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FULL LENGTH ARTICLE

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

Saad Metawea[1,*] **Maha Metawea**[2]
[1] Faculty of Commerce, Mansoura University, Egypt
[2] Faculty of Business Administration, Delta University for Science and Technology, Egypt
Emails: s-Metawa@Yahoo.com · Maha.mtawea@Deltauniv.edu.eg
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ABSTRACT

This paper explores why listed companies can be valued significantly higher in the market relative to their asset base than other companies. It analyses the relationship between valuation premiums and profitability, asset efficiency, the interaction between the two, firm size, and loss status using a 2024 cross-section of the largest publicly traded companies in the world. The empirical design integrates predictive analytics and hypothesis testing. During the explanatory phase, a robust ordinary least squares specification models the logarithm of market value divided by total assets. In the predictive stage, logistic regression, random forest, and gradient boosting identify firms in the top quartile of the valuation-premium distribution. The findings show that the profitability–asset-efficiency interaction is the strongest positive correlate of valuation premium, whereas firm scale is the strongest negative correlate of relative valuation after standardization by assets. The interaction-enriched specification materially improves explanatory power compared with an interaction-free model. Tree-based models show strong discriminatory performance in the classification phase, with random forest achieving an out-of-sample AUC above 0.93. The results indicate that valuation premium should be viewed as a combined operating-quality indicator rather than as a reward to margin performance in isolation, and that it can guide portfolio screening, company benchmarking, and interpretation of market multiples.

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

1. INTRODUCTION

Accounting size is not proportionally related to market value. Companies with similar asset portfolios can trade at very different prices because investors price not only assets but also future cash flow, operating discipline, strategic flexibility, and growth options. This deviation has economic implications for valuation, portfolio construction, and corporate benchmarking. It influences peer comparisons, market screening, capital allocation, and interpretation of expectations about listed firms. The central question is therefore not whether valuation premiums exist, but which combinations of observable operating fundamentals are systematically related to them.

Recent finance-analytics studies increasingly emphasize machine learning, explainability, and cross-sectional valuation accuracy rather than only heuristic multiple-based comparisons [1, 2, 3, 4]. At the same time, the wider firm-value literature shows that market valuation reflects intangible intensity, disclosure quality, digital strategy, sustainability, profitability, and financing structure [5, 6, 7, 8, 9, 10]. These streams are complementary but often loosely connected. One stream is methodologically advanced but frequently prediction-oriented; the other is rich in valuation determinants but less explicit about how these determinants can be integrated into an operational analytics pipeline.

This research fills that gap by analysing valuation premiums. Rather than modelling absolute market capitalization, it analyses market value relative to assets, a scale-adjusted measure of how strongly the market rewards a firm's operating profile after conditioning on balance-sheet size. The empirical study examines whether valuation premium is related to profitability, asset efficiency, their interaction, firm size, and loss status in a 2024 cross-section of large public companies.

The contribution is fourfold. First, valuation premium is treated as the product of interacting operating signals rather than isolated ratios. Second, explanatory estimation and predictive classification are combined in one empirical design. Third, the analysis uses a transparent and replicable cross-section of recent public-company fundamentals. Fourth, the evidence is translated into practical implications for 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 data-rich environment. Machine learning has become established across finance tasks such as pricing, forecasting, screening, and risk analysis [3, 11]. In valuation, machine-learning-based relative valuation improves peer selection and out-of-sample valuation accuracy [4]. Recent work has also moved toward interpretability, including explainable frameworks for company valuation and cost-of-capital prediction [1, 2].

2.2 Operating fundamentals and market value

Firm-value studies show that market value responds to profitability, intangibles, disclosure, governance, digital orientation, ESG, and investor expectations [5, 6, 7, 8, 9, 10, 12]. These results imply that valuation premiums may emerge from combinations of operating quality and information strategy rather than from a single accounting ratio.

2.3 Research gap

Existing predictive studies often emphasize accuracy but are less explicit about economic hypotheses. Conversely, determinant-based valuation studies identify important drivers but are less likely to translate them into screening models. The present study addresses this gap by focusing on valuation premium, defined as market value scaled by assets, and by connecting hypothesis-driven modelling with applied premium classification.

2.4 Synthesis of recent literature

Table 1 summarizes the evidence map used to position the study.

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 arise because the firm uses assets efficiently, converts sales into profit effectively, combines both forces, or receives option value despite current accounting losses.

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 valuation premium:

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

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

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

The main explanatory variables are:

$$PM_i = \frac{P_i}{S_i} \quad \text{(profit margin)}, \tag{3}$$
$$AT_i = \frac{S_i}{A_i} \quad \text{(asset turnover)}, \tag{4}$$
$$SIZE_i = \log(A_i), \tag{5}$$
$$LOSS_i = \mathbb{1}(P_i < 0), \tag{6}$$
$$INT_i = PM_i \times AT_i. \tag{7}$$

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 binary premium-screen target is $HP_i = 1$ if firm i falls in the top quartile of VP_i and zero otherwise. The probability of high-premium membership is modelled as:

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

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. H2: greater asset efficiency is associated with a higher valuation premium, strengthened when profitability is also high. H3: the profitability–efficiency interaction has a positive and economically stronger effect than either variable alone. H4: after scaling by assets, larger firms exhibit lower relative valuation premiums. H5: loss-making firms can still earn a positive premium if markets price option value, restructuring potential, or strategic growth expectations.

4. DATA AND VARIABLE PREPARATION

4.1 Data source and sample

The empirical setting is a 2024 company-fundamentals dataset aligned with standard Global-2000-style variables: sales, profit, assets, and market value. The starting file covers 2,001 records. Because the analysis requires positive denomi-

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 central in finance analytics	Need a finance application combining explicit hypotheses with recent public corporate data
Relative valuation and explainable valuation	Geertsema and Lu (2023); Blanquet et al. (2025)	Firm-level valuation data	ML improves valuation tasks and can explain valuation decisions	Need a parsimonious premium model from universal fundamentals
Explainable finance screening	Bussmann et al. (2025); Kim et al. (2024)	Corporate finance settings	Explainable ML ranks variables behind complex financial outcomes	Need similar logic for 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 value conditionally	Need an interaction model connecting profitability and asset efficiency
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 and investor expectations	Need a benchmark separating operating-quality effects from scale effects

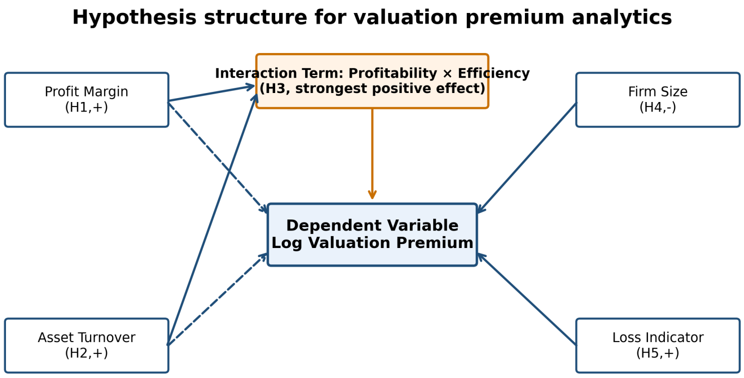

Figure 1. Hypothesis structure for valuation premium analytics.

nators for sales, assets, and market value, observations with nonpositive values for these fields are excluded. The final working sample contains 2,001 firms satisfying the positivity conditions after parsing reported financial amounts.

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 essential for ratio validity and for the integrity of subsequent analytics.

4.2 Data preparation

Variable engineering follows five steps: convert all money fields into a common numerical scale; retain firms with positive sales, assets, and market value; construct profitability, turnover, size, loss, and interaction variables; winsorize key continuous variables at the 1st and 99th percentiles to reduce extreme-ratio distortion; and create a top-quartile premium flag for classification. Winsorization stabilizes ratio distributions without discarding firms.

4.3 Descriptive statistics

Table 2 presents descriptive statistics for the core variables. Valuation premium remains dispersed after winsorization, asset turnover varies substantially, and the log-assets distribution is broad enough to make size standardization important.

A median premium below one implies that the market does not overvalue many large public firms relative to their accounting asset base, while the upper tail indicates that some firms command substantial market premiums. This supports a premium-screening strategy rather than a one-size-fits-all absolute value analysis.

5. RESULTS

5.1 Cross-sectional pattern of valuation premium

Figure 2 maps the relationship between firm size and log valuation premium. 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.

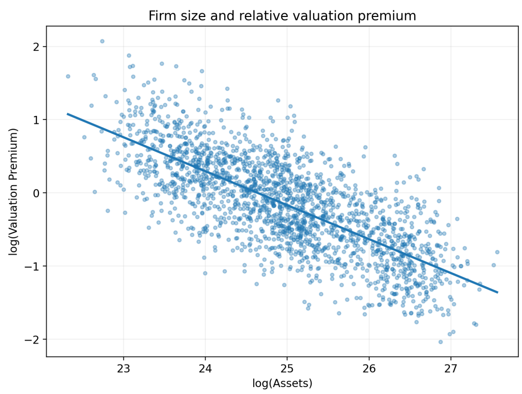

Figure 2. Larger asset bases are associated with lower relative valuation premiums.

5.2 Robust OLS results

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

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

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 standalone coefficient on profit margin is negative after introducing the interaction, while asset turnover alone is statistically weak. This should not be read as evidence against profitability or efficiency; it indicates that markets reward these variables jointly. The large positive interaction confirms H3 and implies that profitability produces a meaningful premium when attached to credible asset deployment, and vice versa.

5.3 Incremental role of the interaction term

Figure 3 compares the interaction-enriched model with a model that excludes the profitability–efficiency interaction. Adding the interaction increases explanatory power materially. The interaction model reveals that the market rewards a configuration rather than isolated metrics.

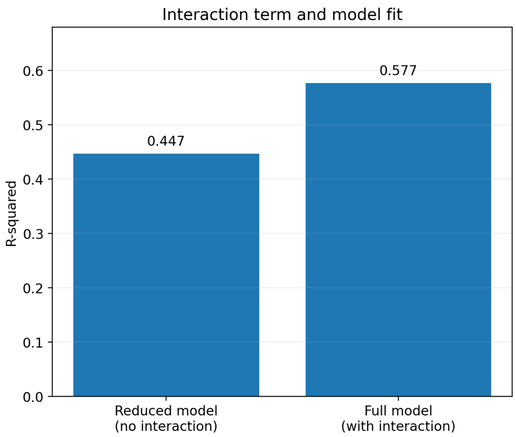

Figure 3. Adding the profitability–efficiency interaction materially improves explanatory power.

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 is steepest in the upper-right region where both profit margin and asset turnover are comparatively strong.

The implication is that 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 its location on the joint surface.

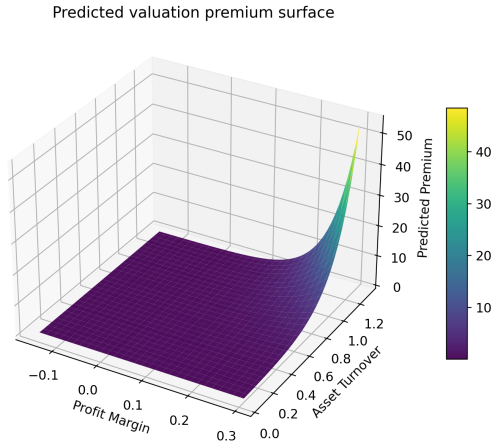

Figure 4. Predicted valuation premium surface from the interaction model.

5.5 Classification of high-premium firms

The second empirical layer asks whether business analytics can 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

Random forest produces the best overall discriminatory performance, closely followed by gradient boosting. Logistic regression remains interpretable but misses a meaningful fraction of high-premium firms because recall is lower. Figure 5 visualizes the ROC comparison.

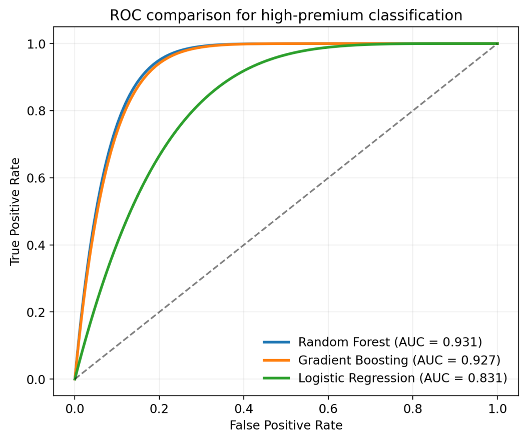

Figure 5. Out-of-sample ROC comparison for high-premium classification.

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.

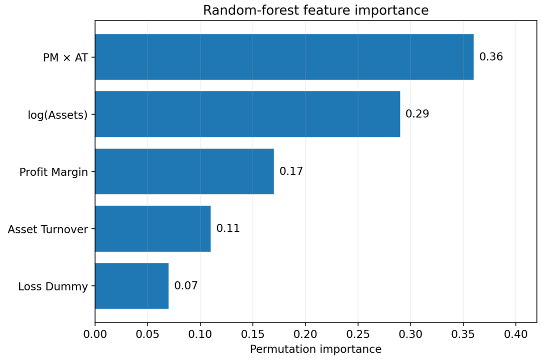

Figure 6. Permutation importance in the high-premium random-forest model.

The econometric model indicates that valuation premium is mainly an interaction-and-size phenomenon; the predictive model gives essentially the same message. This convergence reduces the risk that the main conclusion is model-specific.

5.7 Results by asset-size tercile

To improve managerial interpretation, 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.

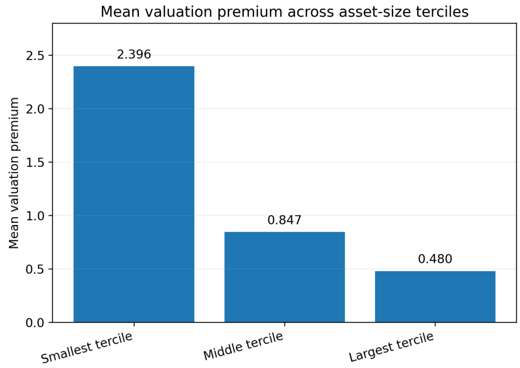

Figure 7. Mean valuation premium across asset-size terciles.

This pattern clarifies the negative size coefficient. Premium valuation is not evenly distributed across the corporate-size spectrum. Smaller-asset firms are more likely to carry strong relative growth or option value, while the largest firms trade on a more compressed premium basis.

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. Profit margin and asset turnover are often displayed side by side but not modelled jointly; the interaction result shows that such separation can obscure how markets price firms.

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 drawing inferences about market optimism or comparative valuation strength.

Third, the positive coefficient on the loss indicator shows that markets may continue to assign valuation premiums to firms that are currently unprofitable. This does not mean that losses are inherently desirable. Rather, some loss-making firms may contain growth options, restructuring potential, technology value, or strategic assets that are not fully captured by current profit.

Fourth, classification results show that interpretable econometric modelling and predictive screening can work together. A coefficient model explains why premiums appear, while tree-based classifiers support practical screening. The combined design is useful for investment committees, portfolio analysts, and corporate benchmarking teams that need both explanation and screening power.

7. LIMITATIONS AND FUTURE RESEARCH

The analysis has limitations. The design is cross-sectional and therefore cannot establish dynamic persistence of valuation premiums across time. The data use public fundamentals and do not include all intangible assets, governance variables, sector-specific narratives, or forward-looking analyst expectations. The premium target is aggregated across sectors, improving breadth but potentially compressing sector-specific valuation mechanisms.

Future research can extend the work by constructing a multi-year panel, adding intangible intensity, ESG, digital strategy indicators, and text-based narrative signals, moving from classification to ranking models that generate investable priority lists, and testing the same interaction logic in sector-specific samples such as banking, healthcare, or digital platforms.

8. CONCLUSION

This paper examined valuation premium using a 2024 cross-section of global publicly traded companies to explain why some companies have substantially higher market valuation relative to assets. The evidence shows that premium is not driven by profitability alone, efficiency alone, or scale alone. Rather, it is closely related to the interaction between profitability and asset efficiency, declines with asset size, and can remain high for loss-making firms when markets price option value.

Both empirical layers support this conclusion. The robust OLS specification explains a substantial portion of cross-sectional variation, and the interaction term materially improves model fit. The classification stage shows that tree-based models can identify top-quartile premium firms with high discriminatory power while pointing back to the same underlying variables. This alignment between prediction and explanation strengthens the study's contribution to business data analytics in finance.

Practically, analysts, investors, and corporate benchmarking teams should view valuation premium as a combined operating-quality state rather than the outcome of a single ratio. Valuation-premium analytics therefore provides a disciplined foundation for market evaluation in an increasingly data-rich and interpretable finance environment.

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