COLOMBO SCIENTIFIC PUBLISHING

INTERNATIONAL JOURNAL OF ECONOMICS FINANCE & MANAGEMENT SCIENCE

E-ISSN: 2536-7897
P-ISSN: 2536-7889

DOI: - https://doi.org/10.55640/ijefms/Volume10Issue11-02 PAGE NO: 09-19

The RANKS Multi-Factor Rating Model for Undervalued Stock Selection

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A R T I C L E I N F O

Article history:

Submission: October 18, 2025
Accepted: November 16, 2025
Published: November 25, 2025
VOLUME: Vol.10 Issue 11 2025

Keywords:
multi-factor model, quantitative analysis, fundamental analysis, hybrid approach, stock selection, undervalued assets, alternative data, alpha-generating strategy.

ABSTRACT

As traditional stock valuation methods struggle with the complexity of modern financial markets, new frameworks are required. This paper presents the RANKS multi-factor rating model, a systematic tool for identifying undervalued public companies. The methodology is based on a hybrid "quantamental" approach, blending the depth of fundamental analysis with the discipline of quantitative algorithms. The model's architecture consists of seven blocks that evaluate over 150 financial, market, and corporate metrics across a universe of 55,000 global companies. A key distinction is its integration of non-traditional data, including operational and human capital indicators, for a more comprehensive assessment. Case studies are analyzed to evaluate the model's empirical effectiveness in generating alpha, positioning it as apractical implementation of advanced active investment strategies.

INTRODUCTION

The modern investor operates within a paradox: an unprecedented volume of available data is coupled with a decline in the predictive power of traditional analytical methods. While in the 20th century, analyzing a few key metrics like revenue, the price-to-earnings (P/E) ratio, and analyst consensus forecasts was sufficient for making investment decisions, today's markets are significantly faster, more complex, and informationally dense. Globalization, the intricacy of supply chains, the influence of geopolitical factors, and the instantaneous dissemination of information through digital channels have led to a situation where stock values are influenced by hundreds of interconnected variables. In this environment, relying on a limited set of classic indicators is not only ineffective but also fraught with increased risks, as it fails to provide a holistic view of a company's true financial health and prospects. The relevance of this study is driven by the need to develop and implement more sophisticated, systematic, and scalable analytical tools capable of processing large, heterogeneous datasets and identifying hidden patterns to make well-informed investment decisions.

Asset pricing theory has undergone significant evolution in its search for factors that explain security returns. The foundational Capital Asset Pricing Model (CAPM), developed in the 1960s, postulated a linear relationship between an asset's expected return and its systematic risk, measured by the beta (β) coefficient (Bender et al., 2013). However, empirical studies revealed anomalies that CAPM could not explain. This led to the development of the Arbitrage Pricing Theory (APT), which proposed that an asset's return is a function of multiple macroeconomic factors or market indices (Bender et al., 2013).

A breakthrough in this area was the work of Eugene Fama and Kenneth French, who in 1993 proposed a three-factor model that explained stock returns through three variables: market risk (beta), the size factor (the premium of small companies over large ones, SMB – Small Minus Big), and the value factor (the premium of undervalued stocks over overvalued ones, HML – High Minus Low) (Bender et al., 2013). Mark Carhart later expanded this model with a fourth factor–momentum (WML – Winners Minus Losers), reflecting the tendency of stocks that have performed well in the past to continue their upward trend (Bender et al., 2013). This research laid the groundwork for factor investing–an approach that involves intentionally constructing a portfolio to capture risk premiums beyond general market risk (Blitz, 2023; Blitz & Vidojevic, 2018).

Meanwhile, for decades, two opposing but equally successful philosophies have dominated investment practice. The first is fundamental analysis, most notably represented by Warren Buffett. His approach is based on a deep study of the business, an assessment of its intrinsic value, management quality, and long-term competitive advantages. A stock is viewed as a share in a business, and decisions are made based on common sense and long-term confidence in the company. The second philosophy is quantitative, or algorithmic, analysis, pioneered by mathematician James Simons. His fund, Renaissance Technologies, uses complex mathematical models to find statistical patterns and short-term market inefficiencies in vast amounts of data.

In recent years, a trend towards synthesizing these two paradigms has emerged, leading to the hybrid, or "quantamental," approach (Aw et al., 2014). This strategy aims to combine the depth and intuition of fundamental analysis with the discipline, scalability, and objectivity of quantitative methods (Aw et al., 2014; Traficanti, 2014). Quantamental models use algorithms to systematically process and filter thousands of stocks based on fundamental indicators, allowing analysts to focus on the most promising candidates for in-depth study (Aw et al., 2014; Traficanti, 2014; Robeco, 2024). The RANKS model, examined in this paper, is a prime example of such a hybrid approach, seeking to replicate the depth of manual analysis but with the speed and reproducibility of an algorithm.

The objective of this study is to present and conduct an academic analysis of the RANKS multi-factor rating model as a systematic tool for selecting undervalued stocks in modern stock markets.

To achieve this objective, the following tasks were formulated:

- To describe the theoretical foundations and methodological architecture of the RANKS model, based on a synthesis of fundamental and quantitative approaches.
- To analyze the structure of its seven evaluation blocks and the key parameters used for a comprehensive assessment of public companies.
- To investigate the role and significance of alternative data integrated into the model as a source of additional predictive power.
- To evaluate the empirical effectiveness of the model based on the presented case studies and to compare its stated returns with relevant market benchmarks.

The scientific novelty of this work lies in the formalization and analysis of a hybrid model that systematically integrates not only traditional financial and market indicators but also a wide range of semi-structured alternative data (e.g., human capital metrics, operational indicators, ownership structure data) to form a single, comparable investment rating. Unlike many academic models that focus on a limited set of factors, RANKS represent a comprehensive framework aimed at practical application in real-world investment processes.

Materials and Methods

This research is based on a qualitative methodology, which is most relevant for studying complex, context-dependent phenomena such as the architecture of a proprietary investment model. The work employs a combination of two key methods: constructive analysis and a systematic literature review.

Constructive analysis involves the deconstruction of the existing RANKS model, a detailed examination of its components, the logical connections between them, and their theoretical underpinnings. The analysis does not involve conducting new empirical tests but focuses on a critical assessment of the model's architecture, operating principles, and reported results.

A systematic literature review was employed to build the theoretical framework of the study and to contextualize the RANKS model within the field of contemporary academic developments. A targeted analysis of peer-reviewed scientific publications from databases such as Scopus, Web of Science, IEEE Xplore, SpringerLink, and the ACM Digital Library was conducted. The analysis was structured into several key thematic areas:

- Factor Investing Theories: Analysis of recognized factors ("value," "quality," "momentum," etc.) and the critique of the "factor zoo," which allows for an assessment of the theoretical validity of the parameters selected in the model.

- Hybrid ("Quantamental") Strategies: A review of academic papers on the advantages and challenges of synergizing fundamental and quantitative approaches to enhance stock selection effectiveness.
- Application of Machine Learning in Finance: Research into the use of algorithms (e.g., Random Forest, LSTM) to identify non-linear dependencies in financial data and their advantages over traditional linear models.
- Use of Alternative Data: Analysis of the role of non-traditional data sources (ESG ratings, HR data, operational metrics) in obtaining leading investment signals and assessing non-financial risks.

Thus, the research methodology ensures a synthesis of theoretical knowledge derived from academic literature and practical analysis drawn from the study of a real-world investment system. This allows for the achievement of the stated objective and ensures the high validity of the results.

Results and Discussion

1. Theoretical Foundations of the Model

The RANKS methodology is built on the synergy of two key investment paradigms. The first, fundamental analysis (the Warren Buffett paradigm), is rooted in the principles of value investing, which demand a deep understanding of the business behind the stock. The model incorporates factors traditionally used in fundamental analysis to assess a company's quality and value. These include the analysis of financial health (profitability metrics like ROA and ROE; debt levels, e.g., Debt/Equity; liquidity ratios), evaluation of dividend policy, and comparative valuation using multiples (P/E, P/S, etc.). This aspect of the model aligns with the academically recognized "Quality" and "Value" factors, which research has shown to have historically provided investors with a risk premium (Bender et al., 2013; Blitz, 2023; Bartram et al., 2021).

The second, quantitative analysis (the James Simons paradigm), is a quantitative approach that ensures systematicity, objectivity, and scalability. This is evident in the processing of large datasets across more than 150 parameters for tens of thousands of companies. The model utilizes algorithmic filters, data normalization, and factor weighting to produce a final rating. This approach helps to avoid behavioral biases inherent in human decision-making and ensures disciplined adherence to the strategy. In an academic context, this correlates with the development of quantitative stock selection strategies, including the application of machine learning methods to identify non-linear relationships in data (Cao et al., 2024; Wang, 2023; Duan et al., 2024).

Thus, the RANKS model is a practical implementation of a "quantamental" strategy, where quantitative methods serve to systematize and broaden coverage, while fundamental principles define the substantive content of the analyzed factors (Aw et al., 2014).

2. Data Sources for Model Construction

The effectiveness of any multi-factor model is directly dependent on the quality and diversity of the data used. The RANKS architecture is built upon a robust data pipeline that integrates information from premier financial data providers such as FactSet, Bloomberg, and Refinitiv Eikon. This ensures access to high-quality, standardized data across its entire coverage universe.

The model's database covers approximately 55,000 publicly traded companies from 139 countries and 158 industries, sourced from all major global exchanges, including but not limited to the New York Stock Exchange (NYSE), NASDAQ, London Stock Exchange (LSE), Euronext, Tokyo Stock Exchange (TSE), and Hong Kong Stock Exchange (HKEX).

The data sources used in the model can be classified as follows:

- Traditional Financial Data: Standardized company financial statements (IFRS, GAAP), including data from the balance sheet, income statement, and cash flow statement, as well as official filings with regulatory bodies like the U.S. SEC.
- Market Data: Information generated during stock market trading, such as historical and current stock quotes, trading volumes, volatility measures, price multiples (P/E, P/S, EV/EBITDA), and short interest data.

- Forecast Data: Aggregated expectations from the professional investment community, including consensus forecasts from leading investment banks on future financial performance and target stock prices.
- Corporate Data: Information disclosed by companies concerning their corporate policies, such as dividend payments, stock buyback programs, share capital structure, and insider trading activities.
- Alternative Data: A wide range of non-traditional, often unstructured data that can provide leading indicators of business health:
- ESG Data: Ratings from specialized aggregators assessing environmental, social, and governance aspects to evaluate non-financial risks.
- Operational Metrics: Industry-specific indicators like capacity utilization, warehouse throughput, or airline load factors, serving as real-time proxies for demand.
- Human Capital Metrics: Data on workforce dynamics, management turnover, and employee attrition, which can indicate internal stability and management effectiveness.
- Business Risk Data: Assessment of revenue dependency on major clients to identify concentration risks.

The technology stack for the product's development includes Python for backend services and data analysis, JavaScript (React/Vue.js) for the frontend user interface, and databases such as PostgreSQL and ClickHouse for efficient data storage and retrieval. This multi-faceted approach allows the model to perform data triangulation, where signals from one source can be confirmed or refuted by data from another, enhancing the overall robustness of the final assessment.

3. Architecture of the RANKS Multi-Factor Model

The central element of the RANKS methodology is its structured architecture, which decomposes a public company's complex activities into seven key analytical blocks. Each block evaluates a specific business aspect, from financial stability to market perception and corporate governance. This approach formalizes a complex analysis into a single, comparable scale.

Within each block, a set of relevant indicators is analyzed. Importantly, these individual metrics are assigned different weights based on their proven predictive power and relevance before being normalized to a 100-point scale and aggregated into a block score. The final company rating, the RANK Score, is formed by a weighted combination of the scores from all seven blocks, with the first four fundamental blocks (Growth, Financials, Valuation, Dividends) typically having a higher aggregate weight than the latter three (Forecasts, Risks, ESG).

The weighting mechanism within the RANKS model employs a hybrid methodological approach. Initially, the selection of factors is grounded in fundamental investment theory and expert judgment to ensure economic rationale. Subsequently, the specific weights for each of the 150+ parameters are calibrated through rigorous empirical validation and iterative back-testing on historical datasets. This process ensures that factors with higher predictive power for future stock returns are assigned greater influence in the final RANK Score, adapting the model to changing market dynamics.

The structure and expanded components of the model are presented in Table 1.

Table 1. Structure and Components of the RANKS Evaluation Blocks (compiled by the author)

#	Block Name	Evaluation Goal	Key Parameters and Metrics
1	**Financial Position**	To determine current financial health and stability.	Profitability (ROA, ROE, ROIC, Net Profit Margin), Leverage (Net Debt/EBITDA, Debt/Equity), Liquidity (Current Ratio, Quick Ratio), Free Cash Flow (FCF) Yield.
2	**Value**	To compare the company's market valuation against peers and historical levels.	Price Multiples (P/E, P/S, P/BV), Enterprise Value Multiples (EV/EBITDA, EV/Sales), Price-to-Free-Cash-Flow (P/FCF).
3	**Business Growth**	To assess the pace and	Revenue/Net Income/Assets Growth (CAGR over

	Dynamics	stability of company scaling.	1, 3, 5 years), Asset Turnover, Diluted EPS Growth.
4	**Analyst' Forecasts**	To aggregate market expectations for the company's future results.	Consensus EPS growth forecast, target price, distribution of recommendations (Buy/Hold/Sell), and Forward P/E.
5	**Dividends**	To evaluate the dividend policy and its attractiveness to shareholders.	Dividend Yield, Payout Ratio, Dividend per Share, history and stability of payments, and stock buybacks.
6	**Speculative Risks**	To measure market sentiment and potential pressure on stock prices.	Short Interest Level, historical and implied volatility.
7	**Ethics (ESG)**	To assess non-financial risks and alignment with sustainable development principles.	Integrated ESG ratings, analysis of individual components (environmental, social, governance).

The logical flow of the model is illustrated in Figure 1. The architecture consists of a central AI-driven core ('RANKS Core') that aggregates data from the seven analytical blocks. Each block (Financial Position, Valuation, Growth, etc.) contributes a weighted score to the core, which then synthesizes these inputs to generate the final RANK Score for each company."

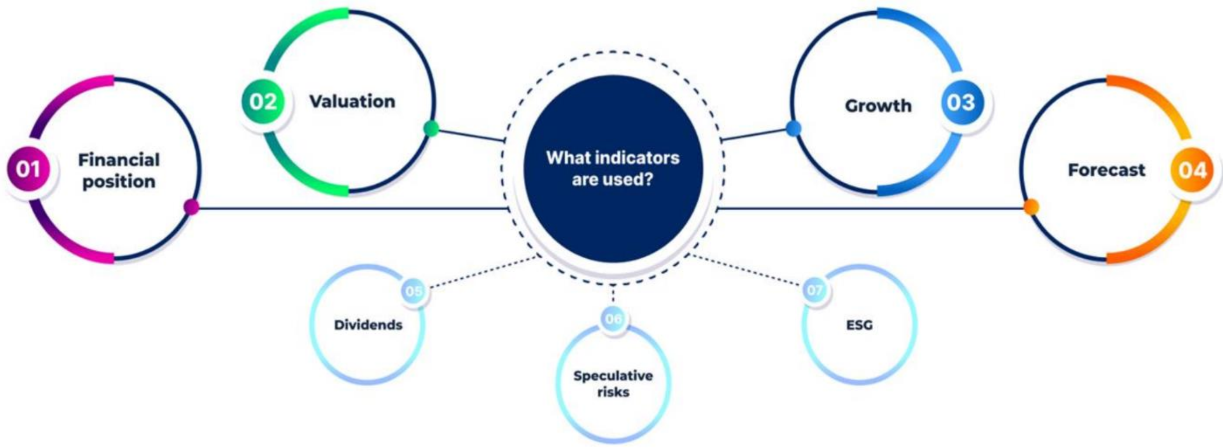


Figure 1. The RANKS Model Architecture: From Data Blocks to Final Score

4. In-Depth Factor Analysis: A Case Study Approach

To illustrate the model's practical application and granular analytical capabilities, this section provides a detailed analysis of RANKS research reports for two distinct companies: PJSC MMC Norilsk Nickel (GMKN), a Russian metals and mining giant, and Microsoft Corp. (MSFT), a U.S. technology leader. These cases demonstrate how the model synthesizes vast amounts of data into actionable insights, highlighting both strengths and weaknesses across its seven-block framework.

Norilsk Nickel received an high overall RANK Score of 99%, indicating a superior profile driven by high scores in fundamental blocks: Financial Position (90%), Growth Dynamics (87%), Dividends (96%), and a strong Valuation score (80%). The model identifies robust financial health as a cornerstone of this high rating. A key driver is the company's high profitability relative to its peers; as shown in Figure 2, Norilsk Nickel's Return on Assets (ROA) consistently and significantly outperforms the industry median, indicating highly efficient use of its asset base to generate profit. In 2022, its ROA was 29.86% compared to an industry median of just over 10%, complemented by an exceptionally high EBITDA Margin of 60.92% (RANKS, n.d.).

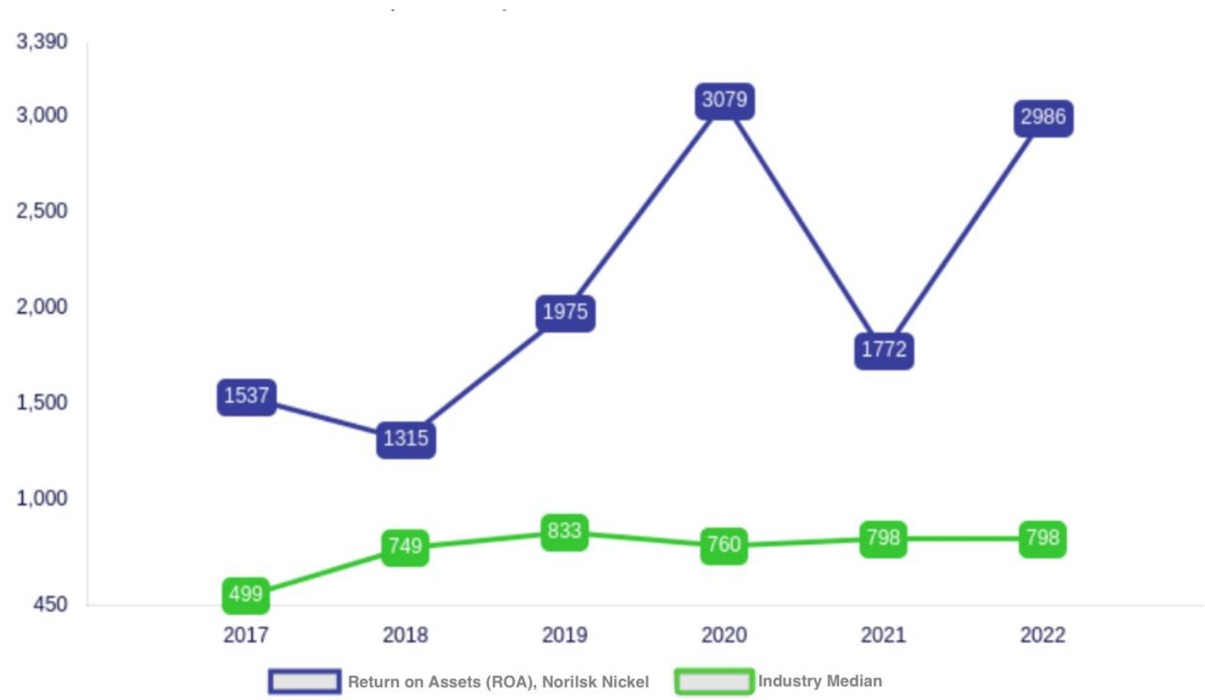


Figure 2. Return on Assets (ROA), Norilsk Nickel vs. Industry Median (RANKS, n.d.)

However, the model also flags its comparatively high leverage, with a Total Debt to Total Equity ratio of 258.76% in 2022. The company's powerful cash flow, evidenced by an Interest Coverage Ratio of 40.95, mitigates this risk, leading the model to weigh profitability more heavily and assign an excellent final score for this block. Turning to its valuation, the high score of 80% is primarily driven by metrics suggesting undervaluation relative to its earnings and cash flow. The 2022 P/E ratio of 7.32 was significantly below the industry median of 12, and as seen in Figure 3, GMKN's P/FCF ratio of 6.86 was also substantially lower than the industry median of 9.22, suggesting the stock is cheap relative to the cash it generates. At the same time, the model provides a nuanced view by highlighting that the P/BV ratio of 11.6 is significantly elevated, preventing a simplistic conclusion of uniform undervaluation (RANKS, n.d.).

Figure 3. P/FCF Norilsk Nickel vs. Industry Median (RANKS, n.d.)

Microsoft Corp. presents a different profile, with a good but not perfect RANK Score of 77%. The model awards an outstanding score for its Financial Position (94%) and strong scores for Forecasts (82%) and ESG (78%). Microsoft's financial strength is robust, with a Net Margin of 36.45%, a negative Net Debt/EBITDA ratio of -0.73 (indicating more cash than debt), and high-percentile efficiency metrics like an ROE of 43.15% and ROIC of 31.35% (RANKS, n.d.).

However, the model clearly identifies the primary weaknesses: Valuation, which scores a low 30%, and Dividends, scoring only 16%. The low Valuation score provides an objective, data-driven counterpoint to market enthusiasm. As seen in Figure 4, Microsoft's P/E ratio has trended significantly above the industry average, culminating in a reading of 41.8 in 2022 and confirming its overvalued status. This is further supported by a high P/S ratio of 12.1 and a P/BV ratio of 17.8. The model also assigns a "very weak" score to its dividend policy; while the dividend is growing, the Dividend Yield is a mere 0.67%, making it unattractive for income-seeking investors (RANKS, n.d.).

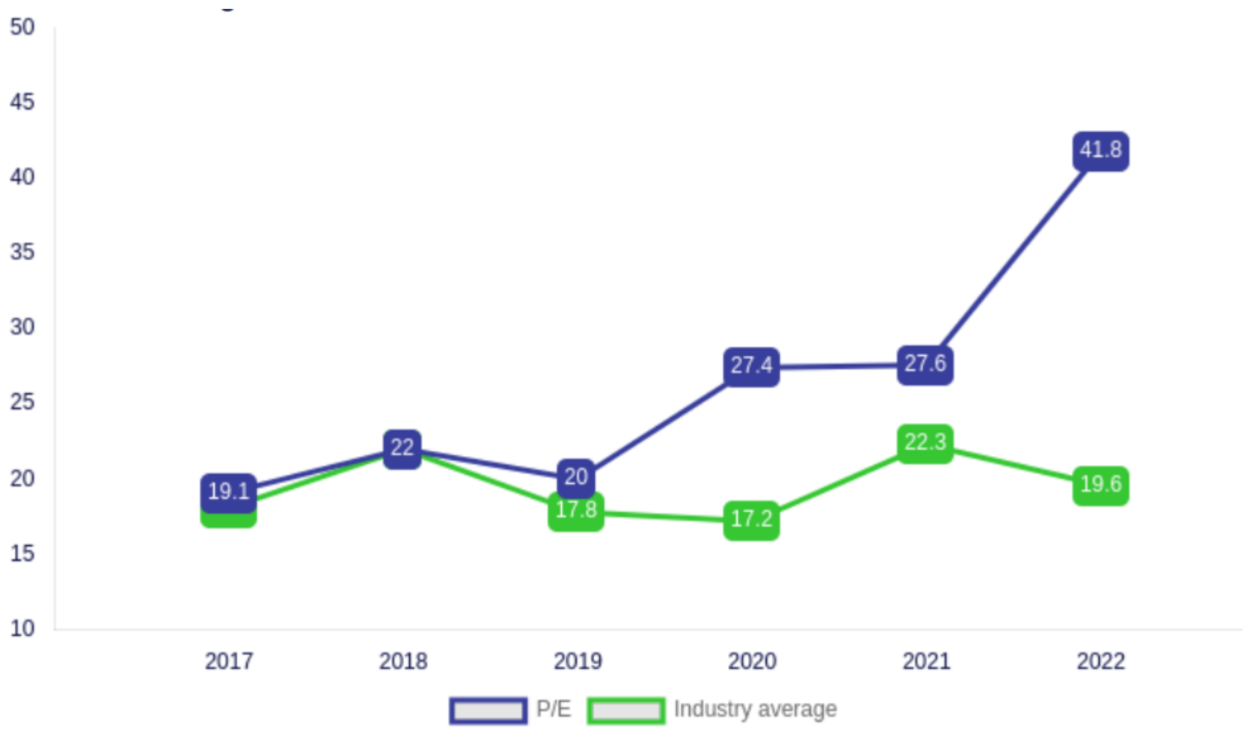


Figure 4. Price-to-Earnings (P/E) Ratio, Microsoft vs. Industry Average (RANKS, n.d.)

These case studies demonstrate the model's utility. For GMKN, it identifies a financially strong, undervalued company while flagging specific risks like high leverage. For MSFT, it confirms a high-quality business but quantifies the significant valuation risk, allowing investors to make a more informed risk-reward assessment.

5. The Role of Alternative Data in Enhancing Predictive Power

A key element that distinguishes the RANKS model from classic scoring systems is its systematic integration of alternative data. There is a growing understanding in both academic and practical circles that traditional financial reports, being retrospective in nature, cannot always promptly reflect changes in a company's operational efficiency or corporate governance. Alternative data helps to bridge this information gap by providing more timely and often more objective signals.

Consider the analytical value of some non-traditional factors used in the RANKS model:

- Human Capital Metrics: Indicators such as top management turnover and the percentage of shares owned by insiders are important indicators of corporate governance quality (the 'G' component in ESG). High turnover in senior leadership may signal strategic instability or internal conflict, a significant risk for investors. Conversely, active stock purchases by management (insiders) are often interpreted as a strong positive signal of their confidence in the company's future prospects. Employee headcount dynamics can also serve as a leading indicator: sharp staff reductions may signal impending financial difficulties, while steady growth correlated with revenue growth confirms healthy business development.

- Operational Indicators: Metrics like warehouse utilization, flight load factors for transport companies, or even parking lot occupancy at shopping centers provide near-real-time information on economic activity. This data can indicate a rise or fall in demand for a company's products/services long before the quarterly financial report is published, creating an information advantage.
- Structural Business Risks: Analyzing dependence on major clients helps to identify hidden concentration risks not visible in a superficial analysis of total revenue. The loss of one or two key customers could critically impact a company's financial condition, and the model aims to quantify this risk. Similarly, tracking equity dilution through additional stock issuances is a direct indicator of management's regard for minority shareholders. Companies that constantly dilute the stakes of existing investors receive a lower score.

The integration of these and other alternative factors allows the model to form a deeper, more multifaceted view of a company, going beyond standard financial ratios to identify potential risks and opportunities missed by traditional analysis (In et al., 2019).

6. Analysis of Empirical Effectiveness: Case Studies and Market Comparison

The effectiveness of any investment model is determined by its ability to consistently generate returns that exceed the market average (alpha). The following analysis is based on a retrospective review of internal data from real client portfolios. An analysis of these practical case studies confirms that the RANKS methodology can achieve this objective across various market conditions and for clients with different risk profiles, demonstrating a significant outperformance over market benchmarks.

While the portfolios' performance is primarily presented in absolute returns, the comparative analysis demonstrates a significant excess return relative to the benchmark indices across the studied periods. In the presented case studies, the strategy consistently outperformed the broader market, delivering positive returns even during periods of significant market corrections. This distinct decoupling of portfolio performance from negative market trends indicates a low correlation with downside market risk, effectively serving the function of capital preservation and alpha generation without relying solely on high-beta exposure.

Case Study #1 (U.S. Market) illustrates the recovery and management of a portfolio previously managed by UBS, which had incurred substantial losses (-40%). The portfolio was taken over in September 2022. Over three years, a cumulative return of +66.8% was achieved (equivalent to 20% annualized), with a financial result of +$420k. As shown in Figure 5, the strategy not only compensated for prior losses but also significantly outpaced the S&P 500 index (RANKS, n.d.).

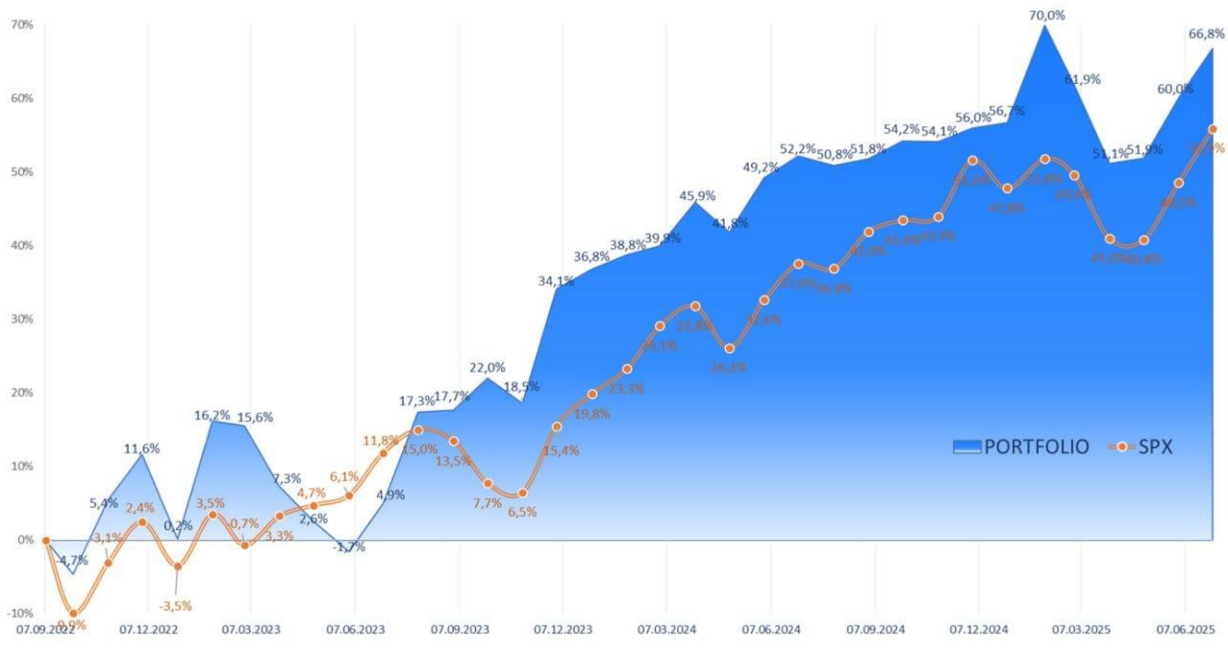
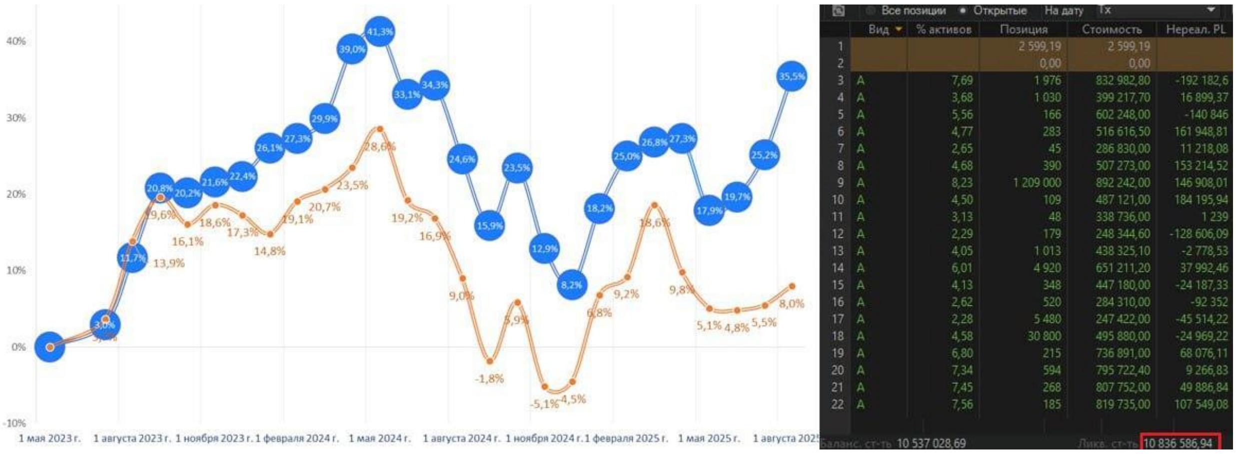


Figure 5. Performance of the RANKS Portfolio (blue) vs. the S&P 500 Index (orange) for U.S. Case #1 (RANKS, n.d.)

Case Study #2 (Russian Market) demonstrates the strategy's resilience in a high-volatility environment. A portfolio initiated with the broker BCS in May 2023 yielded a return of +35.5% over 2.5 years (15% annualized), equivalent to a monetary gain of +2,836,586 ₽. A key performance indicator was the portfolio's ability to remain profitable even as the stock market fell by 35% in 2024. This signifies a threefold outperformance of the market and a high degree of capital preservation (RANKS, n.d.).



	Вид	% активов	Позиция	Стоимость	Нереал. PL
1			2 599,19	2 599,19	
2			0,00	0,00	
3	A	7,69	1 976	832 982,80	-192 182,6
4	A	3,68	1 030	399 217,70	16 899,37
5	A	5,56	166	602 248,00	-140 846
6	A	4,77	283	516 616,50	161 948,81
7	A	2,65	45	286 830,00	11 218,08
8	A	4,68	390	507 273,00	153 214,52
9	A	8,23	1 209 000	892 242,00	146 908,01
10	A	4,50	109	487 121,00	184 195,94
11	A	3,13	48	338 736,00	1 239
12	A	2,29	179	248 344,60	-128 606,09
13	A	4,05	1 013	438 325,10	-2 778,53
14	A	6,01	4 920	651 211,20	37 992,46
15	A	4,13	348	447 180,00	-24 187,33
16	A	2,62	520	284 310,00	-92 352
17	A	2,28	5 480	247 422,00	-45 514,22
18	A	4,58	30 800	495 880,00	-24 969,22
19	A	6,80	215	736 891,00	68 076,11
20	A	7,34	594	795 722,40	9 266,83
21	A	7,45	268	807 752,00	49 886,84
22	A	7,56	185	819 735,00	107 549,08

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Figure 6. Performance of the RANKS Portfolio (blue) vs. a Market Index (orange) for the Russian Federation Case (RANKS, n.d.)

Case Study #3 (U.S. Market) presents the results of an account managed at Interactive Brokers, which was transferred following ineffective management by previous advisors. Starting with $1 million in August 2024, the portfolio generated a return of +$202k by August 1, 2025, corresponding to a +20.5% gain (18% annualized). Figure 7 and Figure 8 visualize both the relative return compared to the SPX index and the growth in the absolute value of assets, confirming the strategy's high effectiveness over a short-term horizon (RANKS, n.d.).

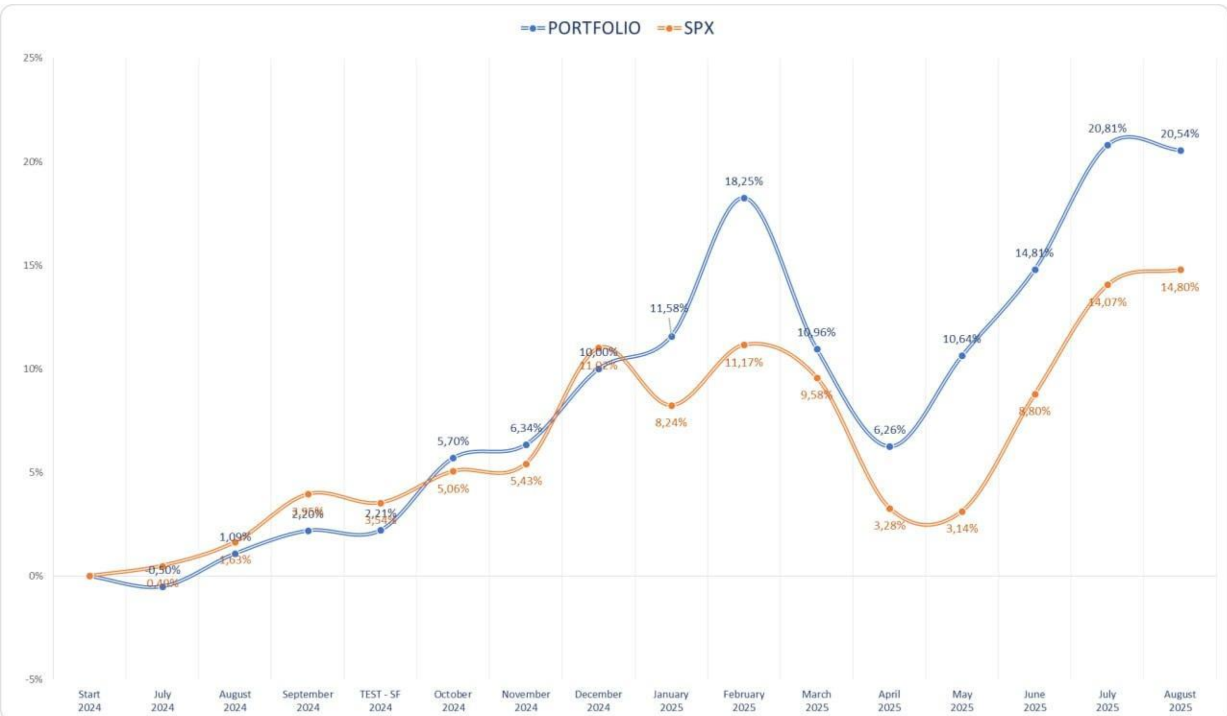

Figure 7. Comparative Performance of the RANKS Portfolio vs. the S&P 500 Index for U.S. Case #2 (RANKS, n.d.)

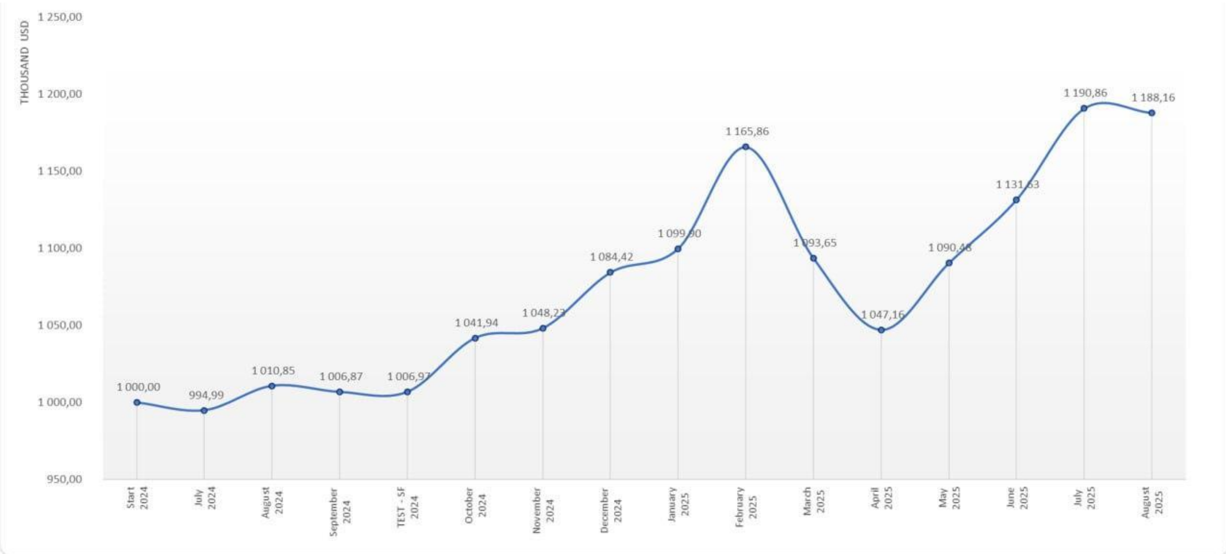

Figure 8. Absolute Portfolio Value Dynamics for U.S. Case #2 (in thousands USD) (RANKS, n.d.)

The presented case studies consistently demonstrate positive alpha and confirm the empirical effectiveness of the RANKS methodology. The approach achieves results that surpass the broader market's performance, driven by both aggressive asset selection and resilience during market downturns.

Conclusion

This study analyzed the RANKS multi-factor rating model, designed for the systematic selection of undervalued stocks. It was established that the model is a comprehensive implementation of a hybrid "quantamental" approach, which organically combines the strengths of fundamental and quantitative analysis.

The tasks set out in the paper were fulfilled. The theoretical basis and architecture of the model were described in detail, consisting of seven logical blocks that cover key aspects of a company's operations, from growth dynamics to ESG factors. The structure of the model and its reliance on over 150 different parameters were analyzed, ensuring depth and comprehensiveness in its evaluations. Special attention was paid to the innovative aspect of the model–the integration of alternative data, which allows for obtaining leading signals and identifying non-financial risks that are inaccessible through traditional analysis. The evaluation of empirical effectiveness based on the presented case studies and comparison with market benchmarks showed that the model has the potential to generate significant alpha in both Russian and foreign markets.

The practical significance of this work lies in demonstrating an effective and scalable framework for making investment decisions in an environment of information surplus. The RANKS model offers investors a tool to move from analyzing individual, often disconnected, metrics to a holistic, structured, and objective assessment of an asset's investment attractiveness.

Future research could be directed towards implementing adaptive mechanisms using machine learning algorithms (e.g., recurrent neural networks like LSTM or gradient boosting) to dynamically weight factors depending on the current market regime, which could potentially further enhance the model's robustness and effectiveness.

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