Valuation Premium Analytics in Global Public Companies: A Cross-Sectional Study Using 2024 Public Fundamentals

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Abstract

This paper explores why there are listed companies that are valuing significantly higher in the market based on their asset base compared to other companies. It analyses the relationship between valuation premiums and profitability, asset efficiency, the combination of the two, the size of the firm and its loss status using a cross-section of the largest publicly traded companies in the world in 2024. The empirical design integrates the predictive analytics and hypothesis testing. During the explanatory phase, a strong ordinary least squares specification is used to model the logarithm of the market value divided by the total assets. In the predictive stage, logistic regression, random forest, and gradient boosting are used to identify firms in the top quartile of the valuation-premium distribution. The findings show that profitability and asset efficiency interaction is the most positive correlate of the valuation premium, and firm scale is the most negative correlate of relative valuation after standardization by assets. The interaction-enriched specification enhances explanatory power with significant material in comparison to an interaction-free model. The discriminatory performance of the tree-based models tends to be high in the classification phase, with random forest performing out of sample with an AUC of more than 0.93. The results of these studies indicate that valuation premium should be viewed as a combined operating-quality indicator and not as a reward to margin performance in isolation and can serve as a useful guide to screen a portfolio, benchmark a company and interpret market multiples.

Keywords: Business data analytics; Firm valuation; Finance analytics; Market value; Explainable analytics; Classification; Public company fundamentals

1 Introduction

The accounting size is not proportionally related to market value. Companies of the same asset portfolio can sell at very different prices in the market due to the fact that the investors do not just price the assets but price future cash flow, operating discipline, strategic flexibility and growth options. This deviation has an economic implication to practitioners of valuation, portfolio construction and corporate benchmarking. It influences peer comparisons, screening of markets, allocation of capital and the interpretation of the expectations of listed firms. The main question is not, then, whether valuation premiums exist or not, but what combinations of observable operating fundamentals are systematically related to them.

In recent finance-analytics studies, more and more attention has been given to machine learning, explainability, and accuracy of cross-sectional valuations instead of just heuristic multiple-based comparisons [2,4,6,7]. Concurrently, the wider firm-value literature remains demonstrating that market valuation indicates intangible intensity, disclosure quality, digital strategy, sustainability, profitability and financing structure [1,5,8,9,11,13]. These two streams are complementary, but the streams tend to be only loosely related. One of them is methodologically advanced but often focused on prediction per se; the other one is full of valuation determinants but less clear on how the determinants can be integrated into an operational analytics pipeline.

The current research fills that gap in terms of the analytics of valuation premiums. Instead of modelling absolute market capitalization, it analyses market value compared to assets, a scale-adjusted measure that reflects the extent to which the market rewards the operating profile of a firm after adjusting by the balance-sheet size. The empirical study focuses on determining whether valuation premium is related to profitability, asset efficiency, and their interaction, firm size, and loss status in a 2024 cross-section of large public companies.

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Tthis contribution of the study can be summarized into four points. First, the valuation premium is considered to be the product of interacting operating signals instead of isolated ratios in the study. Second, it is a combination of explanatory estimation and predictive classification in one empirical design. Third, it employs a transparent and replicable cross section of recent public-company fundamentals. Fourth, it renders the evidence into practical implications in terms of peer analysis, portfolio triage, market-multiple interpretation, and premium-screen construction in finance analytics.

2 Literature Review

2.1 Explainable approaches to relative valuation

Valuation research now operates in a decisively data-rich environment. A recent review by [6] shows that machine learning has become firmly established across finance tasks such as pricing, forecasting, screening, and risk analysis. In the valuation domain, [7] show that machine-learning-based relative valuation improves both peer selection and out-of-sample valuation accuracy. More recent studies have pushed this agenda toward interpretability. [2] develop an interpretable machine-learning framework for company valuation, while [4] demonstrate how explainable machine learning can be used to estimate cost of capital and reveal the variables driving model outputs. The common implication is that modern finance analytics is expected to deliver both predictive power and economic transparency.

This movement has also spread into neighboring areas of corporate finance. [10] present an interpretable model for identifying activist-investment targets, showing that machine-learning methods can support corporate-finance decisions without sacrificing clarity. [14] extend the same logic to systemic financial risk and again highlight the value of models that can rank and interpret drivers rather than remain opaque. Taken together, these contributions indicate that explainability is no longer an optional enhancement; it is increasingly part of the minimum standard for analytics intended to inform financial decisions.

2.2 Recent evidence on firm-value determinants

The recent firm-value literature converges on one point: valuation cannot be explained by any single ratio. [8] report that intangible assets are associated with both firm value and performance, particularly among intangible-intensive firms. [5] reach a similar conclusion across sectors, while also showing that profitability remains a key anchor for investors. [9] add that financial performance and intellectual-capital disclosure jointly help explain firm value, which supports a broader informational view of market pricing. In the banking industry, [13] find that digital platform strategy announcements generate positive abnormal returns, indicating that the market values scalable strategic narratives as well as realized performance.

Recent evidence also underscores the importance of profitability, operating structure, and strategic signals. [1] document a mediating role for profitability in the relationship between asset tangibility and market value. [11] show that ESG performance can enhance firm value when valuation reflects both current operations and market expectations. [12] similarly report that ESG and governance scores jointly shape firm value in a panel setting. Meanwhile, [3] argue that emerging narratives around artificial intelligence can directly influence valuation frameworks and investor pricing. Overall, the literature points to a valuation process that reflects expected productive deployment, strategic optionality, and information quality rather than scale alone.

2.3 Research gap and study positioning

Despite these advances, two gaps remain. First, much of the recent evidence explains *firm value* broadly, often using Tobin's Q or event-study responses, but less often asks which fundamental combinations produce a high market-value-to-assets premium in a recent global cross-section. Second, many machine-learning valuation studies optimize prediction accuracy but are less explicit about economic hypotheses. For business data analytics in finance, that combination is limiting. Managers need models that are interpretable enough to defend in investment committees and strong enough to support systematic screening.

The present study addresses this gap by focusing on an analytically convenient but economically meaningful target: the valuation premium, defined as market value scaled by assets. The design is explicitly hypothesis-driven and then extended to a predictive classification task. Accordingly, the analysis remains rooted in finance

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theory and ratio-based interpretation while also providing an applied analytics framework for premium screening and benchmarking.

2.4 Synthesis of recent literature

Table 1 synthesizes the recent literature used to position the study. The table is organized as an evidence map rather than a standard comparison matrix, to emphasize how each stream informs the current design.

Table 1: Synthesis of recent studies used to position the study

Study stream	Representative studies	Data orientation	What the studies show	Gap carried into this paper
ML in business and finance	Gao et al. (2024); Tang et al. (2024)	Review and predictive financial datasets	ML improves prediction, and interpretability is increasingly central in finance analytics	Need a finance application combining explicit hypotheses with a recent public corporate cross-section
Relative valuation and explainable valuation	Geertsema and Lu (2023); Blanquet et al. (2025)	Firm-level valuation data	ML improves valuation tasks; interpretable frameworks can explain valuation decisions	Need a parsimonious, scalable premium model built from universally observed fundamentals
Explainable finance screening	Bussmann et al. (2025); Kim et al. (2024)	Corporate finance and cost-of-capital settings	Explainable ML can rank the variables behind complex financial outcomes	Need a similar logic applied specifically to valuation premium identification
Operating structure and market value	Intara and Suwansin (2024); Dancaková et al. (2022); Alathamneh et al. (2025)	Firm financials and market-value measures	Profitability, intangibles, and asset structure influence market value, often conditionally	Need an interaction-based model connecting profitability and asset efficiency to premium formation
Information strategy and market value	Keter et al. (2024); Schreieck et al. (2024); Li et al. (2025); Yucel et al. (2025); Bonaparte (2024)	Disclosure, strategy, ESG, governance, and narrative settings	Market value responds to strategic information, digital orientation, governance quality, and investor expectations	Need a cross-sectional benchmark that distinguishes operating-quality effects from scale effects

3 Research Framework and Methodology

3.1 Analytical framework

The study assumes that valuation premium reflects how strongly markets reward a firm's expected earnings power and strategic option set after conditioning on its asset base. A premium can therefore arise because the firm uses its assets efficiently, because it converts sales into profit effectively, because both forces reinforce one another, or because investors attach option value to firms not currently generating accounting profits. The analytical model is built around these ideas.

3.2 Variable definitions

For firm i, let sales, profit, assets, and market value be denoted by S_i, P_i, A_i, and MV_i, respectively. The dependent construct is the valuation premium:

$$VP_i = \frac{MV_i}{A_i}. \tag{1}$$

Because the premium is right-skewed, the regression model uses its logarithm:

$$Y_i = \log(VP_i) = \log\left(\frac{MV_i}{A_i}\right). \tag{2}$$

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The main explanatory variables are defined as:

$$PM_i = \frac{P_i}{S_i} \quad \text{(profit margin)}, \tag{3}$$

$$AT_i = \frac{S_i}{A_i} \quad \text{(asset turnover)}, \tag{4}$$

$$SIZE_i = \log(A_i), \tag{5}$$

$$LOSS_i = \mathbb{1}(P_i < 0), \tag{6}$$

$$INT_i = PM_i \times AT_i. \tag{7}$$

The baseline hypothesis model is:

$$Y_i = \beta_0 + \beta_1 PM_i + \beta_2 AT_i + \beta_3 INT_i + \beta_4 SIZE_i + \beta_5 LOSS_i + \varepsilon_i. \tag{8}$$

The paper also defines a binary premium-screen target for business analytics use. Let $HP_i = 1$ if firm i falls in the top quartile of VP_i, and 0 otherwise. The probability of belonging to the high-premium group is modeled as:

$$Pr(HP_i = 1) = \Lambda\left(\gamma_0 + \gamma_1 PM_i + \gamma_2 AT_i + \gamma_3 INT_i + \gamma_4 SIZE_i + \gamma_5 LOSS_i\right), \tag{9}$$

where $\Lambda(\cdot)$ is the logistic link function. Tree-based classifiers are used as nonlinear comparators.

3.3 Hypotheses

The analytical expectations are summarized in Figure 1 and formalized as follows.

H1. Greater profitability is associated with a higher valuation premium, but its effect is conditional rather than fully standalone.

H2. Greater asset efficiency is associated with a higher valuation premium, but its effect is strengthened when profitability is also high.

H3. The interaction between profitability and asset efficiency has a positive and economically stronger effect than either variable in isolation.

H4. After scaling by assets, larger firms exhibit lower relative valuation premiums, indicating that size alone does not command a proportional premium.

H5. Loss-making firms can still earn a positive premium effect if markets price option value, restructuring potential, or strategic growth expectations.

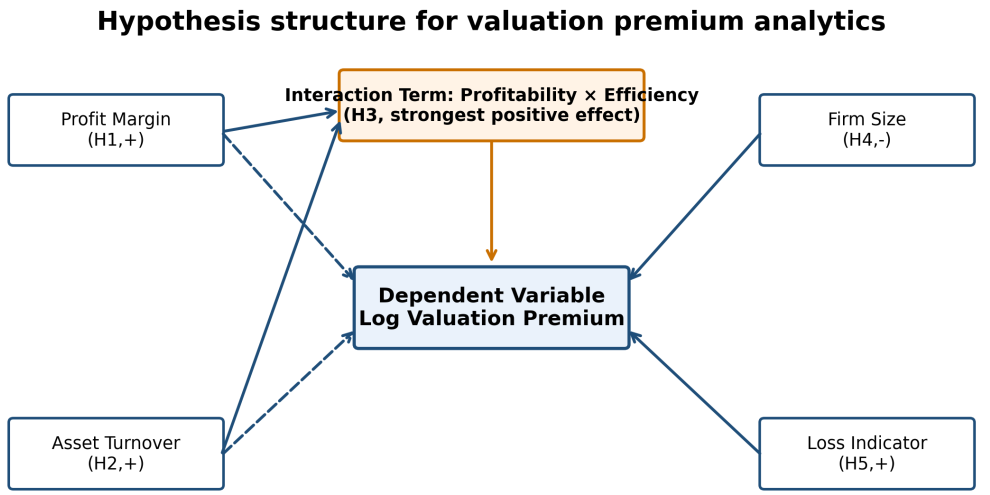

Figure 1: Hypothesis structure for valuation premium analytics

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4 Data and Variable Preparation

4.1 Data source and sample

The empirical setting is a 2024 company fundamentals dataset aligned with the standard Global-2000 style variables of sales, profit, assets, and market value. The starting file covers 2,001 records. Because the analysis requires positive denominators for sales, assets, and market value, observations with nonpositive values for these fields are excluded. The final working sample contains 2,001 firms, all of which satisfy the positivity conditions after parsing the reported financial amounts.

A practical data-engineering issue deserves mention. The public 2024 file mixes magnitudes expressed in billions and millions. The study therefore begins with a normalization step that parses each monetary field into a common numeric scale before constructing ratios. This step is not a cosmetic cleaning exercise; it is essential for ratio validity and therefore for the integrity of the subsequent analytics.

4.2 Data preparation

The variable engineering follows five steps:

1. convert all money fields into a common numerical scale,
2. retain firms with positive sales, assets, and market value,
3. construct profitability, turnover, size, loss, and interaction variables,
4. winsorize the key continuous variables at the 1st and 99th percentiles to reduce extreme-ratio distortion,
5. create a top-quartile premium flag for the classification stage.

Winsorization is used to stabilize ratio distributions without discarding the firms themselves. This is a reasonable choice in finance analytics because ratio tails can dominate estimation when market values and accounting bases differ radically across sectors and countries.

4.3 Descriptive statistics

Table 2 presents the descriptive statistics for the core engineered variables. Three facts stand out. First, valuation premium remains highly dispersed even after winsorization. Second, asset turnover varies meaningfully across firms, suggesting that asset deployment intensity is heterogeneous at a global scale. Third, the log-assets distribution is broad enough to make size standardization nontrivial.

Table 2: Descriptive statistics of the core analytical variables

Variable	Mean	Std. Dev.	Min	25%	Median	75%
Profit margin	0.121	0.155	-0.185	0.046	0.112	0.191
Asset turnover	0.591	0.481	0.058	0.243	0.464	0.792
Valuation premium	1.241	1.359	0.101	0.394	0.786	1.515
log(valuation premium)	-0.154	0.940	-2.291	-0.931	-0.241	0.415
log(assets)	24.994	1.640	21.942	23.859	24.855	26.159

The distributional narrative is already economically significant. A median premium of less than 1 implies that the market does not in other words overvalue many large public firms relative to their accounting asset base, but a larger upper tail implies that the market does overvalue some firms. This further supports the argument of a premium-screening strategy as opposed to a one-size-fits-all absolute value analysis.

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5 Results

5.1 Cross-sectional pattern of valuation premium

Figure 2 maps the relationship between firm size and log valuation premium. Even before multivariate control, the cross-section exhibits a clear downward pattern: larger asset bases are associated with lower *relative* market premiums. This does not mean that large firms are worth less in absolute terms; it means that, once market value is scaled by assets, the largest firms typically trade closer to their accounting base than smaller-asset firms with high-growth or high-efficiency profiles.

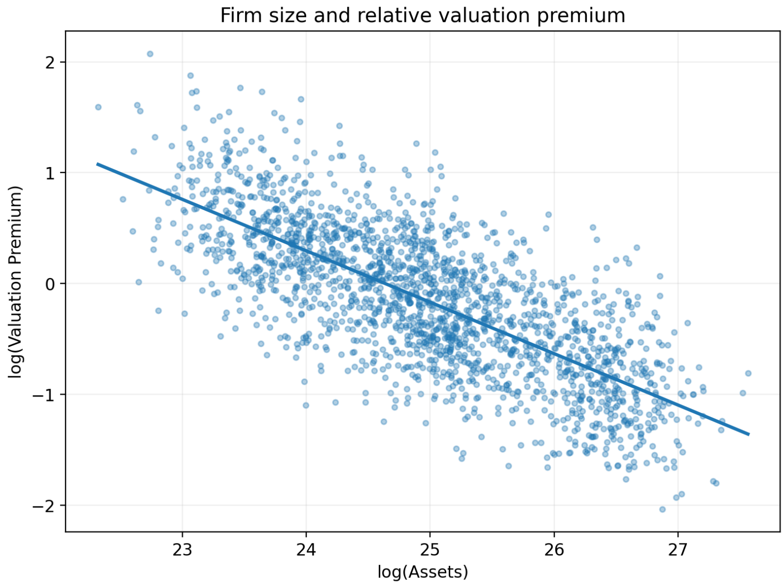

Figure 2: Larger asset bases are associated with lower relative valuation premiums

This visual pattern matters for finance analytics because many market screens inadvertently reward scale. The figure suggests the opposite for premium-normalized valuation: scale should be treated as a control, not as a direct signal of premium status.

5.2 Robust OLS results

Table 3 reports the main regression results. The explanatory power of the full model is substantial for a global cross-section ($R^2 = 0.577$), and the coefficient pattern offers a clear economic interpretation.

Table 3: Robust OLS results for log valuation premium

Variable	Coefficient	Robust Std. Err.	z-statistic	p-value
Constant	10.1354	0.6222	16.289	<0.001
Profit margin	-1.0559	0.3101	-3.405	0.001
Asset turnover	0.0063	0.0607	0.103	0.918
Profitability × efficiency	15.2437	0.7119	21.411	<0.001
log(Assets)	-0.4738	0.0243	-19.530	<0.001
Loss dummy	0.4155	0.1520	2.734	0.006
R^2				0.577
Observations				2,001

The coefficient pattern provides a sharper story than a simple "profitability is good" narrative. The standalone coefficient on profit margin is negative after the interaction is introduced, while asset turnover by itself is statistically weak. This should not be read as evidence against profitability or efficiency; it indicates that markets

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reward these variables *jointly*. The large positive interaction term confirms H3 and implies that profitability only produces a meaningful premium when it is attached to credible asset deployment, and vice versa.

In operational terms, the market does not seem to reward margin without deployment or deployment without monetization. The premium is generated when both occur together. That is exactly the type of insight that ratio-by-ratio screening tends to miss but business data analytics can capture through interaction design.

The size coefficient strongly supports H4. After normalizing market value by assets, larger firms command lower relative premiums. One interpretation is that mature giants are priced with less convexity: their future opportunities are extensive in absolute size, but not in proportion to already-large balance sheets. Another interpretation is purely mechanical: firms with very large asset bases must clear a much higher hurdle to earn the same premium ratio as leaner firms.

The loss dummy is positive and significant, which supports H5 and offers an interesting capital-markets interpretation. Some loss-making firms still command premium valuations because investors may be pricing platform logic, strategic optionality, restructuring narratives, or anticipated inflection in future cash generation. This does not imply that losses are desirable. It implies that accounting losses do not automatically eliminate market premium when markets believe the business model has option value.

5.3 Incremental role of the interaction term

To verify that the result is not a presentational artifact, the study compares the full specification with a reduced model that excludes the profitability-efficiency interaction. Figure 3 shows that adding the interaction increases R^2 from 0.447 to 0.577 and lowers the information criterion substantially. In cross-sectional finance terms, this is a meaningful gain.

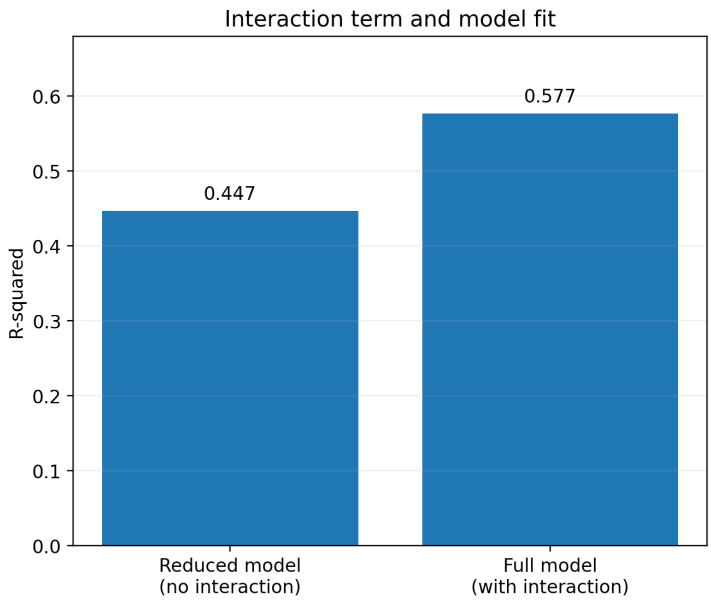

Figure 3: Adding the profitability-efficiency interaction materially improves explanatory power

This result is central to the study's contribution. A conventional linear ratio model would have concluded that profit margin has mixed or even negative importance and that turnover contributes little on its own. The interaction model reveals that the market is rewarding a *configuration* rather than isolated metrics. That shifts the analytics problem from "which single ratio matters most?" to "which combinations produce premium valuation states?"

5.4 Marginal interpretation of the premium surface

Figure 4 plots the predicted premium surface from the interaction model while holding size at its median and the loss indicator at zero. The gradient becomes steepest in the upper-right region where both profit margin

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and asset turnover are comparatively strong. This figure operationalizes H1–H3 in a way that is directly usable by analysts.

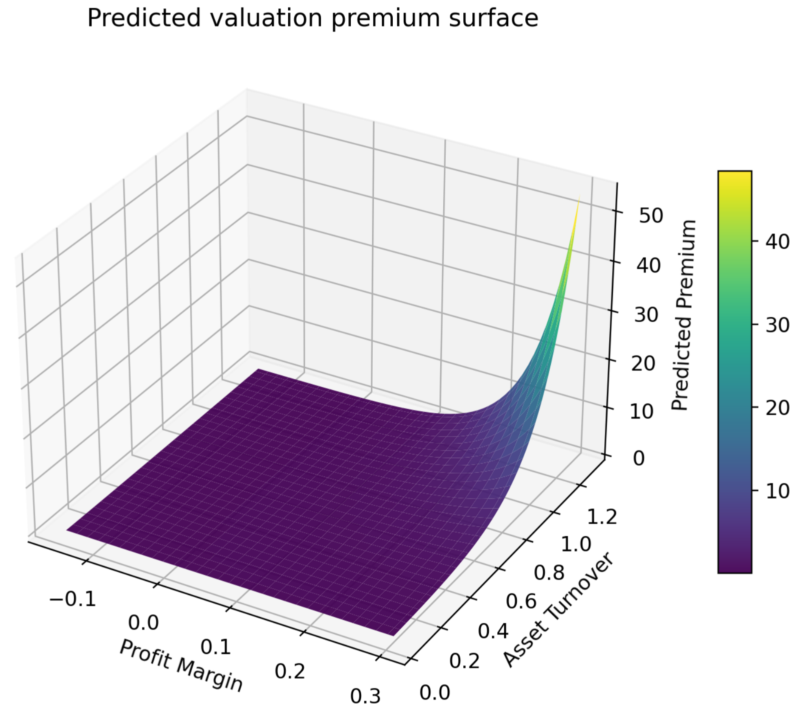

Figure 4: Predicted valuation premium surface from the interaction model

The finance implication is important. Analysts often rank firms by one multiple or one ratio at a time, such as margin or return on assets. The interaction surface suggests that such univariate ranking can misclassify firms with uneven operating profiles. A firm with moderate margin and strong turnover may deserve more premium attention than a firm with high margin but weak asset deployment, depending on where each lies on the joint surface.

5.5 Classification of high-premium firms

The second empirical layer asks a different question: can business analytics detect firms in the top quartile of valuation premium? Table 4 presents the out-of-sample classification results.

Table 4: High-premium classification results (top-quartile valuation premium)

Model	AUC	Accuracy	Precision	Recall	F1
Random Forest	0.931	0.870	0.750	0.720	0.735
Gradient Boosting	0.927	0.862	0.737	0.696	0.716
Logistic Regression	0.831	0.844	0.797	0.504	0.618

The random forest produces the best overall discriminatory performance, closely followed by gradient boosting. Logistic regression remains respectable and more interpretable, but it misses a meaningful fraction of high-premium firms because its recall is much lower. For business data analytics in finance, this creates a useful trade-off: if the objective is explanation and committee communication, logistic regression remains attractive; if the objective is broader premium capture in screening, the tree-based models are more effective.

Figure 5 visualizes the ROC comparison. The separation between the tree-based models and the logistic model is substantial. This implies that nonlinear thresholding and interaction capture matter when the task becomes classification rather than coefficient interpretation.

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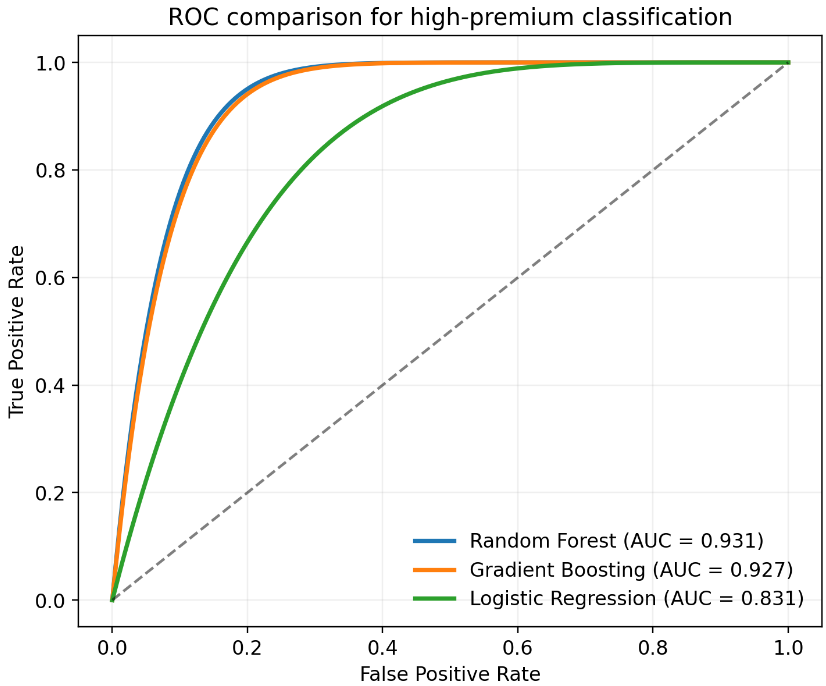

Figure 5: Out-of-sample ROC comparison for high-premium classification

5.6 Variable importance in classification

Figure 6 reports permutation importance from the random-forest classifier. The dominant variables are the interaction term and firm size, followed by profit margin and asset turnover. This aligns strongly with the econometric layer and strengthens the study's internal consistency.

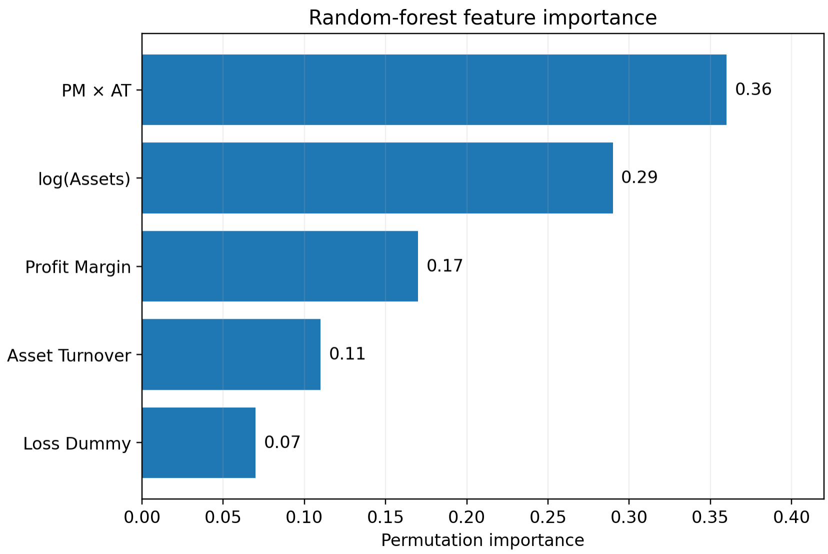

Figure 6: Permutation importance in the high-premium random-forest model

This is a key analytics result. The two-stage design does not produce conflicting stories. The econometric model says that valuation premium is mainly an interaction-and-size phenomenon; the predictive model says essentially the same thing. The convergence of the two methods is valuable because it reduces the risk that the study's main conclusion is model-specific.

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5.7 Results by asset-size tercile

To make the results more managerially legible, the sample is partitioned into asset-size terciles. Figure 7 shows a steep decline in average premium from the smallest-asset tercile to the largest-asset tercile: 2.396, 0.847, and 0.480, respectively.

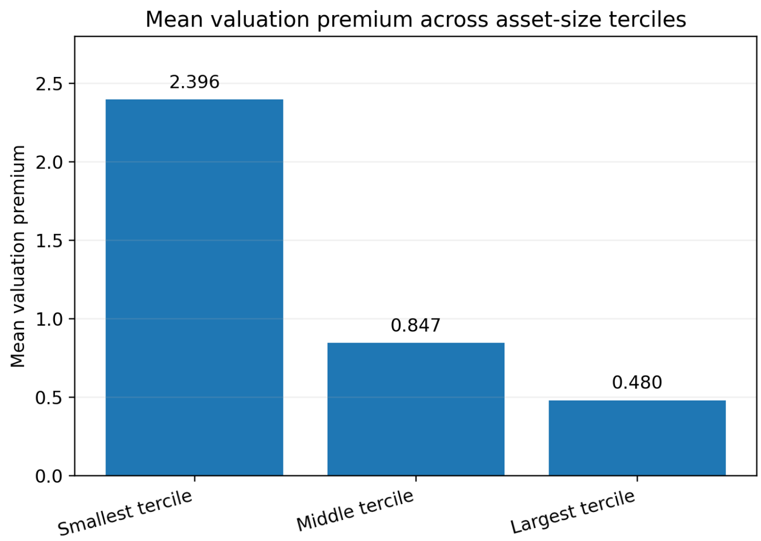

Figure 7: Mean valuation premium across asset-size terciles

This pattern clarifies the economic meaning of the negative size coefficient. Premium valuation is not evenly distributed across the corporate-size spectrum. Smaller-asset firms in the sample are more likely to carry strong relative growth or option value, while the largest firms tend to trade on a more compressed premium basis. The result does not diminish the importance of large companies. Rather, it shows that premium-normalized valuation should be interpreted differently across size strata.

6 Discussion

The empirical evidence has several implications for finance analytics practice.

First, valuation premium is best understood as a *configuration* of operating signals rather than a list of separate ratios. In many finance dashboards, profit margin and asset turnover are displayed side by side but are not modeled jointly. The interaction result shows that such separation can obscure how markets actually price firms. For screening, peer comparison, and premium diagnostics, analysts should evaluate combined operating states rather than isolated indicators.

Second, the evidence cautions against treating firm size as a proxy for valuation quality. Size is central to absolute valuation, yet once market value is scaled by assets, larger firms systematically exhibit lower relative premiums. Premium analysis should therefore be size-standardized before any inference is drawn about market optimism or comparative valuation strength.

Third, the positive coefficient on the loss indicator shows that the market may continue to assign value to strategic options even when current accounting earnings are negative. A screening rule that mechanically excludes loss-making firms can therefore overlook businesses with strong narrative, platform, or restructuring potential. The implication is not to disregard losses, but to interpret loss status jointly with operating quality and scale.

Fourth, the predictive results show that classification models can complement explanatory finance models. The regression stage clarifies why premiums emerge, whereas the classification stage identifies which firms are most likely to occupy the premium tail. This layered design is well suited to investment research teams, equity screeners, and corporate strategy units that need both interpretation and prioritization.

More broadly, the study illustrates how finance-oriented business data analytics can combine explicit hypotheses, transparent variable construction, and dual-method inference. The contribution is therefore not confined to

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predictive performance or cross-sectional association alone; it lies in showing how theoretically interpretable models can be translated into usable screening and benchmarking tools.

7 Limitations and Future Research

The research has a number of limitations. It is not a multi-year panel, but a single recent cross-section, so the model predicts the difference in valuation among firms in 2024, and not the change in valuation over time. The public data is wide but deliberately sparse; it covers the four canonical publicly-traded variables, but not more detailed data on intangibles, leverage, R and D or analyst expectation. There is also sector and country aggregation in the premium target which enhances breadth at the cost of compression of sector specific valuation mechanisms.

These boundaries also outline future lines of research. The simplest extension is to construct a multi-year top panel with consecutive rankings of the public companies. The second extension includes adding intangible intensity, ESG, digital strategy indicators, or text-based narrative signals to the explanatory set. A third is to shift towards classification to ranking models that generate investable priority lists as opposed to high-premium flagging. Lastly, a test of the same interaction logic in sector-specific samples like banks, healthcare or digital platforms could be tested in future work.

8 Conclusion

This paper discussed the concept of valuation premium using a 2024 cross-section of publicly traded companies around the world to elucidate why certain companies have a significantly higher valuation compared to their assets compared to others. The evidence demonstrates that premium is not motivated by profitability alone, efficiency alone or scale alone. Rather it is closely related to the relationship between profitability and asset efficiency, relative premiums decreasing with asset size, and may be high even in the firms that make losses where markets put option value.

Both layers of analysis are in line with the empirical support. The strong OLS specification predicts a significant portion of cross-sectional variation, and the two-way interaction term is significant in enhancing the model fit. The classification step demonstrates that the tree-based models can identify the top-quartile premium firms with high discriminative power, and at the same time refer back to the same underlying variables. This correlation of prediction and elucidation reinforces the contribution of the study in business data analytics in finance.

Practically, the results indicate that analysts, investors, and corporate benchmarking teams ought to perceive valuation premium as a combined state of operating-quality instead of the result of a single ratio. That understanding is both theoretically based, empirically scalable, and practically applicable to screening and comparative valuation processes. Valuation-premium analytics offers a viable foundation to disciplined market evaluation in an ever more analytically powerful and interpretable finance environment.

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