THE SUBJECTIVE POWER OF INTANGIBLES IN A FIRM'S GROWTH: UNLOCKING HIDDEN ASSETS WITHIN A COMPANY STRATEGY

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Abstract

This paper explores the often-underestimated influence of intangible assets, such as brand reputation, customer loyalty, intellectual property, and organizational culture, on firm growth and competitive advantage. Intangible assets are increasingly recognized as critical drivers of sustainable success, yet their subjective nature and challenges in measurement leave gaps in understanding their true impact on a firm's performance. As Hussinki et al. (2024) claim that the discussion around intangibles extends beyond their role in value generation to encompass their impact on a firm's overall risk and value creation profile. Moreover, the recorded goodwill value on companies' balance sheets has grown over time, both as a proportion of their total assets and as a share of their net assets (Chen et al., 2021). This study investigates how these intangible elements contribute to revenue growth. Results indicate a strong correlation between high intangible asset valuation and superior firm growth trajectories, suggesting that intangibles provide firms with unique, hard-to-replicate advantages that fuel resilience and adaptability in dynamic markets. By shedding light on the "subjective power" of intangibles, this research advocates for refined frameworks in accounting and management that better capture the value of these assets, offering insights into optimizing intangible asset investment strategies for long-term growth. This study contributes to the growing field of intangible asset valuation, proposing that a strategic focus on cultivating and leveraging intangibles is essential for firms aiming to maintain relevance and drive sustainable growth in an increasingly intangible-driven economy.

Keywords: Goodwill, Intangibles, Revenue, Strategy, Business Performance, IFRS

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1. INTRODUCTION

The debate surrounding the nature and treatment of goodwill has persisted for decades. Despite concerted efforts by standard-setting bodies such as the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB), a universally accepted definition or accounting method has not been achieved. This ongoing ambiguity underscores the complexity of goodwill — an asset rooted not in tangible worth but in the perception of value, often derived from acquisitions. As Johnson and Kimberley (1999) and Hsissou (2022) point out, goodwill remains an elusive concept in accounting.

This complexity becomes even more relevant in today's economy, where the drivers of firm growth have shifted from physical capital to intangible assets. Firms now gain a competitive edge not by owning more machinery or real estate but by cultivating intellectual property, strong brands, organizational culture, and proprietary knowledge. As Jerman and Manzin (2008) note, these intangible resources are now the backbone of sustainable business models. Yet, despite their importance, these assets are not easily captured in traditional financial statements. Unlike tangible assets, their value often depends on subjective interpretation and market perception, remaining hidden from clear quantitative analysis (Kimouche, 2022).

This paper introduces the concept of the "subjective power" of intangibles — emphasizing how perceived rather than quantifiable characteristics can significantly impact firm performance. This hidden potential of intangibles, particularly goodwill, often plays a decisive role in driving revenue growth, innovation, and long-term sustainability. However, standard accounting practices have yet to develop robust methods to reveal this value clearly, leaving a critical gap in both academic and practical financial understanding.

Goodwill, in particular, serves as a case study in this broader issue. Arising during acquisitions, goodwill represents the excess paid over the fair value of acquired assets. It typically embodies strategic investments in customer relationships, intellectual property, and brand equity. While it does not affect liquidity due to its non-cash nature, goodwill can nonetheless impact perceptions of company value and financial health (Moro-Visconti, 2022). Researching its connection to revenue performance could illuminate whether such acquisitions yield tangible returns or simply inflate balance sheets without performance justification (Jhavary et al., 2024).

Traditionally, goodwill is not directly linked to revenue figures in financial statements. Exploring this relationship is both novel and necessary, as it could help bridge the current disconnect between balance sheet valuations and income statement performance. For example, by studying how firms with high goodwill values perform in terms of revenue generation, researchers might uncover patterns that lead to better forecasting models and improved investment strategies.

This study zeroes in on publicly listed American firms — a natural choice due to their transparency, regulatory compliance, and influence on global markets. The 470 entities analyzed, as of 2023, offer a representative snapshot of U.S. corporate behavior. Although limited to a single year, this dataset allows for a focused, bias-reduced analysis of the impact of goodwill and other intangibles on revenue performance.

Among other variables considered are common stock and property, plant, and equipment (PPE). Common stock serves as a funding mechanism that indirectly supports revenue growth, while PPE plays a direct role, especially in asset-intensive sectors. Strategic use of both can enhance operational efficiency and market presence. However, it is the interplay with intangible assets, especially goodwill, that often drives long-term competitive advantage.

An innovative component of the study lies in considering the psychological dimensions of goodwill. Factors such as corporate culture, ethical leadership, and stakeholder trust all contribute to goodwill in a broader, more holistic sense. This perspective aligns with Panjaitan et al.'s (2024) assertion that intangible assets — ranging from skilled personnel to brand reputation — are key to modern corporate success.

By isolating goodwill from other intangible assets, this study addresses its unique origin and impact. Unlike patents or software, goodwill cannot be separated from the acquiring entity or amortized over time. It is instead tested periodically for impairment — a process subject to management discretion and market sentiment. As Dahmash et al. (2009) observed, goodwill tends to be reported more conservatively, which might hide its true value or overstate risk depending on the context.

In an era where sustainability and intangible value are becoming strategic imperatives, understanding the revenue-generating potential of goodwill is vital. Companies that align intangible assets with their sustainability goals — by fostering innovation, improving transparency, and building stakeholder trust — can achieve superior long-term performance. As Chan et al. (2024) highlight, investor relations and transparency enhance corporate value through intangible means, despite market competition occasionally moderating their effects.

Ultimately, this paper advocates for rethinking how we evaluate intangible assets, especially goodwill. By developing new models and frameworks that better reflect their impact on revenue, analysts and investors can make more informed decisions. As financial markets evolve to prioritize innovation, connectivity, and sustainability, recognizing the true value of intangibles is no longer optional — it is essential.

The chosen sample size of 470 listed American companies was selected based on both practical and statistical criteria. From a statistical standpoint, a sample size above 300 is often considered sufficient for multivariate regression analysis, ensuring adequate degrees of freedom and reducing standard errors. With 470 observations, the model is well-powered to detect medium to strong effect sizes across multiple independent variables, especially given the cross-sectional nature of the study. Practically, the sample is large enough to represent diverse industries and firm sizes while maintaining feasibility for manual data validation and regression diagnostics. The single-year focus reduces the risk of multicollinearity due to time-based structural changes, and it ensures consistency in economic and regulatory environments, thereby enhancing the interpretability of the results.

The structure of this study is outlined as follows. Section 2 provides a comprehensive review of the existing literature on the subject, establishing the theoretical foundation and rationale for this research. Section 3 details the research methodology employed, while Section 4 presents empirical results, including the regression analysis of all relevant variables. Section 5 analyzes and discusses the findings. Finally, Section 6 offers concluding remarks, summarizing the key insights and implications of the study.

2. LITERATURE REVIEW

Victor et al. (2012) state that goodwill reflects the anticipated economic advantages derived from assets that cannot be distinctly identified or independently recognized. It encompasses elements such as customer relationships, business reputation, trademark rights, and other intangible factors. Given the diverse nature of its components, evaluating goodwill presents significant challenges. A key point of debate is whether goodwill qualifies as a true asset in the strictest sense, with expert opinions remaining highly divided. The way goodwill depreciation is recorded can have a profound impact on financial outcomes. Consequently, companies often exploit the theoretical ambiguities surrounding goodwill. In scenarios involving managerial compensation, methods are often preferred that do not influence financial results or key balance sheet indicators.

Goodwill can impact revenue negatively in a few ways, primarily when there is an impairment of goodwill or if its valuation was initially overestimated. While impairment doesn't directly reduce revenue, it impacts profitability, which can influence investor perceptions, potentially leading to reduced market confidence and indirectly impacting revenue through weakened brand perception or reduced market share[1]. Goodwill arises from paying more than the fair value for acquired assets. If goodwill was initially overestimated, it means that revenue expectations were likely inflated to justify that value. Failure to meet those revenue expectations or business performance can trigger impairment, which negatively affects the income statement and shareholder value. Furthermore, if a company has significant goodwill but its revenue growth lags, stakeholders might view the company's prior investments as poor, creating pressure that may further strain business revenue. Sometimes, when goodwill is impaired, it also reflects underlying issues with the acquired entity or its revenue-generating capacity. Reduced customer retention, weakening brand value, or loss of key personnel related to the goodwill asset could directly impact revenue from that segment of the business. Investors and analysts closely monitor goodwill levels as indicators of acquisition success. Impairment might indicate that revenue-generating expectations tied to the acquisition will not materialize, which can also reduce revenue projections and market confidence.

Furthermore, goodwill reflects market reaction and stock performance. Impairments are generally viewed as indicators that acquisitions may not deliver expected financial returns, affecting the company's stock price and brand perception. A significant impairment could deter potential customers, partners, and investors, reducing revenue through lower market support. In short, goodwill can negatively impact revenue when it fails to yield the expected revenue-generating capacity, which triggers impairments and results in negative market and financial consequences that ultimately strain revenue growth.

Chen et al. (2021) claimed that the value of goodwill reported on company balance sheets has grown over time, both as a proportion of total assets and net assets. The rise in goodwill cannot be attributed to an increase in public company acquisitions, which have actually declined over the years. Instead, the increase aligns with changes in goodwill accounting, specifically the shift from amortization to impairment testing. These elevated levels of goodwill may pose a risk to company balance sheets, as potential impairments could significantly affect total and net assets. The FASB has initiated a project to reassess goodwill accounting and is considering a reintroduction of goodwill amortization. This step is commendable, as it could help limit the accumulation of goodwill and reduce associated risks.

A debatable topic of goodwill is the accounting of it (recognition, recording, measurement, capitalization). Jerman and Manzin (2008) endorse that proper recognition, measurement, and management of goodwill are essential. Recent changes in its accounting treatment have significantly altered its handling. Goodwill is no longer amortized but is instead subject to impairment testing. With the introduction of the International Financial Reporting Standards (IFRS) 3, accounting practices took a substantial step closer to American standards. These updates brought two notable changes: the elimination of amortization for goodwill and the discontinuation of the pooling of interests method, mandating the use of the purchase method for business combinations.

Despite aligning IFRS more closely with U.S. Generally Accepted Accounting Principles (GAAP), notable differences persist. Efforts to converge standards are ongoing, and a revised standard is expected to resolve many of these discrepancies, promoting more comparable financial statements globally. However, discussions surrounding goodwill accounting remain contentious. Opinions vary regarding the informational value of impairment charges and the subjective aspects of the new approach. While improved disclosures provide better insights into write-offs, challenges related to goodwill measurement and the broader financial statement impacts of these new standards must also be carefully considered.

Lhaopadchan (2010) stated that although fair value accounting is thought to offer certain advantages, in practice, goodwill impairment decisions often seem influenced by managerial self-interest and concerns over earnings management. Nevertheless, since investors and analysts can adjust or even disregard reported accounting figures, it is less clear whether such reporting practices truly mislead users or substantially diminish the reliability and relevance of financial statements.

Ma and Hopkins (1988) enriched existing literature by stating that internally generated goodwill, which holds economic significance, is not recognized, while acquired goodwill is recognized despite being ambiguous, difficult to interpret, and lacking association with a specific source. By attributing this acquired goodwill solely to the purchased entity, accountants have prioritized convenience over accuracy. This approach risks descending into what can be described as "Alice-in-Wonderland" accounting, undermining professional credibility within the business community. They find that an accurate method to record and amortize goodwill under the historical cost framework is likely unattainable. The decision of several major

[1] When goodwill is impaired (often during an annual review or when business circumstances change significantly), the company must write down the impaired amount. This write-down reduces net income directly, as it's treated as an expense on the income statement.

companies to immediately write off goodwill upon acquisition may reflect an acknowledgment of the impracticality of the capitalization and amortization model. At least this approach aligns with the practice of not recognizing internally generated goodwill. Mard et al. (2002) followed the same conclusions, claiming that the impairment analysis of goodwill plays an important role in the accounting treatment of intangibles.

Seetharaman et al. (2004) promoted that the International Accounting Standards Committee (IASC) must continue its work to improve and harmonize global accounting standards and procedures. A stringent solution for goodwill accounting is critical, and the IASC must ensure compliance among nations to foster standardization. Moreover, regular reviews of goodwill accounting practices are necessary to address emerging issues and update standards to meet evolving accounting needs.

Wines et al. (2007) proved that the process of identifying and valuing cash-generating units (CGUs) necessitates numerous assumptions to estimate fair value, value in use, and recoverable amounts. Given that such units often lack active or complete capital markets, significant ambiguity and subjectivity may arise, increasing the potential for creative accounting practices. Auditors, therefore, must frequently exercise professional judgment, relying on management's competence and integrity, along with robust corporate governance mechanisms like audit committees, to ensure fair valuation of CGUs, goodwill, and related transactions.

Bloom (2009) argued that, although it is generally recognized that the two types of goodwill are indistinguishable in their capacity to generate revenue streams, accounting theorists have nonetheless persisted in maintaining a distinction to align with the constraints of the accounting system. He suggests that, as these and other inconsistencies emerge in practice, the current impairment regime will likely exemplify yet another scenario where issues are framed in a fundamentally unsolvable way. Kwon and Wang (2023) also highlighted the critical role that goodwill plays in shaping investor perceptions and valuation outcomes, particularly in the context of mergers and acquisitions. The significant disparity in goodwill valuation between private and public targets underscores the need for a deeper examination of how goodwill is assessed, disclosed, and understood. Given that goodwill often represents the value of intangible elements such as brand reputation, customer relationships, or managerial expertise — assets that are harder to quantify and verify in private firms — its accurate evaluation becomes essential for ensuring transparency and informed decision-making. As such, investigating goodwill is not only relevant for accounting purposes but also crucial for understanding market behavior, mitigating valuation risks, and improving the quality of financial analysis in M&A activities (Linsmeier & Wheeler, 2021).

While the above studies explore goodwill's conceptual ambiguity and accounting controversies — such as its recognition, impairment, and the shift from amortization to impairment testing — few directly examine its relationship with revenue generation, particularly from a quantitative, empirical perspective, overlooking how goodwill, as an intangible asset, might serve as a proxy for strategic value creation and future earnings potential[2].

Furthermore, the aforementioned studies tend to treat goodwill homogenously, without disentangling its potential differential effects compared to other intangible assets, such as patents or trademarks. This study addresses these gaps by empirically examining the relationship between reported goodwill and revenue using data from publicly listed U.S. firms. It contributes to the literature by offering evidence-based insights into whether goodwill, as currently measured and reported, holds predictive or explanatory power regarding revenue performance, thereby linking balance sheet valuations more closely to income statement outcomes and informing both standard-setting debates and investment analysis.

3. RESEARCH METHODOLOGY

To begin with, removing extreme observations results in a dataset that appears more stable and consistent. These extreme values, while sometimes valid, can also introduce significant noise into the analysis. By excluding them, we can reduce the variability in the data, leading to tighter confidence intervals and more precise estimates.

In many cases, trimming the tails of the distribution also enhances the normality of the data. Many statistical tests — such as t-tests, regressions, or analysis of variance (ANOVA) — rely on the assumption that the underlying data is approximately normally distributed. If the raw data includes substantial skewness or kurtosis due to a few extreme values, these assumptions may be violated, rendering the results questionable. By removing the data beyond ±3 standard deviations, researchers can often restore a closer approximation to the normal distribution, thereby satisfying these assumptions and strengthening the validity of their inferential conclusions.

Lastly, from a practical standpoint, removing outliers can make models more robust and easier to interpret. Excluding a handful of extreme observations simplifies diagnostic checks and improves model fit, especially in regression analysis or predictive modeling contexts, like current research.

Logarithmic transformation is often applied in data analysis to address issues such as skewed distributions, large variances, or non-linearity between variables. By taking the logarithm of a variable, especially when its values span several orders of magnitude, the transformation compresses large values and stretches out small ones, making the data more symmetrical and closer to a normal distribution. This not only stabilizes variance (homoscedasticity) but also makes relationships between variables more linear, which is a common assumption in many statistical models. Additionally, logarithmic transformation can help in interpreting

[2] This study primarily focuses on goodwill, while situating it within the broader context of intangible assets. Goodwill is a unique form of intangible asset that arises specifically from acquisitions and reflects expected future benefits not separately identifiable. Unlike other intangibles such as patents or trademarks, goodwill cannot be independently measured or internally developed, and it is subject to impairment rather than amortization. While the paper draws on broader theories of intangible assets to provide context, the core analytical and empirical emphasis is on goodwill — its valuation, accounting treatment, and its potential relationship with revenue. This approach enables a deeper understanding of goodwill's role in financial performance, distinct from but informed by the wider category of intangibles.

the data in relative terms, turning multiplicative relationships into additive ones, which is useful when modeling growth rates, economic data, or financial variables, where percentage changes or proportional differences are more meaningful than raw values.

Therefore, we calculated the z-scores and removed those with |Z-scores| > 3 and used the original variables, after applying a logarithmic transformation, performing multiple regression analysis. Of the initial 500 observations, 30 were removed, resulting in a final dataset of 470 firms. The excluded observations exhibited extreme values in variables like goodwill and revenue, which, if retained, could have disproportionately influenced the model parameters. Post-removal, the dataset exhibited improved symmetry and reduced kurtosis across key financial metrics, particularly revenue and goodwill. Descriptive statistics showed lower standard deviations and more compact interquartile ranges, confirming a reduction in variability without significantly altering the overall distribution or composition of the sample. To further support the assumptions of normality and homoscedasticity, a logarithmic transformation was applied to all main variables. Logarithmic transformation addresses skewed distributions and large variances by compressing the scale of high-magnitude values, making the data more symmetrical and the relationships between variables more linear. This enhances model performance and interpretability. Therefore, we calculated Z-scores and removed those with |Z-scores| > 3.

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \qquad (1)$$

where, y is *LogRevenue*, x_1 is *LogGoodwill*, x_2 is *LogIntangibles*, x_3 is *LogProperty*, x_4 is *LogCommonStock*, the b_0, b_1, b_2, b_3, and b_4 are the estimators for residuals, *LogGoodwill*, *LogIntangibles*, *LogProperty*, and *LogCommonStock*, respectively.

The basic neural network architecture implemented in this study follows a standard feedforward design, consisting of four input layers and a single output layer. The input layers serve as the entry point, receiving a fixed number of features from the dataset and passing them forward to the network. Each hidden layer is composed of fully connected neurons, enabling the network to learn complex patterns. The number of neurons in each hidden layer is kept modest to maintain computational efficiency while providing sufficient learning capacity. The final output layer adapts to the specific nature of the prediction task: employing a linear activation for continuous outputs in regression problems. This basic architecture is optimized using a gradient-based algorithm (Adam optimizer) and trained by minimizing an appropriate loss function over several epochs. While simple in structure, this architecture forms the foundation of most modern neural network models and provides a solid baseline for learning from structured, tabular, or moderately complex data.

Following, by utilizing the firm's neural networks, we can delve deeper into the nuanced impact of intangibles on the firm's growth. Neural networks, with their ability to learn intricate patterns from large datasets, offer a powerful alternative. Neural networks can identify non-linear relationships that may be overlooked by traditional linear regression models. This capability is particularly valuable in the context of intangibles, where complex interactions between various factors can influence financial outcomes. By capturing these non-linear dynamics, the current study develops a more accurate and predictive model, leading to improved decision-making for investors, analysts, and corporate managers.

In the quest for a deeper understanding of the relationship between intangible assets and firm growth, decision trees emerge as an ideal alternative to traditional regression models. Unlike linear regression, which assumes a fixed, predetermined relationship between variables, decision trees offer a more flexible, data-driven approach. They excel at capturing complex, non-linear interactions between intangible assets — such as goodwill and intellectual property — and financial performance. By systematically segmenting the dataset based on the most influential factors, decision trees provide clear, interpretable decision rules, making them particularly valuable for corporate managers and investors seeking actionable insights. Furthermore, decision trees are inherently robust to outliers and missing data, addressing key limitations in financial datasets. Their ability to identify critical thresholds — such as the level of intangibles at which revenue growth accelerates — offers a more intuitive and strategic perspective. As firms navigate an increasingly intangible-driven economy, decision trees stand out as a powerful analytical tool, bridging the gap between sophisticated machine learning techniques and practical, real-world decision-making.

4. RESEARCH RESULTS

4.1. Training and testing error

The lower value of the testing error (0.141) compared to the training error (0.159) suggests that the model appears to generalize well and does not overfit the training data. In cases of overfitting, we would expect the training error to be significantly lower than the testing error. However, here the difference is minor, which is a positive indication.

Table 1. Model summary for dependent variable *LogRevenue*

Training	Sum of errors	25.630
	Relative error	0.159
Valid	Stopping rule used	1 consecutive step with no decreasing error
Testing	Sum of squares error	9.331
Relative error		0.141

Results from Table 2 provide the adjusted R-squared of the above regression. In essence, adjusted R-squared provides a more reliable estimate of the model's true predictive power by considering both the model's complexity and its ability to explain the variance in the dependent variable. The results in Table 2 show that the predictive power is very high (83.3%). In other words, the proportion of variance in the dependent variable (total revenue) can be explained by the independent variables to a scale of 83.3%. Also, the standard error of estimate (0.359) shows the model's predictions are more accurate and closer to the actual values, implying a better fit of the regression line to the data.

Table 3 shows the independent variables importance results produced by neural networks. This is a ranking of the input features based on their contribution to the model's predictions. It assists in an understanding of which variables are most influential in driving the model's output. Higher scores indicate that the feature has a greater impact on the model's predictions. In our case, *LogProperty* significantly impacts the prediction of *LogRevenue* by 100%, *LogIntangibles* by 29.8%, *LogGoodwill* by 27.8%, and *LogCommonStock* by 8.3%.

Table 2. Model summary

Model	*R*	*R-squared*	*Adjusted R-squared*	*Std. error of the estimate*
1	0.913[a]	0.834	0.833	0.35953

Note: [a] Predictors: (Constant), LogCommonStock, LogGoodwill, LogIntangibles, LogProperty. [b] Dependent Variable: LogRevenue.

Table 3. Independent variables importance

Variable	*Importance*	*Normalized importance*
LogProperty	0.603	100%
LogIntangibles	0.180	29.8%
LogGoodwill	0.168	27.8%
LogCommonstock	0.050	8.3%

4.2. Interpretation of the results

The model appears to perform well and is capable of making fairly accurate predictions on both the training and testing data. A small difference between the training error and testing error may indicate that the model generalizes well, without overfitting overly specific features from the training data.

4.3. Importance of variables

These values indicate how significant each independent variable (such as *LogProperty*, *LogIntangibles*, *LogGoodwill*, and *LogCommonStock*) is in predicting the dependent variable.

- *LogProperty.* This variable holds the highest importance (0.603). This means that the logarithmic value of "property" is the most critical factor in predicting the outcome in your model. In other words, the relationship between property and the dependent variable greatly influences the model's predictions.
- *LogIntangibles.* The logarithmic value of "intangibles" (intangible assets) is also significant, but its influence is less pronounced compared to "property". With a weight of 0.180, this variable plays a smaller role in explaining the dependent variable compared to *LogProperty*.
- *LogGoodwill.* The logarithmic value of goodwill also has a modest but noteworthy impact on the model, with a weight of 0.168. Compared to *LogProperty* and *LogIntangibles*, this variable is less critical for predicting the outcome, but it still contributes to the model.
- *LogCommonStock.* The results for *LogCommonStock* in the regression model indicate that this variable does not have a statistically significant effect on the dependent variable, *LogRevenue*. Specifically, the unstandardized coefficient ($B = 0.004$) is very close to zero, suggesting that changes in common stock are associated with almost no change in revenue. The t-value is 0.165, and the p-value (Sig.) is 0.869, which is far above the conventional significance threshold of 0.05. Therefore, *LogCommonStock* is not a meaningful predictor of revenue in this model. Furthermore, the standardized beta coefficient (0.05) indicates a very weak contribution relative to the other predictors, reinforcing its limited explanatory power in this context.

Table 4. Coefficients

Model		*Unstandardized B*	*Coefficients std. error*	*Standardized coefficients Beta*	*t*	*Sig*
1	Constant	2.547	0.138		18.469	< 0.001
	LogProperty	0.481	0.023	0.650	20.806	< 0.001
	LogIntangibles	0.144	0.021	0.187	6.853	< 0.001
	LogGoodwill	0.151	0.021	0.194	7.336	< 0.001
	LogCommonStock	0.004	0.024	0.05	0.165	0.869

Note: [a] Predictors: (Constant), LogCommonstock, LogGoodwill, LogIntangibles, LogProperty. [b] Dependent variable: LogRevenue.

4.4. Overall interpretation of the results

4.4.1. Model performance

The training and testing errors (0.159 and 0.141, respectively) are relatively close, indicating that the model does not overfit and generalizes well. The fact that the error on the testing set is smaller than the training error is typically a positive sign, suggesting that the model is capable of capturing new observations accurately.

4.4.2. Identification of significant parameters

The variable *LogProperty* is the most significant predictor of the outcome, standing out markedly from the rest. This variable has the greatest influence on the dependent variable. Other variables, such as *LogIntangibles*, *LogGoodwill*, and *LogCommonStock*, have considerably smaller impacts on the dependent variable. Specifically, *LogCommonStock* appears to be the least significant variable for the model.

4.5. Comparison of multiple regression with neural networks

In the case of the neural network, Table 3 provides the following. The analysis revealed intriguing insights into the relative influence of various intangible and tangible factors on the firm's growth. Among them, *LogProperty* stood out with the highest value of 0.603, underscoring the significant role of physical assets in driving the firm's operational stability and scalability. This dominance suggests that property-related investments remain a cornerstone in enabling production efficiency and expansion.

On the intangible front, *LogIntangibles* recorded a value of 0.180, reflecting the growing but comparatively modest influence of non-physical assets such as intellectual property and brand equity. These assets, while less immediately impactful than tangible property, serve as critical drivers of innovation and differentiation in competitive markets.

Closely following was *LogGoodwill*, with a value of 0.168, highlighting the trust and reputation the firm has cultivated. Goodwill's contribution signals the importance of maintaining strong stakeholder relationships and leveraging reputation as a revenue-enhancing tool.

Lastly, *LogCommonStock* came in at 0.050, indicating its relatively minor influence in this context. While common stock represents shareholder equity and potential for future financing, its impact on direct revenue generation appears subdued compared to the other variables.

In conclusion, in multiple regression, *LogIntangibles* and *LogGoodwill* have less influence compared to the neural network, which assigns them higher importance. In the neural network, the variable *LogCommonStock* shows a small yet notable influence, similar to the impact seen in the multiple regression model. Together, these values paint a compelling picture of the interplay between tangible and intangible elements, showcasing how firms balance their asset portfolios to achieve sustained growth and profitability.

4.6. Findings

The performance comparison between multiple regression and neural networks reveals striking differences in predictive accuracy. Starting with the multiple regression model, it demonstrated a root mean square error (RMSE) of 8.449 and a mean absolute error (MAE) of 8.4037. These values indicate that while the model offers a relatively straightforward and interpretable approach to prediction, its accuracy is limited, with errors averaging around eight units from actual values. This suggests potential room for improvement, particularly in capturing complex, non-linear relationships within the data.

In contrast, the neural network model significantly outperformed its regression counterpart, achieving an RMSE of 0.336 and an MAE of 0.2627. These results highlight the neural network's ability to closely approximate true values with minimal deviation, demonstrating its strength in handling intricate patterns and dependencies that the regression model struggled to capture.

The stark reduction in error metrics underscores the neural network's advanced capability as a predictive tool. Its superior performance not only validates its utility for more complex datasets but also suggests that, despite higher computational requirements, neural networks can provide a substantial accuracy advantage when precision is paramount.

4.6.1. Comparison of models

The RMSE for neural networks (0.336) is significantly smaller than that of multiple regression (8.449), indicating that neural networks provide more accurate predictions compared to multiple regression. A lower RMSE signifies that the model's predictions are closer to the actual values; thus, neural networks appear to perform better.

The MAE of neural networks is also substantially lower (0.2627) than that of multiple regression (8.4037). This suggests that, on average, the deviation between the predicted and actual values is smaller for the neural network model. Hence, neural networks not only outperform multiple regression but also exhibit significantly better accuracy in terms of absolute differences.

The stark contrast between the RMSE values for the neural network (0.336) and the multiple regression model (8.449) appears implausibly disparate and likely points to differences in data preparation, model scaling, or evaluation metrics that need closer scrutiny. One possible reason for such a mismatch could be that the neural network model was trained on normalized data, where input and output values were transformed, resulting in smaller numerical values and, consequently, a much lower RMSE. If the multiple regression was evaluated on the original, unscaled data, its RMSE would naturally appear much larger in comparison. This difference in measurement scale can create the illusion that one model vastly outperforms the other when, in fact, they are being assessed under different conditions.

4.6.2. Performance improvement

Neural networks appear to provide much better performance compared to multiple regression, as indicated by significantly lower RMSE and MAE values. The much lower RMSE and MAE values for neural networks imply that this model successfully "learned" the relationships between variables with greater precision.

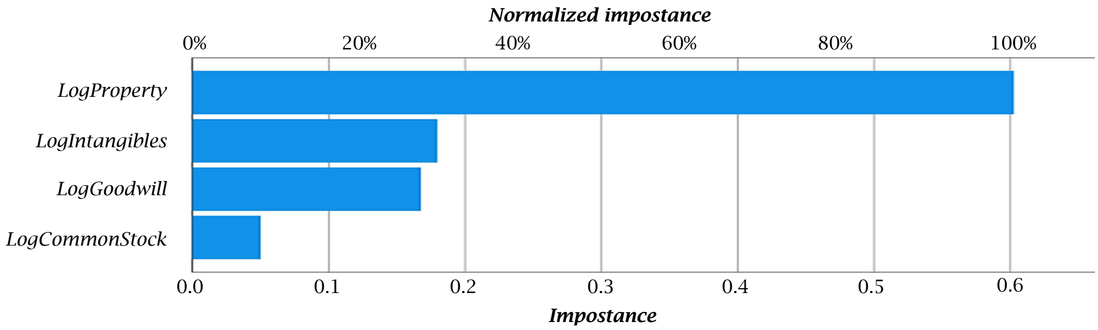
4.6.3. Error interpretation

The RMSE and MAE values for multiple regression are notably higher, indicating larger deviations from the actual values. It is likely that multiple regression is less capable of capturing complex relationships between variables, whereas neural networks, due to their complexity, may perform better in such cases.

4.6.4. Superior performance of neural networks

Neural networks demonstrate a higher capability in reducing prediction errors (Figure 1). This could be attributed to their ability to understand and represent more complex data relationships through their hidden layers. If proper training parameters and an appropriate architecture were employed, this could explain the model's outstanding performance.

Figure 1. Impact on revenue



The significant predictive power of *LogProperty* underscores the centrality of tangible assets, such as PPE, in driving revenue and firm growth. Strategically, this suggests that firms should prioritize investments in these physical resources to ensure operational stability, production efficiency, and scalability. For businesses in asset-intensive industries, such as manufacturing or logistics, this finding reinforces the importance of maintaining modern and efficient infrastructure.

While less impactful than tangible assets, the contributions of *LogIntangibles* and *LogGoodwill* signal that intangible assets remain valuable drivers of innovation, brand strength, and trust. Strategically, firms should focus on cultivating intellectual property, enhancing brand reputation, and nurturing customer relationships. These assets are especially critical in industries like technology, where differentiation and innovation are key to sustaining competitive advantage.

The relatively low influence of *LogCommonStock* implies that shareholder equity, while important for financial structuring, has a limited direct impact on revenue generation. Strategically, this finding suggests that while raising capital through equity is essential, firms should ensure that such funding is effectively channeled into areas with higher revenue-generating potential, such as property or intangible development.

The results highlight the interplay between tangible and intangible resources in driving growth. Strategically, this indicates that firms must balance investments in physical infrastructure with efforts to cultivate intangible assets. Overemphasis on one category may hinder overall growth potential. For instance, while tangible assets enable operational capabilities, intangible assets enhance market positioning and innovation.

5. CONCLUSION

The analysis provides a comprehensive evaluation of the predictive power of multiple regression and neural networks, highlighting their respective strengths and limitations in modeling the relationship between tangible and intangible assets and firm growth.

The multiple regression model demonstrated solid performance, with a relatively low difference between training and testing errors (0.159 and 0.141, respectively). This indicates the model's ability to generalize well without overfitting. The adjusted R-squared of 83.3% further underscores its strong predictive capability, showing that a substantial portion of the variance in revenue can be explained by the independent variables. Among these variables, *LogProperty* emerged as the most significant predictor, with *LogIntangibles*, *LogGoodwill*, and *LogCommonStock* contributing to a lesser extent. While multiple regression is interpretable and reliable, its higher RMSE (8.449) and MAE (8.4037) suggest limitations in capturing more intricate, non-linear relationships.

In contrast, neural networks exhibited superior performance, achieving significantly lower RMSE (0.336) and MAE (0.2627), reflecting their advanced capability to approximate actual values with precision. Neural networks also highlighted the nuanced importance of various variables, with *LogProperty* remaining the dominant factor but *LogIntangibles* and *LogGoodwill* gaining relatively higher importance compared to the regression model. This suggests that neural networks are better suited to uncover subtle patterns and relationships within the data.

The comparative analysis clearly demonstrates that neural networks outperform multiple regression in terms of predictive accuracy. However, the choice between these models depends on the context: while regression offers simplicity and interpretability, neural networks provide unmatched precision and are ideal for handling complex, non-linear datasets.

Ultimately, this study underscores the significant role of both tangible and intangible assets in driving firm growth, with *LogProperty* being the cornerstone variable. The findings also validate the utility of advanced modeling techniques like neural networks for enhancing predictive performance and gaining deeper insights into the interplay of factors influencing business success.

The contributions of *LogIntangibles* and *LogGoodwill* highlight the subjective power of intangible assets as key drivers of a firm's growth, despite their less direct impact compared to tangible resources. These assets — rooted in intellectual property, brand reputation, and stakeholder trust — are crucial for fostering innovation, differentiation, and customer loyalty. Strategically, firms should prioritize the development of these intangible elements to strengthen their market positioning and ensure long-term resilience. Industries heavily reliant on innovation, such as technology and pharmaceuticals, benefit especially from leveraging these assets to maintain a competitive advantage. The low level of influence of intangibles on a firm's revenue can significantly affect its CGUs. This could constrain the capacity of CGUs to consistently generate strong cash flows, as they may lack the value-added benefits of intangibles that enhance profitability. A low influence of intangibles might result in: Lower future cash flow projections: Without significant contributions from intangibles, CGUs may have weaker growth potential. A CGU without a strong intangible influence might struggle to adapt to market changes, impacting long-term cash flow stability. Be more dependent on tangible asset replacement or upgrades, increasing capital expenditure needs, and reducing net cash generation.

The relatively minor influence of *LogCommonStock* reinforces the idea that shareholder equity serves more as a structural financial tool than a direct driver of revenue. Strategically, this suggests that firms should channel equity financing into initiatives that enhance intangible and tangible asset development, with a focus on areas yielding the highest potential returns.

These findings emphasize the intricate interplay between tangible and intangible resources. While tangible assets provide the backbone of operational efficiency, it is the intangible assets that often unlock hidden growth potential, shaping consumer perceptions, fostering innovation, and enhancing value creation. A strategic balance between these two types of resources is essential, as neglecting intangibles could undermine a firm's ability to adapt and thrive in competitive markets.

A low intangible influence might reduce market confidence, affecting equity valuations and borrowing terms. Limit access to funding for CGU expansions or upgrades, constraining their cash generation potential. Low influence of intangibles on revenue often implies a reduced capacity for CGUs to generate strong and sustainable cash flows. This affects both operational efficiency and strategic adaptability, increasing the reliance on tangible assets and heightening financial risks. For businesses, fostering intangible asset development could bolster CGU performance and enhance long-term value creation.

To enhance the practical value of these findings, managers should adopt a more intentional approach to valuing and leveraging intangible assets. Based on the results, firms are encouraged to invest in strengthening brand equity, intellectual property, and innovation capacity, especially in industries where these elements drive competitive advantage, such as technology and pharmaceuticals. Managers should integrate intangible asset development into strategic planning by allocating resources toward research and development (R&D), talent development, and customer relationship management. Additionally, firms should establish internal metrics to regularly evaluate the contribution of intangible assets to CGUs, thereby aligning intangible investment with performance outcomes. Equity financing should be directed toward initiatives that enhance intangible value, not just physical asset expansion. Finally, organizations should foster cross-functional collaboration between finance, marketing, and R&D departments to better capture and communicate the strategic importance of intangible assets in driving long-term growth and resilience.

Regarding the limitations of the study, some of them are the following. The reliance on a cross-sectional dataset, which captures a single point in time and may not reflect the evolving impact of intangible assets on firm growth over time. A longitudinal approach would allow for a better understanding of dynamic relationships and causal inference. Additionally, while neural networks offer high predictive accuracy, their "black-box" nature limits interpretability, making it harder for managers to translate findings into specific strategic actions. The study also focuses on a specific set of industries and financial variables, which may constrain the generalizability of the findings to firms in other sectors or with different intangible asset compositions. Finally, the Z-score outlier removal and logarithmic transformations, while methodologically sound, may mask the influence of extreme but meaningful cases, potentially omitting valuable insights about firms with highly unique intangible profiles. Acknowledging these limitations invites more nuanced interpretation and provides a roadmap for future research.

While this study sheds light on the intricate relationship between intangible assets and firm performance, it also raises compelling questions that warrant further exploration. The journey to understanding the true impact of intangibles is far from complete, and future research can push the boundaries of knowledge in several meaningful ways.

One promising avenue lies in expanding the methodological landscape. While neural networks have proven to be a powerful tool, they are not the only option. Decision trees and gradient boosting models could offer a more interpretable yet highly predictive alternative. These approaches may uncover hidden interactions that traditional regression models or even neural networks overlook, providing a richer, more nuanced understanding of how assets influence firm success.

Beyond methodology, the role of industry dynamics must be explored in greater detail. Intangibles matter differently across sectors — what drives growth in a pharmaceutical giant is vastly different from what fuels success in a tech startup or a manufacturing firm. A sectoral breakdown could reveal whether certain industries derive more competitive advantage from intangible assets than others, allowing for more tailored financial and strategic decision-making.

Another crucial dimension is time. A static snapshot of asset impact is informative, but firm growth is a dynamic process. By incorporating longitudinal analysis, researchers can track how the influence of intangibles evolves over time. Do firms with strong intangible asset bases experience steadier growth during economic downturns? Do investments in goodwill and intellectual property yield long-term returns, or do they fade in significance? Exploring these questions could lead to powerful insights that shape corporate strategy.

Yet, intangibles are not just numbers on a balance sheet — they are deeply intertwined with strategic decision-making. A firm's ability to leverage its intangible assets depends on its leadership, innovation policies, and financial strategy. Are firms that align their intangible investments with clear innovation strategies more likely to succeed? These insights could serve as a blueprint for executives seeking to harness their firm's hidden potential.

Ultimately, the story of intangible assets is still being written. As businesses continue to evolve in an increasingly knowledge-driven economy, future research has the power to unlock deeper insights into the mechanisms that drive sustainable growth. The more we uncover, the more we empower firms, investors, and policymakers to make smarter, data-driven decisions that shape the future of business success.

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APPENDIX

Table A.1. Case processing summary

Sample	Training	324	72.2%
	Testing	125	27.8%
Valid		449	100%
Excluded		21	
Total		470	