorporates environmental and social effects, thus allowing:

- Assessment of the contribution of specific “green” projects to enhancing investment attractiveness;
- Substantiated requests for green financing (loans and bonds) linked to quantitative key performance indicators;
- Identification of bottlenecks in a company’s ESG profile that reduce its appeal to re-sponsible investors.

Secondly, the decomposition of the index into three components—potential, realized opportunities, and risk—transforms it from a static rating into a scenario-based management tool. By varying manageable factors (e.g., R&D expenditure, energy efficiency programmes, and staff training), management can forecast how these changes will affect the final index and, consequently, key performance metrics (ROIC and Tobin’s Q). This allows investment projects to be prioritized not only by their conventional NPV but also by their impact on the company’s long-term attractiveness.

Thirdly, for rapid preliminary screening, we propose a simplified version of the methodology comprising five to seven of the most informative indicators (return on invested capital, debt-to-EBITDA ratio, carbon intensity, fixed asset renewal rate, and current liquidity ratio). This version can be used at the initial screening stage for potential investment targets without the need for full data collection.

Fourthly, the entire computational procedure is algorithmized and can be implemented as an Excel-based model or a web application with automatic data updates from corporate systems and open sources. This reduces the computational burden and makes the methodology accessible to corporate finance departments that do not require in-depth expertise in multi-criteria analysis.

Finally, the results of the pilot application to two major Russian metallurgical companies (MMK and Severstal) demonstrate that the proposed index has predictive power with respect to ROIC at a lag of 1–2 years. This implies that regular monitoring of the index can serve as an early warning system for future changes in operational efficiency, allowing investment policy to be adjusted in a timely manner.

Thus, the methodology not only addresses academic interests for comprehensive assessment, but also provides a practical toolkit for informed investment decision-making under conditions of high uncertainty and an intensifying ESG agenda in the metallurgical industry. Further development of this research envisages the creation of an industry benchmark (based on data from 10–15 companies) and the adaptation of the methodology to related industries.

5.4. Limitations Related to Indicator Multicollinearity

To assess the potential redundancy of the selected indicators, a multicollinearity analysis was conducted using the Variance Inflation Factor (VIF). The VIF was calculated by sequentially regressing each explanatory variable against all other variables, with $VIF = 1 / (1 - R^2)$. The results, presented in Appendix E, revealed a high degree of interdependence among some indicators. The high-est VIF values were observed for labor productivity (x19, VIF = 3406), return on equity (x11, VIF = 2715), the share of premium products (x17, VIF = 2693), the book value of fixed assets (x21, VIF = 2594), and the share of recycled materials (x23, VIF = 2480).

The presence of high multicollinearity suggests that the original set of 30 indicators contains redundant information. This high multicollinearity is primarily attributable to

the logical interrelationships among indicators within each resource group. To address this limitation in future applications, we reduced the number of indicators to the most representative variables per resource group. For example:

- Return on equity (ROE, x11) for the profitability group;
- Current ratio (x2) for the liquidity group;
- Equity ratio (x7) for the financial stability group;
- Labor productivity (x19) and energy intensity (x20) for the production potential group;
- Share of premium products (x17) for the innovation potential group;
- Specific CO₂ emissions (x22) for the environmental potential group;
- Wage-to-subsistence minimum ratio (x25) for the social potential group;
- Inventory turnover (x28) for the business activity group.

To assess whether the high multicollinearity among the original indicators affects the main findings, we conducted a robustness check by recalculating the integral index using a reduced set of 10 of the most representative indicators (one to two from each resource group). The selection criteria for the reduced set are presented in Table 15.

Table 15. Selection of indicators for a reduced set.

Resource Group	Excluded Indicators (VIF)	Retained Indicator (VIF)	Rationale
Liquidity	x1 (175), x3 (234), x4 (52), x5 (126)	x2—Current ratio (292)	Most representative liquidity measure
Financial stability	x6 (850), x8 (369)	x7—Equity ratio (838); x9—Interest coverage ratio (7.71)	Reflect capital structure and debt service capacity
Profitability	x10 (877), x12 (375), x13 (424), x14 (440)	x11—ROE (2715)	Key efficiency metric for investors
Innovation	x15 (N/A), x16 (N/A)	x17—Share of premium products (2693)	Reflects innovation outcomes
Production	x18 (121), x21 (2594)	x19—Labor productivity (3406); x20—Energy intensity (395)	Key operational efficiency metrics
Environmental	x23 (2480), x24 (642)	x22—Specific CO ₂ emissions (181)	Key ESG metric for metallurgy
Social	x26 (1755), x27 (77)	x25—Wage-to-subsistence minimum ratio (389)	Reflects social policy
Business activity	x29 (41), x30 (70)	x28—Inventory turnover (111)	Core asset management efficiency metric

Source: compiled by the authors.

The correlation between the original index (based on 30 indicators) and the reduced index was 0.75 (see Table 16), indicating that the reduction is not trivial and substantially alters the properties of the index. Within Table 16, there are the following indicators: IA0—taking into account data on investment potential for 30 indicators; IA1—taking into account data on investment potential for a reduced pool of indicators.

Table 16. Comparing IA0 and IA1.

Company	Mean IA0	Mean IA1	Correlation	Mean Absolute Deviation
MMK	0.38	0.55	0.72	0.17
Severstal	0.41	0.49	0.78	0.12
Pooled sample	0.39	0.52	0.75	0.15

Source: compiled by the authors.

Furthermore, panel regressions with the reduced index yielded coefficients with opposite signs compared to the original specification for most dependent variables (see Table 17, suggesting that the excluded indicators contain information that is essential for capturing investment attractiveness.

Table 17. Comparison of panel regressions.

Dependent Variable	Coefficient (IA_old)	p-Value	Coefficient (IA_new)	p-Value	Change
ROIC	+2.88	<0.001	−0.47	<0.001	Sign changed
EVA	$+5.97 \times 10^8$	<0.001	-5.85×10^7	<0.001	Sign changed
MVA	$+1.44 \times 10^{12}$	0.002	-7.90×10^{11}	<0.001	Sign changed
Q_Tobin	+2.49	0.008	−1.81	<0.001	Sign changed
P_BV	−22.41 (not significant)	0.115	−37.96	<0.001	Strengthened negative relationship
EVA/EBITDA	+8.02 ($p = 0.077$)	0.077	+10.26	<0.001	Strengthened positive relationship

Source: compiled by the authors.

These results suggest that each of the 30 indicators contributes unique information to the assessment of investment potential and that high VIF values reflect logical interrelationships within resource groups rather than statistical redundancy. Consequently, we retain the full set of 30 indicators in the main analysis, while acknowledging that a simplified version may be developed for practical applications, as suggested in Section 5.3.

5.5. Methodological Limitations and Sample Size Constraints

It should be acknowledged that the empirical basis of this study is limited to two of the largest metallurgical companies in Russia—the PJSC Magnitogorsk Iron and Steel Works (MMK) and PJSC Severstal. Although the time horizon covers 16 years (2010–2025), providing a sufficient number of observations for analyzing the dynamics of each company, the number of cross-sectional units remains extremely limited. This imposes certain constraints on the application of standard panel methods, in particular the use of firm and year fixed effects, which—with only two companies—leave very little independent variation for statistical inference.

In this regard, we emphasize that the presented results are pilot and illustrative in nature. The primary value of the study lies not in statistical generalization to the entire industry, but in demonstrating the operational viability of the proposed methodology and its internal consistency using two enterprises that, by virtue of their size, vertically integrated structure, and global positions, are representative of the Russian metallurgical market. The proposed approach can be adapted and tested on other industry enterprises following appropriate calibration.

To overcome this limitation, future research envisages expanding the sample to 10–15 companies, including enterprises from other leading metallurgical countries (China, India, and Brazil), which would allow for testing the external validity of the methodology and obtaining more robust statistical conclusions. Until then, all findings should be regarded as preliminary and subject to confirmation on an expanded sample.

In addition to the sample size constraints, the cross-correlation analysis employed to assess the temporal structure of the relationships between IA and ROIC does not, by itself, establish causality or predictive power. The maximum correlation occurs at zero lag, indicating a synchronous relationship. While positive correlations at positive lags may suggest a potential leading tendency, confirmation would require more rigorous methods,

such as Granger causality tests or Vector Autoregression (VAR) models with out-of-sample forecasting. Therefore, any inferences regarding the predictive capacity of the index should be treated as preliminary and subject to further validation.

Similarly, the limited sample size constrains the power of the CUSUM test used to assess the stability of the identified relationships. With only 16 annual observations per firm, the test has limited ability to detect structural breaks, particularly in the presence of gradual changes or multiple breaks. Consequently, the failure to reject the null hypothesis of no structural break should not be equated with proof of stability. Rather, it simply indicates that no significant breaks were detected within the observed period. Any claims regarding the stability of the relationships or their extrapolation to other contexts would require longer time series or more powerful testing procedures.

6. Conclusions

Assessing investment attractiveness is important for improving the efficiency of an enterprise's investment activities. In the two case studies presented, the methodology demonstrates its potential for assessing a metallurgical enterprise's ability to implement sustainable projects. However, further validation on an expanded sample is required to confirm its broader applicability. Although our analysis is based on two companies, their size within the Russian metallurgy sector, their vertically integrated structure, and their global position make them relevant cases for pilot testing of the proposed methodology. This provides a foundation for future research with an expanded sample.

Within the framework of these companies, the categories of the investment environment—the concepts of investment potential, investment attractiveness, and investment climate—were examined. To verify the stability of the investment potential values within the investment attractiveness indicator, a weight sensitivity analysis was carried out. This analysis revealed a low average deviation value for all studied weight variation scenarios and the high robustness of the model for the chosen weight assignment methodology.

To assess changes in the value-based indicators of investment attractiveness for both companies, an elasticity analysis of the EVA indicator was conducted. For MMK, it was found that the evolution of EVA elasticity with respect to WACC clearly reflects a transition from financial stability to crisis sensitivity and then to a post-crisis anomaly. For an investor, this means that traditional assumptions about the low significance of financial leverage are no longer relevant, and forecasting must account for the possibility of an inversion of the fundamental relationships between the cost of capital and the company's created value. For Severstal, it was determined that the company gains more from NOPAT growth than it loses from its decline and simultaneously gains more from a decrease in WACC than it loses from its increase. Such a configuration is a sign of a balanced financial–operational profile, where both factors work in favor of shareholder value.

The following hypotheses regarding the financial performance of the studied companies were confirmed:

A statistically significant positive relationship exists between the authors' investment attractiveness indicator and classical indicators of investment attractiveness (ROIC, EVA, and MVA), as well as Tobin's Q. The relationship with P/BV was not statistically significant in the current specification.

Changes in investment attractiveness lead the dynamics of ROIC, allowing it to be used as a predictor of future efficiency.

The identified relationship is stable over time and not subject to structural breaks, despite external shocks.

Decomposition of investment attractiveness into its components (investment potential, opportunities, and risk) made it possible to identify the contribution of each factor to variations in the indicator, thereby providing a basis for scenario forecasting.

Thus, the results obtained for these two companies may serve as a preliminary foundation for further studies transitioning from a retrospective assessment of investment attractiveness to forecasting based on key company performance indicators, subject to validation on an expanded sample. The statistically significant relationship between the authors' indicator (IA) with the return on invested capital (ROIC) and Tobin's Q indicates that investment attractiveness integrates information on investment potential, realized opportunities, and risks into a single metric that is consistent with both operational efficiency and market expectations. The relationship with P/BV was not statistically significant in the current specification, which may reflect the strong influence of accounting policies and market volatility on book-value multipliers. The identified temporal structure of the relationships (the presence of positive cross-correlations at lags of 1–2 years for ROIC and a lag of 3 years for Tobin's Q) suggests a potential leading tendency of investment attractiveness relative to classical indicators. However, this finding is preliminary and requires confirmation through more robust econometric methods, such as Granger causality tests or Vector Autoregression models with out-of-sample forecasting, before it can be used as a basis for constructing predictive models.

Decomposition of investment attractiveness into its components (potential, opportunities, and risk) makes it possible to identify the sources of its changes and to model forecasts through targeted variation. The CUSUM test did not reveal structural breaks throughout the entire observation period, suggesting that the formulated patterns are not merely random within the studied sample. However, given the limited power of the test, with only 16 observations per firm, this finding should not be interpreted as definitive evidence of stability. Extrapolation to other companies or into the future would require further validation on expanded datasets using more powerful testing procedures. However, given the limited sample size, extrapolation to other companies requires further validation on an expanded dataset. Taken together, these results suggest that the proposed methodological indicator has the potential to be used in decision support systems focused on forecasting the investment attractiveness of metallurgical enterprises, subject to further validation on an expanded sample. Future research should focus on the development of econometric forecasting models, related to the development and implementation of sustainable investment policies of metallurgical enterprises. Further research will involve the development of econometric forecasting models (including panel VAR models, models with lag structures, and non-linear specifications) with the aim of quantitatively assessing the impact of changes in potential, opportunities, and risk on future values of investment attractiveness and, consequently, on ROIC, Tobin's Q, and P/BV.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Dynamics of private potential components for PJSC Magnitogorsk Iron and Steel Works in the period from 2010 to 2025.

Code	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
x1	0.31	0.3	0.2	0.1	0.2	0.3	0.3	0.4	0.5	0.7	0.5	0.3	1.0	0.8	0.8	0.3
x2	3.1	3.0	1.6	1.1	1.4	1.4	1.8	1.7	1.7	1.7	1.4	1.6	1.8	1.7	2.0	2.2
x3	1.7	1.8	1.0	0.5	0.8	0.9	1.1	1.0	1.1	1.1	1.0	1.1	1.4	1.3	1.4	1.0
x4	0.6	0.2	0.4	0.6	0.6	0.7	1.2	0.9	1.1	1.0	0.5	1.0	0.8	0.4	0.7	0.5
x5	0.7	0.7	0.4	0.1	0.3	0.3	0.4	0.4	0.4	0.4	0.3	0.4	0.5	0.4	0.5	0.6
x6	1.3	0.9	0.9	1.3	0.2	0.2	1.0	0.8	0.6	0.6	0.4	0.5	0.8	0.7	1.1	1.3
x7	0.6	0.6	0.6	0.5	0.4	0.5	0.7	0.7	0.6	0.6	0.6	0.6	0.7	0.7	0.8	0.8
x8	0.7	0.6	0.7	0.6	0.5	0.7	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9
x9	22.7	−0.5	3.6	−13.6	0.5	8.4	25.2	64.4	97.0	45.5	36.8	144.6	21.7	39.2	42.6	15.8
x10	0.3	0.0	0.1	−0.3	0.0	0.2	0.3	0.3	0.3	0.2	0.2	0.5	0.1	0.3	0.2	0.1
x11	0.1	0.0	0.0	−0.4	0.0	0.2	0.3	0.3	0.3	0.2	0.2	0.6	0.1	0.2	0.2	0.0
x12	0.2	0.0	0.0	−0.2	0.0	0.1	0.2	0.2	0.2	0.1	0.1	0.4	0.1	0.2	0.1	0.0
x13	0.2	0.0	0.0	−0.2	0.0	0.1	0.2	0.2	0.2	0.1	0.1	0.3	0.1	0.2	0.1	0.0
x14	0.2	0.0	0.1	−0.2	0.0	0.2	0.3	0.3	0.3	0.2	0.2	0.5	0.1	0.2	0.2	0.0
x15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
x16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
x17	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4
x18	1.0	1.0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0	0.9	1.0	0.9	0.9
x19	48.9	51.2	55.0	54.1	61.7	62.7	65.7	66.7	68.2	67.7	64.9	75.2	67.7	76.3	67.3	53.8
x20	27.2	26.3	26.1	24.9	22.9	22.4	22.0	22.1	21.4	22.5	21.9	24.7	27.7	25.2	25.6	25.8
x21	148.4	156.1	151.5	131.9	123.0	109.2	112.6	131.9	153.5	170.3	186.5	231.9	307.1	346.2	371.9	365.1
x22	2.4	2.4	2.4	2.4	2.4	2.2	2.2	2.2	2.1	2.1	2.2	2.0	2.2	2.0	2.2	1.8
x23	0.60	0.71	0.69	0.67	0.66	0.67	0.69	0.70	0.69	0.68	0.65	0.65	0.62	0.64	0.61	0.62
x24	0.02	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.04	0.03	0.02	0.02
x25	5.0	5.5	5.6	5.6	5.5	5.3	4.4	4.6	4.6	4.7	5.6	5.3	4.9	5.4	5.4	5.5
x26	420.0	460.0	480.0	490.0	500.0	624.9	561.9	679.7	694.4	591.6	593.1	1003.4	1065.9	1396.4	1700.0	1220.0
x27	0.6	0.7	0.5	0.6	0.3	0.4	1.9	2.0	1.0	0.9	0.7	0.6	0.5	0.8	0.5	0.5
x28	4.7	7.3	6.6	6.7	6.7	6.0	6.2	6.3	6.0	6.5	5.8	7.6	6.7	6.5	5.9	5.5
x29	4.1	5.6	4.7	6.0	9.7	9.7	9.5	9.4	9.6	9.5	9.5	12.1	8.1	8.2	6.8	6.0
x30	103.7	79.1	88.8	67.1	44.1	48.4	45.6	37.3	24.4	17.4	5.3	3.5	24.0	39.8	47.5	53.0

Source: Sustainability Report of the PJSC Magnitogorsk Iron and Steel Works, Interfax-Center for Corporate Information Disclosure [88,89].

Appendix B

Table A2. Dynamics of indicators for risk calculations in the period from 2010 to 2025.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Indicators for Calculating External Risks																
Steel price, thousand RUB	21.5	26.5	24.0	23.0	25.0	32.5	37.5	35.0	40.0	45.0	50.0	67.0	56.5	65.0	75.0	50.0
USD exchange rate	30.4	29.4	31.1	31.9	38.4	61.0	67.0	58.4	62.7	64.7	72.2	73.7	68.6	85.3	92.6	83.6
Key interest rate	7.8	8.0	8.3	8.3	8.0	12.0	10.5	9.0	7.4	7.2	5.0	5.5	12.0	8.5	16.5	19.0

Table A2. Cont.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Indicators for Calculating External Risks																
Apparent steel consumption, million tonnes	37.0	42.0	41.0	41.5	42.0	40.4	38.7	40.0	41.0	43.6	42.5	43.8	42.0	46.2	43.7	37.1
Sanctions	0.00	0.00	0.00	0.00	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	1.00	1.00	1.00	1.00
MET (Mineral Extraction Tax)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.50	0.50	1.00
Inflation	1.09	1.06	1.07	1.07	1.11	1.13	1.05	1.03	1.04	1.03	1.05	1.08	1.12	1.07	1.10	1.08
Ratio of electricity tariffs (current year/previous year)	1.12	1.11	1.12	1.12	1.06	1.08	1.08	1.05	1.05	1.05	1.04	1.05	1.09	1.09	1.09	1.09
Ratio of natural gas prices (current year/previous year)	1.15	1.14	1.15	1.15	1.04	1.08	1.03	1.04	1.03	1.01	1.03	1.03	1.09	1.08	1.11	1.10
Ratio of railway tariffs (current year/previous year)	1.08	1.08	1.08	1.07	1.10	1.10	1.09	1.05	1.05	1.05	1.05	1.07	1.11	1.10	1.10	1.13
Weighted deviations for the current year	0.11	0.10	0.10	0.10	0.07	0.09	0.07	0.04	0.04	0.04	0.04	0.05	0.10	0.09	0.10	0.11
Indicators for calculating internal risks for MMK																
Iron ore self-sufficiency	0.30	0.30	0.22	0.19	0.19	0.19	0.27	0.19	0.19	0.20	0.20	0.18	0.16	0.15	0.14	0.14
Scrap self-sufficiency	1.00	0.00	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.42	0.64	0.00
Coal self-sufficiency	0.40	0.36	0.36	0.37	0.39	0.40	0.37	0.38	0.37	0.00	0.00	0.00	0.40	0.51	0.51	0.00
Average age of employees	39	39	39	39	39	39	39	39	40	40	42	41	41	41	41	41
Population of main factory (thousand)	408	408	408	410	412	415	417	418	418	417	413	413	411	409	409	408
Average headcount	24.99	21.89	21.22	21.65	19.32	18.76	18.08	17.96	17.88	17.66	17.13	16.9	16.58	16.34	16.65	18.60
Debt/EBITDA	2.69	32.39	6.81	−1.98	6.00	1.68	0.41	0.28	0.21	0.16	0.39	0.16	−0.10	−0.06	−0.01	0.61
Indicators for calculating internal risks for Severstal																
Iron ore self-sufficiency	1.00	1.10	1.00	1.00	1.00	1.00	1.10	1.30	1.30	1.30	1.30	1.30	1.00	1.00	1.00	1.00
Scrap self-sufficiency	1.00	0.00	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.42	0.64	0.00
Coal self-sufficiency	0.40	0.36	0.36	0.37	0.39	0.40	0.37	0.38	0.37	0.00	0.00	0.00	0.40	0.51	0.51	0.00
Average age of employees	41.00	42.00	42.00	42.00	42.00	41.50	41.50	41.00	41.50	41.50	42.00	42.00	42.00	42.50	42.50	42.00
Population of main factory (thousand)	309	313	315	316	317	318	319	319	318	317	315	305	301	299	298	408
Average headcount	79,212	69,583	67,297	61,360	50,567	49,462	49,667	50,679	52,221	53,832	49,800	50,000	48,000	46,113	50,553	49,990
Debt/EBITDA	2.69	32.39	6.81	−1.98	6.00	1.68	0.41	0.28	0.21	0.16	0.39	0.16	−0.10	−0.06	−0.01	0.61

Source: compiled by the authors.

Appendix C

Table A3. Dynamics of private potential components for PJSC Severstal in the period from 2010 to 2025.

Code	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
x1	0.5	0.4	0.3	0.3	1.0	0.6	0.6	0.4	0.2	0.6	0.3	0.1	1.0	1.2	0.5	0.2
x2	1.6	1.5	0.8	1.0	2.0	1.1	1.2	1.0	1.5	1.5	0.9	0.8	1.7	1.8	1.1	0.7
x3	0.9	0.8	0.5	0.6	1.6	0.9	0.8	0.7	0.8	1.0	0.7	0.6	1.3	1.4	0.7	0.3
x4	0.2	0.1	0.2	0.4	0.4	0.3	0.6	0.5	1.4	0.9	0.4	0.6	0.6	0.3	0.4	0.2
x5	0.4	0.4	−0.2	0.0	0.5	0.1	0.1	0.0	0.4	0.3	−0.1	−0.3	0.4	0.4	0.1	−0.5
x6	1.2	1.2	1.0	1.6	−0.3	−0.4	0.1	0.4	0.8	0.1	0.5	0.4	0.3	0.1	0.5	2.4
x7	0.6	0.6	0.4	0.5	0.3	0.3	0.3	0.4	0.5	0.4	0.4	0.4	0.6	0.6	0.6	0.7
x8	0.7	0.7	0.6	0.6	0.3	0.4	0.4	0.6	0.5	0.5	0.6	0.7	0.8	0.9	0.8	0.9
x9	4.2	1.1	2.5	2.0	5.2	4.9	32.0	110.8	138.6	15.5	15.8	38.6	17.7	26.7	15.1	15.4
x10	0.3	0.1	0.1	0.1	0.2	0.3	0.5	0.5	0.4	0.3	0.4	0.6	0.4	0.4	0.3	0.2
x11	0.1	0.0	0.1	0.0	0.1	0.3	0.6	0.7	0.7	0.6	0.6	1.0	0.4	0.3	0.3	0.2
x12	0.1	0.0	0.0	0.0	0.0	0.1	0.2	0.3	0.3	0.2	0.2	0.5	0.2	0.2	0.1	0.1
x13	0.2	0.0	0.1	0.0	0.1	0.1	0.3	0.4	0.3	0.2	0.3	0.4	0.3	0.2	0.2	0.2
x14	0.1	0.0	0.1	0.0	0.1	0.1	0.2	0.3	0.3	0.3	0.3	0.6	0.3	0.2	0.2	0.2
x15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
x16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
x17	40.0	41.5	44.0	48.0	49.0	47.0	46.0	46.0	47.5	46.0	44.0	46.0	44.0	49.0	52.0	49.4
x18	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9	1.0	1.0	0.9
x19	224.0	226.6	221.8	222.8	226.0	290.2	288.0	294.0	313.0	318.5	278.6	293.5	286.3	307.0	279.2	288.0
x20	23.9	23.5	23.5	23.0	22.6	22.2	22.0	22.0	22.2	22.5	26.5	28.6	30.8	30.0	30.0	30.2
x21	63.4	73.8	78.7	80.5	80.4	80.4	86.4	90.5	99.1	130.6	186.0	213.8	226.7	234.2	286.1	397.2
x22	2.1	2.0	2.2	2.2	2.2	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.2	2.0	2.2	2.1
x23	0.31	0.30	0.32	0.32	0.32	0.31	0.32	0.31	0.30	0.29	0.32	0.30	0.32	0.34	0.31	0.32
x24	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
x25	6.9	7.2	7.3	7.1	7.1	5.0	6.1	6.4	5.8	5.7	5.6	5.9	5.9	6.6	6.8	7.0
x26	20	23	26	30	35	53	55	60	100	150	170	190	210	274	452	480
x27	1.1	1.4	1.3	1.3	1.4	1.0	1.0	1.0	0.8	0.6	0.7	0.7	0.7	0.6	0.4	0.4
x28	6.5	6.1	5.9	6.5	6.2	6.2	6.4	7.0	6.8	7.4	6.9	7.7	6.0	5.4	5.5	5.9
x29	6.3	9.0	9.6	9.9	7.4	7.2	9.3	12.0	12.2	10.8	9.9	11.9	8.0	11.8	12.5	11.4
x30	56.5	37.1	32.8	28.1	36.4	38.3	33.1	30.3	37.5	37.2	28.2	16.1	19.4	24.3	9.6	−9.1

Source: Annual reports of PJSC Severstal [90].

Appendix D

Table A4. Data for calculating panel regression.

Company	Year	IP	EVA	ROIC	MVA	EVA/EBITDA	Debt_EBITDA	P_BV	Q_Tobin
Severstal	2010	0.34	37,049,316	0.57	133,190,760,614	0.68	2.07	1.69	1.19
Severstal	2011	0.28	393,715	0.14	208,410,543,791	0.03	8.8	2.11	1.37
Severstal	2012	0.3	18,276,933	0.31	133,947,965,633	0.66	6	1.69	1.16
Severstal	2013	0.4	4,126,507	0.18	113,639,692,449	0.24	8.98	1.88	1.43
Severstal	2014	0.27	26,443,719	0.42	167,706,808,719	0.66	4.89	2.4	1.33
Severstal	2015	0.34	42,644,024	0.49	405,333,582,046	0.62	3.07	3.81	2.03
Severstal	2016	0.49	111,297,901	1.13	434,195,867,585	0.93	1.66	3.16	2.19
Severstal	2017	0.45	148,172,708	1.3	482,114,058,253	0.91	0.94	3.08	2.07
Severstal	2018	0.49	141,862,182	1.1	576,013,518,945	0.88	0.99	3.34	2.2
Severstal	2019	0.47	121,954,539	0.79	581,044,924,027	0.86	1.4	3.38	2.16
Severstal	2020	0.45	119,692,435	0.63	560,872,472,658	0.81	1.43	3.29	2.03
Severstal	2021	0.44	329,453,314	1.35	959,686,260,596	0.98	0.66	3.63	2.42

Table A4. *Cont.*

Company	Year	IP	EVA	ROIC	MVA	EVA/EBITDA	Debt_EBITDA	P_BV	Q_Tobin
Severstal	2022	0.36	138,708,076	0.72	334,287,239,726	0.66	0.14	1.73	1.19
Severstal	2023	0.49	185,586,135	0.87	413,443,210,475	0.8	−0.53	1.73	1.18
Severstal	2024	0.46	93,713,480	0.58	644,712,707,638	0.49	0.43	2.07	1.55
Severstal	2025	0.42	53,830,796	0.34	283,743,462,649	0.32	0.71	1.45	1.19
MMK	2010	0.35	7,058,404	0.16	122,395,793,172	0.24	1.63	2.69	1.16
MMK	2011	0.26	−33,999,971	−0.02	65,676,476,070	−9.95	1.35	32.39	0.94
MMK	2012	0.27	−13,253,112	0.07	−66,239,395,108	−0.93	0.66	6.81	0.55
MMK	2013	0.26	−69,266,863	−0.34	−35,607,072,319	1.36	0.72	−1.98	0.85
MMK	2014	0.22	−33,627,169	0.01	−34,609,889,825	−1.65	0.71	6	0.62
MMK	2015	0.3	14,587,884	0.22	49,583,217,229	0.23	1.34	1.68	0.88
MMK	2016	0.34	49,042,416	0.46	95,652,149,366	0.47	1.48	0.41	1.04
MMK	2017	0.35	49,255,807	0.43	194,653,641,498	0.5	1.84	0.28	1.26
MMK	2018	0.41	48,646,578	0.39	270,462,047,767	0.43	2.1	0.21	1.42
MMK	2019	0.41	35,958,895	0.3	227,645,299,941	0.42	1.93	0.16	1.26
MMK	2020	0.39	34,922,783	0.27	210,344,246,478	0.42	1.86	0.39	1.21
MMK	2021	0.44	196,015,469	0.8	345,997,894,363	0.68	1.95	0.16	1.35
MMK	2022	0.35	−21,272,506	0.14	−39,128,790,600	−0.23	0.91	−0.1	0.62
MMK	2023	0.45	34,395,120	0.28	−58,649,357,733	0.19	0.9	−0.06	0.6
MMK	2024	0.44	−25,593,036	0.21	−55,624,327,396	−0.16	0.91	−0.01	0.68
MMK	2025	0.35	−64,342,196	0.05	−254,745,749,279	−0.88	0.59	0.61	0.51

Source: compiled by the authors.

Appendix E

Table A5. Variance Inflation Factor (VIF) analysis results.

Variable	Indicator	VIF	Recommendation
x1	Absolute liquidity ratio	175.22	Exclude
x2	Current ratio	292.19	Keep (representative)
x3	Quick ratio	233.70	Exclude
x4	Operating solvency ratio	52.04	Exclude
x5	Working capital liquidity	125.84	Exclude
x6	Equity-to-working capital ratio	850.26	Exclude
x7	Equity ratio (autonomy)	838.27	Keep (representative)
x8	Long-term sources structure ratio	368.86	Exclude
x9	Interest coverage ratio	7.71	Keep
x10	Return on operating expenses	877.29	Exclude
x11	Return on equity (ROE)	2714.90	Keep (representative)
x12	Return on assets (ROA)	375.29	Exclude
x13	Net profit margin	423.91	Exclude
x14	Economic profitability (EBIT/Assets)	439.60	Exclude
x15	R&D expenses as % of revenue	N/A	Exclude (missing data)
x16	Share of patents and licenses in revenue	N/A	Exclude (missing data)
x17	Share of premium products	2692.63	Keep (representative)
x18	Capacity utilization	120.54	Exclude
x19	Labor productivity	3406.02	Keep (representative)
x20	Energy intensity of production	395.39	Keep (representative)

Table A5. Cont.

Variable	Indicator	VIF	Recommendation
x21	Book value of fixed assets	2594.02	Exclude
x22	Specific CO ₂ emissions	181.09	Keep (representative)
x23	Share of recycled materials	2479.94	Exclude
x24	Environmental program costs	641.54	Exclude
x25	Wage-to-subsistence minimum ratio	389.48	Keep (representative)
x26	Staff training costs	1755.49	Exclude
x27	Lost Time Injury Frequency Rate	76.95	Exclude
x28	Inventory turnover	111.00	Keep (representative)
x29	Receivables turnover	40.52	Exclude
x30	Cash conversion cycle	69.82	Exclude

Source: compiled by the authors.

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